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# The influence of risk preferences, knowledge, land consolidation, and landscape diversification on pesticide use

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Data Appendix Available Online: A data appendix to replicate the main results is available in the online version of this article. Please note: Wiley-Blackwell is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the corresponding author for the article.

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**Abstract**
Researchers have spent substantial effort to identify factors influencing pesticide use intensity. However, few studies have compared the relative importance of these factors. This study examines four categories of factors that potentially influence farmers' pesticide use decisions by evaluating incentivized experiment data, farm survey data, and remote sensing data in China. Our results suggest that land diversification has the largest effect on farmers' pesticide use. Compared with the most rice-intensive landscape type, less rice-intensive systems cause farmers to spray less on middle rice. Heavy pesticide use intensity is associated with land fragmentation as small-scale farms still dominate crop production. Farmers' integrated pest management knowledge has significant effects on pesticide use. We also find that loss and ambiguity preferences, rather than risk preferences, are more likely to affect pesticide use intensity.

**KEYWORDS**
China, land consolidation, landscape diversification, loss and ambiguity aversion, pesticide use, risk preference

**JEL CLASSIFICATION**
Q15, Q18, Q53

## 1 | INTRODUCTION

The negative consequences of pesticide use on human health and ecosystem services have raised concerns worldwide. Studies have shown that pesticide exposure causes acute diseases such as muscular pain and skin irritations (Atreya, 2008; Mancini, Van Bruggen, Jiggins, Ambatipudi, & Murphy, 2005; Maumbe & Swinton, 2003; Sheahan et al., 2017) and chronic diseases such as cancer, neurotoxicity, and bronchitis (Alavanja, Hoppin, & Kamel, 2004; Hoppin et al., 2010). Lai (2017) finds that a 10% increase in rice pesticide use in China negatively affects a key medical disability index by 1% for rural residents over 65 years old, which is equivalent to approximately 2.8 million dollars in medical and family care costs. The environmental impacts of excessive pesticide use include the destruction of beneficial natural predators and parasites, pesticide resistance in pests, groundwater and surface water contamination, and wildlife losses (Pimentel, 2005; Pimentel et al., 1992). The environmental costs of using pesticides in the United States were estimated to be $10 billion annually (Pimentel, 2005).

Pesticide overuse is present in many developing countries, although some countries are still using pesticides below an economically efficient level (Ghimire & Woodward, 2013, Zhang, Jiang, & Ou, 2011). Approximately 6 billion pounds of pesticides were applied in 2012 worldwide, with a total expenditure of nearly $56 billion at the producer level (Atwood & Paisley-Jones, 2017). In 2015, China used approximately 1.8 million tons of pesticide (FAO, 2017), which accounted for 24% of the total volume worldwide. The pesticide use per hectare in China is approximately 13 kg, roughly five times higher than the world average (FAO, 2017).

Scholars with various academic backgrounds have been working to reduce pesticide use. Economic studies mostly consider the influence of farmers' risk preference and knowledge on pesticide use (e.g., Gong, Baylis, Kozak, & Bull, 2016, Liu & Huang, 2013). Farmers' risk preferences have played a significant role in agriculture production, especially in pesticide application (Barham, Chavas, Fitz, Salas, & Schechter, 2014; Feder, 1980, Isik & Khanna, 2003; Just & Zilberman, 1983; Ward & Singh, 2016). Farmers' knowledge of integrated pest management (IPM) is another key factor influencing pesticide use (e.g., Feder, Murgai, & Quizon, 2010). The effects of land fragmentation and farm size on farm performance have also been widely studied (Chen, Huffman, & Rozelle, 2011; Fan & Chan-Kang, 2005; van den Berg et al., 2007), but few studies focus on the effects of land consolidation on pesticide use. As land consolidation in China proceeds, there is a need to examine the effects of land consolidation on pesticide use. Ecological theory predicts that simplified agricultural landscapes will increase pest severity because fewer natural enemies and concentrated host plants will further increase pesticide use (Larsen & Noack, 2017). However, the role of the landscape in pesticide applications has not been adequately supported by empirical studies, partially due to the lack of high spatial resolution crop and insecticide data (Larsen & Noack, 2017).

We first examine the role of farmers' preferences in agricultural production, including risk, loss, and ambiguity preferences. Liu and Huang (2013) found that risk-averse farmers tend to use more pesticides to avoid cotton losses, while loss-averse farmers tend to use less pesticides in China. Researchers have also argued that ambiguity aversion is another key factor affecting agricultural production (Alpizar, Carlsson, & Naranjo, 2011; Barham et al., 2014; Takahashi, 2013). Ambiguity aversion is the additional aversion resulting from being unsure about the probabilities of outcomes (Barham et al., 2014). Since farmers usually do not know the distribution of the impacts of pesticide application on crop yield and human health, ambiguity preferences might be more appropriate than risk preferences.

Farmers' knowledge may also influence agricultural production decisions. The influence of farmers' IPM knowledge of pesticide use has mixed results. Godtland, Sadoulet, Janvry, Murgai, and Ortiz (2004) found that increased IPM knowledge has a significant positive impact on the productivity of potato production in a field study. However, Lekei, Ngowi, and London (2014) found that knowledge of the routes of exposure to the pesticide was not associated with safety practices in Tanzania. Chen, Huang, and Qiao (2013) concluded that on the Northern China Plain, improving cotton farmers' awareness and knowledge could potentially reduce pesticide use by 10–15%.

Ecologists have argued that landscape patterns influence pesticides because simplified landscapes often lead to increased pest severity, which leads to higher pesticide demand (Larsen, 2013; Larsen & Noack, 2017; Meehan, Werling, Landis, & Gratton, 2011). Agricultural intensification has caused landscape simplification due to the expansion of agricultural land, enlargement of field size, and removal of noncrop habitat. Declining landscape diversity may affect the functioning of natural pest control because noncrop land provides habitat, food, and shelter for natural enemies. Therefore, increased landscape diversification has the potential to sustain pest control functions (Bianchi, Booij, & Tscharntke, 2006). Despite the underlying theory regarding the influence of landscape on pesticide usage, empirical support is lacking. A recent study by Larsen and Noack (2017) used data on crop production and insecticide use from over 100,000 field-level observations in Kerr County, California. They found that higher crop diversity reduces insecticide use. Dominik et al. (2017) found that regional-scale landscape heterogeneity explains the composition of rice-arthropod communities in the Philippines. Our study provides the first empirical evidence of the effect of landscape diversity on pesticide usage patterns based on remote sensing and ground-truthing data in China.

Our study implemented a large-scale incentivized experiment in China to solicit a wide spectrum of information on farmers' risk preferences and IPM knowledge, land consolidation, and landscape diversification. The comprehensive dataset allows us to examine the relative importance of the different factors in terms of their effects on farmers' pesticide use decisions. Methodologically, our paper contributes to the literature by combining revealed and stated preference data to analyze farmers' pesticide use behaviors. There is a large body of literature that combines the revealed preference with stated preference data, particularly through survey-based studies (e.g., Adamowicz, Louviere, & Williams, 1994; Boxall, Englin, & Adamowicz, 2003; Huang, Haab, & Whitehead, 1997; Mark & Swait, 2004). Results are generally improved when stated and revealed data are jointly used for estimation (Earnhart, 2001; Whitehead, Dumas, Herstine, Hill, & Buerger, 2008). Our study incorporates the experimental data in addition to the revealed and stated preference data and provides a new perspective to investigate farming decisions by collecting a wide source of information. As a result, our method potentially reduces the omitted variable bias when the farming decisions are influenced by individual preferences reflected in the experimental data.

