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Role of Social Learning in the Diffusion of Environmentally-Friendly Agricultural Technology in China

Qi Li [1], Wanjiang Yang [1] and Kai Li [1,2,*]

[1] China Academy for Rural Development, Zhejiang University, Hangzhou 310058, China; 11320052@zju.edu.cn (Q.L.); wjyang@zju.edu.cn (W.Y.)

[2] School of Management, Fujian Agriculture and Forestry University, Fuzhou 350002, China

* Correspondence: li-kai@fafu.edu.cn; Tel.: +86-591-8639-1829

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Abstract: Reducing the use of chemical inputs is an urgent and challenging task in the transformation toward environmentally-friendly agriculture in China, especially when the efficacy of alternative control measures is not yet fully understood. Based on the data from 601 rice farmer households regarding their adoption of fertilizer- and pesticide-reducing technologies in Zhejiang and Jiangsu Provinces, this study investigated whether social learning can promote the diffusion of fertilizer- and pesticide-reducing technologies, and whether the role of social learning varies when the technologies differ. Empirical analysis using the spatial error model (SEM) showed that social learning positively affects the diffusion of ecological technologies, but the role of social learning varies when the technology characteristics differ. Learning from neighbors promotes the adoption of labor-intensive and high-skilled technologies, but this strategy does not work well in capital-intensive technologies. However, learning from demonstration significantly affected the diffusion of capital-intensive and high-skilled technologies, but did not work well for labor-intensive technologies.

Keywords: environmentally-friendly; rice fertilizer-reducing and pesticide-reducing technologies; social learning; spatial error model (SEM)

1. Introduction

To address the problems of food and clothing scarcity, public concern has been increasing about the importance of avoiding environmental problems related to farming activities. This concern is one of the main forces driving the transformation toward environmentally-friendly agriculture in developing countries. Agriculture in China is facing this challenge. China's agriculture provides food for almost 1.3 billion people, which is about 20% of the world population, creating increasingly Chemical over-usage a danger to agro-ecosystems and an obstacle to China's sustainable agricultural development. According to the results of the first national census of pollution sources in 2010, chemical oxygen demand and total nitrogen and phosphorus emissions, which were the major sources of agricultural pollutants, were 13,240,900, 2,704,600, and 284,700 tons, accounting for 43.7%, 57.2%, and 67.3% of national emissions, respectively. The amount of fertilizers (converted to purified fertilizers) used in China in 2016 reached 59,841,000 tons, and pesticides reached 1,783,000 tons. The amount of fertilizer used per hectare was almost three times higher than the world average, and the average amount of chemical pesticides used was 2.5–5 times higher than that of developed countries. Previous studies reported that the overuse of fertilizers and pesticides has a causal relationship with eco-environmental problems, such as non-point pollution [1–6]. The long-term overuse of chemical fertilizers also decreases the rice yield, yield stability, and sustainability [7]. An ecological footprint analysis in China showed that the overuse of fertilizers and pesticides has aggravated the depletion of resources, which revealed the unsustainable nature of the Chinese agriculture ecological system [8].

Immediately reducing fertilizers and pesticides is essential for maintaining the sustainability of agriculture. However, given long-term rural population transfer, the majority of the laborers in China's agriculture sector are generally older, poorly educated, and risk-averse. Additionally, the increasing price of labor, together with the decreasing prices of agricultural products, prevents possible labor as a good substitute for chemical fertilizers and pesticides due to cost constraints. Thus, promoting the adoption of a series of new technological controls for pests, such as biological, physical, and ecological pest controls, to these farmers is a big challenge for the sustainable development of Chinese agriculture.

Uncertainty, risk aversion, and limited understanding were considered the main factors influencing the overuse of fertilizers and pesticides. An experiment in rural India indicated almost all individuals are moderately risk-averse at high payoff levels [9], and the relationship between risk (uncertainty) and farm production has attracted many scholars and researchers. A study of farmer behavior in terms of pesticide use in China found that higher risk-averse cotton farmers tended to use more pesticides or fertilizers to reduce production uncertainty [10,11].

