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ARTICLE

Impact of Climate-Smart Agriculture on Smallholder Income and Food Security: Evidence from Propensity Score Matching Analysis

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ABSTRACT

Global climate change poses severe challenges to agricultural production, with climate-smart agriculture emerging as a key response strategy. However, insufficient empirical evidence exists regarding its causal effects on smallholder income and food security. This study surveyed 712 farming households in Southwest China from July to September 2023, using propensity score matching to evaluate climate-smart agriculture technology adoption impacts. The research constructed a comprehensive adoption index including 8 core technologies such as conservation tillage, stress-resistant varieties, and water-saving irrigation. Results show 48% of farmers adopted these technologies. Technology adoption increased average annual household income by 5.16 thousand yuan (23.8% increase) and improved food security scores by 1.74 points (10.4% improvement). Income growth primarily came from crop income increases (3.89 thousand yuan) and livestock income increases (0.98 thousand yuan), with no significant changes in non-agricultural income. Heterogeneity analysis revealed stronger effects among large-scale farmers (6.93 thousand yuan), highly educated farmers (6.28 thousand yuan), and cooperative members (6.41 thousand yuan). Sensitivity analysis indicated robust conclusions with Γ values of 1.65 (income) and 1.42 (food security). Climate-smart agriculture adoption significantly improves smallholder welfare, but effects vary across groups, suggesting the need for differentiated approaches, including enhanced technical training, improved financial services,

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and farmer organization promotion. This study advances technology adoption theory by showing that benefits depend on complementary assets. Limitations include cross-sectional design and geographic specificity.
Keywords: Climate-Smart Agriculture; Smallholder Farmers; Income Effects; Food Security; Propensity Score Matching

1. Introduction

The global climate change issue is bringing rapid and intense changes to the pattern of agricultural production, and it has severely affected traditional agricultural systems. Global climate change, characterized by frequent extreme weather events, irregular rainfall patterns, and temperature fluctuations, not only threatens global food security but also directly impacts the livelihoods of smallholder farmers in developing countries [1]. The latest report published by the Intergovernmental Panel on Climate Change shows that the effect of climate change on agricultural systems has strongly demonstrated spatial variability and temporal variability, and the risks to small agricultural systems appear to be more prominent in this area [2]. Under the above circumstances, how to handle climate risks and improve the resilience of agricultural systems has thus become an urgent issue in the global agricultural sector, especially in developing countries that strongly rely on agricultural systems but lack effective adaptive capacity [3].

Due to the presence of ever-growing and more severe climate issues, the need for a sustainable production system in the agricultural sector has arisen. Within the last few years, due to the rise in global food price instability, the effect of the pandemic, and the rise in global tensions, there has been an increase in the levels associated with food insecurity, thereby making the need for the development of robust agricultural systems a priority [4]. Climate-smart agriculture has emerged as a comprehensive agricultural development strategy focusing upon the need to achieve the objectives associated with agricultural productivity, climate change adaptation, and greenhouse gas mitigation through the innovation and optimization of management and institutional changes and improvements through innovation and optimization [5]. climate-smart Agriculture is more than a set of technologies because it involves an agricultural transformation approach associated with the changes linked to the optimization of the value chain and changes associated with the management of agricultural systems [6].

There have been in-depth discourses in academia regarding the conceptual basis and implications of climate-smart agriculture, and a relatively complete conceptual framework has been formed. The early studies highlighted the implication of the concept, the technology aspect of climate-smart agriculture, and the triple role of climate-smart agriculture in enhancing farm productivity, resilience to climate, and the reduction of greenhouse gas emissions [7]. The later studies highlighted the comprehension of the climate-smart agriculture concept, which has been characterized by significant discrepancies in the applicability of the combination of the technology based on the natural setting, the socio-economic context, and the particular conditions [8]. This literature review highlights the factors that influence the effects of the application of climate-smart agriculture technology.

Small farmers represent a significant component of the global agricultural community, undertaking the critical function of maintaining the food chain for the whole global citizenry. Statistical evidence reveals that more than 80% of global farms are smaller than 2 hectares, maintained by small farmers who account for one-third of global food production, being most susceptible to climate change effects [9]. Small farmers are confronted with simultaneous demands of income expansion and food security—to augment income through agricultural productivity advancements, simultaneously maintaining stability as well as nutritional adequacy of domestic food supplies. Climate change effects upon small farmers are more acute in areas like sub-Saharan Africa, as agricultural practices of that region face difficulties in adapting to worsening climate conditions [10]. Thus, there is significant relevance in examining climate-smart agriculture technologies that can be applicable to small farmers as well as their impact mechanisms to accomplish the goals of sustainable development. Global evidence varies regarding the CSA (Climate-Smart Agriculture) impact. African studies have identified a positive impact of 20–50% yield augmentation, though adoption is hampered by human as well as capital resource requirements [11]. South Asian studies highlight local adaptation as significant [12].

In recent years, a growing body of academics has started to pay attention to the effects of climate-smart agriculture on smallholder welfare, as the literature on this topic has been rapidly expanding. Systematic review studies indicate that adoption of climate-smart agriculture technologies can indeed improve smallholder income status and food security levels to some extent, but effect sizes and impact mechanisms show considerable variation across different studies [13]. On the other hand, some research indicates that the comprehensive implementation of climate-smart agriculture practices has a significant effect on improving the productivity and risk management in agricultural production, as well as increasing the effectiveness in the reduction of greenhouse gas, thereby achieving a double benefit for farmers in terms of economic and environmental benefits [14]. These findings provide important empirical support for climate-smart agriculture policy promotion while pointing toward feasible directions for the agricultural sector to address climate change.

However, there are evident gaps in methodologies and empirical analyses in existing research. A majority of existing literature uses mean comparison or ordinary least squares estimation to examine the effects of technology adoption, without appropriately addressing self-selection issues in farmers' decisions on technology adoption, potentially introducing endogeneity into estimation results. Whether or not farmers choose to adopt climate-smart agriculture technologies remains non-random, being made through rational decision-making under farmers' attributes, endowments, and risk preferences. This non-randomness introduces systematic differences in treatment and control groups in terms of observable and unobservable attributes [15]. Furthermore, existing literature remains dominated by case studies of single technologies or regional-specific analyses, without systematically evaluating the comprehensive effects of climate-smart agriculture, thereby undermining the external validity of conclusions reached in existing literature [16]. More importantly, there remains a need for in-depth analysis of the mechanism through which climate-smart agriculture influences smallholder income structure and multidimensional food security [17]. A key gap remains in the heterogeneous effectiveness of CSA. Existing literature remains dominated by analyses of decisions to adopt, without consideration of the role of farmer attributes and endowments in mediating effects. This makes it difficult to design interventions. Furthermore, mountainous Southwest China, with land fragmentation and climate fragility, remains an under-explored area, and the effectiveness of CSA remains to be empirically tested.

