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Spatial dependence of family farms' adoption behavior of green control techniques in China

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ABSTRACT

Based on field survey data from 443 family farms in Shandong and Henan Provinces, the green control techniques(GCT) adoption behavior of family farms was measured in terms of adoption or non-adoption. Based on the global Moran's *I* test, the Bayesian spatial Durbin probit model(BSDPM) was constructed, the appropriate spatial weight matrix was set, the optimal model for parameter estimation was selected, and the direct and spatial spillover effects of family farm characteristics on GCTs adoption behavior of family farms were decomposed by means of the partial differential method. The results show that the GCTs adoption behaviors of adjacent family farmers are spatially correlated and strongest when they are within 2.0 km of each other. Farm leaders' educational level, degree of risk preference, financial status, number of laborers, understanding of GCTs and of the dangers of chemical pesticides, knowledge of other GCT adopters, frequency of communication with neighbors, participation in technical training and the strength of media publicity have significantly positive effects on the GCT adoption behaviors of family farms, which are mainly influenced by the direct effects of characteristic variables. However, the spatial spillover effects of neighboring family farmers' participation in technical training, number of laborers, and financial status cannot be ignored. This result provides not only theoretical support for the demonstration and extension of the effectiveness of GCTs but also a reference for the selection of family farms as model households.

Keywords
Family farm; Green control techniques; Spatial spillover effect; Bayesian spatial Durbin probit model

Introduction

The use of chemical pesticides is an important agricultural consideration for disease and pest control to obtain a stable yield. On average, 2.5–5 times more chemical pesticide per unit area is used by farms in China compared to farms in developed countries (Jin et al. 2017). Agricultural producers in China often

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increase the amount and frequency of chemical pesticide use and do not follow recommendations from scientists and the government, which has led to the widespread problem of pesticide residues (Ying and Xu 2017). This overuse results in not only increased production costs but also environmental pollution.

The safety of agricultural production, agricultural products, and the ecological environment must be ensured, and the sustainable development of agriculture must be promoted to control chemical pesticide use. Thus, the Chinese government has vigorously promoted green control techniques (GCTs). As the focus of integrated pest management (IPM) in China, GCTs[1] are characterized by the use of energy-saving resources and environmentally friendly techniques, such as ecological regulation, biological and physical controls, and the use of chemical pesticides according to recommended guidelines. However, in China, GCTs are primarily employed in experiments and pilot demonstrations, as their widespread implementation and application still face numerous obstacles (Wang, Wang, and Zhao 2015).

Clarifying the influencing factors of farmers' GCT adoption behavior is a necessary prerequisite for the smooth extension of GCTs. Therefore, researchers have conducted numerous studies to identify the factors that influence GCT (IPM) adoption behavior. Studying the characteristics of family leaders, Cai (2013), Liu et al. (2015), Murage et al. (2015), and Korir et al. (2015) confirmed that differences in the gender, educational level, and degree of risk preference of farm leaders that influence their GCT (IPM) adoption behaviors. In terms of resource endowment characteristics, Kabir and Rainis (2013), Hussian, Zia, and Saboor (2011), Yao (2016), and Allahyari, Damalas, and Ebadattalab (2016) indicated that large farm size, a good financial status, and a sufficient number of laborers are favorable conditions for IPM adoption by farmers. Shojaei et al. (2013) and Wu, Zhang, and He (2016) found that the cognitive level is a critical factor that influences the IPM adoption behavior of farmers. In terms of the characteristics of subjective norms, the frequency of communication with neighbors (Genius et al. 2014), the strength of media publicity (Timprasert, Datta, and Ranamukhaarachchi 2014; Zhao and Cai 2012), and participation in technical training (Sharma and Peshin 2016) positively influence the IPM adoption behavior of farmers.

In general, existing studies mainly focus on developing countries such as Kenya, Nigeria and Iran, which all face the same problem of pesticide overuse in agricultural production and have similar characteristics and endowments of farmers. Such studies provide a valuable reference for the further research of this paper. However, existing studies on the influencing factors of farmers' GCT (IPM) adoption behavior do not consider the spatial dependence of farmers' adoption behavior. Existing research has focused on the characteristic variables of farmers that directly affect their GCT (IPM) adoption behavior, and they have ignored neighboring farmers' adoption behavior and characteristic variables as well as the spatial spillover effects. Disregarding spatial dependence not only limits explanations of the impact of the spatial structure on GCT adoption behaviors but also leads to bias in the estimation results (Anselin and Bera 1998; Boncinelli et al. 2015).

Spatial dependence refers to the propensity of an individual to behave in a certain way based on the behavior of that individual's social group, e.g., farmers who are located in close proximity and who make similar behavioral choices (Läpple and Kelley 2015). Lewis, Barham, and Robinson (2011), Bjørkhaug and Blekesaune (2013), Allaire et al. (2015), and Rose et al. (2018) confirmed that farmers' adoption behavior is dependent on that of adjacent farmers. Extant studies are primarily based on samples in developed countries, while research in developing countries is limited. Developed countries promote agricultural techniques through diverse formal information channels; in contrast, developing countries lack formal information sources, and farmers primarily rely on informal informational channels such as neighbors and friends. Therefore, spatial dependence might be more significant in developing countries (Wollni and Andersson 2014).