Social learning based on farmers' social networks can enhance information exchange and human communication, thereby helping to reduce the uncertainty involved when applying new agricultural technologies. As such, the role of social learning in the application and extension of sustainable agricultural technologies has attracted increased attention. Tarde proposed that all behaviors or innovations are disseminated through "imitation" among people [12]. In a group of farmer households with similar social status, economic status, education background, and production characteristics, face-to-face observation and communication were found to be the most effective at persuading potential technology adopters [13]. If a household takes the lead in adopting a certain production technology, farmers nearby can adopt the new technology through imitating and learning from the leading farmer household, thus forming an agglomeration [14,15]. Data from Honduras about the adoption of organic agricultural technologies showed a significant phenomenon of spatial agglomeration. The availability of information from neighboring farmer households and the positive externality of social conformity and technology significantly affected the technology adoption behavior of farmers [16]. A study of New Zealand dairy farmers' adoption of best management practices for protecting water quality showed that farmers located near each other exhibit similar choice behavior, namely spatial agglomeration [17].

Since the role of social learning in solving ecological problems has been discussed, the process of effective social learning requires further study. This study aimed to evaluate the role of social learning in the diffusion of fertilizer- and pesticide-reducing technologies, and to analyze whether the role of social learning varies when the technologies differ. The contributions of this study include the following two points. Firstly, the varieties, amounts, and patterns of fertilizer and pesticide use are closely related to the soil and climate in a particular area, which means that using these technologies has underlying geographical and spatial relevance. Therefore, different from conventional social network analysis, spatial econometric models would be able to determine whether social learning plays positive role in diffusion by testing the agglomeration effect (learning from neighbors) and the demonstration effect (learning from demonstration areas). Secondly, to investigate the different influences of social learning, we selected a set of fertilizer- and pesticide-reducing technologies and classified these measures into three categories: labor-intensive, capital-intensive, and high-skilled technologies, according to the technical attributes. Because we used a set of technologies, the adoption of fertilizer- and pesticide-reducing technologies could not be labeled as either "yes" or "no". To solve this problem, we calculated farmer households' technology adoption scores based on technology classification and the difficulty level of the introduced technology.

2. Methodology and Data

2.1. Theory of Spatial Diffusion of Technology

The Spatial Diffusion of Technology theory introduces the concept of space from the field of economic geography into the theory of technology diffusion to analyze the direction and path of technology diffusion. The theory holds that the diffusion of technology is realized through the interactive process of "learning" or "communication" between individuals. Therefore, the effective transmission of information is a prerequisite for achieving technology diffusion. The key factor affecting information transmission is spatial distance [18]. Scholars of the expanded diffusion theory, such as Darwent and Morrill, believe that technology diffusion follows a path radiating from the center of innovation source to its surroundings. As such, the technology diffusion effect is a function that decreases as spatial distance increases, showing a clear agglomeration effect and a demonstration effect at the center [19,20].

2.2. Spatial Econometric Model

Spatial statistics and econometric methods establish the relationship between statistics and metrology through geographic location and spatial relations. These methods identify and measure the law of spatial variation and determinants of spatial patterns [21,22]. Considering spatial behavioral correlations, spatial models align more with objective agricultural production decisions.

According to the basic economic assumption of rational farmers, farmer decision-making about technology adoption depends on their judgment of utility. The utility of farmer i's adoption decisions Y_i^* can be expressed as:

$$Y_i^* = U_{i1} - U_{i0} \tag{1}$$

where U_{i1} and U_{i0} represent farmers' utility when they adopt and do not adopt technologies, respectively.

The spatial decision-making model for farmer technology adoption assumes that Y_i^* depends not only on a farmer's own characteristics but also on the spatial dependency between the farmer and their neighbors. Y_i^* can be expressed as:

$$Y_i^* = U(X_i, S_i^*) + e \tag{2}$$

where S_i^* represents the impact of the unobservable spatial dependence on a farmer's adoption decisions. S_i^* can be expressed as:

$$S_i^* = S\big(Z_t, Y_j(i)\big) + e \tag{3}$$

where Z_t is a series of exogenous variables in the area where farmer i is located, and $Y_j(i)$ represents the behavior decisions of farmer i's neighbors (i is not j).

