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Study on Agricultural Low-Carbon Production Behavior and Its Influencing Factors: Evidence from Chinese Rice Farmers

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Abstract

It is an inevitable choice to carry out the low-carbon rice cultivation with increasing sink and reducing emission, low carbon and high yield to achieve the goal of “double carbon” and guarantee the “win-win” of national food security. This study employs a boosted regression trees to examine the driving factors on low-carbon production behaviors using the survey data of 2173 rice farmers in Jiangxi Province, China. An empirical test was conducted on the influencing factors and mediating paths of farmers’ adoption of low-carbon rice farming behavior. The results show that the degree of farmers’ adoption of low-carbon rice farming practices is relatively low, and the largest proportion of farmers opt to use organic fertilizers. With the BRT model, the householder’s age (Age), the health conditions of family members (HFM), the proportion of year-round farmers to the total population (PYRFTP), the technical understanding level (TUL) and the importance motivation (MM) all played significant positive roles. The cultivated land fragmentation’s degree (CLF) and the difficulty level in obtaining information about low-carbon rice farming (DOILCRF) played significant negative roles. In view of this, in order to encourage farmers to adopt low-carbon rice cultivation practices, it is imperative to intensify the promotion of low-carbon rice cultivation technologies, utilize the demonstration effects of technology adoption, reinforce training programs for low-carbon rice farming techniques, establish incentive mechanisms for low-carbon rice cultivation, and carry out research and development on relevant low-carbon rice farming technologies.

Keywords

Low-Carbon Production Behavior, Rice Farmers, Rural China, Boosted Regression Trees (BRT)

1. Introduction

Climate change exacerbated by carbon emissions has become a global environmental problem that restricts the development of human society and economy (IPCC, 2021; Hong et al., 2021). Agricultural production has emitted large amounts of greenhouse gases (GHG) including carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) (Yang et al., 2022). Rice paddies are a major source of greenhouse gas (GHG) emissions. For example, rice contributes 22% and 11% of total agricultural methane (CH_4) and nitrous oxide7 (N_2O) emissions, respectively (IPCC, 2021; EPA, 2022; Qian et al., 2023).

Agriculture contributes about 17% of the nation's total GHG emissions in China (Hu et al., 2023). Among them, rice cultivation accounted for about 16% of carbon emissions, and was the main source of CH_4 and N_2O emissions. Notably, in 2023, the country's overall GHG emissions were estimated at 12.3 billion tonnes of CO_2 equivalent ($GtCO_2e$), representing 27% of global emissions. Agricultural low-carbon production behavior can effectively reduce agricultural carbon emissions (Rakotovao et al., 2017).

China is the foremost global producer of rice (FAO. FAOSTAT, 2022). However, rice production is responsible for 22% of the country's total GHG emissions from agricultural activities (Hu et al., 2023). The demand for rice in China is expected to increase to 218 $Mt\cdot year^{-1}$ by the year 2030 (Chen et al., 2014). China's "two-carbon" goal is not only an inevitable choice and long-term plan to solve the prominent problems of resource and environmental constraints and achieve the sustainable development of human society, but also a national responsibility and an important measure to build a community with a shared future for mankind (Hao et al., 2022). To reach this yield target, it is anticipated that rice production activities will be further intensified in the coming years. This presents a significant challenge for China in its pursuit of carbon neutrality in the agri-food sector. Hence, it is imperative to mitigate GHG emissions from rice production for the development of low-carbon agriculture.

Low-carbon production behaviors represent technologies that aim to reduce agricultural carbon emissions and protect the environment (Rakotovao et al., 2017), including increasing green inputs before production, innovating agricultural green production methods during production, and promoting waste resource utilization after production (Jiang et al., 2018; Li et al., 2021a). Practice and theory prove that low-carbon production behavior can reduce CO_2 emissions not only by reducing damage to soil structure, but also by processing waste into fertilizer, feed, and energy (Ye et al., 2017). To promote low carbon production in agriculture, the Chinese government has formulated a series of policies to promote effective and ecologically efficient rice varieties, implement farmland conservation tillage, reduce fertilizer production to increase efficiency, and encourage the comprehensive utilization of crop straw. However, as implementers and stakeholders of low-carbon rice production, small farmers have not responded positively to these policies (Li et al., 2021a; Hou and Hou, 2019).

Extant research on low-carbon production generally includes three aspects. The first one is the evaluation of low-carbon agricultural production. For example, Bai et al. (2019) calculated the production efficiency of low-carbon agriculture from the perspective of carbon emissions and sequestration to explore the impact of climate change on agricultural production. Moreover, Liu et al. (2020) constructed an evaluation index system for low-carbon agricultural production based on supply capacity, resource utilization, environmental quality, ecosystem maintenance, and farmers' lives. The second aspect involves the determining factors associated with farmers' adoption of low-carbon technologies. By applying regression models, such as Logistic and Probit, scholars comprehensively assessed the effects of the demographic, family characteristics, environment, and risk factors on farmers' adoption of low-carbon technologies (Jain and Rekha, 2017; Liu et al., 2019; Zhang et al., 2019), and explored the consistency of low-carbon production intention and behavior regarding straw returning (Li et al., 2021b). Furthermore, studies have shown that low-carbon perception, value perception, and social norms significantly influence farmers' adoption of low-carbon agricultural technologies (Jiang et al., 2018; Yu et al., 2018). The last aspect is intervention policies for farmers' adoption of low-carbon technologies. A study pointed out that subsidies or a reasonable carbon tax contributed to reducing agricultural carbon emissions and promoting the development of low-carbon agriculture (Fan and Dong, 2018). Therefore, governments have the onus to actively promote low-carbon agriculture. Various measures (such as formulating subsidy policies for low-carbon agricultural production, constructing agricultural irrigation infrastructure, and promoting land-use rights transfer) can be undertaken by governments to foster low-carbon production among farmers (Pradhan et al., 2017; Zhu et al., 2018).