## 2 | EXPERIMENTAL DESIGN AND DATA

### 2.1 | Sampling and survey implementation

Our study was conducted in the northern part of Jiangxi province in 2014. Rice farmers were surveyed in Jiangxi, which is one of the major rice production bases and produces approximately 10% of the rice in China (NBSC, 2015). Double season rice (early rice and late rice), middle rice after oil rapeseed, and middle rice alone are the typical crop patterns. Due to its humid subtropical climate, Jiangxi province suffers from serious pest diseases. In Jiangxi, approximately 9% of the rice area was damaged by disease and pests each year. The corresponding rice losses account for approximately 11% of nationwide losses (NATESC, 2017). The northern part of Jiangxi also has diverse landscapes, including the plain near the Poyang Lake and the surrounding mountainous regions. All of these characteristics make rice growers in Jiangxi province an ideal site for studying pesticide use patterns.

We selected 20 experimental sites with different landscape diversity using the following procedures. Each site is located in a different village. First, we identified the 3-hr drive area around Jiangxi Agricultural University (JAU) for site selection to ensure that live specimens could be transported between the study sites and JAU by our ecologist collaborators. Second, we randomly pinned 120 cultivated land plots on the map and calculated the landscape percentages within a 2-km radius using a geographical dataset of remote sensing images. Each site covered a circle centered at the selected cultivated plot with a 2-km radius. Third, we selected 40 sites by excluding those that did not meet our requirements, including plots that were not accessible by road. A group of ecologists and economists checked the 40 sites in the field to ensure that the selected ones would not be threatened by urbanization and to also ensure that rice and rapeseed oil were the typical crops. Finally, we narrowed down 20 sites in 20 villages based on the field check. The study area is shown in Figure 1.

For each site, we randomly selected 16 middle rice plots and interviewed 16 farmers who managed the plots at the time of the survey. We first randomly selected 30 plots from the map and then checked with the farmers in fieldwork. We ensured that the 16 selected plots were planted with middle rice over our survey season, and each plot was operated by a different farmer. The farmers were interviewed face-to-face for the experiment and the survey. We conducted economic experiments to elicit the farmers' behavioral preferences and used the survey to determine their IPM knowledge. We also asked the farmers to record information on their pesticide usages, including the date, the amount and the cost of the application as well as who applied the pesticide. We then recorded the information on pesticide use reported by the farmers as well as their basic socioeconomic information.

A group of graduate students in agricultural economics were selected as interviewers. Another group of eight graduate students from agronomy were selected for ground-truthing the landscape data. The interviewers were trained on how to implement the economic experiments and familiarized with the standardized approach used to test farmers' IPM knowledge. The interviewers also conducted two or three practice interviews with real farmers as a pretest to ensure the interview quality before the actual interviews. To avoid the interviewer effect, the students were randomly assigned to different farmers. Four subgroups with two students each worked on ground-truthing. Each subgroup took one day to finish one-quarter of the whole circle and made corrections on the paper maps if they found the crops in the field were not the same as those shown on the map.

In total, 320 respondents in 20 villages/sites completed the survey. However, 19 respondents did not complete the entire experiment, resulting in a final sample size of 301 (or 94.06% of the original sample size). We compared the individual characteristics of the excluded respondents and the respondents who completed the entire experiment sequence. Due to the small percentage of incomplete surveys, we did not find significant differences in the observed individual characteristics, which alleviated concerns that the exclusion based on the failure to fully complete (or understand) the experiment was nonrandom.

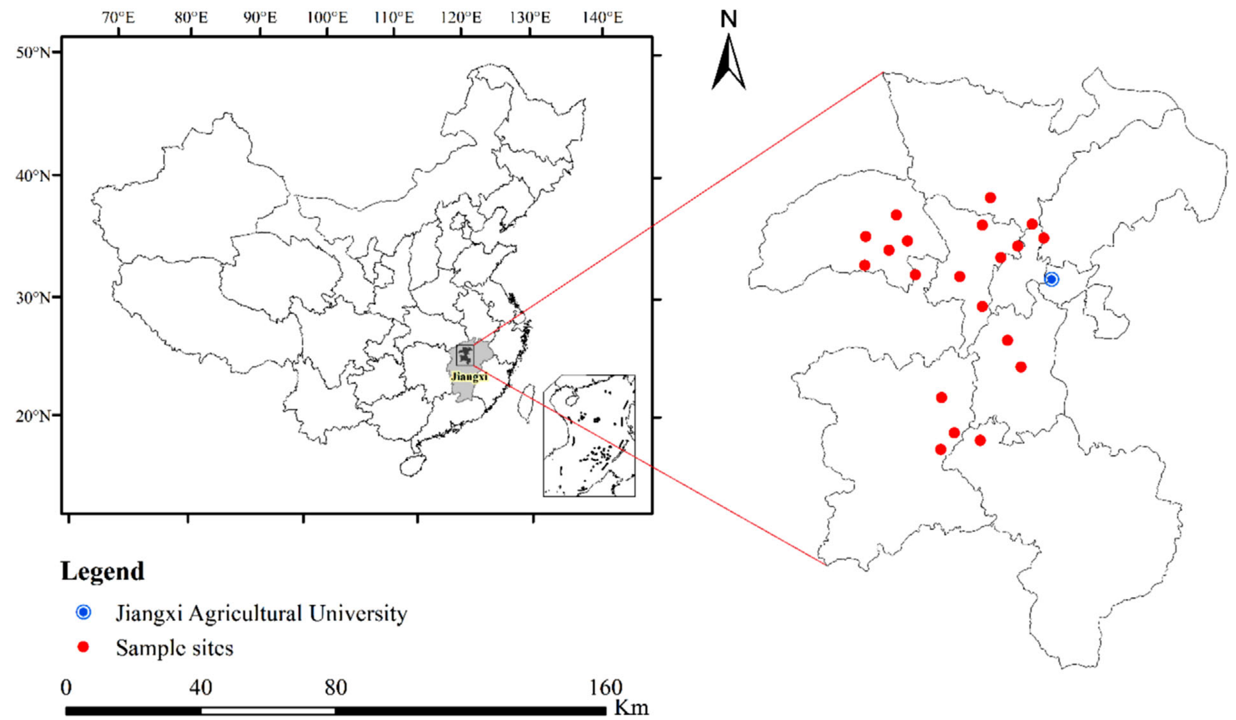


**FIGURE 1** Study area [Color figure can be viewed at wileyonlinelibrary.com]
*Notes*: This figure shows the sampling locations for our survey and experiment. The blue dot represents the location of Jiangxi Agricultural University (JAU). The red dots represent the set of selected sites within a 3-hr drive of JAU. The site selection was based on a number of criteria including landscape patterns, accessibility to the road, and ground-truthing outcomes.

## 2.2 | Risk, loss, and ambiguity preferences

We conducted a set of individual risk, loss, and ambiguity preference experiments under the framework of cumulative prospect theory. The experimental design is based on Liu and Huang (2013), Tanaka, Camerer, and Quang (2010), and Liu (2013). Subjects were first presented with a standardized introduction on how to conduct the experiment. For the illiterate farmers, the interviewers read the instructions for them. Before formal experiments, subjects practiced one sample choice to make sure that they understand the experiment procedures and decisions. Farmers were asked to choose either Option A or Option B for each question. They were presented 35 questions separated into three series for risk and loss preferences (Tables A1–A3 in Appendix 1 in the Supporting Information) and 22 questions into two series for ambiguity preference (Table A4 in Appendix 1 in the Supporting Information). Farmers were told that they only can switch once from Option A to Option B. In the experiment, farmers were incentivized and paid according to the lottery outcomes. The average compensation for the experiments was designed to match the farmers' daily wage, which is approximately 80 yuan per person per day. Tables A1 and A2 present the two payoff matrices used in the experiment to estimate risk preferences. Table A3 presents the payoff matrix to estimate loss preference. The final payment was based on the choices made in a series of experiments to provide economic incentives for the farmers to truthfully reveal their preferences. The survey lasted approximately 2 hr. The details of the experiment are included in Appendix 2 in the Supporting Information.

