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The Impact of Digital Technology Application on Agricultural Low-Carbon Transformation—A Case Study of the Pesticide Reduction Effect of Plant Protection Unmanned Aerial Vehicles (UAVs)

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Abstract: The promotion of pesticide use reduction is an inevitable requirement for advancing green and low-carbon transformation of agriculture. Analyzing the impact and mechanism of agricultural digital technology applications, represented by plant protection unmanned aerial vehicles (UAVs), in reduction of pesticide application intensity by farming households is of great significance for exploring feasible pathways for low-carbon transformation in rice production. Based on the survey data of 455 sample farming households in Jiangxi Province, China, this paper employs the Ordinary Least Squares (OLS) and Propensity Score Matching (PSM) methods to examine the relationship between plant protection UAVs and the intensity of pesticide application. The research results indicate that the use of plant protection UAVs substantially reduces the intensity of pesticide application in rice by 24.9%. Heterogeneous analysis reveals that the inhibitory effect of plant protection UAVs on pesticide application intensity is more pronounced among non-aged farming households, large-scale farming households, and part-time farming households. Therefore, in order to achieve the goal of rlow-carbon transformation in rice production, it is essential to improve agricultural support policies and establish market promotion and application mechanisms to jointly promote the adoption of plant protection UAVs aerial spraying technology and other agricultural digital technologies.

Keywords: digital technology application; agricultural low-carbon transformation; plant protection unmanned aerial vehicle(UAVs); pesticide application intensity; agricultural socialization services

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1. Introduction

In the wake of the swift progression of the "dual carbon" objectives, the rural economic and social development faces a substantial dilemma: mitigating agricultural carbon emissions without compromising the stability and growth of food production. Taking pesticides as an example, in the context of China's grain production, an average of approximately 50 million tons of grain yield is saved annually through the application of pesticides [1]. However, this has resulted in China consistently ranking first globally in the pesticide application volume [2]. Furthermore, the predominant method of pest control in China remains reliant on extensive pesticide spraying, with only 20% to 30% of applied pesticides effectively reaching the target areas [3]. The substantial dosage of pesticides combined with a low effective utilization rate not only contributes to significant agricultural non-point source pollution and ecosystem damage, but also facilitates the entry of pesticides into the human body through environmental diffusion and the food chain, thereby increasing health risks to humans [4]. In response to these challenges, the Ministry of Agriculture of China introduced the "Action Plan for Zero Growth of Pesticide Use by 2020" in 2015, which set a target for the utilization rates of fertilizers and pesticides to reach 40% by 2020. Subsequently, in 2022, the State Council of China launched the "14th Five-Year Plan for Advancing Agricultural and Rural

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Modernization," with an aim to achieve a utilization rate of over 43% for major crops by 2025. Despite a reduction in the total volume of pesticide application, it continues to exceed the "optimal dosage" from an economic perspective [5], and excessive pesticide application among farming households remains prevalent [6]. Therefore, improving the scientific use of agricultural chemicals has become a key aspect of the low-carbon transformation in agriculture.

Since the implementation of the Digital Rural Strategy, emerging digital technologies such as big data, the Internet of Things (IoT), and remote sensing have gradually become popular in the agricultural sector, providing a viable pathway for low-carbon development in agriculture. Taking plant protection unmanned aerial vehicle(UAVs) as an example, exhibit advantages such as high safety, water and pesticide conservation, flexibility, spraying efficiency, and non-destructiveness, thereby mitigating issues of missed or repeated spraying associated with traditional mechanical and extensive pesticide application methods [7], representing a significant coupling of digital technology and agricultural development. Consequently, plant protection UAVs have garnered significant global attention. In 1983, the Agricultural Aviation Association, affiliated with the Ministry of Agriculture, Forestry and Fisheries of Japan, commissioned Yamaha Motor Co., Ltd. to undertake research on unmanned agricultural plant protection equipment. Subsequently, in 1985, Yamaha introduced the world's first agricultural UAV, the Model Rmax, specifically designed for pesticide application. This medium-sized unmanned helicopter boasted a payload capacity of 5kg [8]. Since 2019, Japan's Ministry of Agriculture, Forestry, and Fisheries (MAFF) has been promoting the adoption and demonstration of intelligent agricultural technology at farming sites through the "Smart Agriculture Acceleration Implementation Project"[9]. Furthermore, the Federal Aviation Administration of the United States has waived single takeoff and landing fees for agricultural aircraft, including UAVs. In 2016, the administration issued the "Operation and Certification of Small Unmanned Aircraft Systems," further facilitating the utilization of plant protection UAVs. Currently, over 65% of chemical pesticides in the United States are applied by airplanes, with the spraying ratio in rice cultivation reaching 100%[10].

The Chinese government has also been intensifying its promotion and support for plant protection UAVs. In 2014, the Central Committee of the Communist Party of China and the State Council issued the "Some Opinions on Comprehensively Deepening the Rural Reform and Accelerating the Modernization of Agriculture," emphasizing the need to strengthen agricultural aviation infrastructure. In 2017, the National Agricultural Mechanization Work Conference announced that plant protection UAVs would serve as pilot projects and receive corresponding subsidies. Additionally, in the "Guiding Opinions on the Implementation of Agricultural Machinery Purchase Subsidies from 2021 to 2023" issued in 2021, plant protection UAVs was included in the nationwide subsidy program. By 2022, China had deployed over 130,000 plant protection UAVs, covering more than 267 million mu of agricultural land.

The question of whether the application of digital technologies represented by plant protection UAVs can lead to a reduction in pesticide usage is a subject worthy of academic discussion, with existing research reflecting diverse perspectives on this issue. A majority of studies indicate that plant protection UAVs facilitate a decrease in pesticide application while simultaneously enhancing efficiency. Specifically, the efficiency of agricultural UAVs with a payload of 20kg is reported to be 3-4 times greater than that of tractors equipped with sprayers and 30 times higher than manual sprayers [11]. Additionally, experimental research demonstrates that aerial spraying for the control of rice leaf roller pests is more effective than conventional pesticide application methods [12]. An experiment by Zhang et al. [13] in a wheat field in Wanrong County, Shanxi Province, revealed that the pesticide utilization rate of plant protection UAVs was 57.31%, significantly surpassing the rates of 36.69% and 29.56% associated with backpack electric sprayers and backpack electric fan-sprayers, respectively. These findings underscore that the pesticide utilization rate when using UAVs is considerably higher than that of ground-based spraying equipment.