The basic form of the spatial decision-making model for farmer technology adoption is:

$$Y_i = \rho W \cdot Y_i + \beta X_i + u \tag{4}$$

$$u = \lambda M \cdot u + \varepsilon, \varepsilon \sim N(0, \sigma^2 I_n) \tag{5}$$

where u is the error term; W and M are the spatial weight matrices of Y and u, respectively; ρ is the spatial autoregressive coefficient; and λ is the spatial autoregressive error coefficient. The mainstream spatial econometric models include the spatial error model (SEM), spatial lag model (SLM), and the spatial Doberman model (SDM). The basic assumptions of the spatial error model and spatial lag model correspond to $\rho = 0$ and $\lambda = 0$, respectively. The basic assumption of the spatial Doberman model is that the coefficient is not zero, $\rho \neq 0$, and $\lambda \neq 0$.

As previously reported [23–32], independent variables (X_i) include personal and family characteristics, production and organizational characteristics, technology and information channels, and production services. Specific variables and their distribution are listed in Table A1.

2.3. Model Setting

The spatial proximity that determines the extent to which changes in farmer j influence the adoption probability of farmer i is dependent on a special weights matrix W_{ij}. Two main methods can determine the spatial weight matrix: contiguity based spatial weights (W_{ij} is defined if farmer i and farmer j are conterminal) and distance based spatial weights (W_{ij} is defined on the inverse distance between farmer i and farmer j). The paddy fields crisscross, therefore measuring an accurate distance was difficult. At the same time, the distance between any two villages is much longer than the radius of villages. Given these facts, we used the "village" definition of "neighbors" as outlined in Holloway et al. [33] and Ying and Xu [34]. In this matrix, if farmer i and farmer j are farmers in the same village, then $W_{ij} = 1$; otherwise, $W_{ij} = 0$.

First, we depict the autocorrelation of the spatial distribution of the scores for sample farmers' adoption of fertilizer- and pesticide-reducing technologies with Global Moran's I. The results (Table 1) show that the Moran's I indexes of the adoption scores of the three categories of fertilizer- and pesticide-reducing technologies were all significantly positive at the 1% level, indicating that the farmers with higher technology adoption scores tend to be geographically close to farmers of the same type, which means that using a spatial econometric model for estimation was reasonable.

Table 1. Global Moran's I index testing results.

Testing Indicators	Labor-Intensive Technologies	Capital-Intensive Technologies	High-Skilled Technologies
Moran's I	0.578	0.375	0.424
Moran's I-Probability	<0.001	<0.001	<0.001

Secondly, with the Lagrange Multiplier (LM) and testing of its robustness (Robust LM, or R-LM), we selected a suitable spatial econometric model. According to the testing method used by Anselin et al. [35], if the spatial error-LM is more significant than the spatial lag-LM, and the spatial error-R-LM is significant, whereas spatial lag-R-LM is not significant, the Spatial Error Model (SEM) should be used. Otherwise, the Spatial Lag Model (SLM) should be used. When both LM and the robustness testing are significant, the Spatial Dubin Model (SDM) should be used.

Based on the test results of the three types of fertilizer- and pesticide-reducing technologies (Table 2), the significance of spatial error-LM was higher than that of spatial lag-LM, and, moreover, spatial errors-R-LM were all significant at the 1% level. Therefore, it was most appropriate for us to use the SEM for estimation.

Table 2. Lagrange Multiplier testing results.

Testing Indicators	Labor-Intensive Technologies		Capital-Intensive Technologies		High-Skilled Technologies	
	Statistic	*p*-Value	Statistic	*p*-Value	Statistic	*p*-Value
Spatial error						
Lagrange Multiplier	994.370	<0.001	76.214	<0.001	213.57	<0.001
Robust Lagrange Multiplier	798.138	<0.001	77.779	<0.001	205.57	<0.001
Spatial lag						
Lagrange Multiplier	197.077	<0.001	0.188	0.664	15.01	<0.001
Robust Lagrange Multiplier	0.844	0.358	1.754	0.185	7.01	0.01

2.4. Research Area and Basic Data

The data in this paper were obtained from an investigation of rice farmers in Zhejiang Province and Jiangsu Province, China, from July to September 2017. We selected these two provinces due to the rice production and the amount of chemical overuse. Rice is the main crop in both Zhejiang and Jiangsu Provinces, accounting for 65% and 42% of grain acreage, respectively. The average excessive amount of fertilizer for the major rice-producing provinces in the middle and lower reaches of the Yangtze River was 583.5 kg/hectare and the amounts in Jiangsu and Zhejiang Provinces were 516.75 and 312.9 kg/ha, respectively [36]. Household survey data from Zhejiang and Jiangsu Provinces reflected the real situation of excessive use of chemical fertilizers and pesticides in the rice industry in East China, which was helpful to summarize the fertilizer and pesticide reductions and explore a reasonable path for policy promotion.

