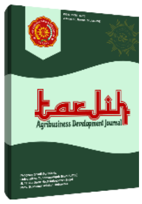
Tarjih: Agribusiness Development Journal. Volume 06 Number 01 (2026) Page: 54 - 63
DOI: https://doi.org/10.47030/tadj.v6i01.1138

e-ISSN: 2798 - 0782
Tarjih: Agribusiness Development Journal
Journal Homepage: https://jurnal-umsi.ac.id/index.php/agribisnis



Determinants of Climate Smart Agricultural (CSA) Technology Adoption in Purbalingga Regency, Central Java

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Received : May 30, 2026
Revised : June 04, 2026
Accepted: June 20, 2026

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ABSTRACT

Climate change poses a growing threat to the sustainability of agricultural systems and food security across numerous countries. Climate Smart Agriculture (CSA) has emerged as a strategic instrument for simultaneously increasing agricultural productivity, strengthening adaptive capacity, and reducing greenhouse gas emissions from the agricultural sector. In Indonesia, CSA implementation has been operationalized through the Strategic Irrigation Modernization and Urgent Rehabilitation Project (SIMURP) since 2021. Despite this, the level of CSA technology adoption among farmers remains uneven and suboptimal. This study aims to analyze the determinants of simultaneous adoption of six CSA practices namely improved seed varieties, Alternate Wetting and Drying (AWD) irrigation, balanced fertilization, organic matter application, organic fertilizer use, and integrated pest management (IPM). This study was carried out in Bukateja and Kemangkon Districts, Purbalingga Regency, Central Java, Indonesia. A total of 88 respondent farmers were selected as the study sample through simple random sampling. Data were analyzed using the Multivariate Probit (MVP) model, which accommodates correlations across simultaneous adoption decisions of multiple CSA practices within a single estimation framework. The results indicate that CSA adoption decisions are significantly influenced by education, farming experience, land area, land tenure status, farmer group membership, access to credit, and farm income, with varying degrees of influence observed across individual CSA practices. Farm income uniquely predicted adoption of all six CSA technologies simultaneously, establishing financial capacity as the most critical and universal driver of CSA adoption.

Keywords: *Climate Smart Agriculture, Multivariate Probit Model, Rice Farmers, Technology Adoption*

INTRODUCTION

Climate change represents one of the most formidable challenges confronting the agricultural sector worldwide (Abid et al., 2015). Agriculture is among the most vulnerable sectors exposed to the consequences of climate change phenomena (Gebre et al., 2023; Howden et al., 2007). Manifestations of climate change, including shifts in rainfall patterns, extreme temperatures, and the increasing frequency of floods and droughts, have resulted in significant declines in agricultural productivity (Zheng et al., 2024). The cascading impacts of these changes are wide ranging, encompassing reduced food supply, economic stagnation, growing inequality, population displacement, poverty, biodiversity loss, and widespread disruption to rural livelihoods and employment opportunities (Belay et al., 2017; Huang et al., 2015). Furthermore, climate change is projected to induce shifts in planting seasons, intensify pest and disease outbreaks, and elevate the risk of crop failure due to flooding and prolonged drought (Auliya et al., 2024). Estiningtyas (2025) estimated that a temperature increase of 1.0-2.5°C combined with a 5-25% reduction in rainfall could reduce national rice production by as much as 50%. Such

DOI: https://doi.org/10.47030/tadj.v6i01.1138

conditions would substantially heighten food insecurity and continued sustainability of farming systems over the long term (Baffour-Ata et al., 2025).

As a direct response to these multifaceted challenges, Climate Smart Agriculture (CSA) has been introduced as a strategic intervention framework pursuing three interconnected objectives: (1) achieving sustainable growth in agricultural output and household farm income; (2) building and reinforcing farmers' capacity to adapt and withstand the adverse impacts of climate change; and (3) reducing or eliminating greenhouse gas (GHG) emissions from agriculture where feasible (FAO, 2017; Pusat Penyuluh Pertanian, 2022). The implementation of CSA encompasses a broad spectrum of technologies and practices, including the utilization of stress-tolerant improved varieties, optimized irrigation management, crop rotation, intercropping, row planting systems, and the use of organic fertilizers (Rouw, 2018).

