RESEARCH ARTICLE

Environmentally friendly agricultural technology based on discrete selection experiment

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Traditional agricultural production models are often accompanied by a large amount of resource waste and environmental pollution, causing serious damage to ecosystems. To achieve sustainable agricultural development and reduce adverse impacts on the natural environment, this study used discrete selection experiments to promote environmentally friendly agricultural technologies. This study visited two representative northern and southern provinces in rice cultivation in China and integrated three representative environmentally friendly agricultural technologies and policy subsidies into a survey questionnaire. Data analysis was conducted on farmers' selection preferences using a hybrid logit model and a latent category model to obtain promotion methods and suggestions for environmentally friendly agricultural technologies. The results indicated that some farmers in the southern region had a sense of self-environmental protection, and in addition, they provided training and learning, resulting in higher satisfaction with environmentally friendly agricultural technologies. However, another part of farmers' attitude towards choosing agricultural technology depended on the amount of policy subsidies. Due to the vast territory and sparse population, coupled with the impact of climate, the attitude of farmers in the northern region depended on the cost of time or labor. This study evaluated the feasibility and effectiveness of environmentally friendly agricultural technologies in agricultural production, promoting the application and promotion of environmentally friendly agricultural technologies.

Keywords: environmentally friendly agricultural technology; discrete selection experiment; hybrid logit model; potential category model; policy subsidies.

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Introduction

With the continuous growth of population and sharp reduction of resources, research on environmentally friendly agricultural technologies (AETs) has become particularly important [1]. The development of AETs can effectively reduce the negative impact of agriculture on the environment and improve agricultural production efficiency. The Chinese government is unanimously committed to the promotion of AETs, not only proposing the environmental protection concept of reducing sources, controlling pollution, intercepting, and repairing, but also developing various targeted environmental protection technologies in fields such as pollution prevention, pest control, and scientific fertilization [2]. Many European countries have a strong awareness of protecting agricultural arable land due to the insufficient area of agricultural production [3, 4]. Sarpong *et al*. proposed an environmentally friendly agricultural technology that utilized microbial inoculation, nutrient infusion, and pest prevention to address the environmental threat caused by the excessive use of agricultural chemicals in the field of food production. The results indicated that the practical application of this technology had a positive effect on plant growth and maintaining soil health, while also greatly improved crop productivity [5]. Lu *et al*. found that the current chemical medium used for the degradation of aniline blue enzyme had a high cost and a significant impact on the environment. Therefore, the research team proposed an alternative chemical reagent as a medium for agricultural waste rich in organic acids, such as grape skin, grape seeds, or orange peel. The results showed that the effective degradation rate of aniline blue enzyme by this alternative chemical reagent reached 97.4%, achieving a cheap and environmentally friendly effect [6]. While promoting AETs, many incentive policies and corresponding illegal restrictions have been introduced regarding agricultural environmental protection [7]. However, both domestically and internationally, although all parties have made tremendous efforts, the promotion effect is not satisfactory. Farmers selectively use or discard these technologies on the grounds of their own interests and labor costs, but the actual AETs used are less than 30% [8].

Discrete choice experiment (DCE) is a commonly used research method for evaluating the decision-making process of individuals when facing discrete choices. Sicsic *et al*. proposed a single file discrete selection experiment to evaluate vaccination intentions for unnamed diseases under multiple factors. This experiment recruited over 1,200 healthcare professionals to complete an online questionnaire survey and used the logit model for sample estimation. The experimental results indicated that, except for the management stance, the level of all attributes had a significant impact on vaccination decision-making with an average vaccination rate of 58% in all cases [9]. Robinson *et al*. investigated 100 study subjects including parents and medical service providers through a discrete selection experiment to understand the preferences of parents and hospitals for the management of pediatric febrile diseases in emergency department. The experimental results indicated that, when dealing with pediatric febrile diseases, parents and medical staff were of great importance to reduce treatment time, avoid pain caused by invasive examinations, and obtain diagnostic insights faster [10].