In some developing countries, low-carbon agricultural materials (such as soil testing formula fertilizer and biological pesticide) and technologies (such as intermittent irrigation and straw returning) with well-documented emission reduction effects have been gradually promoted in major agricultural production areas (Liu et al., 2019; Li et al., 2021b). However, the adoption rates of low-carbon agricultural materials and technologies remain low among farmers. Although farmers are willing, the adoption behavior is rarely observed, which is described as the phenomenon of "high intention, low behavior" (Vande Velde et al., 2018). Little emphasis has hitherto been placed on such psychological and behavioral phenomena, with most studies focused on the impact of demographic, economic, and environmental factors on farmers' adoption of low-carbon technologies (Jain and Rekha, 2017; Liu et al., 2019; Zhang et al., 2019). Interestingly, social media has an essential impact on farmers' adoption of low-carbon agricultural technologies (Yang et al., 2021), and farmers of the same clan usually participate in the same agricultural activities (Jiang et al., 2022). In addition, a psychological study showed that individual behavior is affected by environmental factors, and psychological factors such as cognition, emotion, and intention play an essential role

(Strack et al., 2016). Accordingly, this paper intends to examine the psychological and situational factors that influence farmers' decision-making on adopting low-carbon technologies. Rice is widely acknowledged as a food crop that significantly emits greenhouse gases during its growth period (Maraseni et al., 2018), thus rice farmers were selected as the study subject in this study. In order to reduce greenhouse gas emissions from the production process of rice farmers, this study aims to address the following questions: 1) What are the farmer's resource endowment factors and farmer's low-carbon cognition that determine the adoption of low-carbon technologies by rice farmers? 2) What is the weight of the impact of these factors on their adoption behavior? 3) How to effectively guide rice farmers to participate in low-carbon rice production? These answers provide the basis for developing countries to effectively promote low-carbon agricultural technologies to protect the global climate.

2. Theoretical Background

In contrast to traditional production behaviors, low-carbon production behaviors exhibit high adoption costs but demonstrate outstanding comprehensive benefits. Firstly, the adoption of low-carbon agricultural methods involves more varied and intricate procedures, demanding substantial labor and monetary commitments from farmers (Liang et al., 2021), even when confronting diminished outputs due to improper application (Martey & Kuwornu, 2021). Secondly, a series of low-carbon production behaviors, such as soil and water conservation technology, integrated pest and disease management, fertilizer substitution technology, and straw returning to the field, can maximize product quality and premium income while protecting the agricultural ecological environment through carbon sequestration and emission reduction (Brako et al., 2021; He et al., 2021; Kumar et al., 2023). This indicates that farmers may consider the costs and benefits of adoption when making decisions, thereby influencing their low-carbon production behaviors. However, in the case of limited resource endowment, it is difficult for farmers to minimize the cost or maximize the benefit of low-carbon production behaviors (DeFries et al., 2017).

The adoption of low-carbon technologies by rice farmers refers to the use of low-carbon agricultural materials and management measures to reduce agricultural greenhouse gas emissions and improve the agricultural ecological environment (Liu et al., 2020). Over the past years, substantial emphasis has been laid on the impacts of demographic factors (Jain and Rekha, 2017), economic factors (Liu et al., 2019), and environmental factors (Zhang et al., 2019) on farmers' adoption of low-carbon farming technologies. Overwhelming evidence substantiates that psychological factors can change farmers' adopting behavior (Jiang et al., 2018; Yu et al., 2018), and no research has analyzed from the perspective of farmers' cognition of low-carbon farming technologies to date. In this paper, based the actual situation of low-carbon rice production in Jiangxi Province of China, we selected seven low-carbon technologies with the best carbon emission reduction effects, namely two low-carbon agricultural materials (i.e., soil testing formula fertilizer (Liu et al., 2019; Yu and Luo, 2022) and organic fertilizer (Popovych et al., 2014; Yang et al., 2025)), four field management measure (i.e., rice straw returning (Li et al., 2021a; Li et al., 2024), agricultural plastic film recycling (Yang et al., 2023; Judl et al., 2024), conservation tillage techniques for paddy fields (Peigné et al., 2007; Cárceles Rodríguez et al., 2022) and crop rational rotation (Havlin et al., 1990; West & Post, 2022)) and biological agricultural model (i.e., rice-duck (Gao et al., 2025), rice-fish co-culture (Luo et al., 2025), rice-crabs and other breeding types (Bao et al., 2022)), were selected based on the research conclusions of agronomy and crop science experts. Moreover, it analyzed the influencing factors of farmers' adoption of low-carbon rice cultivation methods from two perspectives: farmers' resource endowments and their cognition of low-carbon rice cultivation techniques. Furthermore, based on questionnaires from rice Chinese farmers (n = 2173), the theoretical model was empirically tested by BRT. Notably, it was discovered that when farmers lacked fundamental cognitions regarding climate change, low-carbon technologies, and environmental awareness, they were unable to perceive the value of adopting low-carbon technologies, which in turn impeded the formation of intention and the actual adoption behavior.

3. Data and Methodology

3.1. Data and Sampling

The data for this study came from the special questionnaire survey of "Low-carbon rice farming behavior of farmers in Jiangxi Province" carried out between January to March 2022. Located in central China, Jiangxi Province is one of the major grain producing areas in China. In 2023, the total rice planting area and rice yield in this area accounted for 11.69% and 10.02% of China's total rice planting area and rice yield, respectively. In addition, the total agricultural carbon emissions of Jiangxi Province ranked seventh in China in 2020 (Liu et al., 2026), which mainly originated from agriculture rice planting (59%). For these reasons, we selected the main rice producing areas in Jiangxi Province as the survey area for this study. We used a stratified sampling and random sampling technique to select sample households. According to the level of economic development and grain production, stratified random sampling was carried out in all counties (districts) of the province.

Firstly, we selected 11 prefecture-level cities by stratifying according to topography, level of economic development, and proportion of agricultural industry. Secondly, in each type, 8 counties (cities and districts) were selected, and then 2 to 4 townships were randomly selected in the counties (cities and districts), and 1 to 3 administrative villages were randomly selected in the townships, and 5 to 15 rice farmers were randomly selected in each village. The survey sites covered different topographic regions of plains, basins, hills and mountains in Jiangxi Province, as shown in **Figure 1**. In the field investigation and visit, the anonymous form is used, and the trained investigators enter the household to answer and fill in the "one-to-one".