Under the influence of the market economy and agricultural modernization, Chinese farmers are classified as either traditional peasants, who have multiple jobs and decentralized features, or as family farmers, who are characterized by specialization, integration, systematization, and socialization. These classifications have coexisted for many years (Gao et al. 2017a). Family farms are different from traditional peasant farming in terms of production factors such as land, capital and labor and in the labor and product attributes of the operators. Compared with traditional peasant farmers, family farmers have the necessary scale of cultivated land to apply GCTs, and they must achieve cost savings and increase their income through technological advancements (Gao et al. 2017b). Thus, the influencing factors of GCT adoption behaviors are different for family farmers than for traditional peasants. However, most Chinese studies use traditional peasants as research subjects and rarely examine family farmers.

China's agricultural development is trending toward family farms, and family farms are playing a leading role in the application of scientific and technological achievements and in green development (He 2016). At present, there are more than 870,000 family farms in China, and their cultivated land area accounts for 13.4% of the country's total cultivated land. In this context, the current study examined a sample composed of 443 family farms in Shandong Province and Henan Province.

The contributions of this study are as follows: First, because existing Chinese studies mainly examine traditional peasants, the current study extends the stream of research by focusing on the GCT adoption behaviors of family farmers. Second, unlike previous studies, this work focuses on spatial spillover effects; this approach not only explains the impact of the spatial structure on the GCT adoption behaviors of family farms but also prevents bias in the estimation results. Third, this study examines farms in China to fill a gap in existing research, which mainly focuses on developed countries.

Research method

Spatial correlation test

A spatial correlation test is necessary for structuring a spatial econometric model (Hui and Liang 2016). Existing studies have used the global Moran's I test to verify spatial correlation (Gong and Xu 2017). If spatial correlation is validated by the test, then the GCT adoption behaviors and characteristics of neighboring family farms are confirmed to have spatial spillover effects on the GCT adoption behaviors of the focal family farm.

The absolute values of the results of the global Moran's I test represent the strength of the spatial correlation. When the indicated spatial correlation is $-1 \leq Moran's\, I < 0$ or $0 < Moran's\, I \leq 1$, the former represents a negative spatial correlation, while the latter represents a positive spatial correlation. When $Moran's\, I = 0$, no correlation exists. The formula is as follows:

$$Moran's\, I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(y_i - \bar{y})(y_j - \bar{y})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{1}$$

where n is the sample size, y_i is the observed value of family farm i's adoption behavior, y_j is the observed value of family farm j's adoption behavior, and $W$is an $n \times n$ vector that represents the spatial weight matrix based on geographic distance. $S^2 = \frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y})^2$, where $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$.

Bayesian spatial Durbin probit model (BSDPM)

Schmidtner et al. (2012) argue that the adoption behaviors of farmers can be regarded as investment decisions. If family farm i's expected net income from adopting GCTs, $E[U_i^{ad}]$, is higher than the net income from non-adoption, $E[U_i^{no}]$, then family farm i will adopt GCTs. This premise is defined as follows:

$$y^* = E[U_i^{ad}(\pi_{ad} - G + P_{red})] - E[U_i^{no}(\pi_{no})] > 0 \tag{2}$$

where G represents family farm i's GCT adoption cost, including the information collection cost, the cost for investment in equipment, such as insect trapping lights, and the initial income losses due to errors in technique. The reduction in chemical pesticide costs when family farm i adopts GCTs is represented by P_{red}. The profit of family farms is represented by $\pi_k(k = ad, no)$ and is derived as follows:

$$\pi_k = \begin{cases} p_k \cdot q(f_k, F) - c_k \cdot f_k + s & if \;\; k = ad \\ p_k \cdot q(f_k, F) - c_k \cdot f_k & if \;\; k = no \end{cases} \tag{3}$$

where p_k is the agricultural production output price; q is the quantity produced, which depends on input factor f_k (for example, land suitability, labor input, agricultural materials, and mechanization and irrigation facilities) and spatial factor F (such as the distance to the agricultural product market); c_k represents the input prices; and s represents agricultural subsidies obtained from the family farm's adoption of GCTs.

The expected net income of a family farm cannot be immediately observed. However, whether a family farm adopts GCTs can be observed: When $E(U^{ad}) > E(U^{no})$, family farms adopt GCTs; when $E(U^{ad}) < E(U^{no})$, family farms do not adopt GCTs. Thus, an indicative function is defined as follows:

$$y = \begin{cases} 1 & if \;\; E(U^{ad}) > E(U^{no}) \\ 0 & if \;\; E(U^{ad}) < E(U^{no}) \end{cases} \tag{4}$$

When spatial correlation is observed, in this study, the spatial Durbin probit model is structured as follows:

$$y = X\beta + \rho Wy + WX\theta + \varepsilon \tag{5}$$

where y is the vector of the observed values of the family farm's GCT adoption behavior. The characteristic variable vectors of the family farm are represented by X, β represents the vectors of the regression coefficients, and $X\beta$ indicates the direct effects of family farm i's characteristics on its GCT adoption behavior. The spatial weight matrix is represented by W; ρWy is the spatial lag, which indicates the indirect effect of the adoption behavior of neighboring family farm j on family farm I, and ρ represent the vectors of the regression coefficients. The spatially weighted linear combination of the characteristic variables of the neighboring family farm is represented by $WX\theta$, which indicates the indirect effect of the characteristic variables of neighboring family farm j on the adoption behavior of family farm i, θ represents the vectors of the regression coefficients, $\varepsilon \tilde{N}(0, I_N)$ represents a random error term, and I_N is an n-dimensional matrix. The prior distributions of β, ρ, and $\theta$are set as a normal distribution, beta distribution, and beta distribution, respectively, based on the studies by Lesage (1997), Wollni and Andersson (2014) and Yang and Sharp (2017).