This study aimed to evaluate and promote the use of AETs in major rice-growing regions of China and to explore ways to promote technology adoption. By using DCEs, hybrid logit models (MXL), and latent class models (LCM) to analyze farmers' preferences, this study revealed the heterogeneity in the selection of AETs and suggested targeted promotion strategies. The results of this study would be helpful to guide the effective promotion of AETs for sustainable development of agriculture and environmental protection.

Materials and methods

Discrete choice experiments (DCEs)

DCEs are a declarative preference measurement method used to evaluate and compare the benefits and preferences of different options. In DCEs, participants are required to make choices within a given set of discrete options to express their preference for each option [11, 12]. The main steps of DCE were shown in Figure 1. The orange section was designated as an important discrete selection experimental element, typically including experimental design, participant recruitment, task selection, data collection, and analysis [13]. The experimental design could be understood as a selection set, where the number of samples provided alternative solutions. The main method for determining the sample size was shown in equation (1).

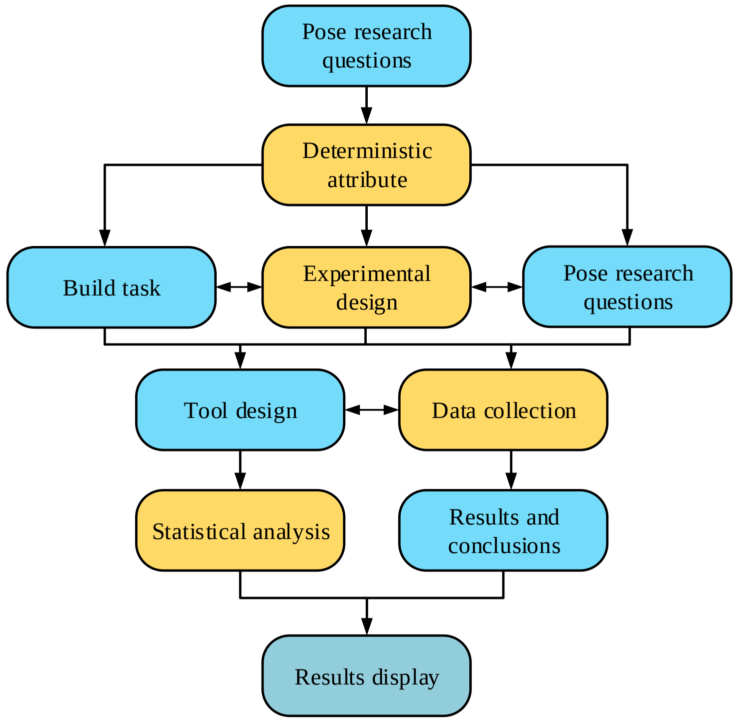

Figure 1. The flowchart of discrete choice experiment (DCE).

$$N > \frac{500 * c}{t \times a} \tag{1}$$

where N represented the sample size. c was the number of attribute levels. t was the number of selection sets. a was the number of options available for each selection set. The discrete selection model was a method for describing statistical analysis. The commonly used DCEs were the logit model, and its expression formula was as follows.

$$p = \frac{P(Y=1)}{(P(Y=1) + P(Y=0))} \tag{2}$$

where $P(Y=1)$ represented the probability of event Y occurring. $P(Y=0)$ represented the probability that event Y would not occur. The commonly used logit models were mainly divided into multiple logit models (MNL), conditional logit models (CLM), MXL, and LCM. The calculation formula for MNL was shown in equation (3).

$$\log(\frac{p_{ij}}{1-p_{ij}}) = \beta_{0i} + \beta_{1i}x_{1j} + \beta_{2i}x_{2j} + \cdots + \beta_{ki}x_{kj} \tag{3}$$

where P_{ij} was the jth level probability of the ith classification variable. x_{1j} and x_{2j} were the independent variables related to the jth level. β_{0i} and β_{1i} were the correlation coefficient of the ith classification variable. The calculation formula for the CLM was shown in equation (4).