The Environmental Kuznets Curve shows that environmental improvement occurs after economic development. In China, in 2017, Zhejiang and Jiangsu Province were ranked one and two, respectively, in terms of Per Capita Disposable Income (excluding municipalities) (the data are from *China Statistical Yearbook of 2017*). These two provinces also led the green transformation of agriculture, which could provide references for other regions. Both Zhejiang and Jiangsu have created a good policy environment for the sustainable production of rice. The government of Zhejiang set a goal of building a strong culture of green agriculture practices in the province and issued *The Action Plan for Fertilizer Reduction and Efficiency Enhancement in Zhejiang Province* and *The Action Plan for Pesticide Reduction in Zhejiang Province*, outlining the overall requirements, objectives, tasks, technical routes, and work priorities for reducing fertilizer and pesticide use and increasing efficiency. Jiangsu Province proposed the concept of green agricultural development in the section about the development and planning of modern agriculture in the "13th Five-Year Plan" and launched the special campaign called "two reductions, six controls, and three improvements" in 2017. The plan requires the implementation of fertilizer and pesticide reduction projects and the promotion of reduction technologies to ensure zero growth of pesticide application.

Demonstration areas are usually set up in paddy fields owned by farmers. The government specifies the types of technologies that need to be demonstrated, guides the operation of the technologies, and provides necessary financial and material support. Family farms or large grain producers perform weeding, irrigation, and other daily management. The size of the demonstration areas varies with the kind of technologies and the size of family farms.

Households were randomly selected based on a multi-stage cluster sampling. In the first stage, we chose six counties in Zhejiang Province and two counties in Jiangsu Province that had begun demonstration areas the earliest. In every county, two villages with demonstration areas were randomly selected from a list of demonstration areas provided by local government, with three villages in the largest county. Then, two villages around first-selected village but without a demonstration area were chosen. A total of 17 villages with demonstration areas and 34 villages without demonstration areas were selected. Then, 10–13 households were randomly selected in each of the villages. The survey was conducted one-to-one, from July to September 2017. A total of 638 questionnaires were distributed, of which 601 were considered valid collections, with a response rate of 94.20%.

3. Results and Discussion

3.1. Adoption of Fertilizer-Reducing and Pesticide-Reducing Technologies

Rogers noted that the new technology itself can explain 49–87% of the technology adoption rate [13]. The differences in the level of technology benefits, the level of risk, and the degree of dependence on resources account for the differences in decision-making with regard to technology adoption by farmers [37]. Based on Rogers' theory, a set of technologies were, using the Delphi method, screened according to ease and applicability of technical use (Table 1). Different from the usual measurement of adoption responses of "yes" or "no", after referring to previously methods [38–40], we decided to calculate the adoption score.

Next, the fertilizer- and pesticide-reducing technologies were divided into three types: capital-intensive, labor-intensive, and high-skilled technologies (Table 3). Capital-intensive technologies are mainly achieved through the use of new materials such as efficient plant protection machinery. Labor-intensive technologies require more labor input, but almost no new material or technology is required. High-skilled technologies are characterized by complexity, which means lasting, in-depth learning is necessary. In addition to the differences in technical attributes, the level of difficulty in terms of adopting technologies with the same attributes also varies. Based on the evaluation of plant protection and soil fertilizer experts, three levels of difficulty (easy, moderate, and difficult) were defined and assigned the weights of 1, 2, and 3, respectively. In summary, the formula for calculating rice farmers' score of technology adoption Y_i is:

$$Y_i = \sum_{k=1} T_{ik} \times Q_{ik} \quad (6)$$

where i represents the technology category, k is the sub-technologies in each of the three technical categories, T is whether the kth sub-technology is adopted, and Q is the adoption weight.