LeSage and Pace (2009) believe that when maximum likelihood estimation is used to estimate the likelihood function, it is impossible to conduct formal tests for significant differences between the likelihood functions of different spatial weight matrix models because they are non-nested. Bayesian estimation, on the other hand, requires no nesting of models and is more applicable. Therefore, for parameter estimation, this study adopts the Bayesian estimation method based on the Markov chain Monte Carlo (MCMC) sampling algorithm. This method combines the likelihood function $p(y|\tau)$ and the prior distribution $p(\tau)$ to estimate the unknown parameters $\tau = (\beta, \theta, \rho)$. The role of prior information is fully considered, thus optimizing the results of the statistical inference and solving the problem of parameter uncertainty (LeSage et al. 2011). The data obtained from the parameters to be estimated are referenced, and prior distribution information is provided. Then, Bayesian theory is applied to obtain the posterior distribution information of the parameters $p(\tau|y)$ as follows:

$$p(\tau|y) \propto p(y|\tau)p(\tau) \tag{6}$$

The MCMC sampling algorithm is used to sample the posterior distribution of the BSDPM. The sampling sequence converges at the joint posterior distribution of the model parameters. The mean and standard deviations of the converged sequence are calculated to obtain the estimates and the standard errors of the parameters.

Optimal model selection

Spatial dependence is characterized by decay along a distance; thus, a suitable threshold is necessary to ensure that each family farm has at least one neighboring family farm (Wollni and Andersson 2014). Roe, Irwin, and Sharp (2002) indicate that spatial spillover effects do not influence the adoption behaviors of farmers after a certain threshold value and that all spatial weight matrices W_{ij} are assumed to be zero, which is defined as follows:

$$W_{ij} = \begin{cases} d_{ij}^{-1}, & 0 \le d_{ij} \le d \\ 0, & d_{ij} > d \end{cases} \tag{7}$$

where d is the threshold value of the spatial spillover effect at zero. The spatial dependence radius of family farm technology adoption behavior is approximately 2.0–4.0 km (Wollni and Andersson 2014). This paper refers to Wollni and Andersson (2014) and Yang and Sharp (2017) and, combined with the actual survey data, uses 1.5 km,[2] 2.0 km, 2.5 km, 3.0 km, 3.5 km, and 4.0 km (in intervals of 500 m) as different thresholds, thereby establishing 6 BSDPMs. These alternative models are then compared using posterior model probabilities. The model with the highest posterior model probability is the preferred model and is used for the parameter estimation. As a method commonly used in the existing literature for microscopic empirical analysis based on a spatial Durbin model, the posterior probabilistic optimal model not only makes full use of the information but also ensures high test validity (Tao and Yang 2014).

Spatial impact decomposition

The estimation results of the spatial Durbin probit model can only confirm the positive or negative effects of the characteristic variables on the GCT adoption behavior of family farms and cannot reflect the direct and spatial spillover effects of each characteristic variable (Yang and Sharp 2017). Therefore, it is necessary to decompose the direct and spatial spillover effects. LeSage and Pace (2009) argue that the point estimate method can lead to model estimation errors, whereas the partial differential method can avoid this problem. Therefore, this study adopts the partial differential method to decompose the spatial effects of the characteristic variables on the GCT adoption behaviors of family farms into direct and spatial spillover effects. Specifically, formula (5) is converted into the following:

$$y = (I_N - \rho W)^{-1}(X\beta + WX\theta) + (I_N - \rho W)^{-1}\varepsilon \tag{8}$$

Therefore, the partial differential equation matrix of y on X is as follows:

$$\begin{bmatrix} \frac{\partial y_1}{\partial X_{1K}} & \frac{\partial y_1}{\partial X_{2K}} & \cdots & \frac{\partial y_1}{\partial X_{NK}} \\ \vdots & \vdots & \cdots & \vdots \\ \frac{\partial y_N}{\partial X_{1K}} & \frac{\partial y_N}{\partial x_{2K}} & \cdots & \frac{\partial y_N}{\partial X_{NK}} \end{bmatrix} = (I_N - \rho W)^{-1} \begin{bmatrix} \beta_K & W_{12}\theta_K & \cdots & W_{1N}\theta_K \\ W_{21}\theta_K & \beta_K & \cdots & W_{2N}\theta_K \\ \vdots & \vdots & \cdots & \vdots \\ W_{N1}\theta_K & W_{N2}\theta_K & \cdots & \beta_K \end{bmatrix} \tag{9}$$

To the right of the equation, the mean value of the diagonal elements represents the direct effect, which indicates the direct influence of a family farm's characteristic variables on its GCT adoption behavior. The mean value of the nondiagonal elements represents the spatial spillover effect, which indicates the indirect influence of the adjacent family farmer's characteristic variables on the GCT adoption behavior of the focal family farm.

Variables and data

Variable selection

Farmer behavioral theory emphasizes that farmers adopt the family as the basic economic unit and pursue utility maximization under limited endowment conditions; additionally, their subjective attitudes affect their individual behaviors (Becker 1965). Based on farmer behavioral theory, the theory of planned behavior emphasizes that farmers' behavior is not entirely voluntary; rather, it is also based on other control factors such as neighbors, media, and extension departments (Ajzen 1991). The GCT adoption behavior of family farms is influenced by a combination of the characteristics of farm leaders, resource endowments, psychological cognition, and subjective norms.[3] The specific descriptions follow below.