$$P_i(j) = \frac{\exp(z_{ij}\beta)}{\sum_{m=1}^{j} \exp(z_{ij}\beta)} \tag{4}$$

where z_{ij} was the scheme attribute of the ith classification variable and the jth horizontal probability. $P_i(j)$ was the probability of individual i choosing scheme j. m was the random error term. Unlike the above two models, MXL and LCM were not limited to normal distributions and were therefore widely used in the field of data processing. The calculation formula for MXL was as follows.

$$P(y=i)=\sum(j=1,j)\lambda j * P(y=i|G=j) \quad (5)$$

where $P(y=i)$ represented the probability of selecting i. λj was the selection probability of the jth scheme set. MXL could also be expressed as the integration of traditional logit models on parameters, and its expression was shown in equation (6).

$$P_{njt}=\int L_{nj*t}(\gamma_n) f(\gamma_n|\theta) d\gamma_n \quad (6)$$

where γ_n was the coefficient. $L_{nj*t}(\gamma_n)$ was the probability of coefficient γ_n on traditional logit models. When the distribution $f(\gamma_n|\theta)$ of coefficient γ_n was in a discrete state, the calculation formula could also be used for the expression of LCM. The calculation formula for LCM was shown in equation (7).

$$prob(n, j*t|c)=\mathrm{C}_{t=1}^{T} \frac{e^{\gamma_n x_{nj*t}}}{\sum_{j=1}^{J} e^{\gamma_n x_{nj*t}}} \quad (7)$$

where n was the decision-maker. c was the model category to which the decision-maker belonged to. t was the selection scenario. j was a selection item. No matter which options the decision-maker chooses, they will gain a certain degree of utility. The expression formula for utility was shown in equation (8).

$$U_{njt}=V_{njt}+\varepsilon_{njt} \quad (8)$$

where V_{njt} was fixed utility and ε_{njt} was the random term. Among them, the random term was only related to unobservable option attributes and individual preferences. The utility calculation formula under specific circumstances was shown in equation (9).

$$V_{njt}=\gamma_n x_{njt} \quad (9)$$

where x_{njt} was the attribute variable group of option j, and γ_n was the vector coefficient. In reality, the technological choices of farmers in different agricultural areas are diverse. Therefore, for the adoption of technology by farmers, this study used the MXL and potential category model in the above models for correlation estimation. The calculation formula was shown in equation (10).

$$Y_{ij}^{*}=X_{ij}\beta_j+\varepsilon_{ij}, j=1,2,3 \quad (10)$$

where i represented the farmer. j represented the available technology. Y_{ij}^{*} represented the actual technology chosen by farmers. β_j represented a vector for estimating parameters. X_{ij} was the explanatory variable. ε_{ij} was a random term. Considering the multiple factors that affected farmers' technology adoption, willingness to accept (WTA) had been taken into consideration [14]. The expression formula of WTA was shown in equation (11).

$$WTA=\Delta R+C_Q \quad (11)$$

where ΔR was the income loss caused by farmers abandoning direct production activities due to their choice of AETs. C_Q was the loss of cultivation by farmers in the agricultural area who had converted from non-ecological to ecological quality. The expression of the influencing factors of WTA was shown in equation (12).

$$WTA^{*}=c+x\beta+\mu \quad (12)$$

where x was the vector of heterogeneity characteristics of farmers and other factors. β was the feature vector to be estimated. μ was the random error term. The government promotes AETs while providing appropriate

Table 1. Factors and attributes.

