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Exploring Socio-Economic Factors Influencing the Adoption of Climate Smart Agriculture

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ABSTRACT

The suboptimal income of tidal rice farmers, who are increasingly affected by climate change, is a major challenge in improving their welfare. Climate Smart Agriculture (CSA) technology is expected to be a solution to increase farmer productivity and income. This study aims to analyze the level of adoption of CSA technology and examine the influence of socio-economic factors on its adoption, as well as its impact on farmer income and productivity. The research respondents were tidal rice farmers in Telang Makmur Village. To test the relationships between socio-economic variables, CSA adoption levels, and productivity, Structural Equation Modeling (SEM) with the Partial Least Squares (PLS) approach was applied using SmartPLS 4.0 software. The results of the study indicate that socio-economic factors such as age, education level, family size, farming experience, cultivation area, and other income have a significant influence on the level of adoption of CSA technology. In addition, the use of CSA technology has been shown to significantly increase farmer income and productivity. Therefore, there should be increased socialization and training related to CSA technology for farmers, as well as the provision of subsidies and technological assistance to encourage wider adoption.

1. INTRODUCTION

Climate change had a significant impact on the agricultural sector, especially in areas with unique characteristics such as tidal lands [1, 2]. It has the potential to harm farming, particularly by increasing salinity and reducing water availability [3, 4]. Farmers in these regions often face challenges such as low productivity and income due to limited access to technologies that are adaptive to climate change [5, 6]. Therefore, it is important to apply appropriate technologies that meet the timing and needs of the crops in order to increase rice productivity in tidal lands [7]. One approach that has proven effective in enhancing agricultural resilience and productivity is Climate Smart Agriculture (CSA) technology [8-10]. CSA offers innovative solutions by integrating increased productivity, adaptation to climate change, and reduced greenhouse gas emissions. While Climate-Smart Agriculture practices can boost agricultural production under adverse climate conditions and reduce greenhouse gas emissions, they require significant investment and coordination for their widespread impact [11].

In this context, CSA technology has emerged as an approach that offers solutions to increase agricultural resilience and productivity. CSA, as described by Balo and Mahata, which integrates productivity enhancement, climate change adaptation, and greenhouse gas emission reduction [12]. According to research by [13, 14], the implementation of CSA focuses on sustainability and resource efficiency, providing numerous benefits for smallholder farmers by increasing food security and enhancing their ability to adapt to the challenges posed by climate change [15]. The results of Kurgat et al. [16] demonstrated that policy and programmatic efforts influenced smallholder farmers' adoption of a specific CSA technology in Tanzania, as well as the adoption of additional technologies. Similarly, the study by Amadu et al. [17] reported a positive and significant effect of the typology's potential for wider application on CSA adoption. However, although the benefits of CSA technology are widely recognized, its adoption remains very limited, particularly in areas with complex environmental conditions such as tidal flats [18]. This is due to various factors, including a lack of farmer knowledge, limited infrastructure, and other socio-economic barriers [19]. Therefore, more in-depth research is needed to understand the factors influencing the adoption of CSA technology in these regions.

This study analyzes the adoption rate of CSA technology in Telang Makmur Village, Muara Talang District, Banyuasin Regency, and examines the factors that influence its adoption. It also explores the potential of CSA technology to improve the welfare of farmers in tidal lands. In addition, this study evaluates the impact of CSA technology on farmers' income and productivity. The results of this study are expected to contribute to encouraging farmers to maximize the implementation of CSA, thereby increasing their productivity and income sustainably.

2. METHODOLOGY

2.1 Location and time of the study

This research was conducted in Telang Makmur Village, Muara Telang Subdistrict, Banyuasin Regency, Indonesia, as can be seen in Figure 1. The research location was determined using Simple Random Sampling, considering that Telang Makmur Village is a tidal swamp area where CSA technology has been adopted. This research was conducted from August to October 2024.