Despite the considerable potential of CSA to enhance yields and improve farm income, the rate of adoption among smallholder farmers remains markedly low (Alemayehu et al., 2024; Amare & Simane, 2017). Abegunde et al. (2019) reported that CSA technologies were adopted by only 17.7% of farmers in South Africa, with the low adoption rate attributed to small farm sizes that render implementation economically inefficient. Similarly, (Pusat Penyuluh Pertanian, 2022) found that CSA technology adoption in Vietnam remained limited to specific technologies, particularly the System of Rice Intensification (SRI) and Alternate Wetting and Drying (AWD) irrigation systems. In Indonesia, the policy framework for CSA implementation has been operationalized through the Strategic Irrigation Modernization and Urgent Rehabilitation Project (SIMURP), which has been in operation since 2021 across 17 regencies in 8 provinces. The program promotes seven CSA technologies, namely: (1) improved seed varieties, (2) water-saving irrigation through intermittent or Alternate Wetting and Drying (AWD) systems, (3) balanced fertilization, (4) organic fertilizer application, (5) organic matter application, (6) the Jajar Legowo planting system, and (7) integrated pest management (IPM) (Pusat Penyuluh Pertanian, 2022).

Purbalingga Regency is among the SIMURP implementation sites in Central Java Province, with Bukateja and Kemangkon Districts designated as the primary areas for CSA activity since 2021. Both districts constitute the main rice production centers in Purbalingga Regency, with a combined harvested rice area of 7,966.70 hectares, representing 27.16% of the regency's total rice harvested area (BPS, 2025). Despite several years of program implementation, the adoption rate of CSA technologies among farmers in the field remains uneven and suboptimal. The gap between technology availability and actual adoption at the farm level is a well-documented phenomenon in the diffusion of agricultural innovations (Rogers, 2003), and necessitates a deeper understanding of the factors that govern farmers' adoption decisions.

Empirical research on the drivers of CSA technology adoption has been conducted across varied agricultural and socioeconomic contexts worldwide, including sub-Saharan Africa (Abegunde et al., 2019; Negera et al., 2022), South Asia (Aryal et al., 2020), and Southeast Asia (Tran et al., 2019; Vatsa et al., 2023). However, the majority of these studies have analyzed the adoption of individual CSA practices in isolation, employing single equation probit or logit models that fail to account for potential correlations across simultaneous adoption decisions. This methodological approach risks yielding inefficient estimators by overlooking the structural interdependencies among CSA practices that farmers frequently adopt in a complementary manner c. Moreover, empirical research on CSA adoption within the SIMURP program context in Indonesia, particularly on the island of Java, remains scarce, leaving a significant knowledge gap that warrants a more comprehensive empirical investigation.

Against this backdrop, this study aims to simultaneously analyze the determinants of adoption of six CSA practices namely improved seed varieties, AWD irrigation, balanced fertilization, organic matter application, organic fertilizer use, and integrated pest management using the Multivariate Probit (MVP) model developed by (Cappellari & Jenkins, 2003). The application of the MVP model enables a more holistic analytical approach by accommodating correlations among adoption decisions across multiple CSA practices within a single, integrated estimation framework (Abdurezak et al., 2026; Aryal et al., 2018; Kule et al., 2025). The results of this study are expected to contribute empirical evidence to the growing body of literature on CSA technology adoption in developing countries, while providing a robust evidence base to inform the formulation of more targeted agricultural extension strategies and policies aimed at accelerating CSA adoption in Purbalingga Regency and comparable regions across Indonesia.

RESEARCH METHODS

This study was conducted in Bukateja and Kemangkon Districts, Purbalingga Regency (**Figure 1**). Site selection was carried out purposively, based on the consideration that both districts serve as implementation areas for Climate Smart Agriculture (CSA) activities under the SIMURP Project in Purbalingga Regency since 2021. Furthermore, both districts constitute the primary rice production centers in the region, with a combined harvested rice area of 7,966.70 hectares, accounting for 27.16% of the total rice harvested area in Purbalingga Regency (BPS, 2025).