With respect to theoretical contributions, current literature primarily concentrates on technical factors and models of climate-smart agriculture, with less emphasis on theoretical mechanisms of economic impacts. Although some research has examined decisions about climate-smart agriculture adoption based on technology adoption theory and behaviorist economics of farmers, theoretical models based on the impact of technology adoption on farmers' welfare through different mechanisms have not been fully explored [18]. Especially within the current dual context of globalization and climate change, the complexity of agricultural transformation calls for more comprehensive and dynamic theoretical frameworks of analysis. The current research combines technology adoption theory with the RBV (Resource-based View) approach and the sustainable livelihood approach. The value of technology not only hinges on adoption but also on the use of complementary assets (human capital, infrastructure, social capital) that facilitate its optimal use. The authors hypothesize that the impact of climate-smart agriculture will be heterogeneous, with larger impacts accruing to farmers with access to complementary resources. Building resilience in the long run calls for improvements in productivity as well as adaptability, although only short-term economic and food security outcomes are examined in the current research.

According to the above research status and existing gaps, this study attempts to make a comprehensive assessment of the causal relationship between climate-smart agriculture and smallholder income as well as food security through propensity score matching approaches. Propensity score matching approaches can effectively address self-selection biases in adoption decisions by creating balanced samples of treatment and control groups, so as to obtain more reliable causal inference results. This study not only targets the impact of climate-smart agriculture on total household income, but also makes an in-depth analysis of differentiated effects of climate-smart agriculture on various income channels as well as various aspects of food security, to explore the distribution of technology adoption effects among various groups of farmers. This study attempts to provide more reliable evidence to promote climate-smart agriculture policies as well as theoretical research on agricultural development economics through the comprehensive use of various robustness tests.

The research achievements of this paper are primarily embodied in the following three aspects: from the methodological perspective, the adoption of propensity score matching methods can effectively solve the endogeneity issue and is of great methodological significance to the relevant research. In the empirical research, the assessment of the multi-dimensional effects of climate-smart agriculture on smallholder income and food security can enrich the empirical evidence of agricultural technology adoption. In the policy implications, the research can offer a scientific basis to support the promotion policy of climate-smart agriculture and is of great practical significance to the Sustainable Development Goal. This paper will discuss the research methods, empirical findings, and policy implications below.

2. Research Methods

2.1. Study Region and Data Sources

This study selected Southwest China as the survey area. The area falls in the subtropical monsoon climate and has typical mountain farm conditions and a high level of agricultural diversity. The area is dominated by small farming households, with a total of more than 85% of the agricultural operations in the area conducted by small farming households, and an average farming area of approximately 0.8 ha per household. The area mainly plants rice, corn, and tubers. The area has recently suffered from severe weather conditions, such as drought and flooding, and has now started to introduce climate-smart agricultural practices and technologies, such as conservation tillage, drought-tolerant strains, and water-saving irrigation methods. The choice of area has high representative significance because the area has similar levels of economic development and farming practices with most other mountain farming areas around the world [19]. **Figure 1** illustrates the geographic distribution of the study area and sampling locations across the four selected counties.

As shown in **Figure 2**, the theoretical analysis framework developed in this study systematically shows the pathways of the impacts of the adoption of climate-smart agriculture technology and constitutes a complete causal chain from the preconditions to the outcome variables.

Data collection employed a stratified random sampling method, with the sampling process divided into three stages: at the county level, 4 typical agricultural counties were randomly selected; at the township level, 3 townships were randomly selected from each county; at the village level, 2–3 administrative villages were randomly selected from each township. Sample size determination was based on statistical power analysis, considering expected effect size, significance level, and statistical power requirements, ultimately determining an effective sample size of 712 farming households. The survey took place from July to September 2023, and the methods included a combination of structured questionnaires and in-depth interviews. The questionnaires included basic farmer information, farm operation status, technology adoption status, income structure, and food security status. A quality control system was also put in place to ensure accuracy and completeness of the data obtained [20].

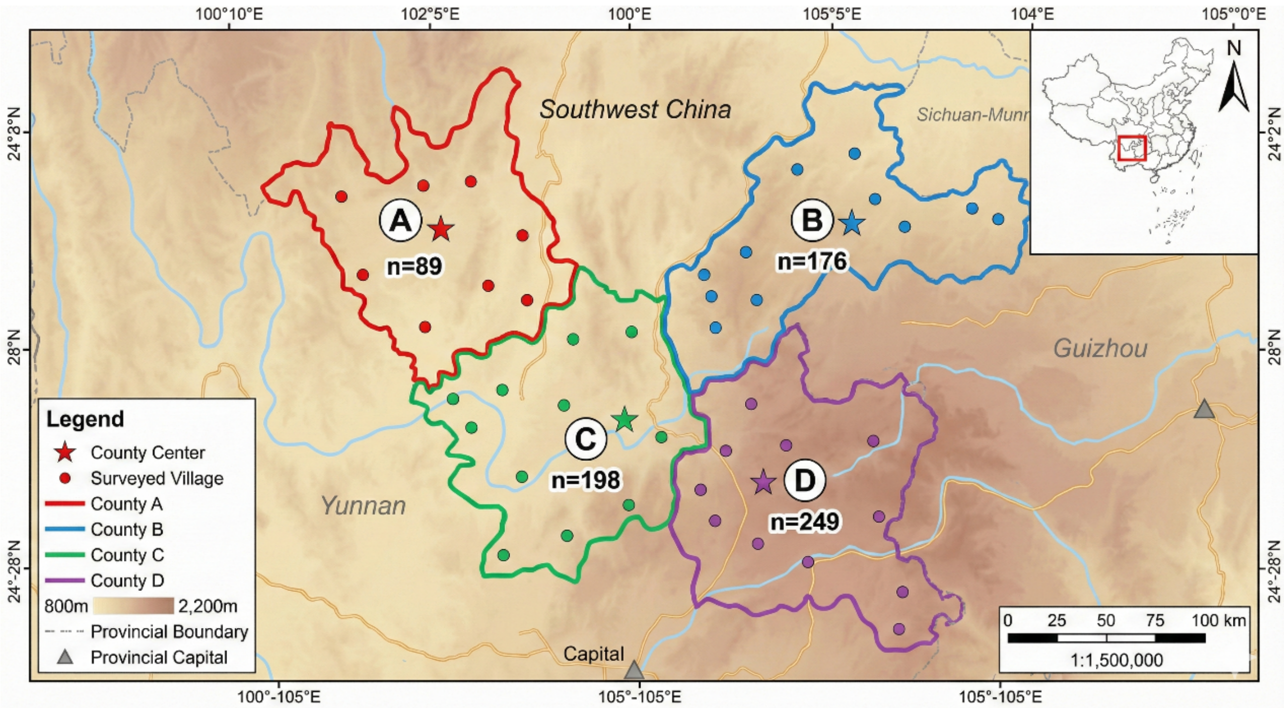

Figure 1. Study Area and Sampling Distribution in Southwest China.