Conversely, some studies arrive at different conclusions. For instance, Zhang et al. [14] conducted experiments in summer corn fields in Shijiazhuang, Hebei Province, revealing that conventional dosage spraying by plant protection UAVs can lead to phytotoxicity in corn,

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consequently resulting in yield reduction. Moreover, some scholars contend that small-scale farming households require support in evaluating new pesticide reduction technologies, such as plant protection machinery, in order to achieve optimal reduction targets [15]. As a result, some researchers have investigated the interplay between outsourcing services, the use of plant protection machinery, and pesticide usage. The majority of these studies confirm that the adoption of Agricultural Management Systems enhances the efficiency of plant protection machinery utilization, thereby reducing pesticide usage [16]. Furthermore, research by Sun et al. [17] indicates that the outsourcing of plant protection services significantly decreases the frequency of pesticide applications. Nevertheless, some studies present conflicting conclusions, suggesting that non-professional outsourcing organizations may deviate from recommended machinery and operational procedures, which potentially increases the risk of pollution [18].

Despite the rich theoretical foundation provided by existing research, several shortcomings remain. Firstly, the existing literature predominantly emphasizes empirical studies on the impact of pest control aerial application technology on pesticide application efficiency, with limited exploration of effects and mechanisms from the micro-level of individual farmers. Secondly, current research on pesticide reduction often overlooks the variations in farmers' resource endowments. Based on this, this paper employs survey data from 455 rice farming households in Jiangxi Province, utilizing OLS linear regression and Propensity Score Matching (PSM) to analyze the influence of plant protection UAVs usage on pesticide application intensity and the heterogeneity among farming households. The contributions of this research are twofold: Firstly, by analyzing survey data from a prominent rice-producing region, the study discerns the micro-level impact of aerial plant protection UAVs application on pesticide usage in rice production, thereby enriching theoretical research on the low-carbon transformation of rice agriculture and offering theoretical support for the digitalization of agricultural practices. Secondly, the study elucidates variations in the pesticide reduction efficacy of plant protection UAVs across different age groups of farming households, farming scales, and levels of dual occupation, thereby providing empirical evidence for policymakers to develop differentiated strategies for the promotion and application of agricultural digital technologies, such as plant protection UAVs.

2. Theoretical Basis and Research Hypotheses

2.1. The Impact of Using Plant Protection UAVs on the Intensity of Pesticide Application

Compared with traditional plant protection machinery, plant protection UAVs exhibit significant advantages [19]. On the one hand, over 90% of small-scale agricultural machinery such as manual sprayers and backpack motor sprayers use outdated conical nozzle technology, which is prone to excessive pesticide application [20]. On the other hand, the reliance on manual spraying and the lack of technical knowledge among farming households often lead to overuse of pesticides. For instance, in some areas, farming households use high-volume rain-style spraying methods, where large droplets fail to adhere to the leaves, leading to substantial pesticide loss and waste, thus significantly reducing the effectiveness of pest and disease control. Plant protection UAVs, as a new digital technology, offers the advantages of water saving, pesticide saving, environmental protection, and high spraying efficiency, thereby compensating for the shortcomings of traditional plant protection machinery to some extent [19]. Plant protection UAVs has been shown to reduce pesticide usage by 30% compared to traditional methods [21], and the rotor wash produced in the course of spraying ensures coverage of the crop canopy, guaranteeing potential savings in pesticide and effective management [22]. Moreover, the utilization of plant protection UAVs has facilitated the integration of productive agricultural services, indirectly achieving a reduction and increased efficiency in pesticide use. Small-scale farming households have changed their pesticide application habits by purchasing pesticide outsourcing services from socialized service organizations, which introduces new elements such as environmentally friendly pesticides and new technologies such as plant protection UAVs into the agricultural production process [23]. Furthermore, these social service

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organizations are inclined to reduce pesticide usage on their own initiative, aiming to maximize profits by reducing the intensity of the pesticide application per unit area to lower the cost of inputs.

In light of the foregoing, the following hypotheses are proposed in this article:

Hypothesis 1 (H1). *The use of plant protection UAVs for pesticide application reduces the intensity of pesticide application.*

2.2. The Impact of Farming Households Differentiation on the Pesticide Reduction Effect of UAVs

According to of subjective expected utility theory, decision-makers are not absolutely rational and have unique preference characteristics. They choose their actions based on the maximization of subjective expected utility [24]. In rural areas, differences in human resource endowment are widespread, involving different levels of individual, family, and agricultural production, such as age, business scale, and labor force [25]. Farming households with different endowments have varying perceptions of the importance of low-carbon development, which in turn influences the extent of their adoption of agricultural digital technologies, leading to differences in the effectiveness of pesticide reduction. Therefore, this article attempts to explore the differences among farming households with different endowments in the impact of UAVs on pesticide application intensity.

Existing research shows that age is a key factor distinguishing the pesticide application intensity among agricultural producers [26,27]. It was discovered that aged farming households are linked to a decreased probability of using UAVs presently. Older farming households might be less inclined to invest in agricultural digital technologies like UAVs due to their limited planning horizons [28]. Aging farmers find it challenging to modify their long-established pesticide application methods. Even after acquiring plant protection UAVs, they often struggle to spray pesticides in accordance with the prescribed techniques and dosages, which diminishes the devices' potential to reduce pesticide usage. Furthermore, the risk-averse mindset of aging farmers leads them to believe that minimizing pesticide application could result in reduced crop yields and lower income. As a result, they frequently impose specific requirements on pesticide application rates, thereby hindering the reduction initiatives of social service organizations. In contrast, non-aged farming households typically exhibit a stronger ecological awareness. Following the purchase of plant protection UAVs or services, they are more likely to focus on scientifically determined pesticide dosages. Consequently, the pesticide reduction effects associated with UAV usage are significantly more pronounced among non-aged farming households compared to their older counterparts.