Murage et al. (2015) point out that because women are more cautious when facing decisions, female-headed farms tend not to adopt IPM. Farm leaders with extensive farming experience tend to follow traditional methods of disease and pest control (Kabir and Rainis 2015). In contrast, the higher the educational level of a farm leader is, the more objective he or she will be in evaluating IPM (Korir et al. 2015). Farm leaders with a high level of risk preference are more likely to accept the uncertainty involved in GCT adoption (Chu 2015). Therefore, this study selects gender, farming experience, educational level, and the degree of risk preference as measurement indices of farm leader characteristics.

The basic conditions of farms for agricultural production, including the amount of farmland, financial status, and the number of laborers, reflect their resource endowment and have certain effects on the GCT adoption behavior of farmers. Specifically, a small amount of farmland limits IPM adoption by family farms (Goldberger and Lehrer 2016), financial shortages may contribute to a lack of motivation to adopt IPM (Rezaei, Hayati, and Rafiee 2014), and fewer laborers on a family farm can limit the ability to study and implement GCTs. Therefore, these factors can induce stress and hinder GCT adoption by family farms (Gao et al. 2017b). This study uses farmland size, financial status, and the number of laborers to measure farms' resource endowment.

The psychological understanding of a family farm leader may influence his/her GCT adoption behavior. Vidogbéna et al. (2015) demonstrate that farmers who understand IPM methods are more likely to adopt IPM. Additionally, Stallman and James (2015) confirm that family farmers who understand the dangers of chemical pesticides are often willing to adopt IPM. Therefore, this study uses the degree of understanding of GCTs and of the dangers of chemical pesticides to reflect the psychological cognition characteristics of family farm leaders.

Media publicity greatly influences farmers' decision making and their willingness to adopt IPM (Timprasert, Datta, and Ranamukhaarachchi 2014). Läpple and Kelley (2015) find that family farmers who personally know organic farmers have an adoption probability that is 10.9% higher than that of farmers who do not know organic farmers. Tang, Folmer, and Xue (2013, 2016) believe that communication between farmers and their neighbors will accelerate their adoption of water-saving irrigation technology. Mannan et al. (2017) argue that the participation of farmers in field training can significantly improve their technique cognition and practical abilities, thereby promoting their adoption of green fertilizer technology. Therefore, the strength of media publicity, knowledge of other GCT adopters, the frequency of communication with neighbors, and participation in technical training are used in this study as measurement indices for subjective norm characteristics.

The specific valuation methods of the variables are as follows. (1) Regarding the dependent variable, the GCT adoption behavior of family farms, considering that GCTs are a set of sophisticated technologies, combined with the actual situation of GCTs in the research region, this study conducts a questionnaire that obtains data on GCTs such as insecticidal lamp technology, control technology related to color plate traps, food source trapping, insect network control technology, biological pesticide technology, the artificial release of natural enemies, and the prevention of disease-resistant varieties by means of pictures showing a family farm. When a family farm adopts one or more of these seed technologies, the value is 1 and 0 otherwise. (2) Regarding the independent variables, the farmer's gender is evaluated as follows: male = 1 and female = 0. The farmer's number of years farming is measured by the actual farming years. The farmer's educational level is measured by the actual years of schooling. The cultivated land area is measured by the actual cultivated land area. The labor force is measured by the sum of actual household laborers and long-term employees. Farmers who have adopted GCTs and have participated in technical training are measured as follows: yes = 1 and no = 0. All other variables are measured by 7-point Likert scales.

Data sources and descriptive statistics

Data sources

Shandong and Henan Provinces were selected for this field study for several reasons. First, Shandong and Henan Provinces rank first and fourth, respectively, among the 31 provinces in China in terms of the number of family farms; thus, they show promise for future development.[4] Second, Henan and Shandong Provinces are important agricultural production areas, with the second and third highest grain output, respectively, among the 31 provinces of China.[5] Third, both provinces face serious challenges in pest control (Gao et al. 2018). Fourth, GCT demonstration zones have been established in the two provinces, and certain areas have been designated for the promotion and application of GCTs.

The survey was divided into two stages. The first stage was the pilot stage. In October 2017, 20 family farms in Shandong Province were randomly selected for household interviews. The clarity of the questionnaire was improved based on this stage. The second stage was the formal survey, which was conducted from January to March 2018. A stratified random sampling method was used to gather data. First, all counties in each province were sorted based on regional GDP and were divided into five categories: very high, relatively high, medium, relatively low, and very low. One county was randomly selected from each category. Then, within each sampled county, all townships were sorted based on the number of family farms registered with the industry and business departments and were divided into three groups: high, medium, and low. One township was randomly selected from each group. Finally, 16 family farms were randomly selected from each sampled township. Therefore, the sample for each province covered 5 counties, 15 townships, and 240 family farms. Overall, 480 questionnaires were distributed, and 443 valid questionnaires were returned. A valid response rate of 92.3% was achieved after eliminating questionnaires that omitted key information or presented self-contradictory information (for instance, where the farmer's age is less than his or her number of years of education).

Descriptive statistics

Of the 443 completed questionnaires, 174 family farms had adopted GCTs based on the farmers' picture recognition, accounting for 39.3% of the farmers surveyed. This result was consistent with the research results obtained by Hu et al. (2017) (Table 1).