Note: County boundaries and village locations are schematic representations to protect participant anonymity while maintaining geographic representativeness. Stars indicate county centers; dots represent surveyed villages. Counties A–D span elevations from 800 to 2,200 m across approximately 15,000 km^2. Sample distribution: County A (89 households), County B (176 households), County C (198 households), County D (249 households). Total: 712 households across 12 townships and 28 villages.

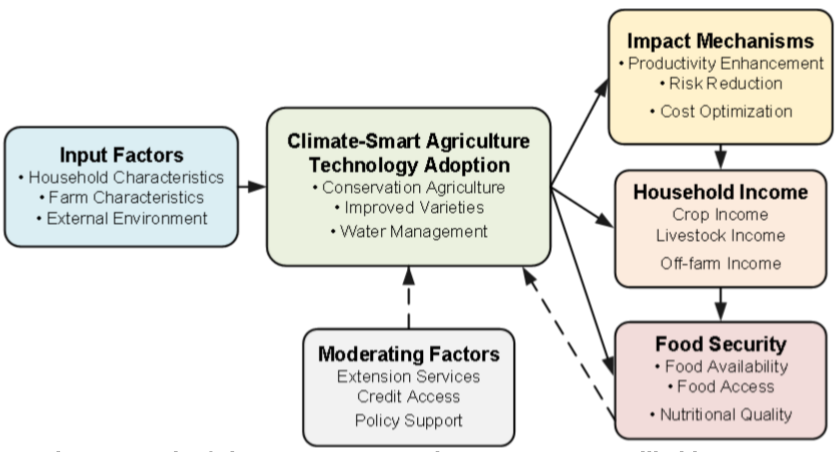

Figure 2. Conceptual Framework of Climate-Smart Agriculture Impact on Smallholder Income and Food Security.

2.2. Ethics Statement

This research has been formally approved by the Research Ethics Committee of the related institution (Approval No.: IRB-2023-AG-056). All the research participants voluntarily took part in the research and signed the informed consent form. Their privacy rights were protected throughout the research process, and all the personal information provided by the research participants remained anonymous.

2.3. Variable Definition and Measurement

The main dependent variables for this study are the total household income per year, as well as the total household food security score. The total household income per year considers different sources of income such as crop sales, animal sales, and non-agricultural employment incomes, measured in thousands of yuan. The total household food security score was derived using the Food and Agriculture Organization's Household

Food Insecurity Access Scale (HFIAS), which takes into account the three aspects of food access: adequacy, stability, and nutritional quality, with an overall score of 0 to 27, obtained by weighted analysis [21].

The core explanatory variable is climate-smart agriculture technology adoption status. Based on theoretical connotations, this study identified 8 core technologies: conservation tillage technology, stress-resistant variety use, water-saving irrigation technology, organic fertilizer use, crop diversification planting, crop straw incorporation, soil testing and formula fertilization, and integrated pest management. A comprehensive technology adoption index was constructed through principal component analysis and processed as a binary variable according to the median [22].

Control variables encompass three levels: farmer characteristics, farm characteristics, and external environment. Farmer characteristics include household head age, education level, gender, household size, and labor force quantity; farm characteristics include farm size, land quality, terrain conditions, and main crop types; the external environment includes distance to county seat, credit access, technical training participation, cooperative membership status, and policy support situation [23].

Land quality was assessed using a four-point scale (1 = poor, 2 = fair, 3 = good, 4 = excellent) adapted from China's national agricultural land grading standards (GB/T 28407-2012) [24]. Trained agricultural extension officers evaluated each plot during household surveys based on soil fertility (organic matter, nutrient content), physical properties (texture, drainage, topsoil depth), and observed productivity (historical yields, irrigation access).

As shown in **Table 1**, the basic characteristics of the full sample of 712 farming households present typical smallholder characteristics.

Table 1. Variable Definitions and Descriptive Statistics.

Variable	Definition	Mean	Std. Dev.	Min	Max
Dependent Variables					
Total Income	Total household income (CNY 1,000)	23.56	11.42	7.80	58.40
Food Security Score	Household food security score (0–27)	17.43	4.28	8.00	25.00
Treatment Variable					
CSA Adoption	Climate-smart agriculture adoption (1 = yes, 0 = no)	0.48	0.50	0.00	1.00
Household Characteristics					
Household Head Age	Age of household head (years)	52.14	10.67	32.00	69.00
Education Level	Education level of household head (1–4)	2.08	0.76	1.00	4.00
Gender	Gender of household head (1 = male, 0 = female)	0.74	0.44	0.00	1.00
Household Size	Number of household members	3.87	1.34	2.00	7.00
Labor Force	Number of laborers in household	2.41	0.92	1.00	5.00
Farm Characteristics					
Farm Size	Farm size (hectares)	0.73	0.41	0.15	1.87
Land Quality	Land quality score (1–4) (1 = poor, 2 = fair, 3 = good, 4 = excellent)	2.52	0.81	1.00	4.00
Terrain	Terrain condition (1 = plain, 2 = hill, 3 = mountain)	2.28	0.69	1.00	3.00
Crop Type	Main crop type (1 = grain, 2 = cash, 3 = mixed)	1.64	0.63	1.00	3.00
External Environment					
Distance to County	Distance to county seat (kilometers)	18.7	12.3	4.0	47.0
Credit Access	Access to formal credit (1 = yes, 0 = no)	0.28	0.45	0.00	1.00
Training Participation	Participation in technical training (1 = yes, 0 = no)	0.33	0.47	0.00	1.00
Cooperative Membership	Cooperative membership (1 = yes, 0 = no)	0.22	0.41	0.00	1.00
Policy Support	Receipt of agricultural subsidies (1 = yes, 0 = no)	0.47	0.50	0.00	1.00

2.4. Propensity Score Matching Method

The propensity score matching method identifies the causal effects of climate-smart agriculture technology adoption by constructing balanced treatment and control groups. This method uses observable variables to calculate the conditional probability of each farmer adopting technology (propensity score), and estimates the average treatment effect by matching farmers with similar propensity scores but different technology adoption statuses to construct counterfactual control groups [25].