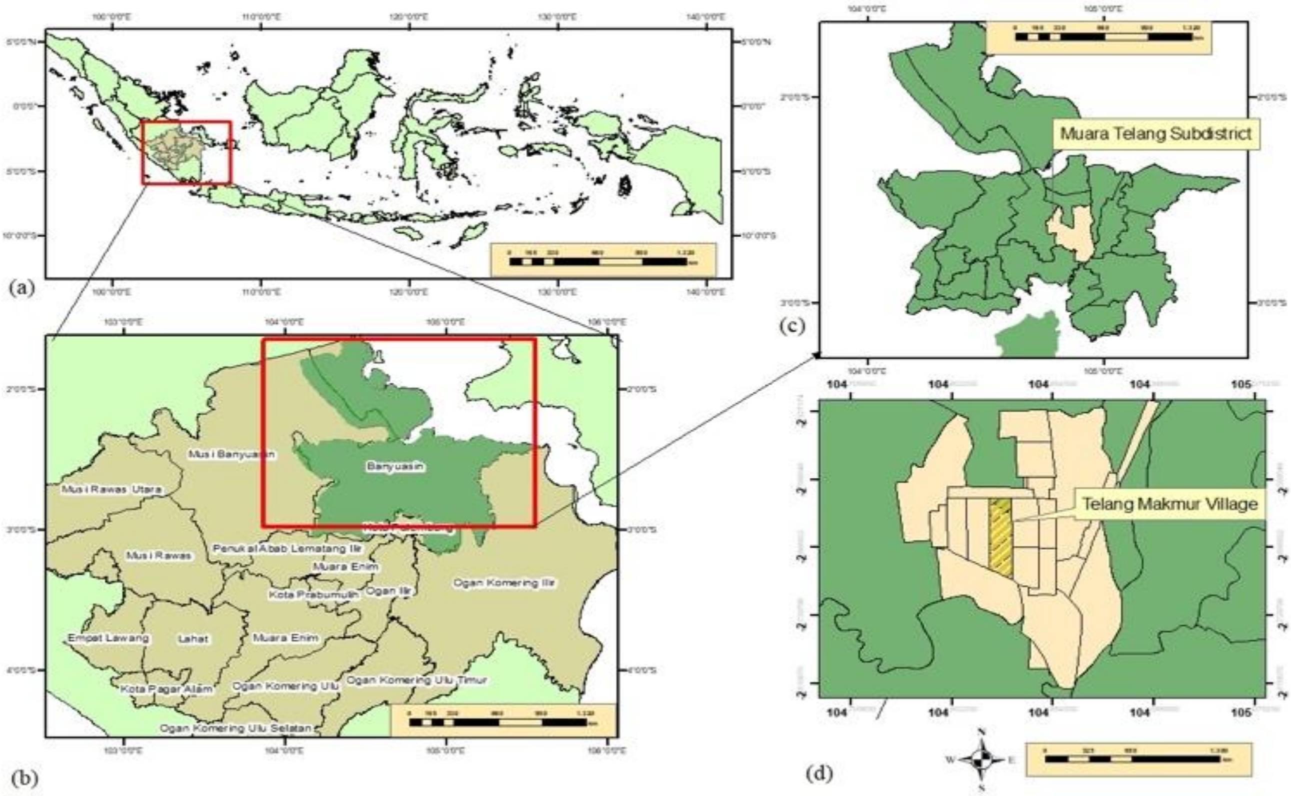

Figure 1. Research location map: (a) Indonesia, (b) Banyuasin Regency, (c) Muara Telang Subdistrict, (d) Telang Makmur Village

2.2 Data collecting methods

This study employed a survey method, with data collected through direct observation, interviews, and questionnaires. Data collection involved on-site visits and face-to-face interviews with sample farmers representing the population of Telang Makmur Village, Muara Telang Subdistrict, Banyuasin Regency. The sampling technique utilized was Simple Random Sampling, in which each member of the population has an equal probability of selection. In Structural Equation Modeling (SEM), the minimum required sample size is typically determined using the 10-times rule method, which recommends a sample size at least ten times the number of indicators in the model. This study includes 18 valid indicators, requiring a total of 180 farmers to be selected as respondents.