The mean value of the gender of family farmers was 0.867, indicating that most of the family farmers surveyed were male. The mean value for farming experience was 12.696 years. Regarding educational level, the largest number of family farmers, 256 (57.8%), had from 6 to 9 years of schooling, or a junior high school education, which is consistent with the labor structure of secondary education in China. In terms of farmland size, the mean value was 8.909 acres. These data reflect the characteristics of the moderate-scale management of family farms in China. The mean value of the number of laborers was 7.985. With regard to the distribution characteristics of the variables, the results were similar to those obtained by the Ministry of Agriculture for family farms in 2018; therefore, the sample of this survey was adequately representative.

Regarding financial status, the sample average was 2.921, indicating that the sample family farms' financial status was not good. For participation in technical training, the sample average was 0.771, which means that most of the family farmers had participated in technical training. A total of 66.4% of the family farmers in the sample knew other GCT adopters, indicating that the family farmers had close relationships through their work. In addition, the mean values for the degree of risk preference, degree of cognition about GCTs, degree of cognition about the dangers of chemical pesticide use, strength of media publicity, and frequency of communication with neighbors were 4.287, 4.538, 4.566, 4.375 and 4.297, respectively.

Model estimation results

Spatial correlation test results

The result of the global Moran's I test of the spatial weight matrix based on geographic distance was 0.326, with a significance level of 0.01. This result

Table 1. Descriptive statistics of the variables.

Variable type	Variable	Measure	Mean	Std. dev.
Dependent variable	GCT adoption behavior	1 = *yes*; 0 = *no*	0.393	0.441
Characteristics of the farm leader	Gender	1 = *male*; 0 = *female*	0.867	0.435
	Farming experience	*Farming years of the family farmer*	12.696	7.314
	Educational level	1 = *primary school or below*; 2 = *junior middle school*; 3 = *technical school or high school*; 4 = *college or above*	8.029	2.155
	Degree of risk preference	1 = *strong aversion*; 2 = *aversion*; 3 = *relative aversion*; 4 = *neutral*; 5 = *relative preference*; 6 = *preference*; 7 = *strong preference*	4.287	1.647
Resource endowment characteristics	Farmland size	*Actual cultivated farmland area (acre)*	8.909	6.652
	Financial status	1 = *very scarce*; 2 = *scarce*; 3 = *relatively scarce*; 4 = *neutral*; 5 = *relatively abundant*; 6 = *abundant*; 7 = *very abundant*	2.921	1.432
	Number of laborers	*Total number of family laborers and long-term employees*	7.985	5.109
Psychological cognition characteristics	Degree of cognition about GCTs	1 = *very low*; 2 = *low*; 3 = *relatively low*; 4 = *neutral*; 5 = *relatively high*; 6 = *high*; 7 = *very high*	4.538	1.742
	Degree of cognition about the dangers of chemical pesticide use	1 = *very low*; 2 = *low*; 3 = *relatively low*; 4 = *neutral*; 5 = *relatively high*; 6 = *high*; 7 = *very high*	4.566	1.439
Subjective norm characteristics	Strength of media publicity	1 = *very low*; 2 = *low*; 3 = *relatively low*; 4 = *neutral*; 5 = *relatively high*; 6 = *high*; 7 = *very high*	4.375	1.828
	Knowledge of GCT adopters	1 = *yes*; 0 = *no*	0.664	0.473
	Frequency of communication with neighbors	1 = *very low*; 2 = *low*; 3 = *relatively low*; 4 = *neutral*; 5 = *relatively high*; 6 = *high*; 7 = *very high*	4.297	1.399
	Participation in technical training	1 = *yes*; 0 = *no*	0.711	0.500

indicates that the GCT adoption behaviors of adjacent family farmers have a significantly positive correlation with those of the focal family farmers; thus, the adoption behaviors are not randomly distributed across space but instead are spatially correlated. This positive correlation can be attributed to daily communication and business relationships, which frequently exist between adjacent family farmers and indicate a strong peer effect (Dharshing 2017). Therefore, structuring the BSDPM was necessary, and the spatial dependence of the GCT adoption behavior of family farms must undergo further empirical testing.

Optimal model selection results

A total of five models using different threshold values ranging from 1.5 km to 4.0 km were tested in this paper to establish a suitable spatial weight matrix. As shown in Table 2, when 2.0 km was used as the threshold value, the posterior model obtained the highest probability; this model is thus considered to be the optimal model. Therefore, this paper presumes that if the distance between family farms exceeds 2.0 km, then the spatial spillover effect of family farm GCT adoption behavior is zero.

Estimation results of the BSDPM

When 2.0 km was used as the threshold value and the spatial weight matrix was established, the structure of the BSDPM was optimal. The estimation results in Table 3 indicate that the spatial lag of adjacent family farmers' adoption behavior is significant and that the coefficient ρ is positive. This finding implies that the GCT adoption behavior of family farms has spatial dependence; a family farm is likely to adopt GCTs if its neighboring family farms are also adopters. This result also indicates that all spatial lags in the characteristic variables, except that of farmland size, passed the significance test. This result implies that the GCT adoption behavior of family farms is influenced by the characteristics of neighboring family farms.

Of the farm leader characteristics, educational level and degree of risk preference have significantly positive effects on the GCT adoption behavior of farm leaders, whereas being male and having more farming experience have significantly negative effects. The reasons for these results are as follows. First,

Table 2. Model comparison.

