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Factors influencing farmers' adoption of eco-friendly fertilization technology in grain production: An integrated spatial–econometric analysis in China

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ABSTRACT

Encouraging more farmers to adopt eco-friendly fertilization technology is essential for achieving sustainable grain production. To systematically explore the factors influencing farmers' adoption of such technology, based on a logistic regression model and three mutually complementary spatial analysis models, our study proposes a spatial-econometric analytical framework. Using data from household surveys, farmland quality investigations, remote-sensing images, and a digital elevation model, we test our study framework in 30 neighboring villages in Taojiang County, China. The results indicate that major socioeconomic influential factors include the age and education level of the household head, farm size, and degree of farmland fragmentation; geographic influential factors involve landform characteristics, drainage capacity, irrigation capacity, and topsoil thickness. In addition, the type of technology promoter and the farmer's perceived usefulness of the technology play important roles affecting farmers' technology adoption willingness. To increase the probability of technology adoption, more energy should be spent on relatively younger and better-educated farmers and farmers who occupy a larger cultivation area. Non-adopter-dominated areas should also be targeted during the technology promotion process. Further, local policymakers should consider strong measures that encourage adopters to become active technology promoters.

1. Introduction

As a country with almost 20% of the world's population but less than 7% of its total arable land, national food security has always been seen as fundamental to maintaining China's social stability. Even under the pressure created by rapid population growth, the per capita share of grain has dramatically increased in China, from 298 kg to 445 kg, over the past four decades, benefiting from the continuous growth in total grain output (National Bureau of Statistics of China, 2019). Concurrently, due to the rapid development of the social economy and accelerated urbanization and industrialization, both the quantity and quality of farmland in China have been declining (Song and Liu, 2017); thus, the growth of total grain output has been dependent entirely on the increase in grain yield per unit area. Unfortunately, the most important driver behind this increase has been the overuse of agricultural chemicals (Wu et al., 2018) and the extensive use of machinery (Qi et al., 2021), which have resulted in serious damage to the farm environment as well as to the upstream and downstream agricultural sectors (Vitousek et al., 2009).

With the continuous deterioration of the agricultural environment, researchers and policymakers alike have realized that the grain production patterns that sacrifice environmental quality for food security are unsustainable. To reduce the environmental costs of grain production, scholars have proposed a number of remarkable eco-friendly fertilization technologies (EFFTs) and associated management technologies (Chen et al., 2014a), such as improved nutrient and water management technologies (Mueller et al., 2012), integrated soil-crop system management technologies (Chen et al., 2011), and advanced crop and nutrient management technologies (Chen et al., 2014b). These technologies have made significant contributions to address the twin

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challenges of food security and environmental sustainability in China. In tandem, the Chinese government has developed a series of policy measures aimed at promoting the spread of these technologies such as the "National action plan on popularization of testing soil for formulated fertilization technology" (Ministry of Agriculture of China, 2012), "Zero growth program of fertilizer and pesticide usage by 2020" (Ministry of Agriculture of China, 2015), and "Action plan for tackling agricultural and rural pollution" (Ministry of Ecological and Environment of China, 2018). Local governments have also designed various types of subsidies for eco-friendly fertilizers and pesticides (Zheng et al., 2019).

Although researchers and policymakers have spent considerable effort to encourage rural households to adopt EFFTs in grain production, the proportion of farmers willing to adopt them is not promising (Luo et al., 2013). Previous studies have shown that, even though a lot of farmers have heard of EFFTs, the proportion of farmers who have adopted them in many major grain producing areas of China is less than one-third (Ma et al., 2014; Wang et al., 2018). Therefore, understanding the factors that influence farmers' adoption of EFFTs would help in the development of specific policy measures to affect their decision-making behavior.

To date, although there have been numerous studies on the factors influencing farmer decision-making behavior, only a few have focused on the factors influencing farmer adoption of EFFTs. The results in these studies indicate that there are four main types of factors that may affect farmers' adoption of EFFTs: characteristics of the household head (Ma et al., 2014), family characteristics (Luo et al., 2013), farmland characteristics (Han and Yang, 2011), and technology characteristics (Wang et al., 2018). Specifically, age and education level have been widely regarded as the key influencing factors in previous studies. The older farmers are, the more reluctant they are to adopt eco-friendly technologies. This may be due to the slow and inefficient acceptance of new knowledge and technologies by older farmers, which hinders their adoption of EFFTs (Lei, 2020). In terms of education level, farmers with better education are more likely to understand the importance of green development and realize the long-term economic benefits of eco-friendly behaviors, so they are more proactive in adopting EFFTs (Lei, 2020). Besides, off-farm income, labor force, and farm size have also been regarded as the influencing factors (Qu and Zhao, 2020).