## 2.3 | Risk and loss preferences

Our utility function follows Tanaka et al. (2010) and enables the joint estimation of risk aversion, loss aversion, and nonlinear probability weighting. We used a utility function in the form of

$$U(x,y,p,q) = \left\{ \begin{array}{c} v(y) + \pi(p)(v(x) - v(y)) \text{ if } x > y > 0 \text{ or } x < y < 0 \\ \pi(p)v(x) + \pi(q)v(y) \text{ if } x < 0 < y, \end{array} \right)$$

where the value function

$$v(x) = \left\{ \begin{array}{c} x^{\sigma} \text{ if } x > 0 \\ -\lambda(-x)^{\sigma} \text{ if } x < 0 \end{array} \right)$$

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and the probability weighting function

$$\pi\ (p) = \frac{1}{\exp\left(\ln\left(\frac{1}{p}\right)\right)^{\alpha}}.$$

In the above equations, parameters $p$ and $q$ are the probabilities associated with outcomes $x$ and $y$, respectively. Parameters $\sigma$ and $\lambda$ denote the concavity of the value function $v(\cdot)$ and the degree of loss aversion, respectively. $U(\cdot)$ denotes the individual utility function. The model reduces to an expected utility model when $\alpha = \lambda = 1$. We use $\sigma$ as the parameter for the curvature of the value function, and $\alpha$ indicates the probability sensitivity parameter in Prelec's weighting function (Prelec, 1998). When $\alpha < 1$, the weighting function $\pi(\cdot)$ is inverted S-shaped and is consistent with prospect theory (Tversky & Kahneman, 1992), where individuals overweight small probabilities and underweight large probabilities. Similarly, when $\alpha > 1$, individuals underweight small probabilities and overweight large probabilities. A higher $\sigma$ ($\lambda$) implies greater risk (loss) aversion.

The payoff matrix shown in Tables A1 and A2 was carefully designed so that the set of parameters cover a wide spectrum of individual preferences under the cumulative prospect theory framework. The Option A columns are always riskless, while the Option B columns resemble simple lotteries. The respondents were asked at which point they were willing to switch to the other option. Following Liu and Huang (2013), Tanaka et al. (2010), and Liu (2013), we imposed the monotonic preference restriction where the respondents were only able to switch their preferences from the riskless option to the lottery option once. The individual switching points were used to place a boundary on the preference parameters based on the utility specification. For example, if a respondent switched preference at Question 6 in Table A1 and switched preferences at Question 7 in Table A2, a set of inequalities can be used to specify the boundaries of the range of $\sigma$ and $\alpha$. Specifically, we have

$$\begin{cases} 5^{\sigma} > 2.5^{\sigma} + \frac{20.5^{\sigma}-2.5^{\sigma}}{\exp\left(\ln\left(\frac{1}{0.1}\right)\right)^{\alpha}} \\ 5^{\sigma} < 2.5^{\sigma} + \frac{23.5^{\sigma}-2.5^{\sigma}}{\exp\left(\ln\left(\frac{1}{0.1}\right)\right)^{\alpha}} \\ 20^{\sigma} > 2.5^{\sigma} + \frac{34.5^{\sigma}-2.5^{\sigma}}{\exp\left(\ln\left(\frac{1}{0.7}\right)\right)^{\alpha}} \\ 20^{\sigma} < 2.5^{\sigma} + \frac{36.5^{\sigma}-2.5^{\sigma}}{\exp\left(\ln\left(\frac{1}{0.7}\right)\right)^{\alpha}} \end{cases}.$$

Consistent with the literature, we chose the midpoints in the value ranges and assigned the median values to individual respondents. The detailed calculations can be found in Tanaka et al. (2010). We also include the corresponding $\sigma$ and $\alpha$ values for each switching point in Tables A5 and A6 in Appendix 1 in the Supporting Information. In our case, a pair of switching points (6, 7) implies that $(\sigma, \alpha) = (0.7,\ 0.7)$. The parameters chosen in these tables are based on a scaled version proposed in Ward and Singh (2016). Following Tanaka et al. (2010), if an individual chose not to switch, approximate values near the boundary were used as the preference parameters.

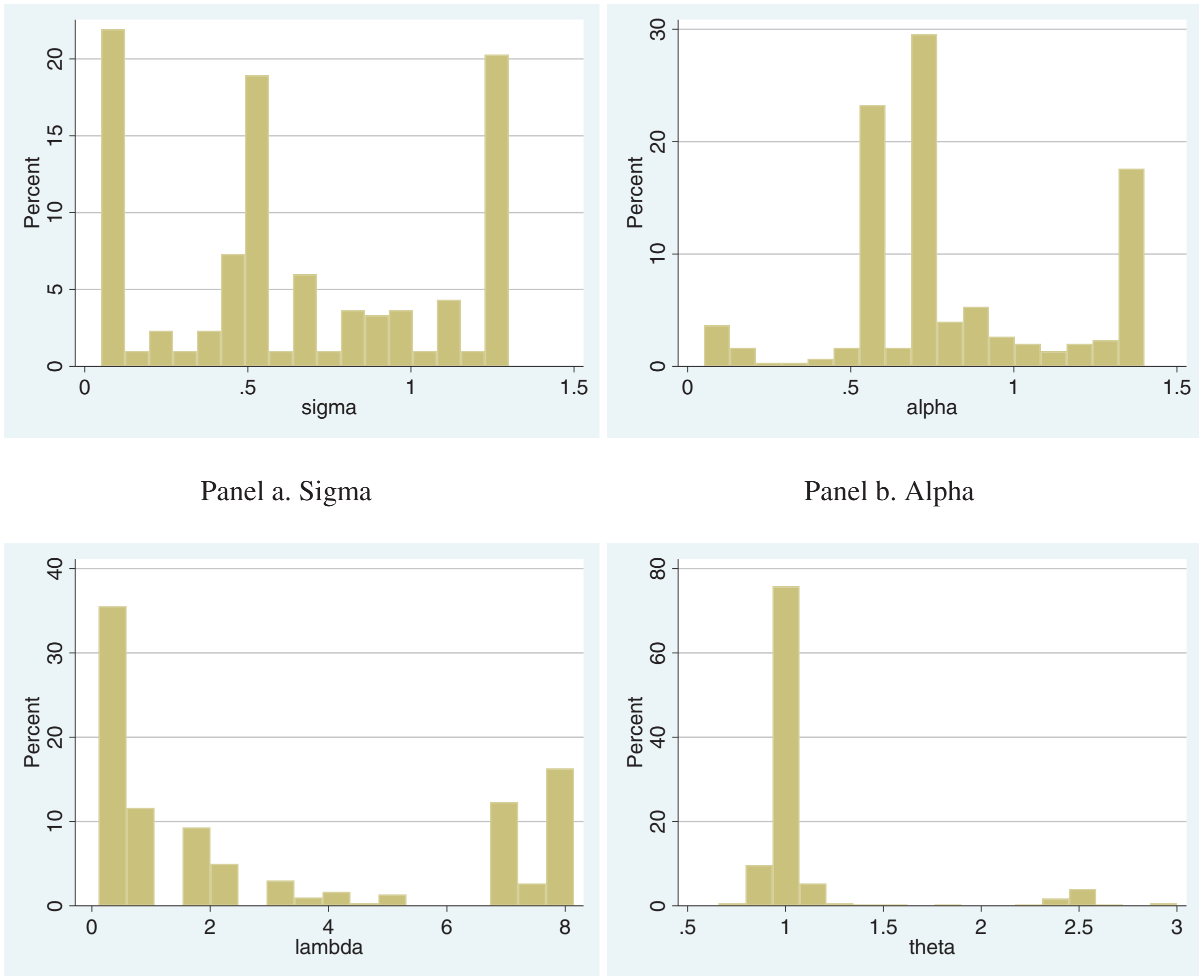
After identifying $\sigma$ and $\alpha$, Table A3 was used to estimate the loss aversion parameter $\lambda$. When the individual switched her choice from Option A to Option B, a range of $\lambda$ could be identified for each switching point depending on the value of $\sigma$. In, Table A7 in Appendix 1 in the Supporting Information, we show the threshold value of $\lambda$ under different $\sigma$s associated with each question. Based on Table A7, if the individual switched at Question 4 when $\sigma = 0.5$, then $1.73 < \lambda < 2.24$. We also used the middle value of $\lambda$ to approximate individual loss aversion preferences. The distributions of the parameters are shown in Panel c, Figure 2.