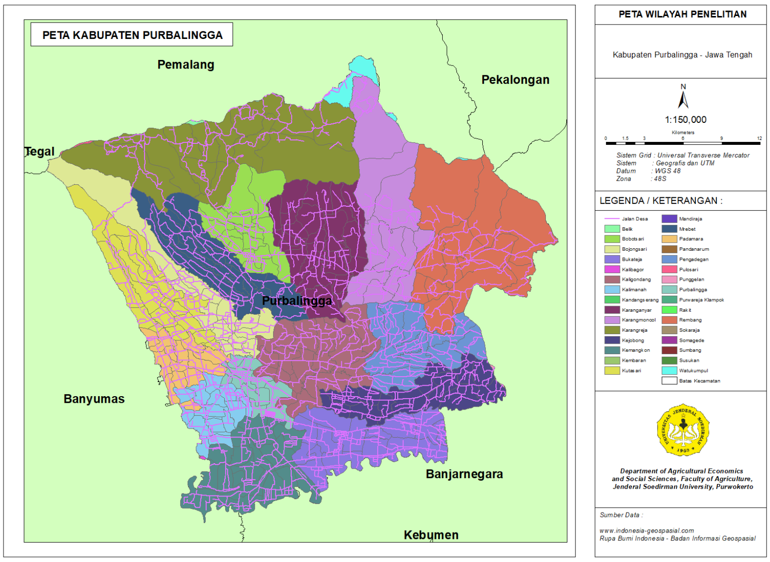

Figure 1. Study area

This study utilized both primary and secondary data. Primary data were collected through structured interviews and in-depth interviews with farmers, farmer group leaders, agricultural extension officers, and the Purbalingga Regency Agriculture Office. Secondary data served as supplementary information obtained from publications of various institutions relevant to this study.

Sample size determination followed the formula proposed by Isaac & Michael (1995), with a margin of error of 5% and a confidence level of 95%. Based on this calculation, a total of 88 farmers were identified as the sample. Respondents were selected using simple random sampling, whereby every member of the population had an equal probability of being chosen. The sampling frame, consisting of a complete list of farmers, was obtained from the Agricultural Extension Center (Balai Penyuluhan Pertanian) of Kemangkon and Bukateja Districts.

Data analysis employed the Multivariate Probit (MVP) model developed by Cappellari & Jenkins, (2003). The MVP model was selected for its capability to simultaneously analyze adoption decisions across multiple Climate Smart Agriculture practices within a single estimation framework, while accommodating potential correlations among equations arising from unobserved factors that jointly influence the adoption of more than one practice. The use of separate probit models for each CSA practice would overlook the interdependencies among these practices, thereby yielding inefficient estimators Cappellari & Jenkins, (2003).

Following Abegunde et al. (2019; Alemayehu et al. (2024); Kule et al. (2025), the CSA adoption decision outcomes estimated within a random utility maximization framework.

$$y_1 = 1(\alpha y_2 + x_1\ \beta_1 + \varepsilon_1 > 0) \quad (1)$$
$$y_2 = 1(x_2\ \beta_2 + \varepsilon_2 > 0) \quad (2)$$
$$y_n = 1(x_n\ \beta_n + \varepsilon_n > 0) \quad (3)$$
$$(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n | x_1, x_2, \ldots, x_n) \sim N(0,0,1,1,\ldots,n\rho) \quad (4)$$

The function 1(.) serves as a binary mapping that assigns unity to observations satisfying the enclosed logical condition and zero to all remaining cases. While α, β_1, β_2 constitute the regression parameters governing each equation, the term N(., ., ., ., ρ) reflects a standard bivariate normal distributional structure characterized by correlation coefficient ρ; the variance terms are standardized to one, a normalization convention that preserves the generalizability of the estimation framework.