Despite the significant contributions of extant studies, they are still two obvious gaps in the literature. First, the existing studies have been conducted only from the perspective of conventional econometric analysis. Therefore, although land resource endowments—which have significant spatial diversity—could influence the farmers' agricultural production decisions (Qi and Dang, 2018), few studies have taken these into consideration. Second, differences in the individuals who act as technology promoters could affect the farmers' willingness to change their behavior (Zhang et al., 2017), however, few studies have considered this either. These limitations not only constrain the systematic analysis of the factors influencing farmers' adoption of EFFTs in grain production, but also prevent policymakers from developing robust policy instruments to influence farmers' decisions.

To bridge these gaps, based on an integrated spatial-econometric analysis, our study answers the following questions: (1) What are the main factors influencing farmers' adoption of EFFT? (2) Does the spatial distribution of farmers making different adoption decisions reflect certain patterns? (3) How can policy instruments be developed to increase the probability of farmer adoption of EFFT? Although there are many EFFTs involved in grain production, testing the soil for formulated fertilization technology (TSFFT) has been the most vigorously promoted EFFT by the Chinese government department in the past decade (Li et al., 2015). Therefore, we focus on this technology to explore the factors that influence the adoption behavior of farmers.

2. Analytical framework and methods

2.1. Analytical framework

As a land-dependent production activity, farmers' decisions on grain production depend not only on their own socioeconomic characteristics, but also on their farmland resources and spatial locations. Moreover, in general, farmers use the technologies they are familiar with for grain production. However, when a new technology appears, awareness of it will influence farmers' adoption decisions. To systematically explore the factors influencing farmers' adoption of EFFTs in grain production, we built the following analytical framework, illustrated in Fig. 1.

Overall, there are four types of factors that may influence farmers' adoption decisions: socioeconomic characteristics of the household, the technology's promotion and perception, farmland resource endowments, and the spatial location of the households. Among them, the socioeconomic characteristics of the household are factors that have received the most attention in recent studies (Zhang et al., 2018). Technology promotion and its perception capture farmer perception of the technology and how to access it (Qin et al., 2016). Farmland resource endowments, including geologic, physical, and chemical characteristics of the farmland, constrain farmers' choice on technology usage (Burnham and Ma, 2016). The spatial location of the household relates closely to the accessibility of technology information, which could affect the farmers' choices (Staal et al., 2002).

Based on the framework, we apply an integrated spatial-econometric analysis to explore the factors influencing farmers' adoption of TSFFT. Specifically, we develop a binary logistic regression model for our econometric analysis of the influence of socioeconomic characteristics of the household and technology promotion and perception; and we use three spatial analysis models to detect the influence of farmland resource endowments and the spatial location of the household.

2.2. Development of the logistic model

Most technology choices that farmers consider in their decision making are between "adopt or not adopt" (Mariano et al., 2012). In our study, farmers are asked whether they have adopted TSFFT, which is, thus, a binary variable. Overall, the logistic model is a binary discrete selection model whose logical distribution is the probability distribution of random error terms; it is the ideal and widely used model for analyzing individual decision-making behavior (Liu and Liu, 2016). Therefore, we develop a binary logistic regression model to conduct econometric analysis of the factors influencing farmers' adoption of TSFFT.

In this model, farmers' decisions are set as the dependent variables, with adoption defined as $Y = 1$ and non-adoption as $Y = 0$. Then, the binary logistic regression model is constructed as follows:

$$P(Y=1)=\frac{e^{(\beta_0+\beta_1x_1+\beta_2x_2+\ldots+\beta_nx_n+\varepsilon)}}{1+e^{(\beta_0+\beta_1x_1+\beta_2x_2+\ldots+\beta_nx_n+\varepsilon)}} \tag{1}$$

where $P(Y = 1)$ is the probability of adopting TSFFT, β_0 is a fixed intercept, x_1, x_2, …, x_n are the independent variables representing various factors that influence the farmers' adoption decisions on TSFFT, β_1, β_2, …, β_n are the coefficients of each independent variable, and ε is the error term.

The logistic transformation of $P(Y = 1)$ is as follows:

$$\log\left[\frac{P(Y=1)}{1-P(Y=1)}\right]=\beta_0+\beta_1x_1+\beta_2x_2+\ldots+\beta_nx_n+\varepsilon \tag{2}$$

where $P(Y = 1)/[1-P(Y = 1)]$ denotes the odds that farmers would adopt TSFFT, that is, the ratio of the probability that $Y = 1$ to the probability that $Y = 0$.