Table 3. Fertilizer- and pesticide-reducing technologies for rice.

Technology Category	Technology Name	Technical Attributes	Level of Difficulty of Technology Adoption
	Fertilizer-reducing technologies		
Nutrient replacement technologies	Organic fertilizer (biogas slurry), fertilizer application technology	Capital-intensive/high-skilled	Moderate
	Straw back to the field technology	Capital-intensive/high-skilled	Difficult
Fertilizer enhancement technologies	Slow release fertilizer application technology	high-skilled	Moderate
	Mechanical side deep application technology	Capital-intensive	Moderate
	Soil testing and formulation technology	high-skilled	Easy
	Fertilizer control and harm reduction technology	high-skilled	Easy
	Pesticide-reducing technologies		
Ecological regulation and control technologies	Planting of flowering plants technology	Labor-intensive	Difficult
	Planting of insect-inducing plants technology	Labor-intensive	Difficult
Biological prevention and control technologies	Trichogramma release technology	Labor-intensive/high-skilled	Difficult
Physical and chemical induction technologies	Sex attractant trapping technology	Capital-intensive	Easy
Drug efficacy enhancement technologies	Efficient plant protection machinery application technology	Capital-intensive	Moderate

Farmers' adoption scores with regard to fertilizer- and pesticide-reducing technologies are still low (Table 4), and the level of technology adoption needs to be rapidly improved. From a distribution perspective, the average adoption level of labor-intensive technologies was low, with over 60% of the households scoring zero. Only 30.28% of the farmers had a score over six points for capital-intensive technologies. Over half of the farmers have an adoption score of four to six points for high-skilled technologies.

Table 4. Score distribution of rice farmers' adoption of fertilizer- and pesticide-reducing technologies.

Technology Category	Score Distribution			
Labor-intensive technologies	0	3	6	9
Proportion of farmer households (%)	61.73	19.13	17.30	1.83
Capital-intensive technologies	0–2	3–5	6–8	9–10
Proportion of farmer households (%)	9.15	60.57	24.29	5.99
High-skilled technologies	0–3	4–6	7–9	10–12
Proportion of farmer households (%)	21.96	53.25	18.47	6.32

3.2. Analysis of the Role of Social Learning by SEM

According to the estimation results for labor-intensive technologies (Table 5), λ was positive and significant at the 1% level, indicating that a significant spatial autocorrelation exists among the adoption levels of labor-intensive technologies. Social learning (learning from neighbors) played positive role in the extension of labor-intensive technologies. The main reason is that, at close range, farmers can exchange pest control information conveniently. The impact of the second kind of learning, learning from demonstration areas, was negative, showing that farmers closer to the demonstration areas have higher technology adoption scores. However, the variable was not significant; the demonstration areas do not have a demonstration effect on the surrounding farmers' adoption of labor-intensive technologies. This might be because directly observing the chemical-reduction effect of flowering and insect-attracting plants through rice growth in the demonstration areas is difficult, and there is no need to learn the technical specifications through the demonstration areas given the simplicity of the operation of labor-intensive technologies.

According to the estimation results for capital-intensive technologies (Table 5), λ was positive but not significant, indicating that there was no significant agglomeration effect. The distance between farmers and demonstration areas had a negative impact at the 1% level. In other words, learning from demonstration had a significant effect on surrounding farmers' adoption of capital-intensive technologies. The insignificant agglomeration effect may be attributed to the fact that the implementation of such technologies mostly occurs through the purchase of machinery services. Therefore, promotion is not only constrained by the development level of local agricultural machinery services. This is especially notable for agricultural machinery services that meet the requirements of small-area cultivation, but also related to whether farmers are willing to purchase agricultural machinery services.

According to the estimation results for high-skilled technologies (Table 5), λ was positive and significant at the 5% level, indicating that a significant spatial agglomeration effect exists, which verifies the positive role of the first type of social learning. The distance between farmers and demonstration areas showed a significant negative impact at the 5% level, meaning the second social learning type had a significant demonstration effect on surrounding farmers' adoption of technologies. This confirms the positive role of the second kind of social learning. The reason high-skilled technologies show both the agglomeration effect and the demonstration effect is that farmers have to master the operation essentials through observation as well as study in the demonstration areas to communicate with each other to reduce technical uncertainty when the production technology requirement is high.