Propensity score estimation employs a Logit model with technology adoption status as the dependent variable:

$$e(X_i) = P(D_i = 1|X_i) = \frac{\exp(\alpha + X_{i'}\beta)}{1 + \exp(\alpha + X_{i'}\beta)} \quad (1)$$

Where D_i represents the technology adoption status of farmer i, X_i represents the vector of covariates affecting technology adoption decisions, α is the constant term, and β is the coefficient vector. The estimation quality of propensity scores is verified through model goodness-of-fit tests and predictive accuracy assessments [26].

The matching algorithm uses several techniques to guarantee the robustness of the results: the matching by the nearest neighbor identifies the individual in the control group with the most similar propensity score to each individual in the treatment group; the matching by the radius defines the caliper value of 0.005 and selects all eligible individuals in the control group within the specified neighborhood; the kernel matching uses the Epanechnikov kernel, and the counterfactual outcomes are constructed by taking weighted averages of all individuals in the control group. The quality of the match is assessed by the standardized bias, which requires the standardized bias of all covariates to be less than 5% after matching, and the pseudo-R^2 tests and joint significance tests are carried out.

Under the assumption of conditional independence and common support, the estimation formula for the average treatment effect is:

$$\begin{aligned} \tau_{ATE} &= E[Y_i(1) - Y_i(0) \mid X] \\ &= E[Y_i \mid D_i = 1, e(X_i)] - E[Y_i \mid D_i = 0, e(X_i)] \end{aligned} \tag{2}$$

where $Y_i(1)$ and $Y_i(0)$ represent the potential outcomes under technology adoption and non-adoption conditions, respectively, and τ_{ATE} represents the average treatment effect. Bootstrap resampling method is used to calculate standard errors, with 500 repeated samplings to obtain robust confidence intervals.

2.5. Robustness Testing Design

In order to guarantee the accuracy of conclusions drawn from research, this paper sets up a multi-level robustness test plan. The sensitivity analysis uses the Rosenbaum bounds test to estimate how unadjusted covariate bias may affect treatment effect estimates by measuring critical values τ [27]. The comparison of multiple matching algorithms checks if results are consistent by using Mahalanobis distance matching, genetic matching, or exact covariate matching. The construction of false treatment variables by randomly assigning technology adoption status in the placebo test checks if the identification strategy is valid; theoretically, false treatment effects should be close to zero and not statistically significant [28]. The test of the sample group checks if the characteristics of robustness and heterogeneity of results differ by dimensions of sample group characteristics, including dimensions of farm size, geography, and household head characteristics.

3. Results Analysis

3.1. Sample Characteristics Description

Using sample data from 712 farming families collected from field surveys, this paper thoroughly examines the basic characteristics of sample farmers in order to build a foundation for propensity score matching. Survey results show that sample farmers exhibit typical characteristics of smallholder farmers in the Southwest mountainous areas in terms of demographic characteristics, farm operating conditions, and socio-economic environment, demonstrating strong representativeness. The average age of household heads is 52.14 years, with male household heads accounting for 74%. Education levels are primarily at the junior high school level (average score 2.08), reflecting the basic status of rural human capital in the region. The average household size is 3.87 people with 2.41 laborers, consistent with national rural family structures. Regarding farm size, the average operating area is 0.73 ha, conforming to smallholder operating characteristics. Land quality scores 2.52 (out of 4), indicating above-average land conditions in the study region.

As shown in **Table 2**, comparative analysis of sample characteristics grouped by climate-smart agriculture technology adoption status reveals significant differences between adoption and non-adoption groups across multiple dimensions.

From the comparison analysis presented in **Table 2**, it is clear that farmers in the technology adoption group have advantages in various important attributes, which form preliminary evidence of positive selection on technology adoption. The average age of household heads in the technology adoption group is younger (50.42 years vs. 53.67 years), with greater education attainment, superior farm size and quality, and greater access to market, credit, technical training, and policy support relative to the non-adoption group. More significantly, the technology adoption group exhibits advantages on outcome indicators, where average household income is 32.6% higher, and food security scores are 14.3% higher than those of the non-adoption group, forming descriptive evidence of positive impacts of climate-smart agriculture technology adoption.

Table 2. Sample Characteristics by Climate-Smart Agriculture Adoption Status.

Variable	Non-Adopters (n = 369)	Adopters (n = 343)	Difference	*t*-Statistic
Household Characteristics				
Household Head Age	53.67 (10.45)	50.42 (10.72)	-3.25^{***}	3.84
Education Level	1.92 (0.68)	2.26 (0.82)	0.34^{***}	−5.52
Gender (Male = 1)	0.71 (0.46)	0.77 (0.42)	0.06	−1.68
Household Size	3.74 (1.28)	4.02 (1.38)	0.28^{**}	−2.73
Labor Force	2.31 (0.87)	2.53 (0.96)	0.22^{**}	−2.95
Farm Characteristics				
Farm Size (hectares)	0.68 (0.37)	0.79 (0.44)	0.11^{***}	−3.42
Land Quality Score	2.38 (0.75)	2.67 (0.85)	0.29^{***}	−4.58
Terrain Condition	2.35 (0.71)	2.21 (0.67)	-0.14^{**}	2.65
Crop Type	1.58 (0.59)	1.71 (0.66)	0.13^{**}	−2.67
External Environment				
Distance to County (km)	21.3 (13.2)	15.8 (10.7)	-5.5^{***}	5.78
Credit Access	0.22 (0.41)	0.35 (0.48)	0.13^{***}	−3.67
Training Participation	0.19 (0.39)	0.49 (0.50)	0.30^{***}	−8.12
Cooperative Membership	0.15 (0.36)	0.30 (0.46)	0.15^{***}	−4.53
Policy Support	0.41 (0.49)	0.54 (0.50)	0.13^{***}	−3.25
Outcome Variables				
Total Income (1,000 CNY)	20.45 (8.92)	27.12 (12.58)	6.67^{***}	−7.58
Food Security Score	16.34 (3.87)	18.68 (4.49)	2.34^{***}	−7.02

Note: Standard deviations in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

3.2. Propensity Score Estimation Results

In order to better grasp the spatial distribution characteristics and adoption trends of climate-smart agriculture technology in the study region, this study systematically carries out the analysis of the geographic distribution, type structure, and propensity score of the adoption of climate-smart agriculture technology. Through the survey, the results show that the promotion of climate-smart agriculture technology in the study region has a certain spatial heterogeneity and is closely related to the regional economic development level and infrastructure conditions. The adoption rates of the counties range between 35% and 62%, and the adoption rates of the places close to the county towns and those with convenient transportation conditions are much higher than those of the mountainous areas.