In light of the foregoing, the following hypotheses are proposed in this article:

H2. *The suppressive effect of agricultural UAVs on pesticide application intensity is more pronounced among non-aged farming households.*

The essence of moderately scaled farming operations lies in the optimization of the combination of production factors [29]. This optimization is achieved by expanding the scale of production and management units, which can lead to a more rational distribution of production inputs, thereby contributing to the mitigation of excessive pesticide application [30]. Firstly, moderately scaled operations address the conflict between fragmented farmland and agricultural environmental protection, enhancing the scale and specialization of UAV pest control, subsequently improving pesticide utilization efficiency. Secondly, large-scale operators possess intrinsic incentives for reducing pesticide usage. Specializing in agricultural production, they are driven by self-interest and are sensitive to rice prices, making them more inclined to choose high-quality rice varieties. However, high-quality rice is more susceptible to pest and disease infestations. Therefore, using UAVs for pest control enables them to reduce pesticide use and cut production costs. Thirdly, large-scale operators are more responsive to consumer demand for food quality and safety. When employing UAVs for pest control, they not only improve pesticide application efficiency but also enhance the safety and quality of agricultural products, thus increasing their market competitiveness. In contrast, small-scale farming households often lack environmental awareness and view UAV pest control merely as a

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labor-saving technology. In households where young labor is abundant, the inclination to adopt UAV pest control is relatively low. As a result, the inhibitory effect of UAV usage on pesticide application intensity is less pronounced among small-scale farming households to large-scale farming households.

In light of the foregoing, the following hypotheses are proposed in this article:

H3. *The inhibitory effect of plant protection UAVs spraying on pesticide application intensity is more pronounced among large-scale farming households.*

The choice of production factor inputs for farmer households depends on the expected utility brought by various factor combinations; under given endowment conditions, farming households choose the production factor combination that maximizes their expected utility of income. Part-time farming households, with non-agricultural income as their main source, mainly aim to maintain the operational rights to their land, and with a priority for young labor to shift towards the non-agricultural sector, there is a shortage of labor input in agricultural production. Thus, they are more inclined to mitigate the labor shortage by increasing the input of agricultural chemicals [31]. Moreover, pest and disease control have the characteristics of timeliness and emergency; due to untimely pesticide spraying by part-time farming households, the severity of pests and diseases might increase, which can only be compensated by increasing the amount of pesticide used. Agricultural machinery, including UAVs, not only compensates for labor shortages but also ensures the timeliness and quality of pest control activities, thus UAVs spraying can reduce the intensity of pesticide application more effectively in part-time farming households. In contrast, pure farming households typically rely on a single source of household income and have a relatively abundant supply of agricultural labor, which decreases their motivation to replace labor with machinery. Consequently, the inhibitory effect of plant protection UAVs spraying on pesticide application intensity is less pronounced among pure farming households compared to their part-time counterparts.

In light of the foregoing, the following hypotheses are proposed in this article:

H4. *The inhibitory effect of plant protection UAVs spraying on pesticide application intensity is more pronounced in part-time farming households.*

3. Data Sources, Variable Selection, and Research Methods

3.1. Data Introduction

The micro data used in this paper comes from a questionnaire survey conducted by the research team on rice farming households in the main production areas of Jiangxi Province from November 2020 to February 2021. The main content includes individual characteristics of rice farm decision-makers, household characteristics, agricultural production and operation conditions, green technology applications, and agricultural socialized services, etc. The research team adopted a combination of stratified and random sampling methods, dividing 100 counties (cities, districts) in Jiangxi Province into three levels based on per capita GDP. Three sample counties were randomly selected from each level, two townships were randomly selected from each county, three villages were randomly selected from each township, and ten farming households were randomly selected from each village, resulting in 540 valid questionnaires, which can be considered a representative sample of the entire province. Based on the required indicators for the study, the head of household samples were screened, and those with missing or abnormal values were removed, resulting in 455 valid samples.

3.2. Variable Description

3.2.1. Dependent Variable

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Pesticide Application Intensity. In the process of rice production, compound element pesticides need to be applied, and different farming households choose different pesticide brands and concentrations, resulting in differences in the types and contents of elements in unit pesticides. Therefore, it is impossible to accurately calculate the pure amount [32]. This paper follows the method of Wang et al. [33] and Liu et al. [34], using the logarithm of "the total cost of pesticides per unit sown area of rice annually" to measure pesticide application intensity.

3.2.2. Core Independent Variable

Plant Protection UAVs spraying. Use the question "Do you use plant protection UAVs for the pesticide spraying?" to measure with the answer "Yes" coded as 1 and "No" coded as 0.

3.2.3. Control Variables

To avoid model estimation bias caused by omitted variables, this paper follows the methods of Zhang et al. [35] and Shi et al. [23], selecting individual characteristics of rice farm decision-makers (age, the education level, non-agricultural employment), household characteristics (number of the agricultural labor force, the proportion of agricultural income, whether to join rice farming cooperatives), village characteristics (village transportation conditions, distance from the operated land to the county), and rice management characteristics (agricultural operation scales, the number of plots, the degree of plot contiguity, the convenience of agricultural machinery use) as control variables. The variables involved in the model and the descriptive statistical results are shown in Table 1.

Table 1. Main variables and descriptive statistics.

	Variable Declaration	Mean	Standard Deviation
Dependent variable			
Pesticide application intensity	the total cost of pesticides per unit sown area of rice annually (logarithm)	7.516	0.620
Core Independent variables			
Plant protection UAVs spraying	Do you use plant protection UAVs for the pesticide application? (0= No,1= Yes)	0.226	0.419
Control variable			
Age of the householder	According to the actual survey data (age)	57.073	9.190
Education level of the householder	Householder's education level of rice farm decision-makers (1= primary school or below; 2= junior high school; 3= high school /technical school; 4= vocational college; 5= undergraduate degree or above)	1.765	0.757
Non-agricultural employment	0= No,1= Yes	0.426	0.495
Number of the agricultural labor force	According to the actual survey data (number of person)	1.932	0.610
The proportion of agricultural income	The proportion of agricultural income in total household income (1=10%; 2=10%~50%; 3=51%~90%; 4=90%)	2.574	1.143
Whether to join the rice farming cooperatives	0= No,1= Yes	0.288	0.453
Village transportation conditions	1= very bad; 2= poor; 3= general; 4= good; 5= very good	3.910	0.907
Geographical location features	The distance of the operating land from the county (km)	30.414	15.049
Agricultural operation scales	According to the actual survey data (ha)	8.520	36.711
The number of plots	According to the actual survey data (number of plots)	63.879	265.428

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Degree of plot contiguity	1= very dispersed; 2= relatively dispersed; 3= partial contiguous; 4= all contiguous	2.556	1.018
The convenience of agricultural machinery usage	1= inaccessible; 2= inconvenient; 3= general; 4= more convenient; 5= very convenient	4.125	0.980

Note: *, **, *** represent significance at the 10%, 5% and 1% levels, respectively, with standard errors in parentheses.