Based on the econometric studies of factors influencing farmers' decision-making behavior (Greiner, 2015; Raza et al., 2019), this study

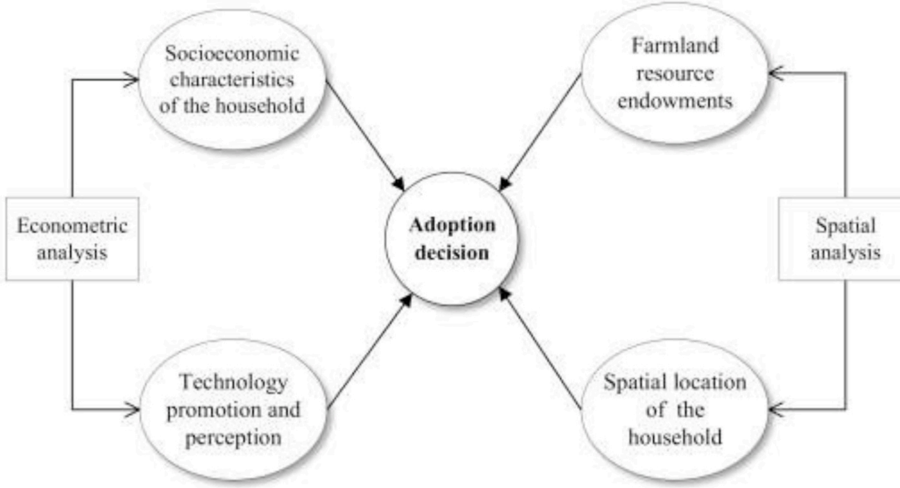

Fig. 1. Framework analyzing the factors influencing farmer adoption of eco-friendly fertilization technology in grain production.

selects the characteristics of the household head, family economic status, farming conditions, and technology promotion and perception as the main variable types for exploring farmers' adoption decisions. Among them, the characteristics of the household head, which usually cover gender, age, and education level, affect households' preferences (Lu et al., 2018). Family economic status covers mainly income level, primary source of income, and agricultural labor force, which may constrain farmers' choices in terms of livelihood strategy (Xie and Jin, 2019). Farming conditions are a fundamental variable that directly reflects whether a farmer's agrarian asset is easy to use for a particular purpose (Xie et al., 2017). Technology promotion and perception capture the different possible technology promoters along with the farmers' perceptions of the technology, which are combined to affect farmers' adoption rate (Franzel et al., 2011). The definitions of variables are given in Table 1.

Table 1
Definition of econometric variables used in the technology adoption model.

Variables	Definition	Expected direction
Characteristics of the household head		
Gender	Male = 1; female = 2	?
Age	The actual age of the household head	−
Education level	The farmer's years of formal education	+
Family economic status		
Income level	Very low = 1; low = 2; moderate = 3; high = 4; very high = 5	?
Primary source of income	Off-farm = 1; on-farm = 2	+
Agricultural labor force	The number of people engaged in agricultural production	+
Farming conditions		
Farm size	Total area of farmland	+
Degree of farmland fragmentation	Number of plots	−
Use of machinery	No = 1; Yes = 2	?
Technology promotion and perception		
Type of technology promoter	Formal promoter = 1 (e.g., government, agency, enterprise); Informal promoter = 2 (e.g., relative, acquaintance, friend)	?
Perceived usability of technology	Very difficult = 1; difficult = 2; normal = 3; simple = 4; very simple = 5	+
Perceived usefulness of technology	Very useless = 1; useless = 2; normal = 3; useful = 4; very useful = 5	+

2.3. Development of spatial analysis models

Although farmers' socioeconomic characteristics and technology perceptions are key factors that could affect their adoption decisions, the influence of geographic factors may also play an important role because grain production is a land-dependent activity. To explore the spatial distribution pattern of farmers making different adoption decisions and related geographic factors that may influence their decisions, we introduce three mutually complementary models—kernel density estimation, Global Moran's I, and the geographical detector—for spatial analysis. Their details are as follows:

Kernel density estimation is a non-parametric way to estimate the probability density function of a random variable (Sheather, 2004). Through this method, we can estimate the adoption probability of a technology by farmers at different locations in the study area. Let (x_1, x_2, …, x_n) represent a sample of the adopters; its underlying probability density can be estimated by the following kernel density function:

$$\hat{f}(x)=\frac{1}{nh}\sum_{i=1}^{n}K\left(\frac{x-x_i}{h}\right) \tag{3}$$

where n is the sample size, h is a smoothing parameter called the bandwidth, (x–x_i) is the distance between an estimation point (x) and a sample point (x_i), and $K(\bullet)$ is a kernel function.