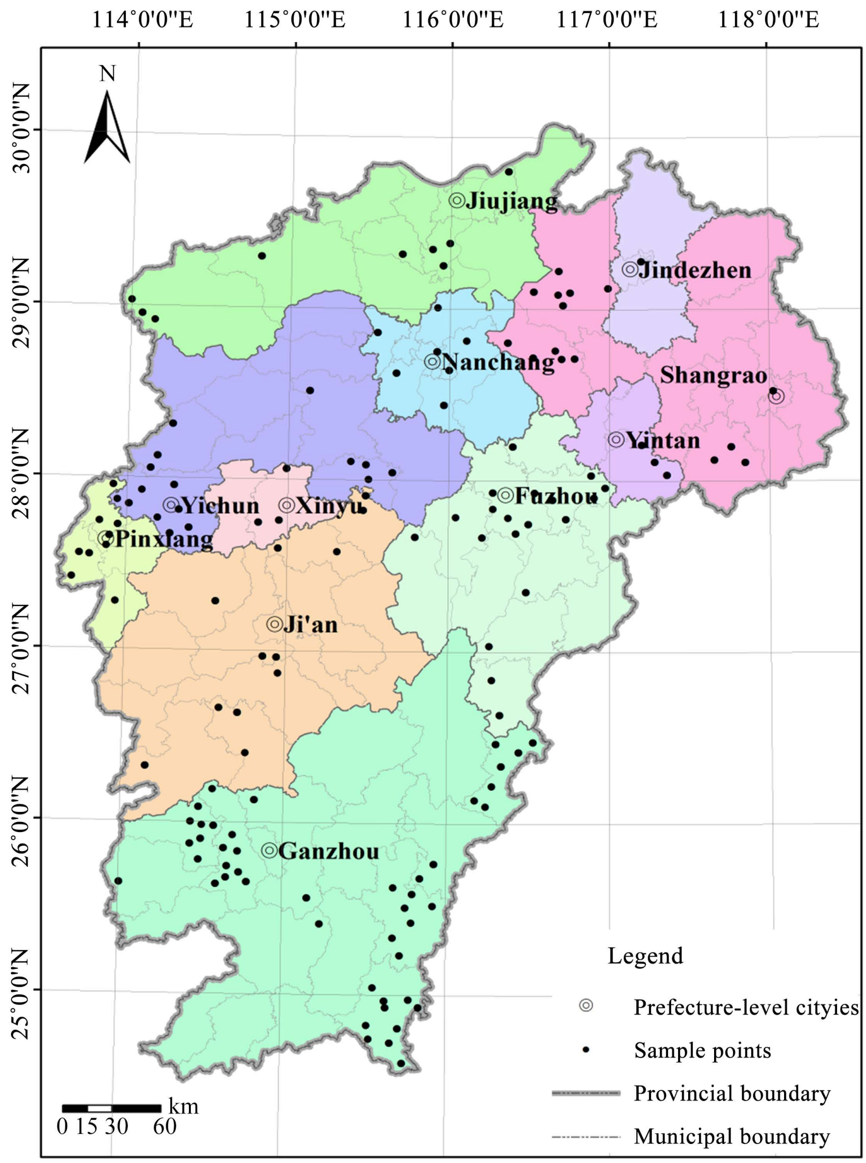

Figure 1. Location of Jiangxi province and counties surveyed.

According to the above sampling method, we completed a survey of 314 villages, resulting in total sample of 2314 households. A total of 2173 valid samples were obtained in this study, after eliminating the questionnaires with missing key information and outliers.

The questionnaires were obtained, and 2173 were actually valid, with an effective rate of 93.91%, The contents of the questionnaire include: 1) the basic information of farmers, mainly including the age, gender, family population, family income, etc.; 2) Farmers' cognition and adoption of low-carbon rice cultivation technology, including farmers' cognition, willingness and adoption of each type of low-carbon rice cultivation technology; 3) Farmers' views and opinions on low-carbon rice cultivation technology involved farmers' views and attitudes towards government policies and technology adoption benefits. The basic statistical characteristics of 2173 valid questionnaires are listed in Table 1. Household survey involved 2173 peasants, of whom 1629 householders are male, accounting for 74.67%; 544 householders are female, accounting for 25.03%. The main distribution of householders' age was "from 46 to 55" and "from 56 to 65", accounting for 38.66%and 23.93% of the total samples, respectively. The relatively high average age (50.93 years) indicates an apparent ageing of the farming population.1838 householders with primary or junior school education were surveyed, accounting for 84.59%. 932 householders with less than 20 years farming experience were surveyed, accounting for 42.89%. The survey results presented in Table 2.

Table 1. The basic characteristics of the surveyed rice farmers.

Characters	Item	Frequency (N = 2173)	Percentage
Gender	male	1629	74.97
	female	544	25.03
Age	less than 35	144	6.63
	from 35 to 45	403	18.55
	from 46 to 55	840	38.66
	from 56 to 65	520	23.93
	more than 66	266	12.24
Education level	primary school	915	42.11
	Junior school	923	42.48
	Senior school	241	11.09
	college	94	4.33
Farming experience (years)	≤20	932	42.89%
	21 - 30	558	25.68%
	31 - 40	406	18.68%
	41 - 50	206	9.48%
	≥51	71	3.27%
Occupation	farming	725	33.36%
	Part-time jobs mainly involving farming	564	25.95%
	Part-time jobs mainly involving working	577	26.55%
	working	307	14.13%
Agricultural income proportion	≤20%	1141	52.51%
	20% - 40%	416	19.14%
	40% - 60%	260	11.97%
	60% - 80%	195	8.97%
	>80%	161	7.41%

Table 2. Rice farmers' adoption of low-carbon agricultural technologies.

low-carbon agricultural technologies	cognition level from 1 to 5		Status of adoption	
	sample	average	Frequency	percentage
soil testing formula fertilizer	2173	3.62	484	22.27%
straw returning	2173	2.44	1445	66.50%
application of organic fertilizer	2173	2.36	1522	70.04%
agricultural plastic film recycling	2173	2.95	909	41.83%
conservation tillage	2173	3.26	724	33.32%
crop rational rotation	2173	2.73	1213	55.82%
biological agricultural model	2173	3.35	441	20.29%

3.2. Measurement of Key Variables

We have selected seven low-carbon rice production methods covering the entire rice generation process, which constitute a subset of farmers' low-carbon production behaviors. The seven low-carbon production methods include conservation tillage such less tillage or no-tillage of paddy fields, the use of soil formula fertilizer, the use of organic fertilizer, rice straw crushing and returning to the field, agricultural film recycling, crop rational rotation and biological agricultural model (e.g. rice-ducks, rice-fish co-culture, rice-crabs and other breeding types). In order to quantify farmers' low-carbon production behaviors as a whole, this study uses the comprehensive value of the sum of the number of farmers' low-carbon production behaviors to measure.

This study comprehensively considers the influence of rural household resource endowment and farmers' low-carbon cognition and draws on previous studies (Lu et al., 2022). The number of low-carbon rice cultivation methods adopted by farmers was selected as dependent variables. From the rural household resource endowment, fourteen variables in the four categories of householder's characteristics, regional geographical conditions, household's economic development level and household's physical condition were selected as independent variables. Householder's characteristics include age, gender, education, career and understanding the permanent basic farmland system. The regional geographical conditions include accessibility of cultivated land roads, the cultivated land fragmentation's degree, whether designated as self-consumption farmland, landform and water supply availability. The household's economic development level includes agricultural machinery holdings, the completeness of farmland infrastructure and the proportion of year-round farmers to the total population. Physical condition refers to health status of rural household members.