Factor	Level	Variable name	Variable definition
Fertilization technique	Pressure differential fertilization	PDF	Categorical variable
	Soil testing and formula fertilization	STF	Categorical variable
	Side strip fertilization	SBF	Categorical variable
Pest control technology	Biological control	BIC	Categorical variable
	Plant resistance cultivation	PRC	Categorical variable
	Information technology control	ITC	Categorical variable
Soil augmentation techniques	Straw returning to field	RWSR	Categorical variable
	Green manure returns to the fields	GMR	Categorical variable
Skill training	Field	FIELD	Categorical variable
	Village	VILLAGE	Categorical variable
	Town	TOWN	Categorical variable
Ecological ditch	No requirement	ECODITCH	Continuous variable
	15 meters		
	30 meters		
Policy compensation (¥/acre/year)	400	P	Continuous variable
	600		
	800		

financial subsidies to farmers to benefit the people and achieve the best of both worlds [15].

Selection of factors and levels

The first step in this study was to measure the selection utility of various existing AETs. At present, AETs can be roughly divided into disease and pest control technologies, soil fertilization technologies, and environmentally friendly fertilization technologies. Secondly, government policy subsidies had a certain targeted effect on farmers' choices. Refined regional subsidy quotas were more conducive to the authenticity of experimental results. The specific factors and attributes were shown in Table 1.

(1) Selection set design

There are many factors and classifications related to AETs with a large number. Therefore, designing multiple selection sets reasonably on the grounds of local policies and farmers' cognitive level is beneficial for subsequent choices. The selection set for this study was combined using the orthogonal arrangement method and statistically classified using SPSS software (IBM, Armonk, New York, USA). This study randomly generated 22 pairs of choice sets among all possible combinations, which fully represented the balanced orthogonality of the experiments with the preference of fertilizer technology, pest management technology, ditching technology, training methods, and policy subsidies as the dominant choice set 1, and the preference of fertilizer technology, pest management technology, ditching technology, training methods, and a small amount of policy subsidies as the dominant set 2. After removing the dominant set from all the choice sets, 20 pairs were remained with 8 pairs in Heilongjiang, China and 12 pairs in Guangxi, China. Three comparison programs existed for each pair of choice sets. Option 1 was differential pressure fertilization, biological control, straw return, field training, no ecological ditch, and ¥400 (Chinese yuan)/acre policy subsidy. Option 2 was side-strip fertilization, plant resistance development, straw return to field, village training, 15 m ecological ditch, and ¥600/acre policy subsidy. Program 3 was soil test formula fertilization, scientific and technological pest control, green manure returning to the field, training in towns, 30 meters of ecological ditches, and a policy subsidy of ¥800/acre. As a representative rice production region in the northern part of China, Heilongjiang

Table 2. Descriptive statistical table of survey in southern region.

Socioeconomic variable	Interpret and assign values	Statistical value	
GEN	Gender (male =A, female =B)	A	69.58%
		B	30.42%
AGE	Age (year old)	Mean (SD)	62.16
INCOME	Annual household income (¥10,000)	Mean (SD)	4.11
UAET	Have you used AETs before? (used =A, not used =B)	A	5.32%
		B	94.68%
APAE	Whether agricultural production has an impact on the environment (no =A, yes =B)	A	64.06%
		B	35.94%

Province has long been known for its rice cultivation industry. Combining local data and similar questionnaire survey results in recent years, the study divided the choice set of preference for economic subsidies and technical support into 8 groups with all of them showing a preference for fertilization technology and economic subsidies. Another 12 pairs in Guangxi, also based on local data and research results, were found to prefer pest and ditching technologies.

(2) Questionnaire and data collection and processing

Among the current ecological pollution sources, rice field production contributes the most to pollution. The Pearl River Basin and Northeast China are the main rice grain-producing areas in China. This study investigated and analyzed the available AETs in rice production in combination with other technologies, examined the selection behavior of farmers in these areas regarding the combination attributes of AETs, and proposed AETs suitable for the region. The research group conducted a questionnaire survey by visiting households and summarized the information of the paper and electronic versions of the questionnaire. Among them, there were 132 valid questionnaires in Heilongjiang and 89 in Guangxi, totaling 221.