Global Moran's I is widely used to test for the presence of spatial dependence in observations (Li et al., 2010). We employ it to analyze the spatial distribution characteristics (i.e., dispersed, random, or clustered) of farmers who make different adoption decisions. Global Moran's I is defined as:

$$I=\frac{n\sum_{i=1}^{n}\sum_{j=1}^{m}w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{m}w_{ij}\sum_{i=1}^{n}(x_i-\bar{x})^2} \tag{4}$$

where n is the total number of interviewed farmers, x_i/x_j is the attribute value (1 represents an adopter and 0, a non-adopter) of the ith/jth farmer, $\bar{x}$ is the mean value, and w_{ij} is the space weight matrix. In this study, first, we generate a farmers' Voronoi diagram based on their spatial positions, and then, second, we use the rook contiguity to define w_{ij} (Zhao et al., 2017), namely, $w_{ij}=1$ indicates that the ith farmer is adjacent to the jth farmer and $w_{ij}=0$ indicates the opposite situation.

The geographical detector is a method of detecting spatial variability (Wang and Xu, 2017). It can be used to detect the degree to which an indicator (X) explains the spatial variability of farmers making different adoption decisions (Y). The calculation formula is as follows:

$$q = 1 - \frac{\sum_{h=1}^{m} n_{h,i}\sigma_h^2}{n\sigma^2} \quad (5)$$

where n is the total number of samples in the entire region, m is the number of sub-regions, $n_{h,i}$ is the number of sub-regional samples, σ^2 and σ_h^2 are, respectively, the variance of Y of the entire region and the sub-region h, and q is the detection result with a value range between 0 and 1—the higher the q value, the stronger the influence of X on Y. Previous studies have shown that farmland resource endowment is a core geographic element that affects grain production; it includes site condition, soil physical properties, soil chemical properties, and obstacle factors (Li et al., 2016). Based on the four elements, we select a corresponding eight indicators to conduct geographical detector analysis (Table 2).

3. Study area and data sources

3.1. Study area

Thirty neighboring villages, located in the east of Taojiang County, were selected as the case study area (Fig. 2). These villages occupy an area of approximately 134.4 km^2, and the average distance from the nearest urban settlement is about 10.2 km.

Taojiang County has a humid subtropical monsoon climate, with an average annual rainfall of 1435 mm, a mean annual temperature of 16.7 °C, and an annual sunshine duration of 1580 h (Qi and Dang, 2018). The climate conditions are suitable for double cropping and this county has a long history as an important commodity grain base in China. Over the past couple of decades, to improve grain yield to ensure food security, chemical fertilizers have significantly increased in usage in Taojiang County (Investigation team of rural economy, 2016). The overuse of chemicals has caused serious environmental pollution (Qi et al., 2018). To avoid the further deterioration of soil and water quality, the local agricultural department began to promote TSFFT actively in grain production as of 2011.

3.2. Data sources

The data used in this study were collected from ASTER GDEM V2 and Google Earth images, household surveys, and farmland quality investigations. To clarify the topographical features and main grain growing areas of Taojiang County, we combined ASTER GDEM V2 and Google Earth images to carry out a three-dimensional visualization analysis using ArcGlobe. Subsequently, to take into consideration the suggestions of local officials in the agriculture sector, 30 representative villages were selected (Fig. 2).

We conducted a series of household surveys in these villages in 2018. First, we interviewed the village officials to understand the profile of local farmland resource endowments and grain production status. Then, 10 to 14 farm households who were engaged in grain production and were aware of TSFFT were randomly interviewed in each village. Finally, we collected a total of 312 valid responses, which covered a wide range of information such as farmers' perceptions and adoption decisions on TSFFT, characteristics of the household head, family economic status, farming conditions, and spatial locations.

The data on farmland resource endowments, including site condition, soil physical properties, soil chemical properties, and obstacle factors, were collected from a series of farmland quality investigations. These investigations were conducted by the agriculture bureau of Taojiang County in 2016.

Table 2
Indicators for geographical detector analysis.

Geographic elements	Indicators
Site conditions	Landform characteristics
Soil physical properties	Soil texture
	Topsoil thickness
Soil chemical properties	Organic matter
	Available phosphorus
	Available potassium
Obstacle factors	Drainage capacity
	Irrigation capacity

4. Results and discussion

4.1. Influence of socioeconomic characteristics and technology promotion and perception

In general, among the 312 farm households who had heard of TSFFT, only about 25% had adopted it. The descriptive statistical results of the variables are shown in Table 3. Overall, males accounted for 62.8% of the total heads of households managing the grain production practices in Taojiang County. More than 66% of the farmers involved in grain production were 50–70 years old, had a junior high school education or below, with a farm size between 2 and 6 mu,[1] and their primary source of income coming from off-farm employment. It is worth noting that over 57% of the farmers received information on TSFFT from informal promoters such as relatives, acquaintances, and friends, rather than from formal promoters such as governments, relevant agencies, and enterprises.