3.3. The Empirical Method

3.3.1. Benchmark Regression Model

The intensity of pesticide application was a continuous variable, so a linear regression model of OLS was constructed to analyze the direct relationship between plant protection UAVs spraying and pesticide application intensity. The specific model expression is as follows:

$$strength_i = \alpha + \beta airplanet_i + \delta control_i + \mu_i \quad (1)$$

Equation (1) represents the pesticide application intensity per hectare of rice of the i-th farmer; the virtual binary variable $airplanet_i$ indicating whether to use the plant protection UAVs for pesticide application; and $control_i$ indicates the control variable, including the individual characteristics, household characteristics, village characteristics and rice management characteristics of the i-th farmer. α is the constant term, β and δ are the parameters to be estimated and μ_i is the random disturbance term.

3.3.2. Propensity Score Matching (PSM)

The OLS linear regression model does not control for other observed variables affecting behavior, which may lead to biased results when estimating the relationship between specific behaviors and outcomes. Therefore, referring to Liu's et al. [36] study, the Propensity Score Matching (PSM) method is used for robustness testing. The advantage of the PSM method is that it does not assume homogeneous treatment effects among the population and restricts estimation to the matched subsample, effectively reducing bias from using the full sample [37]. This paper divides the sample farming households into a treatment group (using plant protection UAVs for pesticide application) and a control group (not using plant protection UAVs for pesticide application), where the initial conditions of the control group are similar to those of the treatment group. This simulates the counterfactual situation of the treatment group and then compares the intensity differences when farming households use plant protection UAVs for pesticide application.

First, a Logit model is used to estimate the probability of farming households using plant protection UAVs for pesticide application based on observable characteristics, obtaining the propensity score:

$$P(X_i) = Pr(D_i=1|X_i) = E(D_i=0|X_i) \quad (2)$$

In equation (2), D_i is the dummy variable indicating whether farmer i uses plant protection UAVs for pesticide application; if D_i=1, it is the treatment group, indicating the use of plant protection UAVs; if D_i=0, it is the control group, indicating no use of plant protection UAVs; X_i represents observable individual characteristics, household characteristics, village characteristics, and rice farming characteristics. $P(X_i)$ is the conditional probability of farmer i using plant protection UAVs for the pesticide application under given characteristic conditions, i.e., the propensity score.

After obtaining the propensity scores, a control group with similar characteristics to the treatment group is constructed as the counterfactual. Theoretically, different matching methods may introduce bias, leading to varying results. To ensure robustness, this paper selects three matching methods: k-nearest neighbor matching, kernel matching, and local linear matching. Finally, the average treatment effect on the treated (ATT) is estimated by comparing the control and treatment groups:

$$ATT=E(Y_1|D_i=1)-E(Y_0|D_i=1)=E\left(Y_1-Y_0\middle|D_i=1\right) \tag{3}$$

In equation (3), Y_1 and Y_0 represent the pesticide application intensity of farming households in the treatment and control groups, respectively; ATT is the average treatment effect on the treated after matching, representing the net impact of using plant protection UAVs on pesticide application intensity. $E(Y_1|D_i=1)$ is the directly predicted factual outcome, while $E(Y_0|D_i=1)$ is the counterfactual outcome constructed by the propensity score matching method.

4. Empirical Study on the Impact of Plant Protection UAVs Spraying on Pesticide Application Intensity

4.1. OLS Regression Results of Plant Protection UAVs Spraying on Pesticide Application Intensity

Table 2 presents the benchmark regression results of the impact of plant protection UAVs spraying on pesticide application intensity, reporting the regression coefficients and robust standard errors of the OLS model. The p-value of the model is significant at the 1% level, indicating the model is appropriately chosen. From model (1), it can be seen that without control variables, the impact of plant protection UAVs spraying on pesticide application intensity is negatively significant at the 1% level. In model (2), which controls for individual characteristics, household characteristics, village characteristics, and rice farming characteristics based on model (1), the regression results show that the regression coefficient of plant protection UAVs spraying is -0.198, which is significant at the 1% level, indicating that plant protection UAVs spraying significantly reduces the pesticide application intensity of rice. Compared with farming households who do not use UAVs, those who use plant protection UAVs can reduce pesticide application intensity by 19.8%. Hypothesis H1 is verified.

Table 2. OLS regression results of the intensity of pesticide application in plant protection UAVs.

Variable	Interpreted variable: pesticide application intensity	
	model (1)	model (2)
Plant protection UAVs spraying	-0.206*** （0）.074	-0.198*** (0.074)
Age		0.009*** (0.003)
Degree of education		-0.028 (0.036)
Non-agricultural employment		0.043 (0.059)
Number of the agricultural labor force		-0.049 (0.049)
The proportion of agricultural income		-0.068*** (0.025)
Whether to join the rice farming cooperatives		-0.110* (0.063)
Village transportation conditions		-0.058** (0.029)
Geographical location features		0.003** (0.002)
Rice management area		0.009* (0.005)
The number of plots		-0.001* (0.001)
The degree of plot continuity		0.078*** (0.030)

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The convenience of agricultural machinery usage		0.073*
		(0.040)
Prob> F	0.005	0.000
R2	0.019	0.149
Obs	455	455

3NNoteNote: *Note: *, **, *** represent significance at the 10%, 5% and 1% levels, respectively, with standard errors in parentheses.

Among the control variables, age, geographical location features, agricultural operation scales, the degree of land contiguity, and the convenience of machinery use significantly positively influence pesticide application intensity. Older farming householders have relatively weaker environmental awareness and are more likely to have the erroneous perception that higher application intensity is safer, indicating that under certain environments, farmer behavior is influenced by subjective assessments of random event probabilities [38]. The further the operated land is from the county, the less perfect the market monitoring mechanism, leading farming households to be more inclined to purchase cheaper pesticides, requiring higher doses for the same pest control effect. The larger the rice management area, the more dependent they are on agricultural operations, increasing the likelihood of over-application due to risk aversion. farming households with contiguous land and convenient machinery use tend to purchase their equipment, but due to insufficient professional knowledge, they may cause pesticide use to lack a scientific basis. The proportion of agricultural income, membership in rice farming cooperatives, village transportation conditions, and the number of plots significantly negatively influence pesticide application intensity, indicating a favorable condition for reducing pesticide usage. This result suggests that households with a higher proportion of agricultural income relative to total household income and those managing a larger number of plots are often larger farming operations. These households tend to place greater emphasis on reducing planting costs to achieve higher profits, and therefore are more inclined to use pesticides rationally. Joining rice farming cooperatives increases awareness of the hazards of over-application, changing unreasonable application methods. Villages with improved transportation conditions demonstrate a greater receptiveness to government initiatives promoting low-carbon transition and exhibit a higher propensity to actively implement measures for reducing pesticide use.