Table 5. Model estimation results for factors influencing the adoption of fertilizer- and pesticide-reducing technologies.

Variable	Labor-Intensive Technologies		Capital-Intensive Technologies		High-Skilled Technologies	
	Coefficient	Z Value	Coefficient	Z Value	Coefficient	Z Value
Distance	−0.0209 (0.0399)	−0.5200	−0.2055 *** (0.0659)	–3.1200	−0.2166 ** (0.0883)	−2.4500
Education background	−0.1008 *** (0.0344)	−2.9300	0.2355 *** (0.0752)	3.1300	0.4037 *** (0.0867)	4.6600
Years of planting rice	−0.0022 (0.0019)	−1.2000	−0.0057 (0.0038)	−1.5000	−0.0010 (0.0041)	−0.2400
Number of laborers	0.0474 *** (0.0177)	2.6800	0.0215 (0.0390)	0.5500	−0.0571 (0.0449)	−1.2700
Employment/business level	−0.0018 ** (0.0009)	−2.1300	0.0031 (0.0019)	1.6100	−0.0029 (0.0023)	−1.2600
Willingness to adopt technologies	0.0141 (0.0327)	0.4300	0.1011 ** (0.0440)	2.3000	0.2438 *** (0.0610)	4.0000
Planting area	−0.0249 (0.0183)	−1.3600	0.0529 (0.0490)	1.0800	0.0113 (0.0572)	0.2000
Degree of mechanization	−0.0340 (0.0331)	−1.0300	0.0929 (0.0671)	1.3800	0.0761 (0.0841)	0.9100
Degree of organization/cooperatives	0.0211 (0.0528)	0.4000	0.0278 (0.1107)	0.2500	0.0048 (0.1275)	0.0400
Subsidy	0.0002 (0.0006)	0.4100	0.0030 *** (0.0011)	2.8100	0.0128 *** (0.0013)	9.5000
Production area of double-season rice/crop	0.2909 *** (0.0618)	4.7000	0.0730 (0.1483)	0.4900	−1.5773 *** (0.1857)	−8.5000
Technical training	0.0082 (0.0175)	0.4700	0.1023 ** (0.0433)	2.3700	0.2316 *** (0.0514)	4.5100
From the government's agricultural technology department (compared with the channel of neighbors, relatives and friends)	−0.0652 (0.0651)	−1.0000	0.1967 (0.1288)	1.5300	0.5416 *** (0.1526)	3.5500
From television and the Internet (compared with the channel of neighbors, relatives and friends)	0.0689 (0.0969)	0.7100	0.2551 (0.2013)	1.2700	0.1642 (0.2411)	0.6800
Unified prevention and control	−0.1915 (0.1971)	−0.9700	0.8050 ** (0.4016)	2.0000	−0.9740 ** (0.4283)	−2.2700
Plant protection or soil testing information	0.1148 * (0.0603)	1.9000	0.1980 * (0.1168)	1.7000	0.1517 (0.1514)	1.0000
Provision of field crop seeding (Unified provision of high-quality fertilizers)	0.7148 *** (0.2729)	2.6200	0.7081 (0.6458)	1.1000	2.9165 *** (0.3731)	7.8200
Interactive term 1	−0.0188 (0.0437)	−0.4300	0.1806 * (0.0930)	1.9400	−0.0148 (0.0976)	−0.1500
Interactive term 2	0.0354 (0.0589)	0.6000	0.1231 (0.1437)	0.8600	0.0459 (0.0984)	0.4700
constant	1.2578 *** (0.1467)	8.5700	2.3482 *** (0.4040)	5.8100	1.4313 ** (0.5928)	2.4100
λ	0.0099 *** (0.0030)	3.2900	0.0014 (0.0013)	1.1400	0.0035 ** (0.0018)	1.9600
σ	0.3150 *** (0.0148)	21.3200	1.0902 *** (0.0323)	33.7100	1.2848 *** (0.0379)	33.8800
R^2-adjusted	0.47		0.61		0.69	

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

4. Conclusions

According to the Spatial Diffusion of Technology theory, based on spatial error model, we analyzed the role of social learning in the diffusion of rice fertilizer- and pesticide-reducing agricultural technologies. We found that the roles of two kinds of social learning varied when technologies differed.