Results and discussion

Empirical analysis of friendly agricultural technologies in the southern environment

(1) Descriptive statistics

For the southern region, the Lingui District in Guilin City (Guangxi, China), an important rice-growing area which produces rice of excellent quality and abundant yield, has the necessary conditions for growing high-quality rice with its unique climate environment and geographical resources was chosen as the sampling area. There were 128 farmers with an average age of 62 years old and an average of 4 people in each household including 2 people working in agriculture participating in the questionnaire survey. Most respondents had an education level below junior high school with an average annual household income of ¥41,100. The specific descriptive statistics of this study were shown in Table 2. The surveyed farmers in the southern region all presented a typical state of small farmers in China, mainly manifested as low annual income, small cultivation area, small number of laborers, small scale of breeding, and low education level. Agricultural profits were low, and there was little support for farmers' income. Except for the busy farming and harvest season, the income most of the rest of the time was earned by young people working outside. In the survey, most respondents had not used AETs, surpassing the general belief of farmers that there was a trend toward improving the agricultural environment.

(2) Hybrid logit model

After inputting the above survey data into an MXL, attribute variables and policy subsidies

Table 3. Potential class model estimation results.

	The first group		The second group	
Variable	**Coefficient mean**	**Standard deviation**	**Coefficient mean**	**Standard deviation**
P	-0.007	0.004	0.007	0.002
STF	2.157	0.867	0.717	0.817
SBF	-0.796	0.627	-0.803	0.637
PDF	-1535	0.553	0.244	0.294
RWSR	0.778	0.552	0.191	0.526
GMR	-1.856	0.498	0.304	0.448
PRC	0.153	0.515	0.101	0.369
ITC	0.249	0.319	1.402	0.483
ECODITCH	-0.118	0.072	-0.058	0.036
FIELD	-0.186	0.548	0.002	0.335
VILLAGE	0.665	0.323	0.999	0.266
TOWN	0.876	0.618	-0.862	0.335
AGE	0.014	0.027	0.016	0.278
EDU	-0.152	0.449	-0.136	0.625
INCOME	-0.218	0.085	0.682	0.998

were added. The mean and standard deviation of the coefficients of the attribute variables were used as reference indicators of the observed technology preferences of farmers and their heterogeneous outcomes. The results showed that the mean values of pressure differential fertilization, soil testing, and side-strip fertilization were 0.094 ± 0.301, 0.495 ± 0.414, and 0.454 ± 0.112, respectively. The mean values of straw return to the field, green fertilizer return to the field, and the plant resistance culture were 0.339 ± 1.083, -0.287 ± 0.887, 0.264 ± 0.385, respectively. The mean value of IT control and ecological ditches were 0.298 ± 0.103 and -0.393 ± 0.241, respectively. The mean values of fields, villages, and towns were -0.227 ± 0.011, 0.214 ± 0.513, and -0.384 ± 1.032, respectively. The average coefficient of ecological ditch technology was negative, which indicated a low preference for this technology and indicated that farmers were unwilling to build ecological ditches. The numbers of soil testing formula fertilization technology (STF) were relatively large, indicating that farmers had a stronger preference for fertilization technology that reduced the amount of fertilization, but the waste utilization rate was increased by about 20%. For the straw returning technology in soil fertilization, farmers tended to prefer a simple and convenient operation method. Among the three technical training methods, the village training was positive, while the fields and towns were both negative, indicating that farmers were only willing to learn nearby and were not willing to participate in training in towns.

(3) Latent class model (LCM)

The LCM model can accommodate the heterogeneity preferences of respondents, using the mean and standard deviation of coefficients as reference indicators. It selected the two optimal groups of farmers as the high-quality model and investigated the AETs selection willingness of these two groups of farmers. The specific potential category model estimation results were shown in Table 3. The first group of users showed a preference for soil testing and fertilizer application and straw return to the field and a preference for bio-pesticides to manage pests. In addition, this group of users had a high willingness to construct ecological ditches and had no requirement for high subsidies. The second group of users were the opposite of the first group and fully accepted any technology while accepting high subsidies. According to common sense, farmers in the first group needed

Table 4. Descriptive statistical table of survey in northern region.