From the farmers' low-carbon cognition, nine variables were selected as independent variables. They include difficulty in obtaining information about low-carbon rice farming, technical understanding level, do you think the implementation of low-carbon rice farming will increase agricultural income, the quality of cultivated land has changed in recent years, whether you think that implementing low-carbon rice farming will increase the cost of rice production, the interviewed farmers believe in the importance of low-carbon rice cultivation technology, the average value is calculated by accumulating the seven types of technologies, whether you often communicate with relatives, friends or villagers about rice production, whether the production behaviors of other villagers around you have some influence on your rice production, and whether you have attended some training on low-carbon rice farming techniques. The definition of each variable and the descriptive statistical results are shown in Table 3 and Table 4.

Table 3. Variables used in the analysis of factors affecting peasant household behavior in low-carbon production from the perspective of farmer's resource endowment.

Category		Variable	Description	Variable assignment
Dependent Variables		Y	The number of low-carbon rice cultivation methods adopted by farmers	-
Independent Variables	The householder's characteristics	Age	The householder's age	-
		Gender	The householder's gender	male = 1, female = 0;
		EL	The householder's education level	primary school = 1, Junior school = 2, Senior school = 3, college = 4;
		Career	The householder's career	full-time farming = 1, part-time farming based on agriculture = 2, part-time farming based on work = 3, off-farming households = 4
		PBF	Do you know permanent basic-farmland?	yes = 1, no = 0
	Geographical conditions	ACLR	Accessibility of cultivated land roads	worst = 1; worse = 2; common = 3; better = 4; best = 5;
		SD	Whether the cultivated land is designated as self-consumption farmland?	yes = 1, no = 0
		CLF	The cultivated land fragmentation's degree	-
		WS	Whether water is sufficient?	yes = 1, no = 0
		Landform	Village landform	plain = 1, hill = 2, mountain = 3
	Economic development level	LFE	Does your home own large farm equipment?	yes = 1, no = 0
		AF	Whether the farmland infrastructure is complete?	yes = 1, no = 0
		PYRFTP	The proportion of year-round farmers to the total population	-
	Physical condition	HFM	Health conditions of family members	worst = 1; worse = 2; common = 3; better = 4; best = 5;

Table 4. Variables used in the analysis of factors affecting household behavior in low-carbon production from the perspective of farmer's low-carbon cognition.

Category	Variable	Description	Variable assignment
Dependent Variables	Y	The number of low-carbon rice cultivation methods adopted by farmers	-
Independent Variables	DOILCRF	Difficulty level in obtaining information about low-carbon rice farming	A. Very low B. Relatively low C. average D. relatively high E. Very high
	TUL[1]	Technical understanding level	-
	EBM	Do you think the implementation of low-carbon rice farming will increase agricultural income?	yes = 1, no = 0
	QCLC	The quality of cultivated land has changed in recent years	A. It's getting worse B. It's not changing C. It's getting better
	ICRP	Do you think that implementing low-carbon rice farming will increase the cost of rice production?	yes = 1, no = 0
	MM[2]	Importance motivation (Farmers perceive the importance of low-carbon rice production methods)	-
	PE	Do you often communicate with relatives, friends or villagers about rice production?	A. few B. less C. average D. more E. A lot
	IC	Do the production behaviors of other villagers around you have any influence on your rice production?	yes = 1, no = 0
	ATLCRF	Have you attended any training on low carbon rice farming techniques?	yes = 1, no = 0

3.3. BRT Method

Boosted Regression Trees (BRT) was employed to analyze impacting factors affecting peasants' low-carbon farming behavior. In the literature, probit and tobit regression have commonly been applied in similar research (Hou and Hou, 2019; Yan et al., 2025). In the process of analysis, probit and tobit regression model were not selected, because they could not handle different types of predictor variables, identify very complex and non-linear association among variables, and compute variable importance. Instead, the BRT model was appropriate. BRT can fit complex linear relationships, and it is highly resistant to inclusion of large numbers of irrelevant predictor variables. The BRT algorithm can reduce the residual of the previous model in the gradient direction during modeling, which can improve the prediction accuracy.

BRT is one of several techniques aiming to improve the performance of a single

[1]TUL: Farmers' awareness of seven low-carbon rice cultivation techniques. The value is calculated by averaging the sum of the seven types of technologies.

[2]MM: The interviewed farmers believe in the importance of low-carbon rice cultivation technology. The value is calculated by averaging the sum of the seven types of technologies.

model by fitting many models and combining them for prediction. This approach is based on an automated, data adaptive algorithm that can be used with a large number of covariates to fit a linear surface. BRT uses two algorithms: "regression trees" is from the classification and regression tree ("decision tree") group of models, and "boosting" builds and combines a collection of models (Elith et al., 2008). This method has powerful capacities for handling different classes of predictor variables (categorical, nominal and continuous) and distributions (Gaussian, Poisson, binomial and others), for accommodating missing data and outliers, and for automatically handling interaction effects between predictor variables (De'ath, 2007; Elith et al., 2008). Furthermore, this method has no prior assumptions about the independence of predictor variables.

The BRT model involves generating a sequence of trees, each grown on the residuals of the previous tree (Hastie et al., 2009). Prediction is accomplished by weighting the ensemble outputs of all regression trees. Therefore, this BRT model inherits almost all of the advantages of tree-based models, while overcoming their primary disadvantages, that is, inaccuracies (Friedman and Meulman, 2003). A single base learner does not make sufficient prediction using the training data, even when the best training data are used. It can boost the prediction performance using a series of base learners with the lowest residuals (Shin, 2015). An advantage of using BRT models is that the technique may abstain from selecting predictor variables with large numbers of missing values, which would make the technique robust and applicable for industrial applications. Another advantage of the BRT models when compared to regression tree models is the improved predictive performance in validation (Hastie et al., 2009). The BRT model lacks native built-in support for p-values, confidence intervals, or formal significance testing. It is categorized as a non-parametric ensemble machine learning algorithm, whose core objective is to optimize prediction accuracy rather than fulfill the requirements of conventional statistical inference. This paper conducts BRT model using the gbm package in R software.

More detailed description of the BRT method can be found in the report of Hastie et al. (2009), and working guides in Ridgeway (2007) and Elith et al. (2008). Chen et al. (2015) used the boosted regression tree method to identify the driving factors for the changes of ecosystem services value in Ganjiang Upstream watershed of China. Chen et al. (2016) used the BRT method to identify the factors that affect their awareness of agricultural non-point source pollution in the Jiangxi Province of China. Yang et al. (2016) used boosted regression tree (BRT) models to map the distribution of topsoil organic carbon content at the northeastern edge of the Qinghai-Xizang Plateau in China. Zhang et al. (2016) used it to determine the optimal lag for meteorological factors at which the variance of hand, foot and mouth disease cases was most explained, and to assess the impacts of these meteorological factors at the optimal lag. Lu et al. (2022) used it to identify the driving factors to affect the peasant households' part-time farming behavior and present some corresponding proposals.