Threshold value	Posterior model probability
d = 1.5 km	0.322
d = 2.0 km	0.476
d = 2.5 km	0.213
d = 3.0 km	0.091
d = 3.5 km	0.066
d = 4.0 km	0.041

Table 3. Results of the Bayesian spatial Durbin probit model.

Variable	Coefficient	P	Variable	Coefficient	P
Gender	−0.225**	0.032	W-Gender	−0.133**	0.044
Farming experience	−0.194***	0.000	W-Farming experience	−0.072***	0.019
Educational level	0.543**	0.041	W-Education level	0.251*	0.052
Degree of risk preference	0.184**	0.015	W-Risk preference degree	0.049**	0.012
Farmland size	0.028	0.352	W-Farmland size	0.004	0.312
Financial status	0.328*	0.066	W-Financial status	0.225**	0.025
Number of laborers	0.286***	0.000	W-Number of laborers	0.124***	0.003
Degree of cognition about GCTs	0.095***	0.004	W-Cognition degree about GCTs	0.044*	0.057
Degree of cognition about the dangers of chemical pesticide use	0.141**	0.011	W-Cognition degree about the dangers of chemical pesticide use	0.053**	0.029
Strength of media publicity	0.266***	0.006	W-Strength of media publicity	0.109*	0.088
Knowledge of other GCT adopters	0.243**	0.012	W-Knowledge of other GCT adopters	0.134**	0.019
Frequency of communication with neighbors	0.253***	0.000	W- Frequency of communication with neighbors	0.132***	0.002
Participation in technical training	0.204***	0.002	W-Participation in technical training	0.165***	0.004
Constant	5.334***	0.001	R^2	0.667	
Spatial lag term ρ	0.641***	0.000	log-likelihood	−132.809	

Note: *, **, and *** denote statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.

a higher educational level provides farmers with additional opportunities to obtain GCT information and a higher capacity for understanding such information, which possibly leads to the adoption of GCTs (Kamau et al. 2018). Second, farmers with a high degree of risk preference tend to be proactive in reducing their costs for chemical pesticides and increasing their production through GCT adoption (Asadpour 2011). Third, compared with male farmers, female farmers are often highly conscious of the safety of agricultural production and of the need for ecological protection; therefore, they are more likely to adopt GCTs (Yin, Gao, and Wu 2017). Fourth, farmers with extensive farming experience tend to be conservative and therefore adhere to traditional pest control methods (Allahyari, Damalas, and Ebadattalab 2016).

With regard to resource endowment characteristics, sufficient funds and laborers are the prerequisites for learning and implementing new techniques on family farms (Grabowski et al. 2016; Schmidtner et al. 2012). Therefore, financial status and the number of laborers have significantly positive effects on the GCT adoption behavior of family farms; however, farmland size does not. This result can be attributed to the willingness of family farms to adopt GCTs when the amount of farmland exceeds a certain threshold due to the scale effect advantage (Cai 2013). In China, the farmland acreage of family farms is standardized by local government regulations and is relatively stable (Gao et al. 2017b).

Regarding psychological cognition characteristics, the degree of cognition about GCTs and the dangers of chemical pesticides has significantly positive effects on the GCT adoption behavior of family farms. A higher awareness of GCTs and of the dangers of chemical pesticides can lead to a higher perceived ease of use and convenience, leading family farms to prefer GCT adoption (Chalak et al. 2017).

With regard to the subjective norm characteristics, participation in technical training, knowledge of other GCT adopters, the frequency of communication with neighbors, and the strength of media publicity have significantly positive effects on the GCT adoption behavior of family farms. These findings can be attributed to the following. First, participation in technical training is the most effective method for helping family farms master GCT specifications and is beneficial for the adoption of GCT practices (Beyene and Kassie 2015). Second, if family farm members know other GCT adopters, they can obtain GCT experience through them in the form of “hitchhiking”, which can promote GCT adoption (Wang and Lu 2016). Third, communication with neighbors can indirectly improve farmers’ access to GCT information, thus accelerating their adoption of GCTs (Bravo-Monroy, Potts, and Tzanopoulos 2016). Fourth, Chinese farmers prefer to watch news and agricultural programs during their free time. The typical experiences and suggestions of GCT adopters presented during these programs can increase family farmers’ cognition of the utility of GCTs and motivate them to adopt GCTs (Wu, Zhang, and He 2016).

Results of spatial impact decomposition

Although the parameter estimation results of the BSDPM confirm the positive and negative influences of certain characteristic variables on the GCT adoption behavior of family farms, the regression coefficients include the feedback effect of adjacent family farms’ GCT adoption behavior. These coefficients may not accurately reflect the direct and indirect influences (Li and Zeng 2016; Yang and Sharp 2017). Therefore, this study uses the partial differential method to decompose the spatial effects into direct and spatial spillover effects (Table 4).

Table 4. Decomposition results for the direct and spatial spillover effects.