2.3 Data analysis methods

The data obtained from the interviews were processed systematically in tabular form and explained descriptively. The first objective, which is to calculate the level of adoption of CSA technology by farmers, was analyzed using a Likert scale. This was done by calculating the total score obtained from the questionnaire responses. Each answer was assigned a different score weight: a score of 5 for "Strongly Agree," 4 for "Agree," 3 for "Doubtful," 2 for "Disagree," and 1 for "Strongly Disagree." Respondents' answers were then categorized into intervals. The formula used to determine the class interval is as follows:

NR =NST–NSR
PI =NR : JIK
Details:
NR =Range Value
PI =Interval Length
NST =Highest Score Value
NSR =Lowest Score Value
JIK =Number of Class Intervals

Based on the processing results in Tables 1-3, the class interval values in the table are as follows:

Table 1. The class intervals and criteria used for measuring technology adoption levels

Class Interval Value (Statement)	Class Interval Value (Indicator)	Class Interval Value (Overall)	Criteria
1.00<x<2.33	5.0<x<11.67	40.0<x<93.33	Low
2.33<x<3.66	11.67<x<18.34	93.34<x<146.67	Medium
3.66<x<5.00	18.34<x<25.0	146.68<x<200	High

Table 2. Class intervals for productivity levels

Description	Criteria
Low Productivity	2,000-4,299
Medium Productivity	4,300-6,599
High Productivity	6,600-9,000

Table 3. Class intervals for income levels

Income Group	Category
Very High Income	>3,500,000
High Income	2,500,000-3,500,000
Medium Income	1,500,000-2,500,000
Low Income	<1,500,000

The level of farmers' productivity and income was measured using the range score method. The range score was calculated by subtracting the minimum value from the maximum value within the dataset. The resulting range was then divided into interval classes to categorize productivity and income levels as high, medium, or low, as presented in Table 2.

Income levels were measured using the standard classification established by BPS (Badan Pusat Statistik) in Table 3. According to BPS, the population is categorized into four income groups: (1) Very High Income Group, with an average income exceeding IDR 3,500,000 per month; (2) High Income Group, with an average income ranging from IDR 2,500,000 to IDR 3,500,000 per month; (3) Medium Income Group, with an average income ranging from IDR 1,500,000 to IDR 2,500,000 per month; and (4) Low Income Group, with an average income of less than IDR 1,500,000 per month.

The data obtained were analyzed using a regression model to identify the relationships between socio-economic variables, CSA adoption rate, income, and productivity. Partial Least Squares (PLS) analysis was used to examine the influence of socio-economic factors on the adoption rate of CSA technology, as well as the impact of CSA adoption on farmer productivity and income. Descriptive analysis was applied to qualitative data, while quantitative data were processed using Microsoft Excel for data cleaning. SEM with the PLS approach was conducted using SmartPLS 4.0 software to test the relationship model between variables.

Partial Least Squares - Structural Equation Modeling (PLS-SEM) is employed to test predictive relationships between variables by examining the existence and strength of relationships [20, 21]. Parameter estimation in PLS-SEM is categorized into three components. First, weight estimation is used to calculate latent variable scores. Second, path estimation reflects the relationships between latent variables and between latent variables and their indicator blocks (loadings). Third, estimates related to means and parameter locations (regression constants) are applied to both indicators and latent variables [22-24]. PLS-SEM utilizes a three-stage iterative process to obtain these estimates: the first stage estimates weights, the second stage estimates parameters for the inner (structural) and outer (measurement) models, and the third stage estimates means and locations (constants) [25]. Model evaluation in PLS-SEM is conducted using non-parametric prediction metrics. Accordingly, assessment typically involves evaluating both the outer model (measurement model) and the inner model (structural model) [26].