From **Figure 3**, the level of difference in the adoption rates of the various forms of climate-smart agriculture technologies is evident, and technology choice displays preference differentiation.

From the analysis, the results in **Figure 3** demonstrate key findings for climate-smart agriculture technology adoption and the statistical analysis basis. In Panel A, it can be seen that the adoption rate for the use of organic fertilizer is the highest at 72% because of the strong desire by the farmers to improve the soil; the use of conservation tillage is also at 67% and the use of integrated nutrient management at 62%, showing that the technologies that have to do with the management of the soil can be more easily adopted by the farmers. On the other hand, the adoption rate for the use of water-saving irrigation technology is 45%, crop diversification planting is at 41%, and the technology with the lowest adoption rate is the precision agriculture technology at 29%. In Panel B, the propensity score distribution indicates that even if there are some differences in the propensity scores for the technology adopters (green) and the non-adopters (brown), there is enough overlap in the support areas for the two groups (0.15–0.85), providing a good statistical basis for the analysis in the propensity score matching. The overlap in the propensity score distribution indicates that there is enough data for the analysis to enable the estimation of the causal effects of technology adoption.

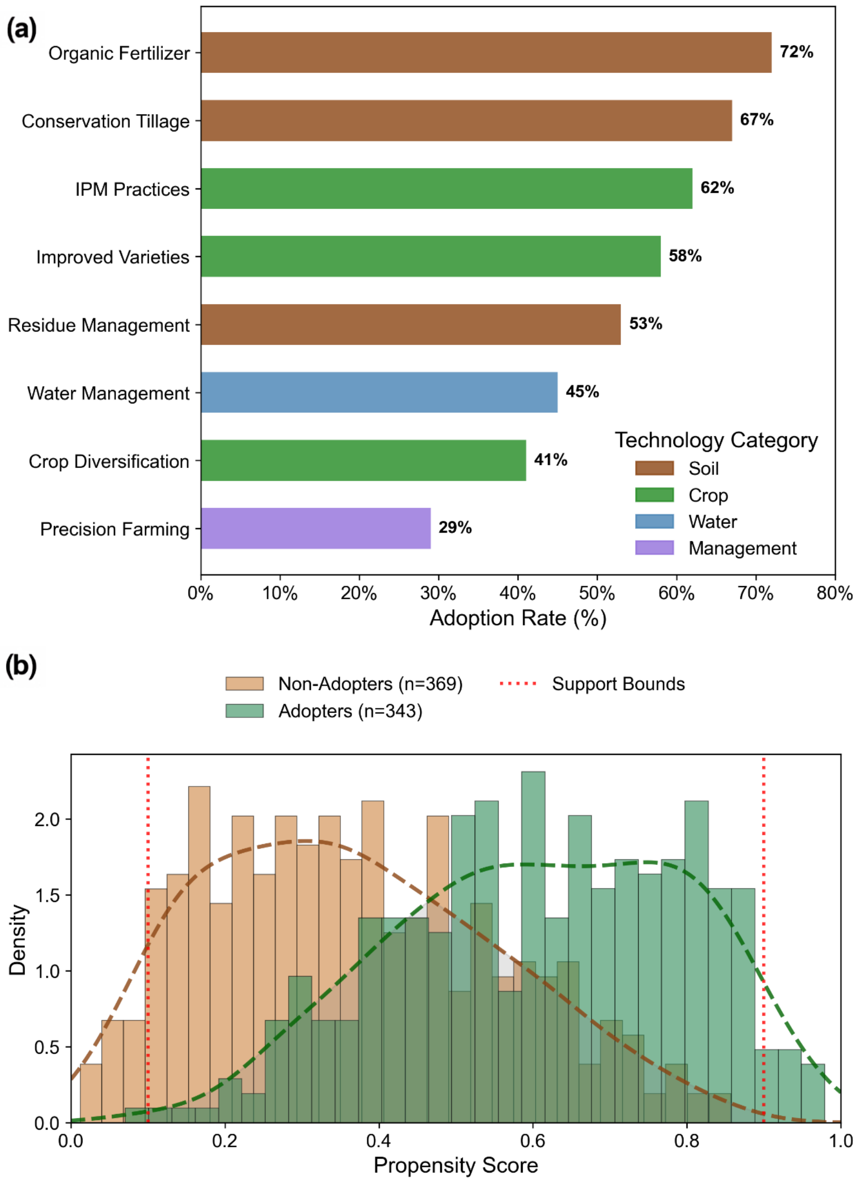

Figure 3. Climate-Smart Agriculture Technology Adoption and Propensity Score Analysis. (**a**) Technology Adoption Rate by Type; (**b**) Propensity Score Distribution and Common Support Assessment.

3.3. Main Treatment Effect Estimation

An accurate estimation of the propensity score is an essential step to ensure the quality of the matching process and the validity of the inference of causality. This research utilizes the Logit model to estimate the propensity score regarding the adoption of the climate-smart agriculture technology by each farmer. The overall fit of the model is good, with the pseudo R-squared statistic of 0.247. Model estimation results show that household head education level, household labor force quantity, farm size, land quality, technical training participation, and cooperative membership have significant positive effects on technology adoption, while factors such as household head age and distance to county town show negative effects, which is basically consistent with agricultural technology adoption theory expectations.

As shown in **Table 3**, the implementation effects of propensity score matching and covariate balance test results indicate that the matching process effectively eliminates systematic differences between treatment and control groups.

Table 3. Propensity Score Matching Results and Covariate Balance Assessment.