This study employs six latent variables (Y^*_{i1}, Y^*_{i2}, Y^*_{i3}, Y^*_{i4}, Y^*_{i5}, Y^*_{i6}), one for each CSA technology (k = 1 to 6), corresponding to each (*i*th) rice farmer. The independent variables used in this study are defined as follows:

Age (Age)	= Age of farmer (years)
Education (Edu)	= Years of formal education (years)
Household Size (HH)	= Number of household members (persons)

Farming Experience (FarmEx)	= Years of rice farming experience (years)
Land Area (Land)	= Cultivated land area (hectares)
Land Tenure Status (LandSta)	= 1 if owner operated land; 0 otherwise
Farmer Group Membership (FarmGM)	= 1 if member of a farmer group; 0 otherwise
Cooperative Membership (CoopMem)	= 1 if member of a cooperative; 0 otherwise
Access to Credit (Credit)	= 1 if farmer has access to agricultural credit; 0 otherwise
Farm Income (Income)	= Total rice farm income (IDR/season)

The latent variables employed in this study are Improved Seeds (Y_{i1}), AWD Irrigation (Y_{i2}), Balanced Fertilization (Y_{i3}), Organic Matter (Y_{i4}), Organic Fertilizer (Y_{i5}), and Integrated Pest Management (Y_{i6}). In this study, the predicted outcome variables are represented by a set of latent variables, each capturing a distinct CSA technology adoption decision, and are formally operationalized as follows:

Y_1 (Improved Seeds): Adoption of improved seed varieties. 1 if the *i*th rice farmer uses improved seed varieties in rice cultivation; 0 otherwise.

$$\mathbf{Y_{i1}^{*}=\beta_{10}+\beta_{11}Age_i+\beta_{12}Edu_i+\beta_{13}HH_i+\beta_{14}FarmEx_i+\beta_{15}Land_i+\beta_{16}LandSta_i+\beta_{17}FarmGM_i+\beta_{18}CoopMem_i+\beta_{19}Credit_i+\beta_{110}Income_i+€_{i1}} \quad (5)$$

Y_2 (AWD): Adoption of Alternate Wetting and Drying (AWD) irrigation. 1 if the *i*th rice farmer implements the Alternate Wetting and Drying (AWD) intermittent irrigation system; 0 otherwise.

$$\mathbf{Y_{i2}^{*}=\beta_{20}+\beta_{21}Age_i+\beta_{22}Edu_i+\beta_{23}HH_i+\beta_{24}FarmEx_i+\beta_{25}Land_i+\beta_{26}LandSta_i+\beta_{27}FarmGM_i+\beta_{28}CoopMem_i+\beta_{29}Credit_i+\beta_{210}Income_i + €_{i2}} \quad (6)$$

Y_3 (Balanced Fertilization): Adoption of balanced fertilization. 1 if the ith rice farmer applies balanced fertilization in accordance with the recommended dosage issued by the Ministry of Agriculture of the Republic of Indonesia; 0 otherwise.

$$\mathbf{Y_{i3}^{*}=\beta_{30}+\beta_{31}Age_i+\beta_{32}Edu_i+\beta_{33}HH_i+\beta_{34}FarmEx_i+\beta_{35}Land_i+\beta_{36}LandSta_i+\beta_{37}FarmGM_i+\beta_{38}CoopMem_i+\beta_{39}Credit_i+\beta_{310}Income_i + €_{i3}} \quad (7)$$

Y_4 (Organic Matter): Utilization of organic matter. 1 if the ith rice farmer utilizes organic matter for in-situ composting activities in rice farming; 0 otherwise.

$$\mathbf{Y_{i4}^{*}=\beta_{40}+\beta_{41}Age_i+\beta_{42}Edu_i+\beta_{43}HH_i+\beta_{44}FarmEx_i+\beta_{45}Land_i+\beta_{46}LandSta_i+\beta_{47}FarmGM_i+\beta_{48}CoopMem_i+\beta_{49}Credit_i+\beta_{410}Income_i + €_{i4}} \quad (8)$$

Y_5 (Organic Fertilizer): Use of organic fertilizer. 1 if the ith rice farmer applies organic fertilizer in rice farming operations; 0 otherwise.

$$\mathbf{Y_{i5}^{*}=\beta_{50}+\beta_{51}Age_i+\beta_{52}Edu_i+\beta_{53}HH_i+\beta_{54}FarmEx_i+\beta_{55}Land_i+\beta_{56}LandSta_i+\beta_{57}FarmGM_i+\beta_{58}CoopMem_i+\beta_{59}Credit_i+\beta_{510}Income_i + €_{i5}} \quad (9)$$

Y_6 (Integrated Pest Management): Integrated pest and disease management. 1 if the ith rice farmer implements pest and disease control practices that prioritize the use of botanical pesticides/biopesticides, biological control, and physical and mechanical control methods; 0 otherwise.