4. Results

4.1. Descriptive Analysis of Sample Characteristics

The rice farmers' sociolect-demographic and farm characteristics are shown in Table 1. The respondents were predominantly male (74.97%) and aged from 46 to 55 (38.66%). Most respondents (42.48%) had junior school education background. Besides farming, 52.5% of farmers held part-time jobs. Agriculture represented a long-term occupation for less than 20 years for 42.89% of farmers. 7.41% of farmers indicated that the majority of their household earnings came from agricultural production. Overall, the sample distribution of socio-demographic and farm characteristics was consistent with the actual situation, indicating that the sample was representative of rice farmers in Jiangxi Province.

4.2. Low-Carbon Production Status

Based on the survey results presented in Table 2, statistical analysis reveals the following characteristics regarding the cognitive level and adoption status of low-carbon agricultural technologies. From the perspective of the technical cognitive level (rated on a scale of 1 - 5), soil testing and formula fertilization attain the highest average score (3.62), which suggests that farmers possess a more profound comprehension of its scientific principles and operational procedures. Conservation tillage (3.26) and the biological agricultural model (3.35) occupy the second position, which indicates their relatively higher levels of technical complexity. Straw returning (2.44) and the utilization of organic fertilizers (2.36) demonstrate relatively lower levels of cognitive understanding, possibly attributable to conventional farming methodologies or insufficient technological dissemination.

In terms of adoption rates, straw returning (66.5%) and the application of organic fertilizers (70.04%) exhibit the highest rates, owing to their low cost and high compatibility with conventional agricultural practices. The adoption rates of soil testing and formula fertilization (22.27%) and the biological agricultural model (20.29%) are the lowest, which requires specialized guidance or increased investment. The adoption of agricultural plastic film recycling (41.83%) and rational crop rotation (55.82%) is at a moderate level, and their implementation degrees are significantly influenced by policy incentives and traditional farming methods.

4.3. The Drivers of Peasant Household Behavior in Low-Carbon Production

The learning rate, tree.complexity and bag.fraction are set to 0.005, 9 and 0.5 respectively. 50% of the data was analyzed, 50% was used for training, and 5 cross-validations were done. From the perspective of farmers' resource endowment, 14 independent variables and 1 dependent variable were adopted for BRT analysis, as presented in Table 3. Based on this analysis, the final gbm model was fitted with a fixed number of 2600 trees. From the perspective of farmer's low-carbon cognition, 9 independent variables and 1 dependent variable were used for the

BRT analysis as presented in Table 4. Based on this analysis, fitted final gbm model with a fixed number of 2900 trees. The results of the BRT method model evaluation are listed in Table 5. The weights of independent variables of BRT analysis in the resource endowment and low-carbon cognition are listed in Table 6. The result of BRT analysis is shown in Figure 2 and Figure 3. It can be seen from Table 5 that training data correlation of the two BRT analysis methods are larger than 0.6, indicating the model fits well on the training data. The mean total deviance and mean residual deviance are close (0.056 vs 0.032/0.036), indicating that the model has strong explanatory power for the training data. The CV correlation coefficient (0.636 and 0.769) was significantly higher than that of the training set, and the standard error (C correlation se) was lower (0.02), indicating that the model had good generalization ability on the validation set and no over-fitting occurred. The estimated CV deviation is small (0.05 and 0.044), combined with the stability of the standard error of the estimated CV deviation, further verifies the reliability of the model. The above data analysis shows that it has good BRT prediction results.

Table 5. The result of BRT model evaluation.

The parameter types	resources endowment	LOW-carbon cognition
mean total deviance	0.056	0.056
mean residual deviance	0.032	0.036
estimated CV deviance	0.05	0.044
estimated CV deviance se	0.003	0.002
training data correlation	0.712	0.614
CV correlation	0.736	0.769
CV correlation se	0.02	0.02

Table 6. The weight of independent variables of BRT analysis from the perspective of resource endowment and low-carbon cognition.

From the perspective of farmer's resource endowment		From the perspective of farmer's low-carbon cognition	
Independent variable	Weight	Independent variable	Weight
Age	0.188	DOILCRF	0.098
Gender	0.021	TUL	0.392
EL	0.045	EBM	0.024
Career	0.063	QCLC	0.044
PBF	0.0389	ICRP	0.042
ACLR	0.062	MM	0.243

Continued

SD	0.031	PE	0.071
CLF	0.234	IC	0.077
WS	0.022	ATLCRF	0.008
Landform	0.0391		
LFE	0.019		
AF	0.038		
PYRFTP	0.131		
HFM	0.068		