Indicators influencing the adoption of CSA technology include:

1) Inner model:
Social=>CSA Technology
Economic=>CSA Technology
CSA Technology=>Income
CSA Technology=>Productivity

2) Outer model:
Social=>Social Indicators
CSA Technology=>CSA Technology Indicator
Economic=>Economy indicator
Income=>Income indicator
Productivity=>Income indicator

3) Latent variables:
CSA Technology
Social
Economic
Income
Productivity

4) Manifest Variables:
SAK =Number of Family Members
SLS =Years of Schooling
SPU =Farming Experience
SS =Tribe/Ethnic
STK =Number of Family Dependents
SU =Age
PBT =Total Cost
PP =Revenue
EL =Land Area
PPR =Production
EP =Income
ETS =Side Income
CTR =Tractor
CBU =Superior Variety Seedlings
CTB =Tabela System
CPO =Organic Fertilization
CBP =Pump and Biopores System
CCH =Combine Harvester

5) Exogenous variables:
Social
Economic

6) Endogenous variables:
CSA
Income
Productivity

The structural relationships analyzed in the PLS-SEM model are illustrated below. These relationships represent the pathways evaluated in the model, based on the measurements and constructs used in this study:

1) The influence of the socio-economic characteristics of farming households on the level of adoption of CSA technology.

$$Y = \beta_1 X_1 + \beta_2 X_2 + \varepsilon$$

Details:
Y =Level of CSA Technology Adoption
X_1 =Social Factor
X_2 =Economic Factor
β_1 =Path Coefficient of Economic Factor =>CSA Technology
β_2 =Path Coefficient of Social Factor =>CSA Technology
ε =Residual error

2) The impact of CSA technology adoption on farmers' Income

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \varepsilon$$

Details:
Y =Income

X_i =Type of Technology
β_i =Coefficient of the Effect of CSA Technology Adoption on Farmers' Income
ε =Residual error

3) The impact of CSA technology adoption on rice productivity

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \varepsilon_{\leftarrow}$$

Details:

Y =Productivity
X_i =Type of Technology
β_i =Coefficient of the Effect of CSA Technology Adoption on Farmers' Income
ε =Residual error

3. RESULT AND DISCUSSION

3.1 Socio-Economic characteristics of farmers

In this study, the socio-economic characteristics of farmers in Telang Jaya Village are identified based on several factors, including the age of the farmers, education level, family size (capital), farming experience, cultivation area, and additional income from non-agricultural sources seen in Table 4. The study involved a total of 180 farmers as respondents.

The socio-economic profile of farmers in Telang Makmur Village reveals a diverse and experienced community. The average age is 50 years, with the majority (40%) falling within the 44-56 age range, indicating a mature and knowledgeable workforce. The average education level is 9 years, suggesting a moderate level of formal education, with a significant portion of individuals (37%) having between 1-6 years of schooling. Household sizes tend to be small, with an average of 3 members, and the family size ranges from 1 to 5 members. The average farming experience is 19 years, with the highest level reaching 40 years, indicating a strong background in agricultural practices. Regarding land cultivation, the majority of farmers (45%) cultivate between 0.95 to 1.75 hectares, with an average area of 1 hectare. Income diversification is evident, with a large portion (66%) earning between IDR 400,000 and IDR 2,199,999 per month, while the average additional income is IDR 2,307,895. These factors are essential for designing targeted programs that can further improve the livelihoods and agricultural productivity of the community.

Table 4. The role of socio-economic factors of farming households in the adoption of CSA technology

Socio-Economy Factors	Household	Percentage	
Age (years)			
18–30	8	4	*Average: 50*
31–43	51	28	*Max: 82*
44–56	72	40	*Min: 18*
57–69	40	22	*Srd: 12*
70–82	9	5	
Education Level (years)			
0	3	2	*Average: 9*
1–6	66	37	*Max: 16*
7–9	52	29	*Min: 0*
10–12	50	28	*Srd: 3*
16	9	5	
Family size (capital)			
1	23	13	*Average: 3*
2	49	27	*Mac: 5*
3	68	38	*Min: 1*
4	34	19	*Srd: 1*
5	6	3	
Experience (years)			
1–8	31	17	*Average: 19*
9–16	38	21	*Max: 40*
17–24	39	22	*Min: 1*
25–32	38	21	*Srd: 10*
33–40	34	19	
Cultivation Area (Ha)			
0,15–0,95	61	34	*Average: 1*
0,95–1,75	81	45	*Max:4*
1,75–2,55	31	17	*Min: 0,15*
2,55–3,35	4	2	*Srd: 1*
3,35–4	3	2	
Other Income (IDR/month)			
400.000–2.199.999	38	66	*Average: 2.307.895*
2.200.000–3.999.999	13	22	*Max: 9.000.000*
4.000.000–5.799.999	4	7	*Min: 400.000*
5.800.000–7.599.999	2	3	*Srd: 1.832.596*
7.600.000–9.399.999	1	2	