4.2. Robustness Test -- Propensity Score Matching (PSM)

To ensure the robustness of the matching results, the sample has gone through k-nearest neighbor matching, kernel matching, and local linear regression matching. Table 3 presents the Average Treatment Effect on the Treated (ATT) of pesticide application intensity by agricultural UAVs, estimated using three different matching methods. After controlling for a series of observable variables with the PSM method, the estimation results of the three matching methods showed no significant differences, indicating consistency in the estimation results.

Table 3. PSM estimation results of the pesticide application intensity for plant protection UAVs spraying.

model (3)	Matching method	Experimental group / Control group	ATT	t price
Pesticide application intensity	K-neighbor matching (k =1)	352/103	-0.259**	-2.18
	Kernel matching	352/103	-0.247**	-2.38
	Local linear matching	352/103	-0.240**	-2.01
	mean	——	0.249	——

Note: *, **, *** represent significance at the 10%, 5% and 1% levels, respectively, with standard errors in parentheses.

As seen from the ATT results, the average treatment effect is 0.249 and was at least negatively significant at the 5% level. It shows that the application of plant protection UAVs can reduce the intensity of pesticide application. Compared with the farming households without using UAVs, the intensity of the pesticide application of the farming households using plant protection UAVs is 24.9% lower. The PSM estimate was 5.1% higher than the OLS estimate, indicating that the benchmark regression model did not consider selective bias leading to an underestimate of the treatment effect.

4.3. Endogenous Problems

Farming households engaged in labor-intensive crop cultivation have increased pesticide usage due to rising labor costs [39]. In order to reduce production costs, these farming households are more inclined to reduce the amount of pesticide application by replacing labor force with agricultural machinery. Therefore, the benchmark regression results may have endogenous problems. In this paper, the Two Stage Least Square (2SLS) tool variable method is used to deal with the potential endogeneity of the model. The selection of instrumental variables needs to meet two basic conditions: one is a strong exogenous relationship with the dependent variables, and the other is a strong correlation with the independent variables. Therefore, following Maluccio [40], "Whether to join the agricultural machinery professional cooperatives" is chosen as the instrumental variable for "plant protection UAVs spraying". The reasons are as follows: firstly, joining the agricultural machinery professional cooperatives has strong exogenous characteristics with pesticide application intensity; secondly, it has a strong correlation with plant protection UAVs spraying. The agricultural machinery professional cooperatives, as important rural agricultural production service entities, provide farming households with comprehensive agricultural machinery services and technical information sources [41].

The 2SLS model results are shown in Table 4. Before performing 2SLS estimation, the Hausman test is conducted. The P-values for the Durbin (score) and Wu-Hausman tests are both 0.000, indicating that plant protection UAVs spraying is an endogenous explanatory variable at the 1% level, validating the necessity of the 2SLS estimation. In the weak instrumental variable test, Shea's Partial R2 for plant protection UAVs spraying is less than 0.048, and the F-value is 15.866 (threshold value: 10), thus rejecting the null hypothesis of weak instrumental variables. The 2SLS results indicate that joining rice farm cooperatives promotes farming households' adoption of UAVs spraying. Compared to the benchmark regression, the coefficient for plant protection UAVs spraying remains significantly negative in the second stage regression, consistent with the benchmark results, indicating the significance of the results after addressing the endogenous problem.

Table 4. Estimated results of the endogenous treatment.

model (4)	**Plant protection UAVs spraying**	
	stage I	stage II
Plant protection UAVs spraying		-1.574*** (0.439)
Instrumental variable: Whether to join the agricultural machinery professional cooperatives	0.281*** (0.070)	
Controlled variable:	control	
Shea's Partial R2	0.048	
One-stage F value	16.133	
Durbin (score) Test P-value	0.000	
The P-values of the Wu-Hausman test	0.000	

Obs	455

Note: *, **, **NotNote: *, **, *** represent significance at the 10%, 5% and 1% levels, respectively, with standard errors in parentheses.

4.4. Heterogeneity Analysis

The previous section verified the significant negative impact of plant protection UAVs spraying on pesticide application intensity. The theoretical analysis suggests that the impact of UAVs spraying on the pesticide intensity varies among different groups. Therefore, the following sections classify the sample based on the household heads of different ages, agricultural operation scales, and types of concurrent occupations to explore the impact of plant protection UAVs spraying on pesticide application intensity among farming households with different endowments.The 2SLS model results are shown in Table 4. Before performing 2SLS estimation, the Hausman test is conducted. The P-values for the Durbin (score) and Wu-Hausman tests are both 0.000, indicating that plant protection UAVs spraying is an endogenous explanatory variable at the 1% level, validating the necessity of the 2SLS estimation. In the weak instrumental variable test, Shea's Partial R2 for plant protection UAVs spraying is less than 0.048, and the F-value is 15.866 (threshold value: 10), thus rejecting the null hypothesis of weak instrumental variables. The 2SLS results indicate that joining rice farm cooperatives promotes farming households' adoption of UAVs spraying. Compared to the benchmark regression, the coefficient for plant protection UAVs spraying remains significantly negative in the second stage regression, consistent with the benchmark results, indicating the significance of the results after addressing the endogenous problem.

4.4.1. Regression Results by Householders of Different Ages

Based on the internationally recognized standard for aging populations [36], the sample is divided into two groups: non-aged farming households (under 65 years old) and aged farming households (65 years and older). Age is removed from the control variables, and the OLS model is used for estimation. Table 5 models (8) and (9) report the regression coefficients for different age groups.

Table 5. Results of regression for the household heads of different ages.

	model (8)	**model (9)**
	Non-aged farming households	**Aged farming households**
Plant protection UAVs spraying	-0.223*** (0.082)	-0.025 (0.127)
Controlled variable	control	control
Prob> chi2	00.00	03.00
PseudoR2	0.1033	0.299
Obs	369	86

Note: *, **, *** represent significance at the 10%, 5% and 1% levels, respectively, with standard errors in parentheses.