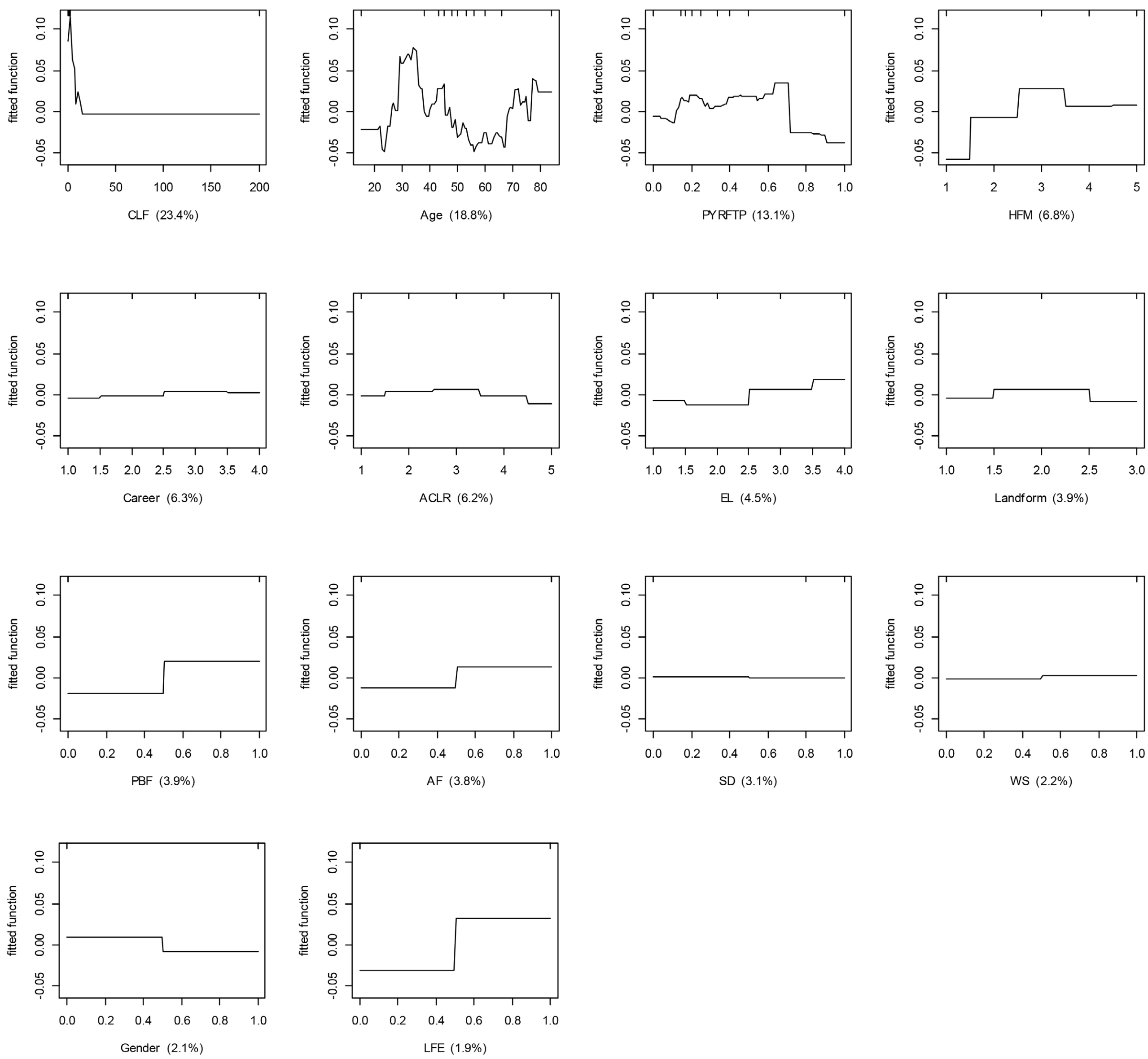

Figure 2. Partial dependence plots for the fourteen most influential variables in the model for farmers' low-carbon rice cultivation behaviors from the perspective of resource endowment. For explanation of variables and their units see Table 3.

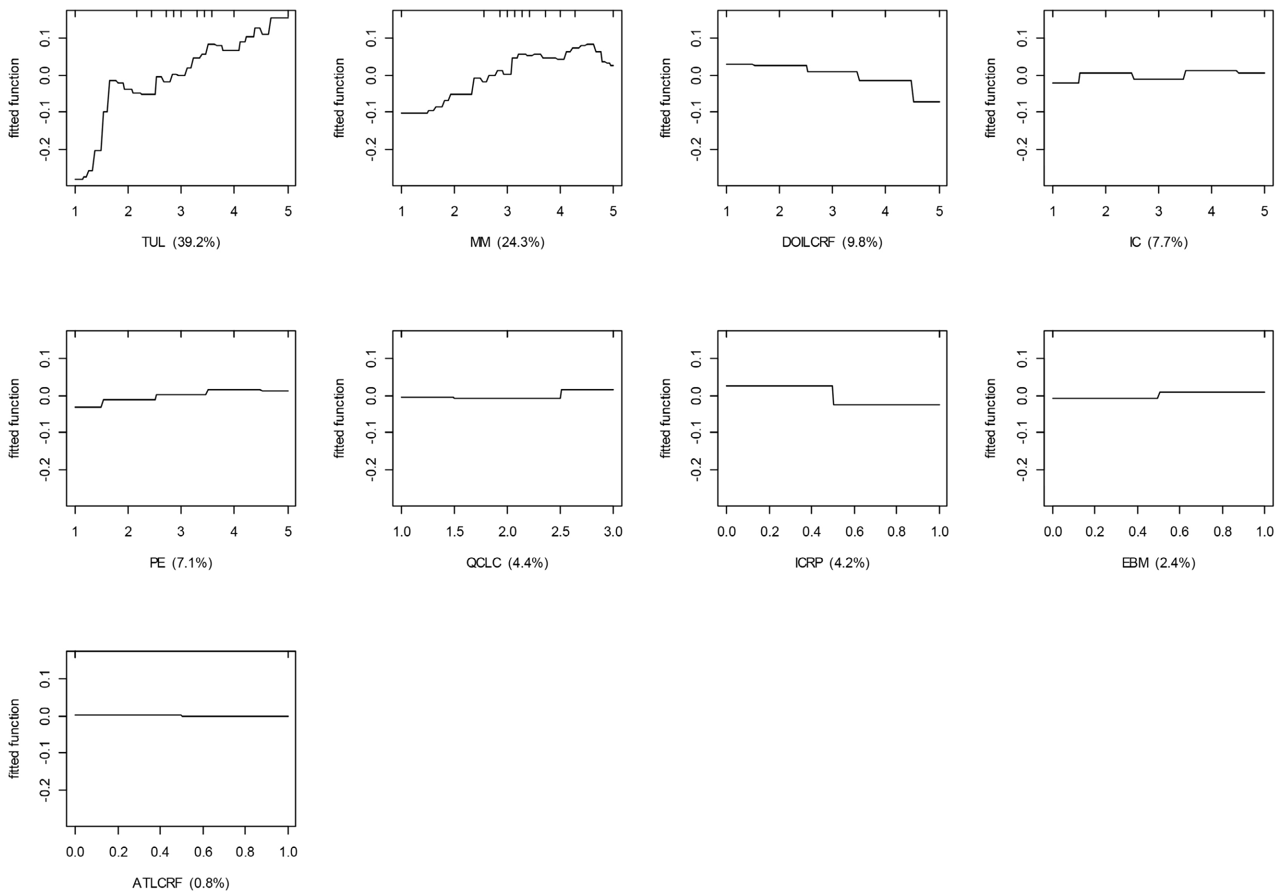

Figure 3. Partial dependence plots for the nine most influential variables in the model for farmers' low-carbon rice cultivation behaviors from the perspective of low-carbon cognition. For explanation of variables and their units see Table 4.