$$\mathbf{Y_{i6}^{*}=\beta_{60}+\beta_{61}Age_i+\beta_{62}Edu_i+\beta_{63}HH_i+\beta_{64}FarmEx_i+\beta_{65}Land_i+\beta_{66}LandSta_i+\beta_{67}FarmGM_i+\beta_{68}CoopMem_i+\beta_{69}Credit_i+\beta_{610}Income_i + €_{i6}} \quad (10)$$

RESULT AND DISCUSSION

Respondent Characteristics

The characteristics of respondent farmers in this study encompass age, educational attainment, household size, rice farming experience, and cultivated land area. These characteristics provide an overview of rice farming performance and the socioeconomic conditions of farmers in Bukateja and Kemangkon Districts, Purbalingga Regency.

Table 1. Characteristics of Respondent Farmers

Karakteristik	Number of Farmers (persons)	Percentage (%)	Mean
Age of Farmers (years)			
≤30	3	4	54.66 years
31-40	9	10	
41-50	16	18	
51-60	32	36	
>60	28	32	
Total	**88**	**100**	
Education			
Elementary School (SD)	29	33	
Junior High School (SMP)	25	28	
Senior High School (SMA)	27	31	
Diploma (D3)	2	2	
Bachelor's Degree (D4/S1)	4	5	
Postgraduate (S2/S3)	1	1	
Total	**88**	**100**	
Household size (persons)			
1-2	13	15	3.76 persons
3-4	51	58	
≥5	24	27	
Total	**88**	**100**	
Rice Farming Experience (years)			
<5	8	9	23.84 years
6-10	11	13	
11-20	25	28	
21-30	18	20	
>30	26	30	
Total	**88**	**100**	
Cultivated Land Area (ha)			
≤0.25	21	24	0.54 ha
0.25-0.50	33	38	
0.51-1,00	24	27	
1.01-2.00	8	9	
>2.00	2	2	
Total	**88**	**100**	

Source: Primary Data Processed, 2025

As shown in Table 1, a total of 88 farmers participated as respondents in this study. The age profile of the respondents is predominantly characterized by the senior age group, with the largest proportion falling within the 51–60 years age bracket (36%) and above 60 years (32%), yielding a mean age of 54.66 years. In terms of educational attainment, the majority of respondents had completed only primary to secondary education, with 33% having graduated from elementary school (SD), 28% from junior high school (SMP), and 31% from senior high school (SMA), while only a small proportion (approximately 8%) had pursued diploma or undergraduate education. Regarding household size, 58% of households consisted of three to four members, with an average of 3.76 persons per household.

Agricultural experience among the respondents was notably extensive, averaging 23.84 years across the sample. The largest single group, comprising 30% of respondents, had dedicated more than three decades to rice farming, reflecting a predominantly seasoned farming community in the study area. However, this extensive farming experience has not been accompanied by substantial land ownership. The cultivated land area among respondents was relatively small, averaging only 0.54 hectares. Specifically, 38% of farmers managed between

DOI: https://doi.org/10.47030/tadj.v6i01.1138

0.25 and 0.50 hectares, while an additional 24% cultivated less than 0.25 hectares. These findings indicate that the farming structure in Bukateja and Kemangkon Districts remains dominated by small-scale or subsistence farmers (*petani gurem*).

Determinants of CSA Technology Adoption: Multivariate Probit Model Results

The Multivariate Probit (MVP) model was employed to analyze the factors influencing farmers' decisions to adopt Climate Smart Agriculture (CSA) technologies in Purbalingga Regency. Based on the field survey, the CSA technologies examined in this study comprise Improved Seeds (Y_{i1}), Alternate Wetting and Drying irrigation/AWD (Y_{i2}), Balanced Fertilization (Y_{i3}), Organic Matter application (Y_{i4}), Organic Fertilizer (Y_{i5}), and Integrated Pest Management (Y_{i6}). The results of the Multivariate Probit (MVP) model estimation are presented in Table 2.