Previous research has found that respondents may bounce back and forth if multiple row switching is allowed, and the distribution of preferences may not be distinguishable from one where respondents are making choices at random (e.g., Reynaud & Couture, 2012). However, switching more than once is inconsistent with a well-defined utility function. To check the consistency of our results with the literature, we compare our results with similar studies. In our study, the means of $\sigma$ and $\alpha$ are 0.64 and 0.82 and the variances are 0.45 and 0.34, respectively. Our $\sigma$ and $\alpha$ are slightly higher than the 0.59 and 0.74 estimated in Tanaka et al. (2010) and the 0.48 and 0.69 estimated in Liu (2013). The mean and variance for the loss aversion in our sample are 3.11 and 4.20, respectively. Our estimate of $\lambda$ is slightly higher than the 2.63 estimate in Tanaka et al. (2010) and the 2.25 estimate in Tversky and Kahneman (1992), while it is slightly lower than the 3.47 estimate in Liu (2013), which is also based on a sample of Chinese farmers. The distribution of the estimated parameters are shown in Panels a and b, Figure 2.[1]

### 2.3.1 | Ambiguity preference

Ambiguity preference, also known as uncertainty aversion, is defined as the preference for known risks or uncertainty over unknown risks or uncertainty. The ambiguity preference plays an important role in individual

[1] In addition, we conducted a simulation exercise where we simulated the distribution of $\sigma$ and $\alpha$ as if the respondents were making random choices. We derived the mean and variance of $\sigma$ and $\alpha$ based on 10,000 bootstrap samples and found that the simulated outcomes were significantly different from our experimental outcomes at the 0.01 significance level.



Panel a. Sigma

Panel b. Alpha

Panel c. Lamda

Panel d. Theta

**FIGURE 2** Distribution of parameters for risk, loss and ambiguity preferences [Color figure can be viewed at wileyonlinelibrary.com]
*Notes*: The sigma and alpha are the risk preference measures, lambda is the loss aversion measure, and the theta is the ambiguity aversion measure.

decision making (Ellsberg, 1961; Hogarth & Kunreuther, 1989; Machina, 2009) and is distinct from risk preference when the probability of uncertainty is known. However, few studies use ambiguity measures to analyze farmers' production behaviors. In our case, the exact consequences of pesticide (over)use are unknown to the farmers. Due to the uncertain condition, ambiguity measure is more appropriate than risk measure. Compared to the risk preference, the measure of ambiguity preference is relatively new and there is no widely established procedure to measure or parameterize the ambiguity preference. There are several distinct measures of ambiguity used in the literature, including Klibanoff, Marinacci, and Mukerji (2005), where a function was used to capture ambiguity aversion, and Engle-Warnick, Escobal, and Laszlo (2007), where a positive willingness to pay was estimated to avoid ambiguity. We follow Ward and Singh (2016) based on a similarity in the research background, where ambiguity aversion was specified as the ratio of two log utilities and use a modified multiple price listing approach to elicit the ambiguity aversion measure.

Specifically, according to Ward and Singh (2016), ambiguity aversion is estimated through a sequence of two experiments. In the first experiment (S1), the subject is asked to choose between a risky option (Option A in Table A4) and a riskless option (Option B) with the probability of win and loss not specified. We assume the lottery for win and loss at the switching point in the first experiment are $x_1$ and $y_1$, respectively, and the riskless option is $x_0$. Therefore, we have $U\ (x_0) = [U(x_1,\ y_1, \tilde{p}, \tilde{q})]^{\theta}$ at the switching point, where $\tilde{p}$ and $\tilde{q}$ are the subjective probabilities associated with the win and loss in the lottery, respectively. The parameter $\theta$ denotes the ambiguity aversion parameter. In the second experiment (S2), the subject is asked to choose between a risky option and a riskless option with the probability of win and loss specified. We further assume the lottery for win and loss at the switching point in the second experiment are $x_2$ and $y_{2,}$ while the riskless option is $x_0$. We have $U\,(x_0) = U(x_2, y_2, p, q)$ at the switching point, which further implies $U\,(x_2, y_2, p, q) = [U(x_1, y_1, \tilde{p}, \tilde{q})]^{\theta}$. Therefore, we have

$$\theta = \frac{\ln\left(U\left(x_2, y_2, p, q\right)\right)}{\ln\left(U\left(x_1, y_1, \tilde{p}, \tilde{q}\right)\right)},$$

where $p$ and $q$ are objective probabilities.[2] Data on subjective probability are obtained by directly asking the respondents. Our results show that when the number of balls is assumed to be equal (when we use (0.5, 0.5) to substitute for $\tilde{p}$ and $\tilde{q}$), the ambiguity measure has a mean of 1.0990 and a variance of 0.391. When the number of balls is imputed using respondents' subjective statements, the subjective ambiguity measure has a mean of 1.0987 and a variance of 0.394, which is close to those under the assumption of an equal number of balls. The distribution of $\theta$ is shown in Panel d, Figure 2. We further find that these two measures have a correlation of 0.993. Therefore, we use only the subjective loss aversion measure (probability imputed by the subjective statement) in the regression analysis.[3] We find that there is substantial variation in the estimated parameter though we cannot reject the hypothesis where the mean of ambiguity parameter $\theta$ equals 1.

## 2.4 | Survey data

We invited the farmers to record the details of their pesticide uses for the whole crop season, that is, when they sprayed, who sprayed, how much pesticide they used, and how much money was spent on buying pesticides for the selected plot. The data show that on average farmers spray 3.3 times during middle rice crop season with a minimum of 0 and a maximum of 7. The average pesticide cost is about 840 yuan per ha with a minimum of zero yuan and a maximum of 1,800 yuan. The two variables have a positive and statistically significant pairwise correlation coefficient. Figure A1 in Appendix 1 in the Supporting Information shows that pesticide expenditure for each spraying time varies within a farm. We also asked farmers why they spray each pesticide. About half sprays are preventive. Over a quarter sprays happen because farmers saw a few pests. Only 10% sprays happen because farmers noticed many pests.

We tested farmers' IPM knowledge using subjective questions during face-to-face interviews following Chen et al. (2013). Three key questions were used to test the farmers' knowledge from three perspectives that is, knowledge of biocontrol, trust in suggested pesticide dosage on package instruction, and negative impacts of pesticides on the environment. Specifically, the first question asks whether the interviewee knew that spiders are predators in rice. The second question collects what the interviewee thought of the suggested amount of pesticide use on the package instructions. The third one asks whether the farmers believed that pesticides can pollute underground/surface water. Question 1 reflects the farmers' knowledge of biocontrol by the predator-pest relationships in rice fields. Question 2 reflects the farmers' knowledge of the scientifically suggested dosage. Question 3 reflects the farmers' concerns regarding environmental pollution generated by pesticide use. Our data show that about one-third of farmers knew that spiders are predators in rice. About 43% of farmers agreed the suggested amount of pesticide use on the package instruction, while nearly 40% thought the suggested dosage is insufficient. Over 60% of farmers had the correct knowledge of environmental pollution from pesticide use.