The logistic regression results of the technology adoption model are summarized in Table 4. The chi-squared test statistic is significant at the 1% level, which indicates the joint significance of the variables. The power of prediction of this logistic model was 0.766, implying that it accurately predicted 76.6% of the observations. Among the four types of variables, characteristics of the household head, farming conditions, and technology promotion and perception had significant impacts on farmers' adoption of TSFFT.

As for the impact of the characteristics of the household head, the older the household head, the less likely he/she would be to adopt TSFFT. However, household heads who had a better education were more likely to adopt TSFFT. One reason may be that younger farmers are more receptive to new technologies and better-educated farmers have a better ability to access and understand relevant technology information.

With respect to farming conditions, a larger farm size was associated with an increase in probability of technology adoption, while a more fragmented farmland reduced probability. One plausible explanation for the former is that although there is no institutional discrimination against small farmers in the promotion of TSFFT, spending more energy on large farmers is obviously more in line with the government's plan and the interests of these enterprises. As for the latter, due to differences in topography and soil physical–chemical properties in different areas: the more fragmented the farmland, the more time farmers had to spend learning about TSFFT. Since most farmers' primary source of income comes from off-farm employment, spending too much time learning TSFFT is clearly counter to their economic interests.

Regarding the influence of technology promotion and perception, both the type of technology promoter and farmer's perceived usefulness of TSFFT had significant impacts on adoption choice. From the perspective of technology promotion, informal promoters (i.e., farmers' relatives, acquaintances, and friends) held more sway than formal promoters (i.e., governments, agencies, and enterprises); this may indicate that farmers are more likely to trust informal promoters than formal promoters when deciding whether to adopt a new technology. In terms of farmers' perceptions of TSFFT, perceived usefulness was more important than perceived usability; this implies that there is some room for improvement in terms of improving the awareness of the impact of technical effectiveness among farmers.

[1] "mu" is a common unit of area used in China (1 ha = 15 mu).

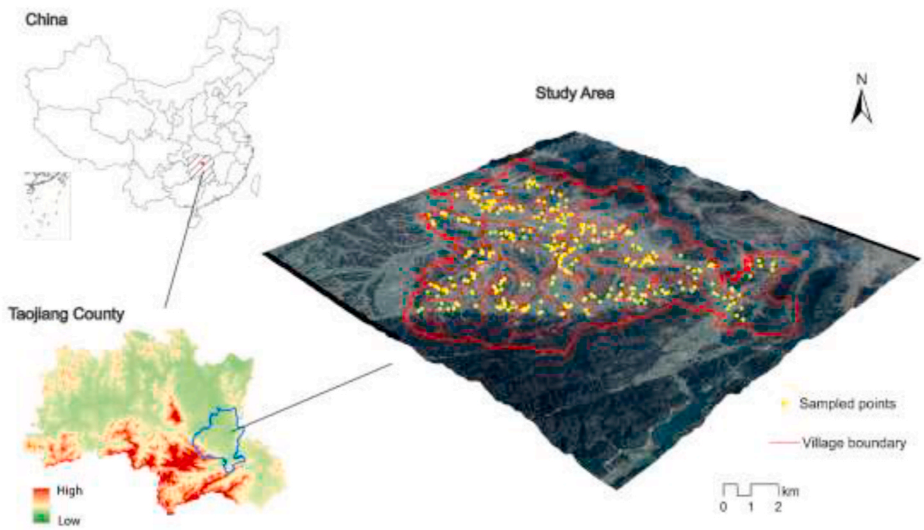

Fig. 2. Location of the study area and spatial distribution of interviewed households.

Table 3
Descriptive statistics of variables used in technology adoption model.

Variables	Mean	S.t.d	Variance	Min	Max
Characteristics of the household head					
Gender	1.37	0.48	0.23	1.00	2.00
Age	54.14	11.28	127.32	24.00	84.00
Education level	7.26	2.83	8.03	0.00	16.00
Family economic status					
Income level	3.10	1.37	1.87	1.00	5.00
Primary source of income	1.32	0.47	0.22	1.00	2.00
Agricultural labor force	2.05	1.05	1.10	1.00	7.00
Farming conditions					
Farm size	8.90	23.61	557.43	0.50	300.00
Degree of farmland fragmentation	6.47	3.69	13.59	0.00	24.00
Use of machinery	1.71	0.45	0.21	1.00	2.00
Technology promotion and perception					
Type of technology promoter	1.57	0.50	0.25	1.00	2.00
Perceived usability of technology	2.93	1.34	1.78	1.00	5.00
Perceived usefulness of technology	3.26	1.45	2.11	1.00	5.00

Table 4
Logistic regression results of the technology adoption model.