Table 2. Determinants of climate smart agricultural technology adoption

Variabel	Improved Seeds		AWD		Balanced Fertilization		Organic Matter		Organic Fertilizer		Integrated Pest Management	
	Coef	Std.Err	Coef	Std.Err	Coef	Std.Err	Coef	Std.Err	Coef	Std.Err	Coef	Std.Err
Age	0.001	0.031	0.017	-0.009	-0.039	0.019	-0.019*	0.021	0.048**	0.027	-0.018*	0.242
Eduction	0.260*	0.164	-0.022*	-0.005	0.150*	0.059	-0.015*	0.064	-0.089	0.069	0.143**	0.071
Marital Status	2.256	2.680	-5.247	0.064	0.061	0.847	-0.431	0.092	-0.362	0.911	-4.295	0.356
Household Size	0.182	0.312	0.129	-0.007	-0.008	0.014	0.424	0.169	-0.080	0.156	-0.156	0.176
Farming Experience	0.079**	0.081	-0.014	0.016	0.016	0.163	0.021*	0.377	-0.052**	0.056	-0.011*	-.018
Land Area	-0.975*	0.083	-0.198	-0.042	-0.042	0.355	0.093	0.184	0.582*	0.780	-0.646*	0.482
Land Tenure Status	0.930*	0.914	0.191	0.393	0.033*	0.097	-0.359*	0.408	-0.012*	0.455	-0.766	0.462
Farmer Group Membership	0.642	2.785	3.811**	0.024	0.324*	0.072	0.349	0.811	4.246*	2.452	-0.81	0.715
Cooperative Membership	13.564	3.150	0.192	-0.205	-0.205	0.53	-0.071	0.486	-0.439	0.58	-0.808	0.344
Access to Credit	-2.685	1.879	-0.851*	0.835	0.835*	0.432	0.219	0.490	1.056*	0.439	0.788*	0.512
Farm Income	1.751*	0.006	0.956***	0.024	0.072**	0.017	5.350***	0.490	0.369*	0.490	-1.364**	0.635
Log likelihood	-676.3											
Prob > χ^2	0.000											
Wald $\chi2$ (66)	1006.47											

Source: Primary Data processed, 2025

The estimation outcomes of the MVP model analysis for CSA technology adoption are presented in Table 2. The Wald test yielded a probability value of p = 0.000, indicating that all variables jointly exert a significant influence on CSA technology adoption decisions. This result suggests the existence of interdependencies among the adoption decisions of different CSA technologies. Similarly, the likelihood ratio test was statistically significant (p=0.000), confirming the overall fit and appropriateness of the MVP model. Accordingly, the MVP model employed in this study is well-specified, and its analytical results are reliable for predicting farmers' decisions to adopt CSA technologies. The following sections present the analysis of adoption determinants for each CSA technology in Purbalingga Regency.

Adoption of Improved Seeds

The use of improved seed varieties under the CSA framework promotes the adoption of high yielding, stress tolerant, and low-emission certified rice seeds. These varieties are characterized by strong vigor and robust root systems, which are expected to deliver high yield potential and superior grain quality under varying field conditions (Pusat Penyuluh Pertanian, 2022). The MVP analysis revealed that the adoption of improved seeds was significantly influenced by education, farming experience, farm income, and land area. Farmers with higher educational attainment demonstrated a better understanding of the characteristics of improved varieties and their yield potential, thereby increasing the likelihood of adoption. This finding is consistent with (Abegunde et al., 2019), who found that educated farmers are more likely to utilize improved seed varieties. Land area, however, exhibited a negative effect, indicating that as farm size increases, the propensity of adopting improved seeds declines. This negative relationship is attributable to the fact that larger land holdings entail higher production costs, which in turn raise the investment required for improved seeds. As noted by (Okeke et al., 2020), certified seed costs represent the largest cost component in farming operations. Smallholder farmers, by contrast, are more flexible in adopting new technologies given their lower initial investment requirements. Farm income had a positive effect, suggesting that higher rice farming income enhances farmers' financial capacity to invest in more expensive improved seeds that offer greater yield potential (Rouw, 2018).