Land consolidation is indicated by the size of the selected plot. We also collected a large set of information on individual characteristics, including gender, age, education of the person who sprays, and the wealth level of the farm. We use the total value of durable goods and the value of the farmer's house to approximate the level of wealth (Liu, 2013). Durable goods include common household items that cost more than 500 yuan. The data show that the selected plot is small with an average size of 1.3 mu (0.09 ha). Most pesticide spray tasks are done by the male (87%). The average age of the person who sprays is 54 and the average education is 6 years. The average wealth level is about 274 thousand yuan.

## 2.5 | Landscape data

Remote sensing digital images with landscape information were first obtained from the Data Center of the Chinese Academy of Sciences. Ground-truthing was conducted by graduate students to cross-check the landscape data of the 20 sites with the remote picture information. Forty-six

[2] Note that our ambiguity preference is measured as the ratio of two log utilities instead of embedded directly in the utility function as the risk preference parameters. We acknowledge it is not a perfect measure. However, we think this is the most appropriate one to use based on the current state of the literature and our research background.

[3] The correlation analysis of the parameters for risk, loss, and ambiguity preferences shows that only two correlation coefficients are statistically significant (Table A8 in Appendix 1 in the Supporting Information). The parameters $\sigma$ and $\lambda$ are significantly negatively correlated with a correlation coefficient of −0.386. There is a significantly positive correlation between $\alpha$ and $\theta$ with a correlation coefficient of 0.387.

categories of land use were specified and then classified into seven major categories for our analysis: early-late rice, middle rice, other cultivated land, forest, grassland, water, and built-up land. The landscape data were categorized into two scale levels. The first level is all the plots within each site sharing the same landscape data within a circle, with 2,000 m as the radius. The other level is the landscape data of each plot within a smaller circle, with 500 m as the radius. For the 2,000-m radius circles, approximately 40% of the land in the survey area was covered by forest, and approximately 32% of the land in the area was covered by early and middle rice. Grassland accounted for approximately 8%. Among the seven categories, water had the lowest coverage and represented approximately 2.6% of the total area. For the 500-m radius circles, early-late rice and middle rice accounted for approximately 15% and 33%, respectively. Approximately 22% was covered by forest.

The summary statistics of the key variables are presented in Table 1. We classify the risk parameters into three categories, extremely risk averse ($\sigma \leq 0.2$, $n = 84$), moderately risk averse ($0.2 < \sigma \leq 1$, $n = 119$), and risk seeking ($\sigma > 1$, $n = 88$). We then compared variables across different risk categories using the moderate risk averse categories as the baseline. The results are presented in Table A9 in Appendix 1 in the Supporting Information. We find that the extremely risk-averse farmers also tend to be more loss averse and significantly poorer compared to the moderately risk averse category, consistent with findings in Ward and Singh (2016). We also find that the farmer's knowledge is correlated with risk preference. We do not find strong correlations between the risk preference and pesticide use measures. Note that we only compare the variables related to farmers' behavior or characteristics and exclude variables such as landscape and plot size.

## 3 | ECONOMETRIC MODEL AND EMPIRICAL RESULTS

In this section, we describe our econometric models and present empirical results. We also compare the relative influence of each variable and variable category on farmers' decisions regarding pesticide use for rice production.

### 3.1 | The regression model

To estimate the impacts of multiple factors on pesticide use, we set up the following model:

$$PI_{ij} = \alpha_0 + \alpha_1 Preference_{ij} + \alpha_2 Know_{ij} + \alpha_3 LS_{ij} + \alpha_4 LC_{ij} + \varepsilon_{ij},$$

where $i$ and $j$ index farmer and village, respectively. The variable $PI$ represents pesticide use intensity. In our case we use three measures for pesticide use intensity, that is, the log form of pesticide expenditures per hectare, log form of pesticide amount per hectare, and number of sprays to indicate pesticide use. We also include four broad categories of explanatory variables, as shown in Table 1. The first set of variables *Preference* includes the risk preference ($\sigma$ and $\alpha$), loss aversion ($\lambda$), and ambiguity aversion ($\theta$) measures. The regression results presented here are based on the subjective loss aversion measure. We have tried using the experimental measurements and find our regression results are almost identical due to a high correlation between experimental measure and the subjective loss aversion measure. We run the models with all the four variables altogether as explanatory variables (columns (1) and (5) in Table 2) as well as with the variables included separately (Columns (2–4) and (6–8) in Table 2).

The second set of variables *Know* represents the farmers' IPM knowledge. A dummy variable is used to indicate whether the interviewee knew that spiders are a major predator in the rice field, with 1 indicating yes and 0 indicating no. A set of dummy variables are used to measure the interviewees' opinions of the suggested amount of pesticide use on the package instructions, with "correct" as the baseline, and "the suggested amount is less," "the suggested amount is more," and "unknown" used for comparison. Another dummy variable is used to represent the interviewee's opinion of whether pesticides can pollute ground or surface water, with 1 indicating yes and 0 indicating no.

The third set of variables *LS* includes landscape variables to reflect landscape diversification. We use the percentage of early-late rice rotations as the baseline. To test the scale effects, we use landscape data on an area with a radius of 2,000 m and an area with a radius of 500 m. The fourth set of variable *LC* is the size of the selected plot to indicate land consolidation. We also control for the characteristics of the farmers and farms. A linear model is used when the dependent variable is the log form of pesticide expenditures per hectare, and a generalized Poisson model is used when the dependent variable is the number of sprays. The standard errors are clustered at the village level.

### 3.2 | Main results

For the alternative models using different landscape scales, we find that all coefficients are similar in the 2,000 m and 500 m models except the landscape effects. We, therefore, report the results for the 2,000 m scale model in Table 2 and the 500 m scale model in Table A10 in Appendix 1 in the Supporting Information. The results for pesticide amount,

**TABLE 1** Summary statistics of the key variables

| Variable | Mean | *SD* | Min. | Max. |
|---|---|---|---|---|
| Dependent variables | | | | |
| Number of pesticide sprays | 3.31 | 1.16 | 0 | 7 |
| Pesticide cost (yuan/ha) | 841.20 | 409.54 | 0 | 1,800 |
| Log form of pesticide cost | 6.55 | 0.80 | 0 | 7.50 |
| Independent variables | | | | |
| Behavioral preferences | | | | |
| Sigma | 0.64 | 0.45 | 0.05 | 1.3 |
| Alpha | 0.82 | 0.35 | 0.05 | 1.4 |
| Lambda | 3.12 | 3.20 | 0.12 | 8.15 |
| Theta | 1.10 | 0.39 | 0.66 | 3 |
| Farmers' knowledge | | | | |
| Whether the interviewee knows that spiders are a major predator of hoppers (1 = yes, 0 = no) | 0.34 | 0.47 | 0 | 1 |
| What the interviewees think of the suggested amount of pesticide use on the package instructions | | | | |
| Percentage of "correct" | 0.43 | 0.50 | 0 | 1 |
| Percentage of "the suggested is less" | 0.39 | 0.49 | 0 | 1 |
| Percentage of "the suggested is more" | 0.05 | 0.22 | 0 | 1 |
| Percentage of no idea | 0.13 | 0.34 | 0 | 1 |
| Do you think that pesticide can pollute underground/surface water (1 = yes, 0 = no) | 0.64 | 0.48 | 0 | 1 |
| Landscape (radius = 2,000 m) | | | | |
| Percentage of early rice | 9.48 | 9.84 | .01 | 30.58 |
| Percentage of middle rice | 22.94 | 9.54 | 7.71 | 40.37 |
| Percentage of other cultivated land | 9.08 | 9.10 | .58 | 33.59 |
| Percentage of forest | 39.34 | 23.16 | 10.41 | 77.41 |
| Percentage of grassland | 8.12 | 6.18 | 1.99 | 24.66 |
| Percentage of water | 2.61 | 1.19 | .85 | 4.62 |
| Percentage of built-up areas | 8.41 | 4.68 | 2.68 | 18.69 |
| Landscape (radius = 500 m) | | | | |
| Percentage of early rice | 14.45 | 16.64 | 0 | 62.29 |
| Percentage of middle rice | 32.55 | 15.91 | 0 | 78.78 |
| Percentage of other cultivated land | 8.71 | 10.09 | 0 | 60.06 |
| Percentage of forest | 21.84 | 19.49 | 0 | 97.24 |
| Percentage of grassland | 8.14 | 7.98 | 0 | 42.86 |
| Percentage of water | 3.14 | 4.46 | 0 | 49.93 |
| Percentage of built-up areas | 11.18 | 7.04 | 0.11 | 39.31 |
| Land consolidation | | | | |
| Plot size of the selected plot (mu) | 1.3 | 0.72 | 0.2 | 5 |
| Control variables | | | | |
| Gender of the person who sprays (1 = male; 0 = female) | 0.87 | 0.34 | 0 | 1 |
| Age of the person who sprays | 54.11 | 9.82 | 18 | 81 |
| Education of the person who sprays | 6.15 | 3.14 | 0 | 15 |
| Log form of the level of wealth (1,000 yuan) | 5.28 | 0.86 | 2.484 | 7.766 |