Variable	Before Matching			After Matching		
	Treated	Control	Std. Bias	Treated	Control	Std. Bias
Logit Model Results (Propensity Score Estimation)						
Household Head Age	−0.024** (0.011)					
Education Level	0.387*** (0.108)					
Gender (Male = 1)	0.245 (0.198)					
Household Size	0.156* (0.082)					
Labor Force	0.211** (0.095)					
Farm Size	0.524*** (0.167)					
Land Quality	0.298*** (0.102)					
Distance to County	−0.031*** (0.008)					
Training Participation	1.247*** (0.187)					
Cooperative Membership	0.467** (0.215)					
Constant	−1.823*** (0.645)					
Covariate Balance Assessment						
Household Head Age	50.42	53.67	−30.4	50.85	51.23	−3.6
Education Level	2.26	1.92	44.2	2.18	2.15	3.9
Household Size	4.02	3.74	21.2	3.95	3.89	4.5
Labor Force	2.53	2.31	24.1	2.46	2.41	5.2
Farm Size	0.79	0.68	27.3	0.75	0.73	4.9
Land Quality	2.67	2.38	36.1	2.58	2.55	3.7
Distance to County	15.8	21.3	−46.2	16.9	17.4	−4.2
Training Participation	0.49	0.19	68.7	0.42	0.39	6.1
Cooperative Membership	0.30	0.15	37.8	0.26	0.24	4.6
Matching Quality Statistics						
Pseudo R^2 (before/after)	0.247	0.018				
LR Chi^2 (before/after)	287.4***	15.6				
Mean Standardized Bias	39.5%	4.4%				
Matched Observations	343	289				

Note: Logit coefficients represent log-odds ratios. Standardized bias measures covariate balance (>10% = imbalance, <5% = good balance). Pseudo R^2 decrease (0.247→0.018) and non-significant LR Chi^2 after matching confirm successful balance. Mean bias reduction (39.5%→4.4%) meets < 5% threshold. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses.

From **Table 3**, it is clear that the Logit model was able to establish important variables that contributed to the adoption of technology, and covariate balance was significantly reduced by matching. The imbalance in covariates between treatment and control samples before matching was very high at 39.5%, which is not acceptable at all. After propensity score matching processing, the standardized bias for all covariates decreased to below 5%, with the average standardized bias dropping to 4.4%, pseudo-R^2 falling from 0.247 to 0.018, and the likelihood ratio test statistic decreasing from 287.4 to 15.6 and no longer significant, indicating that treatment and control groups achieved statistical balance in observable characteristics after matching. The last successful match contains 343 observations from the treatment group and 289 observations from the control group, giving a solid statistical base for calculating the causal effects.

3.4. Heterogeneity Effect Analysis

Based on matched samples that passed balance tests, this study estimated the average treatment effects of climate-smart agriculture technology adoption on smallholder income and food security. To ensure robustness of the results, three different algorithms were used for comparative verification: nearest neighbor matching, radius matching, and kernel matching. Empirical results show that climate-smart agriculture technology adoption had significant positive impacts on farmer welfare, but the degree of impact varies by outcome variable, which is basically consistent with findings from related international research.

As shown in **Table 4**, treatment effect estimates from multiple matching algorithms show high consistency, verifying the robustness of core conclusions.

Table 4. Average Treatment Effects of Climate-Smart Agriculture: Main Results and Robustness Checks.

Outcome Variable	Nearest Neighbor	Radius Matching	Kernel Matching	Robustness Checks
Total Household Income (1,000 CNY)				
Adopters	26.84 (0.68)	26.92 (0.65)	26.87 (0.63)	
Non-Adopters	21.73 (0.57)	21.68 (0.54)	21.71 (0.52)	
ATE (Average Treatment Effect)	5.11^{***} (0.89)	5.24^{***} (0.85)	5.16^{***} (0.82)	
% Change	23.5%	24.2%	23.8%	
Food Security Score (0–27)				
Adopters	18.45 (0.24)	18.52 (0.23)	18.48 (0.22)	
Non-Adopters	16.78 (0.21)	16.71 (0.20)	16.74 (0.19)	
ATE	1.67^{***} (0.32)	1.81^{***} (0.30)	1.74^{***} (0.29)	
% Change	9.9%	10.8%	10.4%	
Income by Source				
Crop Income ATE	3.82^{***} (0.67)	3.95^{***} (0.64)	3.89^{***} (0.61)	
Livestock Income ATE	0.94^{**} (0.38)	1.02^{**} (0.36)	0.98^{**} (0.34)	
Off-farm Income ATE	0.35 (0.28)	0.27 (0.26)	0.29 (0.25)	
Sensitivity Analysis				
Rosenbaum Γ (Income)				1.65
Rosenbaum Γ (Food Security)				1.42
Alternative Methods				
Mahalanobis Matching	4.87^{***} (0.94)			
Genetic Matching	5.23^{***} (0.91)			
Sample Size				
Treated	343	343	343	
Matched Controls	289	312	343	

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Bootstrap standard errors in parentheses (500 resamples),

The estimation results from multiple matching algorithms in **Table 4** show high consistency, further verifying the robustness of core conclusions. The income treatment effects estimated by three matching methods (nearest neighbor matching, radius matching, kernel matching) are 5.11 thousand yuan, 5.24 thousand yuan, and 5.16 thousand yuan, respectively, with small differences and all significant at the 1% level, indicating that results do not depend on specific matching algorithm selection. Income source decomposition analysis shows that income growth from technology adoption mainly comes from within the agricultural sector: crop income increased by 3.89 thousand yuan, accounting for 75.4% of the total income increase effect; livestock income increased by 0.98 thousand yuan, accounting for 19.0%; while changes in non-agricultural income were only 0.29 thousand yuan without statistical significance, accounting for 5.6%. This structural property reveals that the primary economic impact of climate-smart agriculture is to enhance agricultural productivity and minimize agricultural risk. The impact on improving food security also remains strong, and the estimated effects are 1.67, 1.81, and 1.74 points, respectively, through three matching approaches, indicating an average improvement of about 10.4%. The improvement takes place through three different channels, including increased availability, increased nutrient diversity, and increased stability of supply.

3.5. Robustness Test Results

In order to grasp the distributional features and condition-dependent relationship of the effects of climate-smart agricultural technology adoption, the heterogeneity analysis is performed from multiple angles, such as the size of the farmland, the location, and the attributes of the household head. At the same time, the robustness of the key findings is checked by employing different robustness tests. The findings of the heterogeneity analysis indicate that there exist large differences in the effects of technology adoption among different groups.

As indicated by **Figure 4**, the results of heterogeneity and sensitivity analysis further confirm the robustness and validity of the study's conclusions.