Socioeconomic variable	Interpret and assign values	Statistical value	
GEN	Gender (male =A, female =B)	A	30.61%
		B	69.39%
AGE	Age (years old)	Mean (SD)	45
INCOME	Annual household income (¥10,000)	Mean (SD)	5.19
UAET	Have you used AETs before? (used =A, not used =B)	A	30.86%
		B	69.14%
APAE	Whether agricultural production has an impact on the environment (no =A, yes =B)	A	34.42%
		B	67.58%

policy subsidies more. On the contrary, the first group had a higher preference for agricultural operation techniques such as STF, straw returning to field (RWSR), plant resistance cultivation technology (PRC), and construction of ecological ditches. The second group of farmers only cared about having fast and convenient agricultural operations and were very concerned about policy subsidies. They were willing to go to the village instead of going to the households to participate in training in the town. Therefore, this study evaluated the first group of farmers as environmentally friendly. These farmers had low income and low cultural background, but voluntarily participated in ecological protection and agricultural technology development and were less affected by policy subsidies. This study evaluated the second group of farmers as profit-driven, who had high income and average culture, and their development of ecological protection and agricultural technology depended on the amount of subsidies. These farmers had slightly lower environmental awareness and relied more on money for their behavioral trends.

Empirical analysis of friendly agricultural technologies in the northern environment

(1) Descriptive statistics

For the northern region, the Nangang District of Harbin City (Heilongjiang, China) on the southern bank of the Songhua River, an important source of water for rice production, has a now better-known rice production base. Among the 194 participating farmers, most of them were females with an average age of over 45 years old and a general education level of junior high school or below. The annual income level was slightly higher than that of the southern region at ¥51,900. The specific descriptive statistics were shown in Table 4. Due to the influence of climate seasons, the northern region was vast and sparsely populated, so the average farmland holdings of farmers in the northern region were much greater than those in the southern region. Farmers' animal husbandry development was less than that in the south with a value not exceeding 20%. In addition, there were more female farmers in the northern region with lower age and higher education levels than that in the southern region, so promoting AETs had more potential.

(2) Hybrid logit model

The above northern geographical survey data were inputted into an MXL, attribute variables and policy subsidies were added as well. The coefficient means and standard deviations were used as reference indicators to obtain the results of farmers' technology preferences and their heterogeneity. The results showed that the mean values of pressure differential fertilization, soil testing and formulation fertilization, and side-strip fertilization were 0.301 ± 1.801, 0.347 ± 1.501, and 0.386 ± 2.191, respectively. The mean values of straw return to the field, green fertilizer return to the field, and plant resistance cultivation were -0.246 ± 0.782, 0.411 ± 2.093, and -0.408 ± 0.507, respectively. The mean values of IT control and ecological ditches were 0.113 ± 0.003 and -0.261 ± 0.595. The mean values of fields, villages, and towns were 0.347 ± 0.467, 0.288 ± 0.094, and -0.338 ± 0.516, respectively.

Table 5. Potential class model estimation results.

	The first group		The second group	
Variable	Coefficient mean	Standard deviation	Coefficient mean	Standard deviation
P	0.012	0.001	0.014	0.003
STF	0.655	0.298	1.420	0.470
SBF	-0.497	0.349	3.668	0.825
PDF	0.079	0.293	1.742	0.530
RWSR	-0.666	0.226	2.275	0.800
GMR	0.259	0.378	2.329	0.821
PRC	-2.640	0.608	3.850	1.133
ITC	-0.077	0.012	0.040	0.025
ECODITCH	0.381	0.246	-1.952	0.609
FIELD	1.567	0.298	-1.871	0.753
VILLAGE	0.691	0.244	-0.858	0.521
TOWN	-0.424	0.336	-1.512	0.606
AGE	0.042	0.026	0.036	0.276
EDU	-0.328	0.449	-0.187	0.715
INCOME	-0.048	0.073	0.892	1.213

Farmers in the northern region had a general preference for policy subsidies and maintained a resistant attitude towards crop resistance cultivation, straw return to the field, and ecological ditch construction. However, they had a high enthusiasm for side fertilization techniques and participated in technical training. The mean and standard deviation were not significant and there was a certain degree of heterogeneity.