**TABLE 2** Regression results of the factors influencing pesticide use (landscape scale = 2,000 m)

| | Pesticide cost model | | | | Spray frequency model | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Risk, loss and ambiguity preferences | | | | | | | | |
| Risk aversion (sigma) | 0.0782 | 0.1333 | | | −0.0102 | 0.0368 | | |
| | (0.52) | (1.12) | | | (−0.22) | (0.87) | | |
| Probability weighting (alpha) | −0.0382 | 0.0584 | | | −0.0258 | −0.0252 | | |
| | (−0.30) | (0.51) | | | (−0.40) | (−0.40) | | |
| Loss aversion (lambda) | −0.0250 | | −0.0270* | | −0.0190*** | | −0.0185*** | |
| | (−1.62) | | (−2.35) | | (−3.49) | | (−3.77) | |
| Ambiguity measure (theta2) | 0.2011* | | | 0.1602* | −0.0188 | | | −0.0343 |
| | (2.38) | | | (2.57) | (−0.39) | | | (−0.83) |
| Farmers' integrated pest management (IPM) knowledge | | | | | | | | |
| Whether the interviewee knows that spiders are as major predator of hoppers (1 = yes, 0 = no) | −0.1299 | −0.1353 | −0.1477 | −0.1364 | −0.1122* | −0.1032* | −0.1108* | −0.1077* |
| | (−1.34) | (−1.33) | (−1.56) | (−1.38) | (−2.47) | (−2.14) | (−2.39) | (−2.18) |
| What the interviews thinks of the suggested amount of pesticide use on the package instructions (baseline = correct) | | | | | | | | |
| 1 = the suggested one is less, 0 = others | 0.1157 | 0.1370 | 0.1162 | 0.1493+ | 0.1165** | 0.1245** | 0.1183** | 0.1281** |
| | (1.51) | (1.65) | (1.42) | (1.95) | (3.05) | (3.07) | (2.96) | (3.06) |
| 1 = The suggested one is more, 0 = others | 0.1949 | 0.2531+ | 0.2480+ | 0.2390 | 0.0268 | 0.0310 | 0.0188 | 0.0402 |
| | (1.45) | (1.90) | (1.94) | (1.70) | (0.41) | (0.44) | (0.29) | (0.57) |
| 1 = Do not know, 0 = others | −0.1972 | −0.2138 | −0.1995 | −0.1947 | −0.0755 | −0.1008+ | −0.0766 | −0.0988+ |
| | (−0.81) | (−0.91) | (−0.86) | (−0.82) | (−1.31) | (−1.90) | (−1.34) | (−1.89) |
| Do you think that pesticides can pollute underground/surface water (1 = yes, 0 = no) | −0.2160+ | −0.2120+ | −0.1997+ | −0.2092+ | −0.0096 | −0.0127 | −0.0137 | −0.0081 |
| | (−1.82) | (−1.75) | (−1.88) | (−1.83) | (−0.21) | (−0.25) | (−0.31) | (−0.17) |
| Landscape (radius = 2,000 m) | | | | | | | | |
| Percentage of middle rice | −0.0141* | −0.0109 | −0.0113+ | −0.0119+ | −0.0034 | −0.0025 | −0.0038 | −0.0020 |
| | (−2.27) | (−1.62) | (−2.07) | (−1.87) | (−1.09) | (−0.70) | (−1.23) | (−0.54) |
| Percentage of other cultivated land | −0.0259** | −0.0246** | −0.0235** | −0.0233** | −0.0086+ | −0.0081 | −0.0090* | −0.0074 |
| | (−3.32) | (−3.12) | (−3.52) | (−3.23) | (−1.93) | (−1.63) | (−2.05) | (−1.53) |
| Percentage of forest | −0.0096* | −0.0088+ | −0.0080* | −0.0081+ | −0.0036 | −0.0034 | −0.0038 | −0.0029 |
| | (−2.11) | (−1.99) | (−2.13) | (−2.05) | (−1.41) | (−1.22) | (−1.51) | (−1.05) |

(Continues)

TABLE 2 (Continued)

| | Pesticide cost model | | | | Spray frequency model | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Percentage of grassland | −0.0344* | −0.0332* | −0.0328* | −0.0320* | −0.0151*** | −0.0152** | −0.0151*** | −0.0143** |
| | (−2.83) | (−2.46) | (−2.82) | (−2.47) | (−3.50) | (−3.11) | (−3.45) | (−3.00) |
| Percentage of water | 0.0304 | 0.0208 | 0.0347 | 0.0351 | 0.0343* | 0.0307+ | 0.0325* | 0.0318* |
| | (0.68) | (0.44) | (0.83) | (0.73) | (2.24) | (1.74) | (2.18) | (1.90) |
| Percentage of built-up areas | −0.0052 | −0.0058 | −0.0050 | −0.0038 | −0.0224*** | −0.0222*** | −0.0223*** | −0.0215*** |
| | (−0.48) | (−0.50) | (−0.48) | (−0.34) | (−3.89) | (−3.42) | (−3.73) | (−3.24) |
| Land consolidation | | | | | | | | |
| Plot size of the selected plot | −0.2123*** | −0.2118*** | −0.2140*** | −0.2168*** | 0.0316 | 0.0275 | 0.0307 | 0.0270 |
| | (−4.91) | (−5.16) | (−5.04) | (−5.19) | (1.14) | (1.00) | (1.12) | (1.00) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Constant | 8.6085*** | 8.4567*** | 8.6635*** | 8.3141*** | 1.9266*** | 1.7318*** | 1.9045*** | 1.7166*** |
| | (11.97) | (11.10) | (12.98) | (11.03) | (5.41) | (4.52) | (5.27) | (4.59) |
| Observations | 301 | 301 | 301 | 301 | 301 | 301 | 301 | 301 |
| Pseudo $R^2$ | 0.1406 | 0.1265 | 0.1316 | 0.1265 | 0.0440 | 0.0347 | 0.0434 | 0.0341 |

*Notes*: Landscape scale is 2,000 m. *Z*-statistics are in parentheses. Standard errors are clustered by village.

$^{+}p < .1$,

$^{*}p < .05$,

$^{**}p < .01$,

$^{***}p < .001$.

quite similar to those for pesticide cost, are reported in Table A11 in Appendix 1 in the Supporting Information.