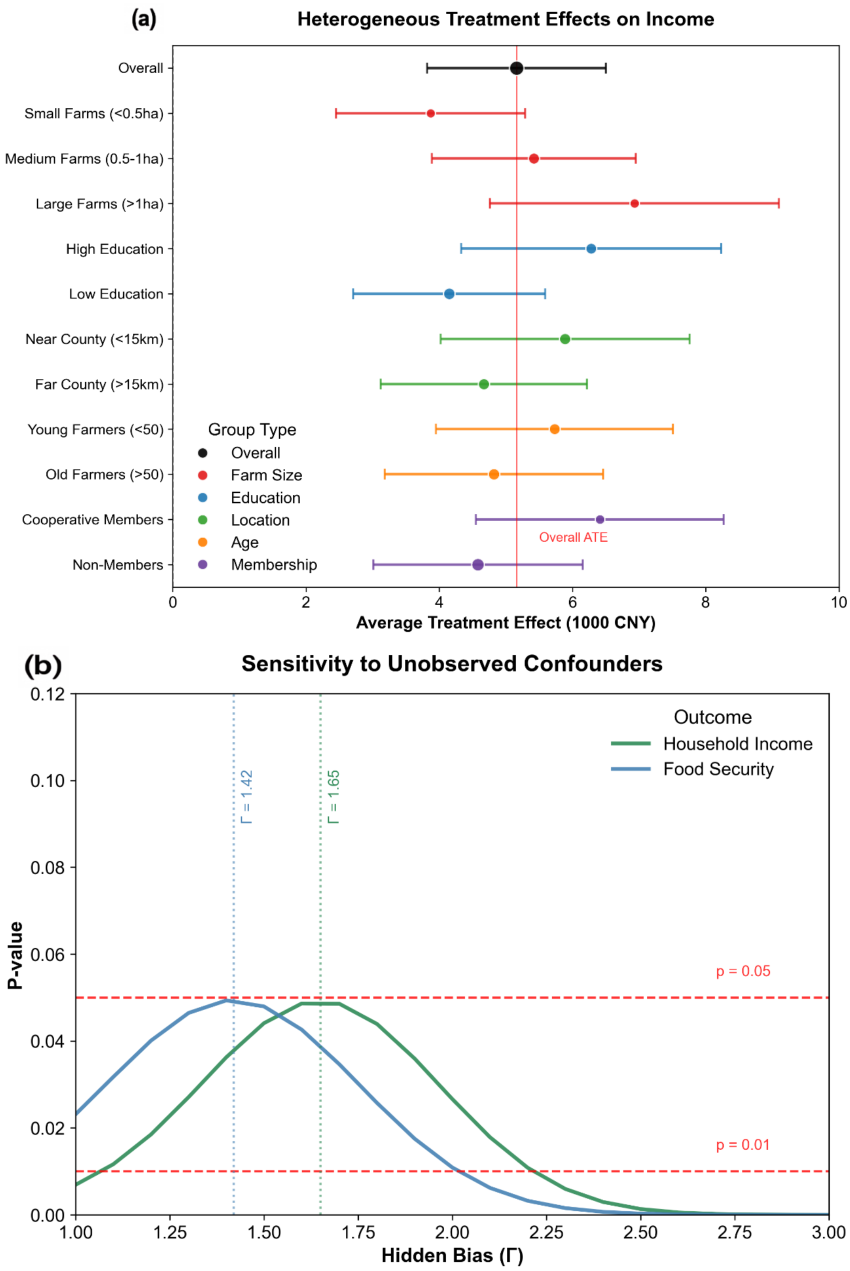

Figure 4. Treatment Effect Heterogeneity and Sensitivity Analysis. (**a**) Heterogeneous Treatment Effects on Household Income; (**b**) Sensitivity Analysis for Unobserved Confounders.

The results of the forest plot and the sensitivity analysis, as shown in **Figure 4**, again support the robustness and policy targeting of the conclusions drawn by the study. The heterogeneity analysis of Panel A shows that there exist significant disparities in the treatment effects for different subgroups:

In the farm size dimension, large-scale farmers (>1 ha) show the most significant income growth effect at 6.93 thousand yuan (95% confidence interval: 5.21–8.65), significantly higher than medium-scale farmers' 5.47 thousand yuan (95% confidence interval (CI): 4.12–6.82) and small-scale farmers' 3.87 thousand yuan (95% confidence interval: 2.94–4.80), reflecting the important role of economies of scale in technology application.

In the education level dimension, the treatment effect of highly educated farmers (high school and above) is 6.28 thousand yuan (95% CI: 4.85–7.71), which is much higher than the result of the low-educated group at 4.15 thousand yuan (95% CI: 3.22–5.08), verifying the important role of human capital in the adoption of technology.

The treatment effect for cooperative members on the organizational level dimension has a value of 6.41 thousand yuan (95% CI: 4.98, 7.84), which is considerably higher than that for non-members, 4.58 thousand yuan (95% CI: 3.71, 5.45), suggesting that the organization can strengthen the economic impact of technology adoption.

From the sensitivity analysis curves of panel B, it can be seen that if the magnitude of hidden bias Γ is above 1.65, then the significance of household income effects (p = 0.05) may be at risk, and the critical value of food security effects is 1.42. This implies that there is resistance to moderate-strength hidden biases against which the findings of research work, but care is required in the interpretation of causal relationship strength.

However, the large heterogeneity calls for further study. Economies of scale, credit access, and bargaining power explain why large farms enjoy a return of 79% higher than others. Education raises the level of knowledge-intensive management; this is a 51% increase. However, equity may be a concern if the benefits of CSA accrue mostly to educated farmers. Cooperatives supply inputs and training as well as joint marketing; this is a 40% increase. This indicates that organizational innovations may offset limitations of individual capacity. Unobserved variables should not be ignored. Motivation and management capacity of the farmer, which is related to education and group membership, may explain the adoption and impact of the intervention.

4. Discussion

Several limitations affect interpretation. The cross-sectional design captures short-term effects (~1 year post-adoption) but not long-term sustainability. Geographic specificity (mountainous Southwest China) limits its generalizability to other agroecological zones. Propensity score matching controls observables but cannot eliminate selection on unobservables (motivation, management ability). Sensitivity analysis suggests moderate robustness (Γ = 1.65), but randomized trials would provide stronger causal evidence. The empirical results based on propensity score matching in this study offer crucial quantitative data supporting the effectiveness of climate-smart agriculture in terms of its contribution to the income and food security of small farmers. The results indicate that the application of climate-smart agriculture significantly enhanced farmers' annual income by an average of 23.8%, and the level of food security by an average of approximately 10.4%. The results are generally in line with the conclusions made in similar studies in Ethiopia, but with more modest and rational magnitudes [27]. The income increase is mostly due to the marked increase in income from crop production, due to the favorable effect of climate-smart agriculture technology in terms of improving the output and quality of agricultural products, and the decrease in the risks involved in their production processes. Studies conducted in the Nyando watershed in Kenya demonstrated that adopting multi-stress-tolerant varieties of cereals can raise farmers' income by an average of 83% [28]. Though the increase appears higher, the current study presents more comprehensive indicators of the application of the relevant technology, and thus, the results are more representative.