Variables	Coefficient	Std. Error	Wald	Sig.	Exp (*B*)
Characteristics of the household head					
Gender	−0.268	0.318	0.710	0.399	0.765
Age	−0.048***	0.015	10.585	0.001	0.953
Education level	0.130**	0.053	5.885	0.015	1.138
Family economic status					
Income level	0.011	0.114	0.010	0.921	1.011
Primary source of income	0.097	0.324	0.090	0.765	1.102
Agricultural labor force	−0.068	0.189	0.130	0.718	0.934
Farming conditions					
Farm size	0.052***	0.019	7.423	0.006	1.054
Degree of farmland fragmentation	−0.095**	0.048	4.000	0.045	0.909
Use of machinery	0.520	0.346	2.263	0.132	1.682
Technology promotion and perception					
Type of technology promoter	0.670**	0.310	4.680	0.031	1.955
Perceived usability of technology	0.090	0.113	0.623	0.430	1.094
Perceived usefulness of technology	0.385***	0.116	10.907	0.001	1.469
Number of obs = 312					
Prob > Chi-squared = 0.000					
Power of prediction (%) = 76.6					
Pseudo R^2 = 0.288					

Note: ** and *** represent 5% and 1% significance, respectively.

4.2. Impact of household spatial location and farmland resource endowments

Using the kernel density estimation method shown in Eq. (3), we estimated the probability of the adoption of TSFFT by farmers at different locations in the study area (Fig. 3a). Overall, farmers located in the central and northern villages were more likely to adopt TSFFT. These villages are relatively close to the urban settlement north of the study area. Moreover, the standard deviational ellipses of adopters and non-adopters indicate that the spatial distribution of both is directional.

According to farmers' spatial positions, the Voronoi diagram was generated using Geoda 1.2.0 (Fig. 3b). Then, the value of Global Moran's I was calculated using Eq. (4), which was found to be 0.1818 (z-score = 6.6710, $P < 0.01$). This indicates that the spatial distribution of the adopters reflected clustering characteristics, and the probability of the random generation of this clustering pattern was less than 1%.

After clarifying the spatial distribution characteristics of farmers with different adoption decisions, the geographical detector method was used to explore the factors that led to spatial variabilities as well as the influence degree of each factor. First, based on the previously selected indicators for the geographical detector analysis (Table 2), maps of the indicators were generated as shown in Fig. 4. Second, the influence of each indicator on the spatial variabilities of farmers making different adoption decisions was detected using Eq. (5). The detection results are summarized in Table 5.

Overall, landform characteristics, drainage capacity, irrigation capacity, and topsoil thickness were the factors that significantly impacted the spatial variabilities of farmers making different adoption decisions (Table 5). Among them, the landform characteristics were the most important factor, explaining approximately 21% of the spatial variabilities ($P < 0.01$); 60.8% of the farm households with farmlands located in a flat area had chosen to adopt TSFFT, while none of the households with farmlands located in upper hill areas had chosen to adopt it. Drainage capacity could explain approximately 17% of the spatial variabilities ($P < 0.05$); the stronger the drainage capacity of the farmland, the more likely it was that the farm household would adopt

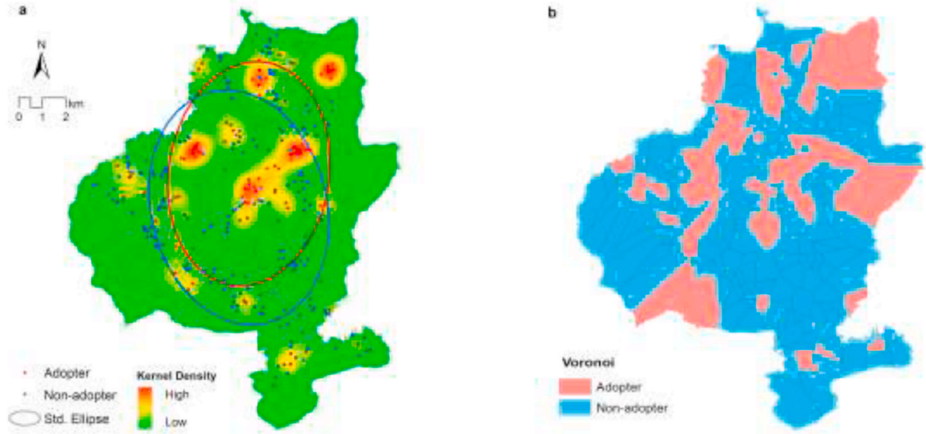

Fig. 3. Spatial distribution characteristics of farmers making different adoption choices: a, Kernel density estimation, b, Farmers' Voronoi diagram.