(3) Latent class model

To better understand the existence of preference heterogeneity among farmers, the study further demonstrated the preference heterogeneity and category characteristics of farmers through a latent category model. In this study, the mean and standard deviation of coefficient were used as reference indicators, and the best two groups of farmers were selected as quality models, and then the farmers' willingness to choose AETs in these two groups was investigated. The specific potential category model estimation results were shown in Table 5. The first group of users showed a preference for soil testing and fertilizer application only and opposed to straw return and bio-pesticide management of pests. There was no significant preference for insect traps, strong resistance to ecological furrows and buffer strips technology, and training preference for rural or field-based training. The second group of users had a high preference for fertilizer application techniques and pest management techniques but were more resistant to any training methods and ditch buffer techniques. The second group had more significant variables and more positive values than that in the first group. The second group only had a low preference for ecological ditch technology, while the remaining fertilization suggestions and straw returning and pest control technologies were significantly recognized. However, the construction of ecological ditches was relatively resistant, as the existence of ecological ditches inevitably reduced the area of agricultural land, thereby affecting agricultural income. The farmers in the first group strongly opposed the options of returning straw to the field and preventing diseases and pests, indicating that these technologies, no matter how randomly combined, could not be chosen by the farmers in this group. The promotion of these technologies was difficult and might require policy subsidies and support. Meanwhile, the first group had a relatively low preference for technology, which was related to their level of education. It was possible that cultural level affected farmers' understanding of AETs, thereby

Table 6. WTA estimates for 4 grouping types.

Variable	Environmentally friendly	Profit-driven	Labor saving type	Time saving
STF	-343.38	-602.34	-243.16	-202.62
SBF				
PDF				
RWSR	-177.18	-499.74	-191.72	-137.78
GMR				
PRC	-190.68	-386.96	-267.74	-191.12
ITC				
ECODITCH (¥/acre/year)	-137.78	-197.36	-157.04	-139.74
BUFFERZONE (¥/acre/year)				
FIELD	118.96	-180.34	-118.38	-178.26
VILLAGE				
TOWN				

hindering the use of these technologies. Therefore, this study evaluated the first group of farmers as labor-saving, which had a lower preference for agricultural technologies containing technological components and preferred traditional farming methods. This study evaluated the second group of farmers as time saving, who were willing to spend more time and labor costs to learn new technologies.

Overall analysis and comparison of the two districts

On the grounds of the survey of AETs preferences among farmers in the north and south regions, to better promote the implementation of AETs, increase farmers' satisfaction, and reduce the heterogeneity of selection for the same characteristic attribute, this study continued to focus on willingness to be compensated, environmental protection, profit-driven, labor-saving, and timesaving as the research objects. By combining the WTA calculation formula and the north-south region to estimate the three types of AETs, the estimated results were shown in Table 6. For environmentally friendly farmers, if the government arranged contracts according to their wishes, they only needed to provide subsidies of ¥343.38, ¥177.18, and ¥190.69/acre/year for the three technologies, which enabled farmers to choose and use these technologies. Among the four farmer models mentioned above, profit-driven farmers had the highest amount of monetary subsidies, and the three technologies required at least ¥602.34, ¥499.74, and ¥386.96/acre/year as subsidies. The subsidies for environmentally friendly and time-saving farmers were the same. The higher the subsidy amount, the higher the likelihood of farmers participating in learning and training and using AETs. To facilitate the observation of farmers' preferences for AETs during the entire rice planting and production process in China, the minimum akaike information criterion (AIC), the minimum bayesian information criterion (BIC), and the consistent akaike information criterion (CAIC) were used as reference indicators to obtain convergence results. The three measurement values of environmentally friendly and time-saving farmers were significantly lower than those of profit-driven and labor-saving farmers (Figure 2), which indicated that these two types of farmers had a high level of survey enthusiasm, and their satisfaction with carrying out AETs was very good. Meanwhile, the average values of these two types of farmers were quite close. The model test values for profit-driven farmers were the highest, indicating that the survey was relatively complex, and farmers had a certain degree of entanglement and resistance towards the provided selection set. Considering the influence of multiple factors, the above data also demonstrated the reasonable design of questionnaires and contract options, which provided flexible choices for farmers, greatly