We can see the relative importance of influential factors on farmers' low-carbon rice cultivation behaviors from the perspective of resource endowment in Figure 2 and Table 6. They are as follows: the cultivated land fragmentation's degree (CLF), the householder's age (Age), the proportion of year-round farmers to the total population (PYRFTP), health conditions of family members (HFM), the householder's career (Career), accessibility of cultivated land roads (ACLR), the householder's education level (EL), and the village landform (Landform). The contribution of these eight factors accumulated to 83%. Among them, the cultivated land fragmentation's degree (CLF) has the biggest influence on farmers' low-carbon rice cultivation behaviors. 23.4% of farmers' low-carbon rice cultivation behavior is determined, which has overall negative correlated with the number of low-carbon rice cultivation methods adopted by farmers. The greater the degree of cultivated land fragmentation, the lower the labor productivity, the less willing farmers are to adopt low-carbon rice farming practices, and the lower the ecological efficiency. The second bigger factor is the householder's age (Age), which determines its change of 18.8% and has the overall positive correlation with it. With the increase in the household head's age, farmers gain more experience and demonstrate a stronger willingness to adopt low-carbon rice farming practices. Elderly farmers, owing to their dependence on traditional practices, elevated health risk aversion, and preference for technically less-complex operations, are more prone to adopt low-carbon rice cultivation technologies. 13.1% of farmers' low-carbon rice cultivation behavior is determined by the proportion of year-round farmers to the total population (PYRFTP), which has overall positively correlation with it. Low-carbon rice farming requires more collective cooperation and higher labor input. 6.8% of farmers' low-carbon rice cultivation behavior is determined by health conditions of family members (HFM), which was overall positively correlated with it. Healthy farmers demonstrate a greater propensity to adopt more low-carbon rice cultivation practices. This can be ascribed to their improved labor capacity, elevated awareness of health risk mitigation, and superior resource allocation abilities, thus attaining dual benefits for both environmental sustainability and human health. 6.3% of farmers' low-carbon rice cultivation behavior is determined by the householder's career (Career), which has overall positive correlation with it. Part-time farmers participating in off-farm employment exhibit a markedly higher propensity to adopt low-carbon rice cultivation practices compared to full-time farmers, attributable to the following factors: 1) an optimized income structure (leveraging non-farm income to mitigate adoption risks), 2) a better technological fit (showcasing a preference for labor-saving low-carbon measures), and 3) more robust social network advantages (facilitating accelerated diffusion via migrant worker communities). 6.2% of farmers' low-carbon rice cultivation behavior is determined by the accessibility of cultivated land roads (ACLR), which has overall positive correlation with it. The better the accessibility of farmland roads, the greater the number of low-carbon rice cultivation practices adopted by farmers. This phenomenon can be attributed to the fact that the improvement of road accessibility substantially enhances farmers' propensity to adopt low-carbon rice cultivation. It achieves this by reducing transportation costs, facilitating the dissemination of technology, strengthening socialized services, and enhancing the synergistic effects of environmental governance. 4.5% of farmers' low-carbon rice cultivation behavior is determined by the householder's education level (EL), which has overall positive correlation with it. The higher the educational level of farmer householders, the greater the number of low-carbon rice cultivation practices they adopt. Highly educated farmers tend to adopt a greater variety of low-carbon rice farming practices. This can be attributed to their advanced technical comprehension, higher efficiency in acquiring policy information, and improved economic decision-making abilities. 3.91% of farmers' low-carbon rice cultivation behavior is determined by the village landform (Landform), which has overall positive correlation with it. The more mountainous the terrain is, the greater the diversity of low-carbon rice cultivation methods adopted by farmers. Mountain residents, constrained by topography, ecological adaptation needs, and policy incentives, tend to adopt low-carbon rice cultivation methods that require less labor intensity and emit fewer carbon emissions.

We can see the relative importance of influential factors on farmers' low-carbon rice cultivation behaviors from the perspective of farmer's low-carbon cognition in Figure 3 and Table 6. They are as follows: technical understanding level (TUL), importance motivation (MM), difficulty in obtaining information about low carbon rice farming (DOILCRF), and "do the production behaviors of other villagers around you have any influence on your rice production?" (IC). The contribution of these four factors accumulated to 81%. Among them, technical understanding level (TUL)has the biggest influence on farmers' low-carbon rice cultivation behaviors. 39.2% of farmers' low-carbon rice cultivation behavior is determined, which has overall positive correlated with the number of low-carbon rice cultivation methods adopted by farmers. As the curve rises, it indicates that farmers with higher understanding of low-carbon rice cultivation methods will adopt more these techniques. Farmers' comprehension of low-carbon rice cultivation techniques exhibits a significant positive correlation with the adoption rates. Specifically, the lower their awareness level (represented by higher numerical values), the fewer techniques they adopt. This finding underscores the pivotal role of technical training and scientific dissemination in the promotion of low-carbon agriculture. The second bigger factor is the importance motivation (MM), which determines its change of 24.3% and has the overall positive correlation with it. Greater perceived importance leads to more adoption of low-carbon rice farming techniques. 9.8% of farmers' low-carbon rice cultivation behavior is determined by difficulty level in obtaining information about low-carbon rice farming (DOILCRF), which has overall negative correlation with it. The greater the difficulty in acquiring information regarding low-carbon rice cultivation, the lower the adoption rate of low-carbon rice farming practices. A notable negative correlation exists between the difficulty of information accessibility and the adoption of low-carbon rice technologies. This is mainly due to the fact that high information barriers impede farmers from establishing technical cognition, acquiring operational skills, reducing risk perception, and weakening social learning effects, which ultimately results in a decreased willingness to adopt these technologies. 7.7% of farmers' low-carbon rice cultivation behavior is determined by "Do the production behaviors of other villagers around you have any influence on your rice production?" (IC), which has overall positive correlation with it. The production behaviors of neighboring villagers significantly and positively influence individual farmers' rice farming decisions and practices through mechanisms including social learning, technological coordination, and externality transmission.