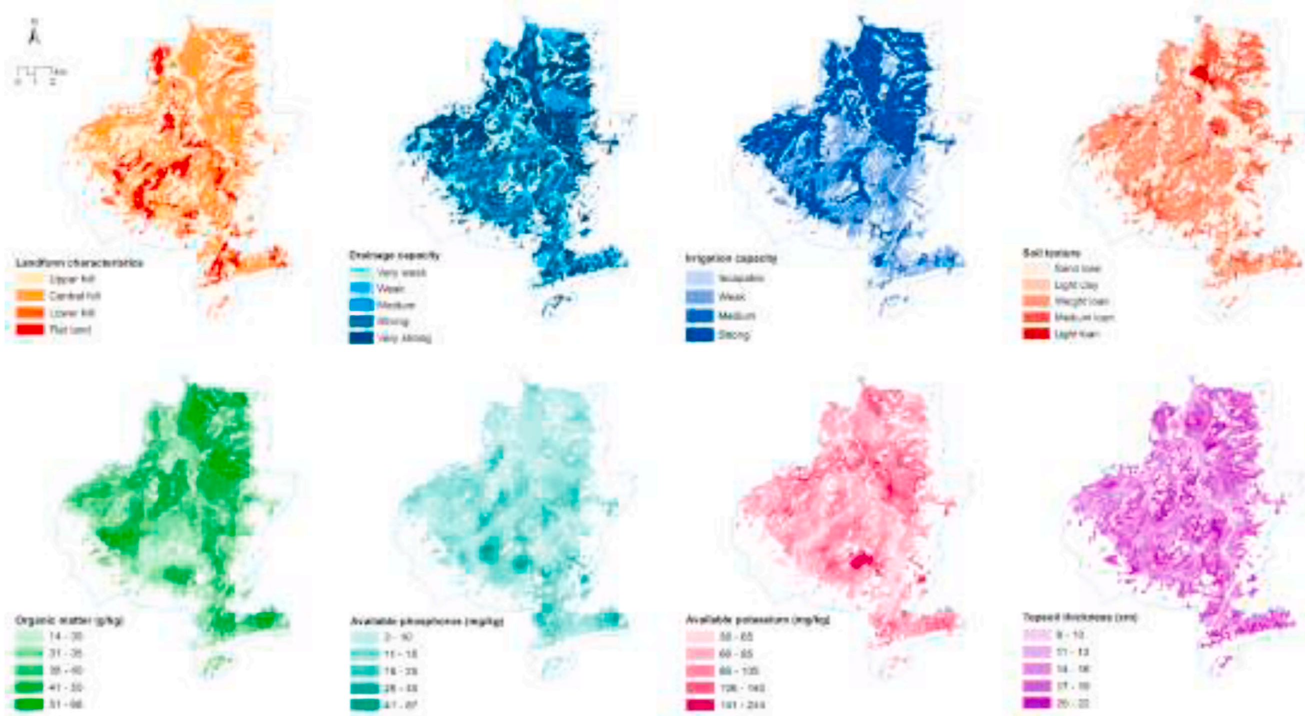

Fig. 4. Indicators detecting the spatial variabilities of farmers making different adoption decisions.

Table 5
Detection results of the geographical detector method.

	Landform characteristics	Drainage capacity	Irrigation capacity	Soil texture	Organic matter	Available phosphorus	Available potassium	Topsoil thickness
q	0.210	0.169	0.126	0.039	0.021	0.005	0.010	0.125
P	0.000	0.012	0.056	0.351	0.166	0.814	0.528	0.047

TSFFT. As for irrigation capacity, a household whose farmland had strong or medium irrigation capacity would have an approximate 30% probability of adopting TSFFT, which would drop to 16% when irrigation capacity was weak. With respect to topsoil thickness, households whose farmlands had topsoil thickness greater than 17 cm were more likely to adopt TSFFT than those with a lower topsoil thickness.

4.3. Discussion

Relying on the excessive input of chemical fertilizers, China's total grain output has doubled over the past couple of decades (Zhang et al., 2013), and national grain self-sufficiency has been achieved in general (Qi et al., 2015). A key measure to maintain national food security while avoiding the further deterioration of agricultural environmental quality has been to actively promote the development and spread of EFFTs. However, despite the extensive efforts of policymakers, there has been no significant increase in the number of farmers adopting these technologies for grain production (Wang et al., 2018). Therefore, exploring and understanding the factors influencing farmer adoption of EFFTs are critical to developing robust policy instruments to increase farmers' adoption rate.