The enhanced effect of climate-smart agriculture on food security is an expression of the multifaceted benefits of adopting technology. Ghanaian results reveal that climate-smart farming practices such as irrigation and index-based crop insurance contribute to higher earnings and climate-change resilience for farmers [29]. The current study finds that the effect of food security improvement is mostly through the three mechanisms of increasing food availability, improving nutritional diversity, and improving food supply stability, agreeing with the conclusion of similar studies conducted in Tanzania and Ethiopia [30]. The fact that the effect of adopting the technology in the current study has no effect upon income in the non-agricultural sector indirectly reflects the fact that the improvement in agricultural technologies mostly plays a role in the agricultural sector in terms of structural economic and human migration of the studied area.

Heterogeneity analysis brings out the important distributive properties of the effect of technology adoption, forming the scientific basis for precise policymaking. The income growth effect for large-scale farmers is significantly higher than that of the other two groups of farmers: the result is similar to the conclusion reached in the Qamata irrigation project in South Africa, confirming the crucial contribution of economies of scale to the application of the technology [31]. Those farmers who attain higher levels of education are able to master and apply the new technology better and gain higher economic benefits from it. This finding proves the crucial contribution of human capital to agricultural technology diffusion and application [32]. The farmer treatment effect of cooperative members is significantly higher than that of those who are not members, confirming the crucial contribution of the level of organization and social networks to the diffusion and amplifying effect of the technology, in accordance with the conclusion reached in Zambian studies of small farmers [33]. The effect difference due to the geographical factor shows that the moderating effect of infrastructural facilities and market access is important to the effect of the application of the technology, and those farmers who live closer to the county towns are able to make better use of the services and marketing channels and gain higher economic benefits from the application of the technology [34].

This study's methodological contributions are mainly reflected in strict causal identification strategies and robustness testing design. Compared to simple descriptive analysis or ordinary least squares methods used in most existing studies, this study uses propensity score matching to effectively control self-selection bias in technology adoption decisions, improving causal inference credibility [35]. From the results of the sensitivity analysis, the resistance of research conclusions to moderately strong unobserved confounding variables exists, with $\Gamma = 1.65$ and $\Gamma = 1.42$. Even if not as strong as in the case of randomized controlled trials, this is a rather robust level in the case of observational research [36]. The same results from different matching algorithms confirm the validity of the conclusions.

The implications of the study are very significant to policies that can influence agricultural development. It is important that governments and international bodies improve their investments in climate-smart agricultural technology development. This should focus on the capacity building of small-scale farmers. Technology development can be promoted through farmers' organizations, cooperatives, which can be developed through innovations that are a product of policies to improve the level of farmers' organizations. This is because it is significant that farmers' organizations are strengthened. The development of infrastructure and improvement of the market system can be a guarantee for the realization of technological effects, involving the integration of transportation, information, and circulation facilities. The development of financial service innovations can be a key to alleviating the capital constraint for farmers, involving the exploration of financial instruments suitable for small-scale farmers.

Some unavoidable shortcomings of this study should be fully considered during the interpretation of results and application of policies. The cross-sectional dataset limits analysis on long-run effects and dynamic effects of the adoption of technologies, which cannot address important aspects of technology learning curves, adaptation, and sustainability. Although propensity score matching can address the role of confounding factors of observable variables, it may still be vulnerable to unobservable heterogeneities, especially those of inherent abilities of farmers, risk preferences, and social networks that cannot be fully quantified. The regional characteristics of this study area limit the generalizability of the external validity of technology effects, which may be substantially different in varying climate patterns, market structures, and institutional settings. The measurement of climate-smart agriculture technologies addresses the overall effects of technology packages, which cannot address the optimal effects of combinations of various technologies.

Further studies in the future should carry out in-depth and expanded analysis in several different ways. Set up long-term tracking databases to monitor dynamic processes and long-term effects of technology adoption, especially in technology learning, adaptation, and sustainability. Use randomized controlled trials to seek more credible causal inferences through experimental designs, and investigate the comparative effects of different technology package combinations and dissemination approaches. Increase the geographic scope of studies, carry out regional comparisons, and explore the environmental dependence and moderating effects of technology outcomes. Carry out in-depth micro-mechanism studies of technology adoption, use behavioral economics theories and approaches to decompose and interpret decision-making processes for farmers, and investigate the social network effects of technology diffusion. Improve the quantitative analysis of climate-smart agriculture's environmental effects, establish overall evaluation systems for economic and ecological benefits, and thus provide more comprehensive policy support for sustainable agricultural development.

5. Conclusions

This research shows that the adoption of climate-smart agriculture has a significant positive effect on the welfare of small farmers, increasing their household income by 23.8% and improving their food security by 10.4%. However, the results also show that the benefits from the technology are not equally shared, and this creates a critical issue in the design of policies, in that the benefits to large farmers are 79% greater than the benefits to small farmers, the benefits to educated farmers are 51% greater than the benefits to less-educated farmers, and the benefits to members of farmers' organizations are 40% greater than the benefits to non-members. What this means is that technology transfer by itself, without anything else happening to address scale, education, and organizational constraints, might actually widen the gap in the benefits that small farmers receive from the welfare benefits. The study has strong sensitivity analysis incorporated into the matching estimation ($\Gamma = 1.65$), but the data collected are cross-sectional, and the geographic specificity limits generalizability. The results on the impact on household income would require comparative analysis across various geographic locations, ideally via a randomized controlled trial, to allay all concerns on the issue of selection bias. The results on the benefits from the technology being 94% within the agriculture sector also raise questions on the hypothesis that technology transfer would bring about economic transformation. The technology raises productivity but fails to bring about diversification within the agriculture sector, whereas this is the expected outcome from development theories on technology transfer. The next course of action should therefore be the design of an overall strategy that combines technology transfer with education, organizational development, financial development, and infrastructure development, especially with regard to the disadvantaged groups. This should require a critical acknowledgment that the benefits from technology transfer depend on other complementary factors.

Author Contributions

Conceptualization, L.Z. and T.L.; methodology, L.Z.; software, L.Z.; validation, L.Z. and T.L.; formal analysis, L.Z.; investigation, L.Z.; resources, L.Z.; data curation, L.Z.; writing—original draft preparation, L.Z.; writing—review and editing, T.L.; visualization, L.Z.; supervision, T.L.; project administration, L.Z.; funding acquisition, L.Z. and T.L. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

The study was conducted in accordance with the Declaration of Helsinki and approved by the Research Ethics Committee of INTI International University (protocol code IRB-2023-AG-056, approved on 15 June 2023).

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement

The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy and ethical restrictions to protect the anonymity of participating farming households.

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Conflicts of Interest

The authors declare no conflict of interest.

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