The Moran's I indexes of the adoption scores of the three categories of technologies indicated that social learning plays a significant role in the diffusion of ecological technology. The spatial error model (SEM) results proved that the role of social learning varied when the technological characteristics differed. First, learning from neighbors will promote the adoption of labor-intensive and high-skilled technologies, but this type of learning did not work well in capital-intensive technologies. Second, learning from demonstration areas had a significant effect on the diffusion of capital-intensive and high-skilled technologies, but did not work well in labor-intensive technologies.

Our evaluation of the role of social learning was based on the result of diffusion, namely the spatial agglomeration and demonstration effects. However, diffusion of agricultural technology also requires time. The cross-sectional data used in this study reflected the current results of diffusion in fertilizer- and pesticide-reducing technologies only. According to Rogers's diffusion of innovations theory, technology diffusion has different characteristics at different stages. If we use micro-panel data, we may obtain more conclusions including diffusion rate, change of diffusion area, and dynamic diffusion characteristics of fertilizer- and pesticide-reducing technologies at different times. However, as mentioned in this paper, since the implementation of a package of fertilizer- and pesticide-reducing technologies only started in 2015, obtaining effective panel data remains difficult. In addition, due to the limitation of the sample size, this study did not include the social capital of farmer households in the regression model. Future research can try to use social network analysis to explain the effect of social learning and explain how social learning shapes the farmer adoption behavior of fertilizer- and pesticide-reducing technologies.

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Appendix A

Table A1. Variable descriptions and descriptive analysis.

Variable	Variable Description and Value Assignment	Mean	Standard Deviation
	Geospatial factors		
Distance	The distance between farmers and the nearest technology demonstration area (meters)	2008.94	1899.26
	Personal and family characteristics		
Education background	1 = primary school; 2 = middle school; 3 = high school; 4 = beyond high school	2.33	0.79
Years of planting rice	Decision-makers' number of years of planting rice	25.50	16.13
Number of labor	Number of family laborers	2.96	1.37
Employment/business level	Proportion of non-farm income to total income (%)	37.90	32.16
Willingness to adopt technologies	1 = not willing at all; 2 = not quite willing; 3 = neutral; 4 = quite willing; 5 = very willing	3.90	1.41
	Production and organizational characteristics		
Planting area	Rice planting area (hm^2)	4.28	112.25
Degree of mechanization	Machinery use in ploughing, seedling transplanting and harvesting: 1 = no machinery used in any of the three areas; 2 = machinery use in one of the three areas; 3 = machinery use in two of the three areas; 4 = machinery use in all three areas	2.51	0.73
Degree of organization/cooperatives	1 = established family farms or joined cooperatives or businesses; 0 = no	0.53	0.50
Subsidy	Annual subsidy for rice planting (Yuan/year)	87.76	48.29
Production area of double-season rice/crop	1 = yes; 0 = no	0.17	0.38

Table A1. *Cont.*

Variable	Variable Description and Value Assignment	Mean	Standard Deviation
	Technology and information channels		
Technical training	Average number of trainings for fertilizer and pesticide application (times/year)	2.34	1.46
From the government's agricultural technology department (compared with the channel of neighbors, relatives and friends)	1 = yes; 0 = no	0.72	0.45
From television and the Internet (compared with the channel of neighbors, relatives and friends)	1 = yes; 0 = no	0.07	0.26
	Production services		
Unified prevention and control	1 = yes; 0 = no	0.30	0.46
Plant protection or soil testing information	1 = yes; 0 = no	0.76	0.43
Provision of field crop seeding	1 = yes; 0 = no	0.12	0.33
Unified provision of high-quality fertilizers	1 = yes; 0 = no	0.15	0.35
	Interactive terms		
Interactive term 1	Unified prevention and control × willingness to adopt technologies	-	-
Interactive term 2	Provision of field crop seeding (unified provision of high-quality fertilizers) × willingness to adopt technologies	-	-

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