In Model (8), the coefficient for non-aged farming households using plant protection UAVs is -0.223, significantly negative at the 1% level; in Model (9), the coefficient for aged farming households is not significant. This indicates that the inhibitory effect of UAVs spraying on the pesticide intensity is more pronounced among non-aged farming households, validating hypothesis H2.

4.4.2. Regression Results for Different Agricultural Operation Scales

Referring to the classification standard of Zhou [42], the sample is divided into small-scale farming households (less than 3.33 hectares) and large-scale farming households (3.33 hectares and

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above). Agricultural operation scale is removed from the control variables, and the OLS model is used for estimation. The regression coefficients are shown in Table 6.

Table 6. Regression results for different agricultural operation scales.

	model (10) small-scale farming households	**model (11) The scale of the household**
Plant protection UAVs spraying	-0.086 (0.125)	-0.162* (0.090)
Controlled variable	control	control
Prob> chi2	0.000	0.001
PseudoR2	0.215	0.167
Obs	270	208

ed lists. NNote: *, **, *** represent significance at the 10%, 5% and 1% levels, respectively, with standard errors in parentheses.

In Model (11), the coefficient for small-scale farming households using plant protection UAVs is not significant, while in Model (10), the coefficient for large-scale farming households is -0.162, significantly negative at the 10% level. This indicates that the inhibitory effect of UAVs spraying on pesticide intensity is more pronounced among large-scale farming households, validating hypothesis H3.

4.4.3. Regression Results for Different Types of Concurrent Occupations

Referring to the classification standard of farming households' concurrent occupations by Weng et al. [43], the sample is divided into four kinds based on the proportion of agricultural income: pure farming households (agricultural income greater than 90%), Type I concurrent farming households (agricultural income between 50% and 90%), Type II concurrent farming households (agricultural income between 10% and 50%), and non-farming households (agricultural income less than 10%). The proportion of agricultural income is removed from the control variables, and the OLS model is used for estimation. Table 7 models (12)-(15) report the regression coefficients of farming households with different types of concurrent occupations.

Table 7. Regression results for different types of concurrent occupations.

	model (12) Pure farming households	**model (13) Type I concurrent farmer**	**model (14) Type II concurrent farmer**	**model (15) Non-farming households**
Plant protection UAVs spraying	0.100 (0.110)	-0.259* (0.142)	-0.281* (0.154)	0.228* (0.126)
Controlled variable	control	control	control	control
Prob> chi2	0.024	0.064	0.000	0.000
PseudoR2	0.207	0.216	0.318	0.369
Obs	126	103	153	73

Note: *, **, *** represent significance at the 10%, 5% and 1% levels, respectively, with standard errors in parentheses.

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From the perspective of different types of concurrent occupations, the coefficients of pesticide application intensity for Type I and Type II concurrent farming households using plant protection UAVs for spraying are significantly negative at the 10% level, while the coefficient for pure farming households is not significant. This indicates that the inhibitory effect of UAVs spraying on pesticide application intensity is more apparent to concurrent farming households, supporting hypothesis H4. Model (15) also shows that using plant protection UAVs for spraying increases the pesticide application intensity for non-farming households. The possible reason is that non-farming households mainly engage in rice production for self-sufficiency and typically apply pesticides below the standard dosage to meet the quality and safety requirements of agricultural products [44]. Therefore, applying plant protection UAVs for spraying increases the pesticide application intensity for this group.

5. Research Conclusions and Discussion

Currently, traditional agricultural production methods in China have led to significant environmental pollution problems, highlighting the urgent need for the widespread adoption of digital technologies to facilitate a low-carbon transformation in the agricultural sector. Based on survey data from 455 farming households in the main rice-producing areas of Jiangxi Province, China, this study employs both Ordinary Least Squares (OLS) and Propensity Score Matching (PSM) techniques to investigate the impact and mechanism of agricultural digital technology, represented by plant protection UAVs, on pesticide application intensity. Additionally, this research investigates the differential impacts experienced by farmers with varying endowments.

The research findings show that, firstly, the adoption of plant protection Unmanned Aerial Vehicles (UAVs) leads to a notable decrease in pesticide application intensity. Specifically, farming households employing plant protection UAVs exhibit a 24.9% lower pesticide application intensity compared to those who do not utilize UAVs. Furthermore, The findings of Yan et al. [45] indicate a 12.40% reduction in pesticide use intensity among farm households using UAV sprayers compared to those using ground-based backpack sprayers, which is generally consistent with the results of this study. Nevertheless, the observed reduction effect is comparatively less significant in their sample, implying that further efforts are needed to enhance pesticide reduction measures in Jiangxi Province. Secondly, the findings from the heterogeneity analysis indicate that the suppressive impact of plant protection Unmanned Aerial Vehicles (UAVs) on pesticide application intensity is more evident in non-aged farming households, large-scale farming households, and part-time farming households. These results not only corroborate the conclusion drawn by Liu et al. [46], which states that aging significantly impedes the reduction of chemical pesticides among farming households, but also resonate with previous research that suggests moderate-scale farming enhances the carbon productivity of cultivated land [47].

Drawing from the aforementioned research findings, to fully harness the high efficiency, accuracy, and environmental benefits of agricultural digital technologies, such as plant protection UAVs, and to facilitate a green and low-carbon transformation in agriculture, thereby elevating the quality and safety standards of rice production, the following policy implications are proposed:

Firstly, from the perspective of promoting green and low-carbon agricultural transformation, government departments should enhance agricultural support policies, bolster policy support for agricultural digital technologies, and strengthen fiscal support for key digital technology research and development, particularly focusing on enterprises specializing in plant protection UAVs. Simultaneously, the government should intensify subsidies for the acquisition of agricultural digital infrastructure and social services for farming household, facilitating the integration of small-scale farming household with modern agricultural development. It is also necessary to clarify the management entity of plant protection UAVs, formulate prudent flight management measures, and foster orderly development of socialized services for plant protection UAVs. Furthermore, the government should actively nurture UAV service entities and encourage them to provide scientific and professional plant protection UAV services to part-time farming households through incentives like subsidies and rewards. It is essential to implement differentiated policies that facilitate the