Adoption of Alternate Wetting and Drying (AWD) Irrigation

The AWD technology is a water saving irrigation system that alternates between flooded and non-flooded field conditions. This practice offers multiple benefits, including reduced water consumption, improved crop lodging resistance, enhanced root development, and significant reduction of greenhouse gas emissions, particularly methane (CH_4), carbon dioxide (CO_2), and nitrous oxide (N_2O) (Pusat Penyuluh Pertanian, 2022).The adoption of AWD was significantly influenced by farmer group membership, land tenure status, and farm income. Farmer group membership demonstrated the strongest effect on AWD adoption. This is attributable to the coordinative nature of AWD technology, which requires collective management of irrigation water, particularly within communal irrigation systems. Farmers affiliated with farmer groups are therefore better positioned to implement AWD irrigation practices. Farmer groups function as platforms for collective learning and coordinated action (Bai, 2024), and serve as catalysts for technology adoption through peer-to-peer learning (Rogers, 2003). Land area also positively influenced adoption, as farmers with larger holdings are more motivated to implement AWD due to its long-term benefits in terms of water use efficiency and productivity enhancement. As argued by Negera et al. (2022), technologies requiring coordination are more successfully adopted through group-based approaches.

Adoption of Balanced Fertilization

The CSA recommended balanced fertilization practice, as stipulated by the Ministry of Agriculture (Pusat Penyuluh Pertanian, 2022), is implemented based on site-specific fertilization recommendations that account for existing soil nutrient status and the actual nutritional requirements of rice crops at each location. This location-specific approach ensures more precise, efficient, and environmentally responsible fertilizer application, minimizing nutrient losses while optimizing crop yield potential and reducing the risk of over fertilization. Education, land tenure status, access to credit, and farm income were found to be significant determinants of balanced fertilization adoption. The application of balanced fertilization requires an understanding of rice crop nutrient requirements, soil analysis, and appropriate application dosages. Educated farmers are better equipped to comprehend fertilization recommendations and adapt them to the specific conditions of their land, thereby increasing their likelihood of adopting balanced fertilization practices. This finding aligns with Geda et al. (2024), who demonstrated that technical knowledge and formal education enhance the adoption of precision crop fertilization practices. Balanced fertilization is generally more costly than conventional fertilization, as it requires a combination of macro and micronutrients. Consequently, access to credit assists farmers in overcoming financial constraints, while farm income serves as an additional enabling factor. Abegunde et al. (2019) similarly found that access to credit significantly promotes the adoption of input intensive agricultural practices and mitigates financial barriers, which constitute a primary obstacle to CSA technology adoption in sub-Saharan Africa.

Adoption of Organic Matter Application

In accordance with Pusat Penyuluh Pertanian, (2022), the CSA recommended organic matter practice involves recycling rice straw through in-situ composting as a direct soil amendment, aimed at improving soil organic matter content, enhancing long-term soil fertility, and reducing dependence on synthetic chemical fertilizers in rice farming. The adoption of organic matter in rice farming was significantly influenced by age, farming experience, land tenure status, and farm income. The negative effect of age can be explained by the labor intensive nature of organic matter application, which involves the transportation, processing, and field application of materials that demand considerable physical effort. Landicho et al. (2023) noted that younger farmers are more inclined used laborintensive sustainable farming practices. Although organic matter application in rice farming yields long term benefits for soil fertility, it requires consistent application over time. As a result, owner operators are more motivated to adopt this practice, as they directly benefit from its cumulative effects. Field interviews revealed that the majority of farmers have practiced organic matter application by recycling post-harvest rice straw as an in-situ soil amendment. This locally available organic input serves as a cost-effective strategy to improve soil fertility and reduce dependency on synthetic fertilizers, reflecting an inherent alignment with CSA principles. Farm income emerged as the variable with the strongest influence, reflecting the high dependency of organic matter utilization on farmers' economic capacity. This is consistent with the findings of Bai (2024), whereby farmers with higher income are better positioned to make long term agricultural investments.

Adoption of Organic Fertilizer

The adoption of organic fertilizer was influenced by age, farming experience, land area, farmer group membership, access to credit, and farm income. Unlike organic matter application, organic fertilizer adoption was more prevalent among older and more experienced farmers, who regard it as a familiar conventional practice. Belay et al. (2017) explained that experienced farmers tend to maintain practices that have proven to be economically beneficial. The positive effect of land area suggests the presence of economies of scale, whereby farmers with larger landholdings can produce organic fertilizer independently from agricultural waste at a lower

DOI: https://doi.org/10.47030/tadj.v6i01.1138

cost per unit. The highest coefficient recorded for farmer group membership underscores the critical role of collective learning in this context, which is consistent with Alemayehu et al. (2024), whose findings underscore the central function of farmer group institutions as catalysts for accelerating the uptake of agricultural technologies that are deeply rooted in local farming knowledge and practices.