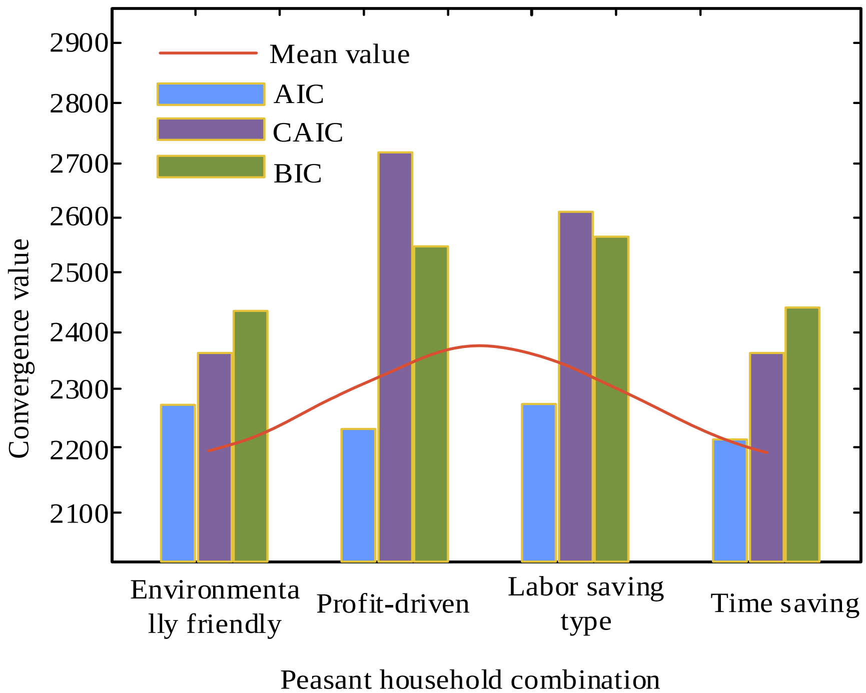

Figure 2. AIC, CAIC, and BIC values when LCMs of different classes converge.

reducing their objections and opening the way for the promotion of AETs.

Conclusion

In response to the gradual deterioration of the agricultural environment and to better promote AETs, this study used the MXL and potential category model in discrete selection experiments to analyze the survey results of farmers in the northern and southern regions of China and summarized methods and suggestions that were conducive to the development of AETs. The results indicated that there was heterogeneity in the selection preferences of farmers in both the north and south for AETs. Therefore, to improve the promotion of technology, it was necessary to cater to the preferences of farmers such as providing policy subsidies and conducting training. From the test results of the MXL and the latent category model, southern farmers were divided into environmentally friendly and profit-driven types. Among them, environmentally friendly farmers voluntarily contributed to environmental protection, had a low level of concern for subsidies, and had a clear preference for various technologies. Interest-driven farmers attached great importance to policy subsidies, and their awareness of protecting farmland was not strong. Northern farmers were divided into labor-saving and time-saving types. Although labor-saving individuals had a higher level of education, there were many limiting factors for choosing AETs. Time-saving farmers had a high adoption of AETs but were unwilling to spend time learning and training. Considering that the per capita arable land area in the north China is much larger than that in the south, implementing AETs in place will inevitably result in more labor costs. In the implementation of environmentally friendly agricultural technology, designing a reasonable promotion model on the ground of the preferences of farmers in different regions can help decision-makers choose the most suitable technical solution.

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