Our results show that loss aversion and ambiguity preferences are associated with pesticide use, while risk-aversion preferences, which are commonly used in studies, have no significant effects on pesticide use in terms of pesticide expenditures and spray frequency. Specifically, we find that loss aversion ($\lambda$) negatively affects both pesticide expenditures and spray frequency, although ambiguity aversion ($\theta$) significantly affects only pesticide expenditures. Risk preferences ($\sigma$ and $\alpha$) have no significant effects on both pesticide expenditures and spray frequency.

The negative coefficient of loss aversion (column (3) Table 2) indicates that if a farmer is more loss averse than the average farmer, she will spend less on pesticide use and reduce the frequency of pesticide application. One explanation for the negative coefficient of the loss aversion measure is that a loss-averse farmer is more concerned about the negative health effect of the family member who sprays instead of the negative health impact on consumers, which is supported by both the theoretical model and the empirical results in Liu and Huang (2013). Another potential explanation is that a more loss-averse farmer reduces pesticide use to avoid the financial losses incurred by purchasing pesticides. Interestingly, the coefficient of the ambiguity measure indicates that when a farmer is more ambiguity averse, she will spend more money on pesticide use but will not increase spray frequency. Farmers may view crop loss as more ambiguous and health loss as more certain. To avoid crop loss, a more ambiguity averse farmer will increase spending on pesticide use. Our results on the influence of ambiguity are comparable to those in Barham et al. (2014) who find that more ambiguity averse farmers are more likely to adopt genetically modified maize and soybean in the United States, although Ward and Sigh (2016) do not find a significant influence of ambiguity aversion on the adaptation of drought-tolerant rice in India. In our study, ambiguity aversion and loss aversion are shown to influence pesticide spending in opposite directions, which complements the existing evidence on the influence of loss aversion and ambiguity aversion on farmers' behaviors, although previous studies often examine only one type of preference.

Farmers' IPM knowledge is also highly associated with pesticide applications. Farmers who know that spiders are predators in a rice field spend approximately 10% less on pesticide expenditures and reduce pesticide application frequency by approximately 12%, although the coefficient is borderline significant in the cost model. If the respondent thinks the suggested amount of pesticide use on the package instruction is low, she will invest approximately 15% more in pesticide use and increase spray frequency by approximately 13%. In our sample, only approximately 5% of farmers think that the suggested amount is too high. If the respondents all have the correct knowledge, they will reduce pesticide usage regardless of whether they think the suggested amount is too high or too low, as both types are currently using more pesticides comparing to the baseline. If a farmer believes that water pollution is caused by pesticide use, she will reduce pesticide expenditures by approximately 20%. These results suggest that improving farmers' IPM knowledge may reduce pesticide use.

Our empirical results show that landscape diversity at the 2,000 m scale can influence the composition of the local ecosystem and change the need to use pesticides, while the landscape effects at the 500 m scale are not significant. Compared to the most intensive rice system (early-late rice rotation), the use of less intensive rice systems will reduce pesticide use. A 1% increase in the use of single-season rice (i.e., middle rice) leads to a reduction of approximately 1.4% in pesticide expenditures (column (1) Table 2). A 1% increase in a type of cultivated cropland other than the early-late rice system leads to a reduction of approximately 2.6% in pesticide expenditures and a 0.9% reduction in pesticide use frequency. A 1% increase in the forest will decrease pesticide expenditures by approximately 1% but will not reduce pesticide use frequency. We also find that a 1% increase in grassland will decrease pesticide expenditures by approximately 3% and reduce spray frequency by 1.5%. One reason is that if there is more early-late rice near the middle rice plot, the pests from the early rice may move to the middle rice in pursuit of food and habitat. The increased pest density may increase pesticide use. Other types of cultivated land, forest, and grassland provide more landscape diversity, which may benefit the predators. A larger number of predators may reduce pests and therefore reduce pesticide use. Our results for landscape diversity are consistent with those in Meehan et al. (2011) who used county-level data from the Midwestern United States to determine that the proportion of harvested cropland treated with insecticides increased with the proportion of cropland and decreased with the proportion of seminatural habitat.

Land consolidation is negatively associated with pesticide expenditures. The negative sign of the coefficient for plot size in the expenditure model indicates that land consolidation may reduce the number of pesticide applications, indicating that farmers with land fragmentation may spend more on pesticide use and that promoting land consolidation has the benefit of reducing pesticide use. Due to the economies of scale, farmers are likely to decrease the per acre pesticide expenditures when the plot size increases. The coefficients of land consolidation in the spray frequency model are insignificant, which means that farmers apply spray frequency on the large plot similar to that on the small plot.

**TABLE 3** Results from the standardized coefficient approach

| | Pesticide expenditure model | | | Pesticide application frequency model | | |
|---|---|---|---|---|---|---|
| | (1) Estimated Coefficient | (2) Standard deviation | (3) X-standardized coefficient | (1) Estimated Coefficient | (2) Standard deviation | (3) X-Standardized coefficient |
| Loss and ambiguity preferences | | | | | | |
| Loss aversion (lambda) | −0.298 | 3.204 | −0.093 | −0.660 | 3.204 | −0.206 |
| Ambiguity measure (theta2) | 0.028 | 0.394 | 0.072 | −0.002 | 0.394 | −0.005 |
| integrated pest management (IPM) knowledge | | | | | | |
| Whether the interviewee knows that spiders are a major predator of hoppers (1 = yes, 0 = no) | −0.031 | 0.473 | −0.065 | −0.073 | 0.473 | −0.155 |
| What the interviewees think of the suggested amount of pesticide use on the package instructions (baseline = correct) | | | | | | |
| 1 = the suggested one is less, 0 = others | 0.029 | 0.488 | 0.058 | 0.087 | 0.488 | 0.178 |
| 1 = The suggested one is more, 0 = others | 0.010 | 0.218 | 0.044 | 0.008 | 0.218 | 0.036 |
| 1 = Do not know, 0 = others | −0.022 | 0.336 | −0.064 | −0.028 | 0.336 | −0.083 |
| Do you think that pesticides can pollute underground/surface water (1 = yes, 0 = no) | −0.048 | 0.480 | −0.101 | −0.028 | 0.480 | −0.059 |
| Landscape (2,000 m) | | | | | | |
| Percentage of middle rice | −1.239 | 9.540 | −0.130 | −0.808 | 9.540 | −0.085 |
| Percentage of other cultivated land | −2.048 | 9.098 | −0.225 | −1.915 | 9.098 | −0.211 |
| Percentage of forest | −4.621 | 23.163 | −0.200 | -6.025 | 23.163 | −0.260 |
| Percentage of grassland | −1.272 | 6.184 | −0.206 | −2.108 | 6.184 | −0.341 |
| Land consolidation | | | | | | |
| Plot size of the selected plot | −0.109 | 0.712 | −0.153 | 0.035 | 0.712 | 0.049 |

*Notes*: This table lists the X-standardized coefficients based on the coefficients estimated and the standard deviation in Table 1. Column (1) shows the coefficients based on the regression results including the coefficients that are either significant or close to significant at the 10% level according to Table 2. Column (2) shows the standard deviation of the independent variables in our sample based on Table 1. Column (3) presents the standardized coefficient value calculated based on corresponding values in Columns (1) and (2), which can be interpreted as the influence of a one standard deviation change in the independent variable on the dependent variable.