5. Conclusions and Discussion

5.1. General Discussion

Different types of low-carbon rice production styles differ in the input intensity of agricultural production, thus bringing different impacts on farmers' low-carbon production behaviors. In the present study, the adoption rates of soil testing formula fertilizer, straw returning, application of organic fertilizer, agricultural plastic film recycling, conservation tillage, crop rational rotation, biological agricultural model by sample rice farmers were 22.27%, 66.50%, 70.04%, 41.83%, 33.32%, 55.82% and 20.29%, respectively. This finding suggested that organic fertilizers are readily available, the straw burning ban and comprehensive utilization management in Jiangxi province achieved remarkable achievements. In Jiangxi Province, the acquisition channels of organic fertilizers are diverse. There is robust policy support, and the recycling systems of planting and breeding are relatively well-established, along with market-oriented services. Farmers can readily acquire organic fertilizers through subsidies (Liu and Xie, 2018), cooperation with enterprises (Li et al., 2021c; Su and Jiang, 2025), or self-production (Akter et al., 2023). Due to farmers' preference for short-term gains, small-scale farmers lack an intuitive perception of the ecological benefits of crop rotation (such as soil remediation). Moreover, continuous cropping of a single crop can simplify the management process, resulting in a slow increase in the rotation rate (Li et al., 2021a). As a result, the traditional continuous cropping model still dominates. The state mandates the recycling of non-biodegradable agricultural films through the "Agricultural Film Management Measures" and promotes the use of thickened high-strength mulch films (≥0.01 mm) to improve the recovery rate (MOA, 2017). Nevertheless, during the actual implementation process, certain regions continue to encounter challenges such as the utilization of non-standard plastic films and incomplete recycling mechanisms, which lead to a recycling rate that only attains a medium level (Zhao et al., 2023). The recycling of agricultural plastic film depends on mechanized collection and social service organizations. However, the fragmented farmland constrains the efficiency of technological application (Zhang et al., 2022). Soil testing and formula fertilization relies on professional institutions to complete soil sampling, testing and formula formulation. However, at present, the coverage rate of the grassroots agricultural technology extension system is insufficient, and some farmers' understanding of scientific fertilization still remains at the empirical level (Li et al., 2018). The cost of soil testing (about 100 to 300 yuan per test) and the premium of formula fertilizers (10% to 20% higher than that of ordinary fertilizers) impose economic burdens on small-scale farmers (Zhao et al., 2022). The areas covered by the full-process service of soil testing and formula fertilization are limited (Zhou et al., 2023). The biological agriculture model exhibits a high level of technical operational complexity, rendering it challenging for ordinary farmers to implement independently (Suh, 2014). The ecological agriculture model requires significant initial investment and has a long payback period, which weakens farmers' willingness to adopt it (Zhang et al., 2023).

The fragmentation of cultivated land leads to scattered plots, making it difficult for large agricultural machinery to operate and restricting the large-scale application of low-carbon technologies such as straw returning to the field. Fragmentation requires farmers to invest additional time and funds in managing scattered plots, which may reduce their willingness to try new technologies (such as low-carbon intercropping) (Hao et al., 2023). The influence of farmers' age on the adoption of low-carbon rice cultivation techniques shows nonlinear characteristics. Young farmers tend to adopt simple techniques. The types adopted by the middle-aged group increase with age but are driven by economic benefits, while elderly farmers may solidify some techniques due to path dependence. Policies need differentiated intervention to adapt to intergenerational differences (Yu and Luo, 2022). The deeper farmers' understanding of the principles of low-carbon technologies (such as the carbon sequestration mechanism of straw returning to the field), the more accurately they can assess the applicability of different technologies, and thus choose more suitable technology combinations. Farmers with high cognitive levels can make more rational judgments on technological risks, reduce their reliance on a single technology, and promote the adoption of diverse technologies (Yan et al., 2025).

Although the survey was conducted in late winter and early spring, when farmers were free from farming, as the survey was conducted in the village, it was inevitable that some farmers in the village went out to work, it was a lack of information on these farmers' samples. The research scope should be expanded. For example, the rural cadres should have the data of migrant workers and conduct telephone surveys to supplement the overall information. Further studies should be expanded. After getting the data from the village cadres, we will conduct a telephone survey to supplement the overall information.

5.2. Conclusions

The previous literature on the drivers of farmers' adoption of low-carbon rice farming practices predominantly used conventional linear regression models (Hou and Hou, 2019; Yan et al., 2025). However, the drivers of farmers' adoption of low-carbon rice cultivation practices are non-linear association among variables, and their relative importance differs significantly. Our results substantiated that the farmers' low-carbon technical understanding level, the farmers' low-carbon importance motivation, the farmers householder's age and the proportion of year-round farmers to the total population directly and positively affected the adoption of low-carbon agricultural technologies. The cultivated land fragmentation's degree and the difficulty level in obtaining information about low-carbon rice farming directly and negatively affected the adoption of low-carbon agricultural technologies. Consequently, it is imperative to implement more supportive policies to enhance farmers' attitudes towards low-carbon production and their perception of behavioral efficiency. This finding validates that promoting a social environment conducive to low-carbon agricultural production is crucial for enhancing farmers' adoption behavior. Such an environment can be utilized to formulate new policies aiming to encourage farmers' adoption of low-carbon technologies.

5.3. Policy Implications

In order to promote the adoption of low-carbon technologies in China and improve the efficiency of grain production, this study puts forward six policy recommendations.

1) The government needs to strengthen the publicity of low-carbon rice farming technology. In view of the low adoption level of low carbon rice cultivation, it is necessary to introduce corresponding policies to promote the promotion of low carbon rice cultivation technology at the social level, popularize the knowledge and technical instructions of low carbon rice cultivation, so as to fully dispel the concerns of the majority of rice farmers.

Meanwhile, measures should be taken to attract young people to rice farming. The government should provide corresponding subsidies and development opportunities, so as to increase the possibility of farmers adopting low-carbon rice farming behavior.

2) The government should increase financial investment in low-carbon rice cultivation technology and subsidies for rice farmers. Some subsidies are given to farmers to alleviate their economic pressure and increase their ability to resist risks. In the process of technology research and application, the government provides certain financial support to form a more perfect and mature measure system to adapt to field rice production. As a new agricultural production technology, it is necessary to increase the research and investment of technology to reduce the worries of farmers adopting low-carbon rice farming behavior.

3) Modern management of rice production should be accelerated. The government should support the construction of large-scale and intensive rice production and management subjects and rice production enterprises. At the same time, it can actively promote the shared use of rice planting machinery and tools among rice farmers, give full play to the use value of agricultural machinery and tools, save costs, improve rice production efficiency, and thus improve the enthusiasm of farmers to adopt low-carbon rice farming behavior.

4) The government should improve the training of low-carbon rice cultivation technology, strengthen the communication between villagers and members of cooperatives and other organizations, alleviate the information constraints and the cognitive bias of rice farming among farmers, so as to fully promote the participation of rice farmers in the dissemination and implementation of low-carbon rice farming technology.

5) The government needs to develop a reward and punishment mechanism in the field of agricultural carbon emissions, reward farmers who carry out technological innovation and adopt low-carbon rice farming behavior, and give certain penalties for adopting serious pollution and high carbon emissions of rice farming behavior.

6) Improve the land transfer system. It is necessary to fully improve the system of rural cultivated land transfer. The government needs to provide corresponding legal system protection to ensure the vital interests of farmers in accordance with the law and regulations, so that farmers' concerns about the loss of cultivated land can be alleviated to a greater extent. At the same time, the cultivated land can be

fully used, and the possibility of farmers adopting low-carbon rice farming behavior can be improved.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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