Adoption of Integrated Pest Management (IPM)

The CSA recommended Integrated Pest Management (IPM) approach, as outlined by (Pusat Penyuluh Pertanian, 2022), adopts a hierarchical pest control strategy that prioritizes ecologically sound methods, including botanical pesticides/biopesticides, synchronized planting schedules, cultivation of pest-resistant varieties, biological control agents, physical and mechanical interventions, pheromone-based monitoring, and the conservation of natural enemy populations. Chemical insecticide application is strictly positioned as the final intervention measure, employed only when all preceding control components fail to adequately suppress pest and disease pressure, thereby minimizing environmental impact and preserving agroecosystem balance. The final CSA technology examined was Integrated Pest Management (IPM), for which age, education, farming experience, land area, access to credit, and farm income were identified as significant determinants. As a holistic approach to pest control, IPM requires a thorough understanding of pest ecology, natural enemies, and economic thresholds, making farmer resource variables such as age, education, and experience critical in shaping adoption decisions. Abegunde et al. (2019) found that formal education enhances the adoption of complex CSA technologies by facilitating the comprehension of technical information. The negative effects of age and farming experience suggest resistance among older, more experienced farmers who are accustomed to conventional chemical pesticide based approaches. According to Negera et al. (2022), the paradigm shift from curative to preventive pest management requires a significant transformation in farmers' mindsets. Furthermore, the negative effect of land area indicates that IPM is more difficult to implement at a larger scale, as it necessitates intensive and continuous monitoring.

CONCLUSION

The MVP analysis revealed that improved seed adoption was significantly influenced by education, farming experience, farm income, and land area. Education and farm income exerted positive effects, while land area had a negative effect on the probability of improved seed adoption. AWD irrigation adoption was significantly determined by farmer group membership, access to credit, and farm income, with farmer group membership exhibiting the strongest effect, indicating that AWD technology is more successfully adopted through collective and coordinated groupbased approaches. Balanced fertilization adoption was significantly influenced by education, land tenure status, access to credit, and farm income, whereby technical knowledge acquired through formal education emerged as a key factor in the application of precision fertilization recommendations. Farmers' decisions to adopt organic matter were significantly influenced by age, farming experience, land tenure status, and farm income. Farm income was the most influential variable, reflecting the high dependency of organic matter application on farmers' economic capacity. Furthermore, organic fertilizer adoption was significantly determined by age, farming experience, land area, farmer group membership, access to credit, and farm income, with farmer group membership recording the highest coefficient, underscoring the importance of collective learning in the adoption of locally knowledgebased technologies. Finally, integrated pest management (IPM) adoption was significantly influenced by age, education, farming experience, land area, access to credit, and farm income. The negative effects of age and farming experience indicate resistance among senior farmers who are accustomed to conventional chemical pesticide based approaches.

Based on the findings of this study, strengthening farmers' human resource capacity is imperative to accelerate CSA technology adoption. Given that education is a significant determinant of improved seed, balanced fertilization, and integrated pest management adoption, the government and agricultural extension services should intensify and improve the quality of CSA-based agricultural extension programs. Training programs and field demonstration plots (demplot) should be designed in a more structured and adaptive manner for farmers with limited educational backgrounds, utilizing visual learning approaches. In particular, demonstration plots should be strategically established in close proximity to or within farmers' existing rice field areas, so that farmers can directly observe, compare, and practice CSA technologies under real and familiar farming conditions, thereby facilitating more effective technology transfer and accelerating adoption.

ACKNOWLEDGEMENT

The first author gratefully acknowledges the financial and institutional support provided by the Institute for Research and Community Service (LPPM) of Universitas Jenderal Soedirman through the Competency

Enhancement Research Scheme (Riset Peningkatan Kompetensi) of 2025, with contract number 14.487/UN23.34/PT.01/V/2025.

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