Variable	Direct effect	Spatial spillover effect	Total effect
Gender	−0.132	−0.053	−0.185 [−0.411, −0.041]
Farming experience	−0.091	−0.056	−0.147 [−0.305, −0.057]
Educational level	0.214	0.058	0.272 [0.199, 0.647]
Degree of risk preference	0.071	0.025	0.096 [0.029, 0.232]
Farmland size	0.004	0.001	0.005 [0.002, 0.007]
Financial status	0.177	0.078	0.255 [0.153, 0.482]
Number of laborers	0.107	0.080	0.187 [0.067, 0.334]
Degree of cognition about GCT	0.096	0.057	0.153 [0.077, 0.357]
Degree of cognition about the dangers of chemical pesticide use	0.118	0.049	0.167 [0.083, 0.399]
Strength of media publicity	0.052	0.022	0.074 [0.031, 0.226]
Knowledge of other GCT adopters	0.083	0.047	0.130 [0.076, 0.334]
Frequency of communication with neighbors	0.076	0.031	0.107 [0.077, 0.311]
Participation in technical training	0.168	0.098	0.266 [0.112, 0.557]

The decomposition results show that educational level, participation in technical training, financial status, and the number of laborers have higher positive effects on family farmers' GCT adoption behavior. First, the educational level of farmers is the most important factor influencing their GCT adoption behavior. The direct effect is 21.4%, and the spatial spillover effect is 5.8%. A high educational level indicates an ability to learn new techniques, thus increasing the possibility of GCT adoption. In addition, family farmers tend to believe and even imitate the adoption behaviors of adjacent family farmers who have higher levels of education (Wollni and Brammer 2012). Second, the probability of GCT adoption by family farmers who have participated in technical training is 26.6% higher than that of family farmers who have not participated in technical training. In this case, the direct effect is 16.8%, and the spatial spillover effect is 9.8%. Agricultural technical training organized by the government aims to achieve public benefits and inclusiveness for all family farms in a region. Adjacent family farmers who participate in technical training can learn from each other and discuss technical specifications, thereby improving their perceptions of ease of use and convenience (Guo et al. 2015). Third, the total, direct, and spatial spillover effects of a family's financial status on its GCT adoption behavior are 25.5%, 17.7%, and 7.8%, respectively. Adjacent family farmers have a relationship that allows them to borrow funds; abundant funds provide strong support for the adoption of new techniques (Gong et al. 2016).

At the same time, the understanding of the dangers of chemical pesticides, knowledge of other GCT adopters, the frequency of communication with neighbors, the degree of risk preference, and the strength of media publicity also positively affect the GCT adoption behavior of family farms, and the total effect gradually decreases. First, the total effect of the number of family laborers on family farms' GCT adoption behavior is 8.7%, while the spatial spillover effect is 8.0%. Laborers often work on adjacent family farms; this ample labor force increases the probability that each family farm will adopt new techniques (Boncinelli, Riccioli, and Casini 2017). Second, understanding the dangers of chemical pesticides has a total effect of 16.7% on the GCT adoption behavior of family farms, and this figure can be decomposed into the direct effect (11.8%) and the spatial spillover (4.9%). The total effect of understanding GCTs on family farms' GCT adoption behavior is 15.3%, which includes a direct effect of 9.6% and a spatial spillover effect of 5.7%. A high level of understanding of family farms leads to a high probability of GCT adoption (Koo and Chung 2014). Communication between neighbors is one way for family farmers to engage in social learning as well. If neighboring family farmers have a high degree of cognition about the dangers of chemical pesticides and the use of GCTs, then the focal family farmers are more likely to adopt GCTs (Grovermann et al. 2017). Third, the direct and spatial spillover effects of knowing other GCT adopters on the GCT adoption behavior of family farms are 8.3% and 4.7%, respectively. If adjacent family farmers know other GCT adopters, then the diffusion speed of GCTs will increase, as will family farmers' confidence and motivation to adopt GCTs (Garbach and Morgan 2017). Fourth, the overall effect of the frequency of communication with neighbors on GCT adoption by family farms is 10.7%, of which 3.1% is due to spatial spillovers. If there is relatively frequent communication between neighboring family farmers, the transmission of GCT information will be enhanced, promoting the adoption of GCTs (Bravo-Monroy, Potts, and Tzanopoulos 2016). Fifth, the total and spatial spillover effects of family farmers' degree of risk preference on their GCT adoption behavior are 9.6% and 2.5%, respectively. If adjacent family farmers accept higher levels of risk, then the focal farmers are more likely to adopt GCTs (Gao et al. 2017b). Sixth, the total effect of the strength of media publicity on the GCT adoption behavior of family farms is 7.4%, which can be decomposed into a direct effect of 5.2% and a spatial spillover effect of 2.2%. A high level of publicity indicates that family farmers can become more knowledgeable about and confident in adopting GCTs, and it is therefore more likely that they will adopt GCTs (Shojaei et al. 2013).

In addition, the probability of female farmers adopting GCTs is 18.5% higher than that of male farmers. This result is due to female farmers having a better understanding of the potential hazards of chemical pesticides than male farmers (Yin 2013). Communication between female farmers is more frequent than that between males, and such frequent communication further promotes the adoption of GCTs by female farmers. Thus, a − 5.3% spatial spillover effect exists (Mzoughi 2011). The total and spatial spillover effects of farming experience on GCT adoption behavior are −14.7% and −5.6%, respectively. Family farmers with extensive farming experience tend to be more circumspect about new techniques. They are also considered respectable people in their region, and their recommendations are valued. This condition will negatively influence the GCT adoption behavior of family farms (Ying and Xu 2014). The total effect of farmland size on GCT adoption behavior is 0.5%. This total effect is smaller than that of the other variables and further indicates that the impact of farmland size on the GCT adoption behavior of family farms is nonsignificant.