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popularization and application of plant protection UAVs, with an emphasis on the dissemination of agricultural digital technologies such as UAV spraying technology among young farming households, large-scale farming households, and part-time farming households. For young farming households, efforts should be expanded to promote the use of plant protection UAVs through increased publicity, enhancing the spread of knowledge about UAVs spraying. For large-scale farming households, the provision of subsidies for the purchase and application of UAVs should be strengthened, reducing costs and improving economic benefits, thereby demonstrating their leading role. Despite the limited impact of pesticide reduction among aging farming households, small farming households, and non-farming households, policy promotion should be further intensified. For instance, utilizing production slogans and promotional guidance manuals to communicate the concept of green production to aging farming households can help accelerate the dissemination of knowledge about plant protection UAVs spraying. Secondly, from the perspective of boosting the operational efficiency of rice production and management, operators should proactively align with the advancement and dissemination of agricultural digital technologies such as plant protection UAVs aerial spraying technology, and establish a market-oriented promotion and application mechanism. UAV manufacturers are advised to enhance their after-sales service, organize professional pilots to train farmers and social service organizations, and expedite the promotion and application of plant protection UAV aerial spraying technology. This will empower large-scale rice growers and cooperatives to assume leadership and exemplary roles. Social service organizations for plant protection UAVss must focus on improving service quality and reducing service costs, thereby gaining the opportunity to provide aerial spraying services for large-scale farmers with contiguous plots and convenient access to agricultural machinery, avoiding excessive competition and inefficient utilization of plant protection UAV aerial spraying within the region.

However, this study has its limitations. Although the sample in this study adheres to a random selection process and reflects regional diversity, its applicability of the conclusions drawn from research conducted in Jiangxi Province to rice-producing areas in Northern China remains uncertain and requires further validation. Future studies should broaden the survey scope to enhance the universality of the conclusions. Additionally, this article explores the effect of pesticide reduction by plant protection UAVs but fails to take into account the impact of other agricultural digital technologies, such as blockchain, artificial intelligence, and cloud computing, on the low-carbon transformation of farming households. Future studies should incorporate supplementary surveys to investigate the differential impacts of these various agricultural digital technologies on the low-carbon transition in agriculture.

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References

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1. Cai, W., Huo, X., & Yang. (2023). Expanding the planting scale or participating in outsourcing services: The logical choice of pesticide reduction. *Journal of Arid Land Resources and Environment*, 37 (02): 50-58.
2. Sun, S., Zhang, C., & Hu, R. (2020). Determinants and overuse of pesticides in grain production: a comparison of rice, maize and wheat in China. *China Agricultural Economic Review*, 12(2), 367-379.
3. Tian Z, Xue X, Li L, Cui L, Wang G, & Li Z. (2019). Research status and prospect of spraying technology of plant-protection unmanned aerial vehicle. *Journal of Chinese Agricultural Mechanization*, (1): 40 37-45.
4. Zhang, W. (2018). Global pesticide use: Profile, trend, cost/benefit and more. *Proceedings of the International Academy of Ecology and Environmental Sciences*, 8(1), 1.
5. Zheng, J., & Zhang, R. (2022). Can outsourcing reduce pesticide overuse?-Analysis based on the moderating effect of farmland scale. J. *Agrotech. Econ*, 2, 16-27.
6. Zhang, C., Guanming, S., Jian, S. H. E. N., & Hu, R. F. (2015). Productivity effect and overuse of pesticide in crop production in China. *Journal of Integrative Agriculture*, 14(9), 1903-1910.
7. Xie, K., Xu, J., & Pan, Z. (2020). Research and application of anti-offset wireless charging plant protection UAVs. *Electrical Engineering*, 102, 2529-2537.
8. Chen, H., Lan, Y., Fritz, B. K., Hoffmann, W. C., & Liu, S. (2021). Review of agricultural spraying technologies for plant protection using unmanned aerial vehicle (UAVs). *International Journal of Agricultural and Biological Engineering*, 14(1), 38-49.
9. Seo, Y., & Umeda, S. (2021). Evaluating farm management performance by the choice of pest-control sprayers in rice farming in Japan. *Sustainability*, 13(5), 2618.
10. Cai L, Li K, Wang L. (2019). Comparison of development of aviation plant protection industries in America, Japan and China and its enlightenment. *China Plant Protection*, 39(07):60-63.
11. Yang, S., Yang, X., & Mo, J. (2018). The application of unmanned aircraft systems to plant protection in China. *Precision agriculture*, 19, 278-292.
12. Qin, W. C., Qiu, B. J., Xue, X. Y., Chen, C., Xu, Z. F., & Zhou, Q. (2016). Droplet deposition and control effect of insecticides sprayed with an unmanned aerial vehicle against plant hoppers. *Crop Protection*, 85, 79-88.
13. Zhang W, Li T, Jin Y, Han P, Li W, Wang M, Shen X, Gao H, & Cao M. (2020). Study on wheat aphids control effect and pesticide utilization rate with different pesticide devices. *China Plant Protection*, 40(10):83-87.
14. Zhang L, Xu J, Zhang L, Zhang Y, Sun G, Liu H, Liu S, & Jiang Y. (2022). Application of Three Types of Herbicides in Weed Control and Reduction of Herbicide Use Efficiency in Corn Fields. *China Plant Protection*, 42(01):79-82.
15. Dinham, B. (2003). Growing vegetables in developing countries for local urban populations and export markets: problems confronting small-scale producers. *Pest management science*, 59(5), 575-582.
16. Li, X., & Zhu, M. (2023). The role of agricultural mechanization services in reducing pesticide input: promoting sustainable agriculture and public health. *Frontiers in Public Health*, 11, 1242346.
17. Sun, D., Rickaille, M., & Xu, Z. (2018). Determinants and impacts of outsourcing pest and disease management: Evidence from China's rice production. *China Agricultural Economic Review*, 10(3), 443-461.
18. Yang, Y., Yu, Y., Li, R., & Jiang, D. (2023). Impact of pesticide outsourcing services on farmers' low-carbon production behavior. *Frontiers in Environmental Science*.
19. Hu, P., Zhang, R., Yang, J., & Chen, L. (2022). Development status and key technologies of plant protection UAVs in China: a review. *Drones*, 6(11), 354.
20. He X. (2019). Research and development of crop protection machinery and chemical application technology in China. *Chinese Journal of Pesticide Science*, 21(Z1):921-930.
21. Wang, S., Han, Y., Chen, J., Du, N., Pan, Y., Wang, G., ... & Zheng, Y. (2018). Flight safety strategy analysis of the plant protection UAVs. *IFAC-PapersOnLine*, 51(17), 262-267.
22. Campos, J., Llop, J., Gallart, M., García-Ruiz, F., Gras, A., Salcedo, R., & Gil, E. (2019). Development of canopy vigour maps using UAVs for site-specific management during vineyard spraying process. *Precision Agriculture*, 20(6), 1136-1156.
23. Shi Z, Fu Y. (2023). Can socialized service promote farmers to adopt pesticide reduction behavior? --Investigation based on the dimension of service specialization. *Chinese Journal of Agricultural Resources and Regional Planning*, 44(03):130-142.
24. Menapace, L., Colson, G., & Raffaelli, R. (2013). Risk aversion, subjective beliefs, and farmer risk management strategies. *American Journal of Agricultural Economics*, 95(2), 384-389.
25. Kussaiynov, T., & Tokenova, S. (2022). Resource Endowment of Rural Areas: Indicators, Assessment Procedures. *Journal of Environmental Management & Tourism*, 13(7), 1859-1866.
26. Ntow, W. J., Gijzen, H. J., Kelderman, P., & Drechsel, P. (2006). Farmer perceptions and pesticide use practices in vegetable production in Ghana. *Pest Management Science: formerly Pesticide Science*, 62(4), 356-365.
27. Isin, S., & Yildirim, I. (2007). Fruit-growers' perceptions on the harmful effects of pesticides and their reflection on practices: the case of Kemalpasa, Turkey. *Crop protection*, 26(7), 917-922.