Selecting the appropriate indicators and methods is crucial for such analysis as the underlying mechanism influencing farmers' decision-making behavior is complex. With reference to conventional studies that focus on socioeconomic characteristics and technology perceptions in econometric analyses, as well as spatial analysis models that explore the impact of geographical elements on farmer adoption decisions, we established a spatial–econometric analytical framework to explore the factors influencing farmers' adoption of EFFTs. Although the framework may have some flaws, the corresponding case study has presented many valuable findings.

In this case, the household survey in 2018 shows that the adoption rate of TSFFT in grain production was 25% in the study area. Although this rate was slightly higher than that in Taihu Basin (23%) (Ma et al., 2014), the promotional effect of this technology was far from promising. However, our findings suggest that the situation can be improved significantly if policymakers can clarify the key factors affecting farmers' adoption decisions and develop targeted policy measures accordingly. Overall, identification of households who are receptive to TSFFT, enhancement of farmers' cognition and trust in TSFFT, and improvement in the agricultural infrastructure are three practical measures.

A careful examination of current promotional patterns of TSFFT in the study area reveals that the promotional pattern in Taojiang County—which was gradually expanded village by village—has been inefficient. As most farmers adopt the technology due to the influence of informal promoters (i.e., farmers' relatives, acquaintances and friends; see Table 4), who are usually located in the same or adjacent villages, targeting the farmers receptive to TSFFT and then regarding them as informal promoters to influence nearby farmers could be an efficient approach to improving adoption. Receptive farmers are those who are relatively younger and better educated and/or occupy a larger cultivated area. Although perceived usefulness has a greater impact on farmers' adoption than perceived usability, for those farmers who were willing but did not adopt TSFFT, more effort should be put into increasing their awareness of the ease of use of TSFFT. Moreover, due to the fact that the spatial distribution of the adopters show clustering characteristics (Fig. 3), more attention should be paid to non-adopter-dominated areas. Furthermore, improving the irrigation and drainage systems in farmlands could increase the probability of farmer adoption of TSFFT.

If the above policy measures can be implemented, the quality of the local agricultural environment will be improved significantly. Because adopters used about 16% less fertilizer than non-adopters in grain production, and the area sown to grain accounts for over 60% of the area sown to crops in Taojiang County in recent years (Taojiang Bureau of Statistics, 2019). However, although there may be differences in the composition and price of the fertilizers used by adopters and non-adopters, this study did not investigate these differences. Future studies on the influencing factors of farmers' adoption of EFFTs are encouraged to carry out an in-depth exploration of these variables.

5. Conclusions

Over the past couple of decades, China has ensured food security at the cost of agro-environmental quality. Under accelerated pressure from environmental deterioration, there is an urgent need to achieve sustainable grain production, which requires the broader use of EFFTs by farm households. To systematically explore the factors that may influence farmers' adoption of EFFT in grain production, our study used a spatial-econometric analytical framework. We took into account four major factors that could be influencing farmers' adoption of EFFT: socioeconomic characteristics of the household, the technology's promotion and perception, farmland resource endowments, and the spatial location of the household. Next, based on a logistic regression model and three mutually complementary spatial analysis models, we applied our framework using Taojiang County as our case study area.

Our findings indicate that farmers' adoption of TSFFT is influenced not only by socioeconomic and cognitive factors but also by geographic and spatial elements. Among them, the age and education level of the household head, the farm size, and the degree of farmland fragmentation are the main socioeconomic factors and the main geographic factors are landform characteristics, drainage capacity, irrigation capacity, and topsoil thickness. Moreover, the type of technology promoter and the perceived usefulness of the technology also affect farmers' adoption willingness. In addition, most adopters are located in villages relatively close to an urban settlement and the spatial distribution of the adopters show clustering characteristics.

To increase the probability of adoption, more energy should be spent on farmers who are receptive to TSFFT during the technology promotion process, encouraging them to become active technology promoters. Improvement in agricultural infrastructure should be focused on irrigation and drainage systems in farmland. However, since there are many differences in grain production conditions, technology promotion patterns, and rural social relations in different countries, the generalizability of this study remains to be further verified.

CRediT authorship contribution statement

Xiaoxing Qi: Conceptualization, Investigation, Methodology, Writing – original draft, preparation. **Fachao Liang:** Formal analysis, Validation. **Wenhua Yuan:** Supervision, Writing-Reviewing. **Tao Zhang:** Investigation. **Jianchun Li:** Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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