Overall, the spatial spillover effect of every characteristic variable is smaller than the direct effect. This finding implies that the GCT adoption behavior of family farms is mainly influenced by the direct effects of the characteristic variables. However, the spatial spillover effects of neighboring family farms' characteristic variables, especially participation in technical training, the number of laborers, and financial status, cannot be ignored. The spatial spillover effect provides not only theoretical support for the effectiveness of GCT promotion through regional demonstrations but also a reference for the selection of the type of family farm that should be used as a demonstration farm.

Conclusions and policy recommendations

In this study, field data from 443 family farms in Shandong and Henan Provinces were used to examine the spatial correlation of GCT adoption behaviors through the global Moran's I test. Then, a BSDPM was developed, a spatial weight matrix was constructed, and an optimal model for parameter estimation was selected. Finally, the partial differential method was adopted to determine both the direct and spatial spillover effects of family farms' characteristic variables on the GCT adoption behavior of family farms.

The main conclusions of this study are as follows. First, the GCT adoption behaviors of family farms are spatially correlated, and their geographic distribution is spatially clustered. Second, when family farms are within 2.0 km of each other, GCT adoption behaviors have a strong spatial dependence. Third, educational level, the degree of risk preference, financial status, the number of laborers, the understanding of GCTs and the dangers of chemical pesticides, the strength of media publicity, knowledge of other GCT adopters, the frequency of communication with neighbors, and participation in technical training have significantly positive effects on the GCT adoption behaviors of family farms. However, being male and having more farming experience have significantly negative influences on GCT adoption behavior. Fourth, the GCT adoption behavior of family farms is mainly influenced by the direct effects of their characteristics. However, the spatial spillover effects of neighboring family farms' characteristics, especially participation in technical training, the number of laborers, and financial status, cannot be ignored.

On the one hand, the development of family farms in China is still in its infancy, and no mature joint relationship among family farms has been formed. On the other hand, limited by their educational level, family farmers lack the ability to collect technical information, identify technical information and master technical operation specifications. Therefore, ecological farmer associations, such as those in Ontario and Iowa in Canada and the U.S., respectively, are relatively rare in China. Policy guidance is needed in China's popularization of agricultural technology. The conclusions of this paper have the following policy implications for GCT promotion policies. First, a "nonequilibrium promotion strategy" should be implemented. Because of the spatial cluster characteristics of family farms' GCT adoption behavior, policies should be implemented in a few regions that already have the foundations for GCT practices to allow these regions to reach a large area of GCT application. Then, the application of GCTs can diffuse to neighboring regions. Second, promotion policies should be multipronged. The internal condition of family farms should be improved by encouraging participation in technical training to reduce the barriers and stresses involved in GCT adoption. For example, the financing environment should be improved, guidance should be provided, family farmers' opportunities for education should be increased, regular technical exchange meetings in villages should be held, and team building in grassroots areas should be strengthened. Third, attention should be paid to the spatial spillover effects. Family farmers who participate in technical training and have abundant laborers and a good financial status should be selected as “GCT adoption leaders”. Such family farms would be ideal to serve as demonstration farms to increase the spatial spillover effects.

This study still has some limitations. First, the research conclusions of this paper are based on family farms in Shandong and Henan Provinces, but whether consistent research conclusions can be drawn in other regions remains to be seen. Second, this paper measures the GCT adoption of family farms in terms of “whether”, and GCT adoption can also be measured in terms of “how much”. Therefore, the spatial dependence of the GCT adoption behavior of family farms, as measured by the “degree of adoption”, remains to be investigated.

Notes

1. GCTs are a complex technology set. At present, physical and chemical inducement and control technology, biological control technology, ecological regulation technology and scientific drug use technology are relatively mature and are widely used in agricultural production activities. Among them, physical and chemical inducement and control technology mainly includes physical inducement and control technology (insecticidal lamp trapping and killing, color plate trapping and killing and insect network controlling technology) and insect pheromone inducement and control technology (sex pheromone, alarm pheromone, spatial distribution pheromone, oviposition pheromone, feeding pheromone, etc.). Biological control technology mainly includes control technology for parasitic natural enemies and predatory natural enemies, mainly through the artificial release of natural enemies. Ecological regulation technology mainly includes disease-resistant variety technology, reasonable combination and mixed planting technology for crops, raw grass covering technology for orchards, control technology for natural enemy trapping and collecting belts, and improved management technology for water and fertilizer. Scientific drug use technology mainly includes technology related to high-efficiency, low-toxicity, low-residue and environmentally friendly pesticides as well as technology related to the rotation, alternate use, precise use and safe use of pesticides.
2. Based on our data, 1.5 km is the minimum threshold distance that we can test because if we choose $d < 1.5$ km, the family farms in the sample will have no adjacent family farm and we will be unable to standardize the spatial weight matrix.
3. In theory, whether a family farm joins a cooperative affects its GCT adoption behavior. However, this survey finds that the proportion of family farms that join cooperatives is very low; thus, this paper does not include “whether farmers join cooperatives” in the model.
4. Rural Economic System and Management Department of the Ministry of Agriculture, Rural Development Institute of Chinese Academy of Social Sciences: “China Family Farm Development Report. 2018”, 1st edition, Beijing, China Social Sciences Press, 2018.
5. Source: “Announcement of the National Bureau of Statistics on Grain Yield in 2017”, http://www.stats.gov.cn/tjsj/zxfb/201712/t20171208_1561546.html.

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