28. Skevas, T., & Kalaitzandonakes, N. (2020). Farmer awareness, perceptions and adoption of unmanned aerial vehicles: Evidence from Missouri. *International Food and Agribusiness Management Review*, 23(3), 469-485.
29. Ma, L., Li, C., Xin, M., Sun, N., & Teng, Y. (2023). Analysis of efficiency differences and research on moderate operational scale of new agricultural business entities in Northeast China. *Sustainability*, 15(12), 9746.
30. Shi, Y., Yang, Q., Zhou, L., & Shi, S. (2022). Can moderate agricultural scale operations be developed against the background of plot fragmentation and land dispersion? Evidence from the suburbs of shanghai. *Sustainability*, 14(14), 8697.
31. Fang, C., Xu, Y., & Ji, Y. (2022). Part-time farming, diseases and pest control delay and its external influence on pesticide use in China's rice production. *Frontiers in Environmental Science*, 10, 896385.
32. Yang C, Qi Z, Huang W, & Ye S. (2020). Study on the Effect of Chemical Fertilizer Reduction in the "Shrimp and Shrimp Co-cultivation" Ecological Agriculture Model: Estimation Based on Propensity Score Matching (PSM), *Resources and Environment in the Yangtze Basin*, 29(03):758-766
33. Wang C, & Liu T. .(2021). Effects of farmer' willingness to abdicate land usufruct on the use intensities of chemical fertilizers and pesticides. *China population, resources and environment*, 31(3): 184 - 192.
34. Liu T, & Wu G. (2021). Do Agricultural Mechanization and Farmland Leasing Enhance Farmers' Willingness of Land Usufruct Abdication? *Journal of China Agricultural University (Social Sciences)*, 38(01):123-133.
35. Zhang M, Chen Z, Weng Z, & Zhang Y. (2023). Research on the Influence of Agricultural Socialized Services on Fertilizer Reduction: Based on the Regulation Effect of Element Configuration, *Journal of Agrotechnical Economics*, (03):104-123.
36. Liu, Y., Shi, X., & Gao, F. (2022). The impact of agricultural machinery services on cultivated land productivity and its mechanisms: A case study of Handan city in the North China plain. *Frontiers in Environmental Science*, 10, 1008036.
37. Gao X, Zhang Y, Zhang M, & Liao W. (2022). Analysis of the impact of use of internet information technology on agricultural productivity: a case study of rice farmers in Jiangxi Province, China. *Acta Agriculturae Zhejiangensis*, 34(12): 2809-2822.
38. Antle, J. M., & Pingali, P. L. (1995). Pesticides, productivity, and farmer health: A Philippine case study (pp. 361-387). *Springer Netherlands*.
39. Yuan B, & Chen C. (2020). Study on the Difference of Pesticide Application Behavior Farmers Under the Background of Rising Labor Cost: Based on the Mediating of Fine Management Technology. *Resources and Environment in the Yangtze Basin*, 29(07):1653-1662.
40. Maluccio, J. A. (1998). *Endogeneity of schooling in the wage function* (No. 54). International Food Policy Research Institute (IFPRI).
41. Wu P, Cao G, Liu X. (2018). Reflections on the Trend of Comprehensive Service of Agricultural Machinery Cooperatives—Based on Research in Anhui and Shandong Provinces. *Agricultural Economy*, (10):54-56.
42. Zhou B. (2010). The Positive Analysis on the Optimization of Planting Area of the Individual Farmer with a Large Scale of Paddy Rice -- Based on the 619 Sample Data in Jiangxi province. *Journal of Agrotechnical Economics*, (04):120-127.
43. Weng Z, Gao X, & Tan Z. (2017) Farmer Endowment, Regional Environment and Concurrent Business of Grain Farmers: Based on a Questionnaire Survey of 1,647 Grain Growers in 9 Provinces. *Journal of Agrotechnical Economics*, (02):61-71.
44. Lyu X, Li D, & Zhou H. (2018). Discussion on Quality and Safety of Agricultural Products: Concurrent Business and Pesticide Application Behavior -- Evidence from Hunan, Jiangxi and Jiangsu Provinces. *China Agricultural University Journal of Social (Sciences Edition)*, 35(04):69-78.
45. Yan A, Luo X, Tang L, et al. (2024). Can socialized pest control service reduce the intensity of pesticide use? Evidence from rice farmers in China[J]. *Pest Management Science*, 80(2): 317-332.
46. Liu E, Luo X, Du S, Yan A & Wang X. (2022). Aging, planting purpose and rice farmers' chemical pesticide reduction. *Acta Agriculturae Zhejiangensis*, 34(12) : 2789-2799
47. Wen G, Wang X, Xie Y, & Hu X. (2023). The impact of operation scale on the carbon productivity of farmers' cultivated land: based on the survey data of 416 farmers in Changde City. *Journal of Hunan Agricultural University (Social Sciences)*, 24(04):16-22.