**TABLE 4** The impact of different variable categories on pesticide use

| Omitted variable category | *F*-stat | *p*-Value | No. of omitted variables |
|---|---|---|---|
| Pesticide cost model | | | |
| Behavioral preferences | 3.96 | .0168 | 4 |
| Farmers' Knowledge | 2.75 | .0492 | 5 |
| Landscape (radius = 2,000 m) | 3.52 | .0164 | 6 |
| Land consolidation | 24.07 | .0001 | 1 |
| Spray frequency model | | | |
| Behavioral preferences | 20.57 | .0004 | 4 |
| Farmers' Knowledge | 15.24 | .0094 | 5 |
| Landscape (radius = 2,000 m) | 33.81 | .0000 | 6 |
| Land consolidation | 1.30 | .2548 | 1 |

One observation is that the pseudo $R^2$ is only between 0.1 and 0.2. The pseudo $R^2$ reflects the amount of variations that are explained by our independent variables. In our survey, we have collected a rich set of variables and other information such as utility parameters. We consulted literature using similar methods with different dependent variables, the pseudo $R^2$ ranges from 0.05 to 0.3. For example, Liu (2013) has the $R^2$ value ranging from 0.07 to 0.17, while Ward and Singh (2016) using random parameters has the $R^2$ value of 0.347. Our study is within the range in the literature. We also run additional robustness checks to control for the village fixed effects (after dropping the landscape variables that are highly correlated with the village dummies) that have little influence on the estimated coefficients.

In summary, more loss-averse farmer will spend less on pesticides and reduce spray frequency. In contrast, a more ambiguity averse farmer will spend more on pesticides but keep spray frequency unchanged. However, risk aversion, commonly used in the literature, has no significant effects on pesticide use in terms of either pesticide cost or spray frequency. Farmers with better pesticide-related knowledge reduce the number of pesticide applications but keep pesticide spending unchanged. Farmers living with a more diversified landscape (or less rice intensive systems) use less pesticide. Land consolidation is also found to associate with less pesticide use. Spray frequency is more sensitive to the factors in general than money on buying pesticides.

## 3.3 | Relative influences of each variable category

We next compare the relative importance of each variable and variable category in pesticide use decisions. We use the standardized coefficient approach to compare the relative importance of each variable. An $R^2$ comparison fails to account for the influence of the degree of freedom (Kvalseth, 1985). We use the $F$-test to compare the relative influences of variables in different categories. Table 3 presents the results using the standardized coefficient approach based on the regression results including the coefficients that are either significant or close to significant at the 10% level according to Table 2. Column (1) of Table 3 shows the new coefficients estimates by dropping highly insignificant variables. Column (2) presents the standard deviation of the independent variables in our sample. Column (3) presents the standardized coefficient value calculated based on corresponding values in Columns (1) and (2), which can be interpreted as the influence of a one standard deviation change in the independent variable on the dependent variable. For example, in the preferences category, if a farmer is more loss averse than the average farmer by one standard deviation, she will spend 9.3% less money on pesticide use, and the spray frequency will be reduced by 20.6%. If he is more ambiguity averse than the average farmer by one standard deviation, she will spend 7.2% more money on pesticide use. In the landscape category, if the percentage of middle rice at the 2,000 m scale increases by one standard deviation, the farmers will spend 13% less on pesticide use. However, a one standard deviation increase in other types of cultivated land, forest, and grassland at the 2,000 m scale will make farmers spend 22.5%, 20%, and 20.6% less on pesticide use, respectively.

The standardized coefficient approach enables us to compare the impact of one standard deviation change in the explanatory variable on the dependent variable (Column (3), Table 3). The results indicate that the landscape variables have the largest impacts on pesticide expenditures, followed by loss and ambiguity preferences and the land consolidation indicators. Farmers' IPM knowledge has the smallest impact on pesticide expenditures among the four categories. However, the order of the importance of the four categories is slightly different in the spray frequency model. Landscape diversity still has the largest impact, while the land consolidation indicators have the

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least impact. Four of the top five single variables are landscape factors. Plot size, which represents land consolidation, ranks fourth in the cost model, while loss aversion ranks fourth in the frequency model.

Table 4 shows the $F$-test results that evaluate the restriction imposed on the full, unrestricted model when a certain category of variables is constrained to be zero. Results show that all four categories have significant influences on pesticide cost and spray frequency except land consolidation on spray frequency. The largest restriction on the cost comes from land consolidation, while in frequency model the largest impacts come from the landscape category. In the cost model, omitting the preference and knowledge categories impose the second and third most significant restrictions on the full model with the $p$-values less than 0.02. But the restriction from the landscape category imposes the largest restriction in the frequency model, which suggests that landscape has the largest effects on spray frequency but comparatively smaller effects on pesticide cost. Omitting the preference parameters category and farmers' IPM knowledge category have similar restrictions on the full model for the spray frequency, indicating that the risk preferences and IPM knowledge have similar effects on spray frequency according to the $F$-test results.

## 4 | CONCLUSION AND DISCUSSION

This paper examines four important categories of factors that may influence farmers' pesticide use in rice fields in China. We discuss the regression results and then use the standardized coefficient approach and $F$-stats to compare the relative importance of each individual parameter as well as the importance of the different categories of variables. Our results suggest that all four categories of factors have significant, but different, effects on pesticide use. The order of the importance of these categories provides evidence for policymakers to set priorities for policy implementation. Among the four categories, landscape diversification has the largest effect on pesticide expenditures and spray frequency. Our result is consistent with the ecological literature indicating that a more natural habitat may support pest control (Larsen & Noack, 2017). However, a comprehensive analysis of the underlying mechanism of landscape effects on pesticide use goes beyond the purpose of this paper. Further studies are needed to investigate landscape effects from ecological perspectives.

Land consolidation has a significant effect on pesticide expenditures. As land consolidation is promoted, farmers' pesticide expenditures may be reduced. Land fragmentation has been a barrier for small-scale farms seeking to supply agricultural products. As urbanization increases, increasing numbers of agricultural laborers migrate to cities for off-farm jobs. Both the pushing and driving factors lead to land consolidation and large-scale farms in China. The Chinese government also promotes land consolidation through policy support, such as enhancing land rental markets. Our results provide empirical evidence on the benefits of land consolidation in terms of reducing agricultural pollution through pesticide use reduction. Farmers' loss and ambiguity preferences and IPM knowledge also have significant effects on pesticide use.

There are a few challenges that could not be fully addressed in our analysis. First, we used solicited risk preference data to infer agricultural production decisions, and the risk or ambiguity preferences exhibited in the experiments may not be representative of the farmers' preferences under more general circumstances. However, Liu and Huang (2013) argued that preferences in monetary domains should be the same as preferences in nonmonetary domains. Future research could explore the implications and the transferability of monetary and nonmonetary risk and use a reliable approach to elicit risk preferences in various domains. Second, standard practice only reports the mean values and standard errors of the risk parameters. However, the variability of the risk parameters may significantly affect the associated dependent variables. Sproul and Michaud (2017) found that a two-component mixed model better explains the field experiment data used in Tanaka et al. (2010), which implies that the elicitation and modeling approaches may have room for improvement.

Our study implies several factors that may influence the pesticide usage, which provides a basis for future studies that use alternative data or methods to identify potential causal relationships to further improve our understanding regarding the mechanisms behind these influences. In addition, the relationship between those aversion measures and optimal pesticide use may not be necessarily linear due to the respective roles of measures in the utility function. Future research could explore the implications of this limitation and use alternative methods to better incorporate different roles of the utility parameters.

The Chinese government is making substantial efforts to reduce agricultural nonpoint pollution and is focusing on pesticides. Our results suggest agricultural policy seeking to optimize pesticide use should consider multiple factors, especially landscape diversification, land consolidation, and the farmers' characteristics. Efforts aimed at altering farmers' pesticide use behavior from only one perspective will have limited impacts. Government policies reducing agricultural land simplification and promoting land consolidation may help reduce pesticide use. Future research could explore the generalizability of our results and ways to consider individual preferences in designing pesticide use policy to account for farmer heterogeneity in terms of behaviors and choices.

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## SUPPORTING INFORMATION

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

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