3.2 Farmer technology adoption level

There are eight types of rice farming technologies applied in tidal lands can be seen in Table 5. These technologies play a crucial role in helping farmers adapt to the impacts of climate change in Telang Makmur Village, which has three planting seasons.

Table 5. Adoption of CSA technology

Types of Technology	Score	Criteria
Tractor	21.71	High
Superior Variety Seeds	22.00	High
Tabela System	22.49	High
Organic Fertilization	20.90	High
Pumping and Biopore System	18.80	High
Drainage and Irrigation	20.46	High
Combine Harvester	22.00	High
Planting Calendar	19.49	High

Based on the data presented in Table 5, the level of technology adoption is measured using a calculated indicator interval scale score for each type of technology, all of which low into the high adoption category. Tabela system recorded the highest adoption score, as it is utilized by all farmers in Telang Makmur Village. Farmers prefer the Tabela system because it saves time and eliminates the need for additional labor costs. In contrast, other planting methods, such as the jajar legowo system, require more labor, making them less attractive to farmers. On the other hand, the pump and biopore system has the lowest technology adoption score. Although this technology is widely known among farmers, not all choose to use it. Some respondents rely solely on traditional water sources, such as river water, without the assistance of pumps. Additionally, the high cost of acquiring this equipment presents a barrier for some farmers, limiting the widespread adoption of the pump and biopore system.

3.3 Farmers' income level

The income level of farmers is classified as moderate due to relatively high production costs presented in Tables 6-7. The costs associated with purchasing fertilizers, quality seeds, pesticides, and land maintenance demand substantial financial resources. When harvest outcomes are suboptimal due to unfavorable weather conditions, pest infestations, or inefficient cultivation practices, the financial burden on farmers increases, often resulting in minimal profits that are disproportionate to the initial capital investment. Furthermore, the average education level of farmers, which is limited to approximately seven years, constrains their ability to adopt modern agricultural technologies and implement more effective marketing strategies. This limitation reduces their capacity to improve production efficiency and enhance competitiveness. Consequently, the uneven adoption of agricultural modernization has contributed to significant disparities in farmer productivity and income. These factors underscore the urgent need for comprehensive interventions, including financial support, educational programs, and improved market access, to promote the welfare and sustainability of rice farming communities.

Table 6. Variable costs, fixed costs, and total costs

No	Description	Planting Season 1 (IDR/Ha)	Planting Season 2 (IDR/Ha)	Planting Season 3 (IDR/Ha)	Average (IDR/Ha/year)
1	Seed	2,287,805	2,285,488	111,220	1,561,504
2	Pesticide	818,333	679,187	16,667	504,729
3	Fertilizer	716,049	806,667	7,317	510.011
4	Rental costs	9,415,366	5,374,902	106,098	4,965,455
	Total Variable Cost	15,282,073	11,291,610	5,780,000	10,784,561
1	Sprayer	198.256			198.256
2	Hoe	29,841			29,841
3	Machete	14,537			14,537
4	Sickle	17,866			17,866
5	Motor	1,283,171			1,283,171
6	Cart	24,268			24,268
7	TR2	245,528			245,528
	Total Fixed Cost				1,813,467
	Total Cost				12,598,028

Table 7. Income level

Total Income (IDR/Month)	Category	Percentage (%)
Very High Income	>3,500,000	76
High Income	2,500,000-3,500,000	7
Medium Income	1,500,000 - 2,500,000	12
Low Income	< 1,500,000	5
	Total	100

3.4 Productivity levels in rice farming

Productivity in this study is measured by calculating the total production divided by the land area. Productivity is strongly influenced by the amount of production; therefore, the higher the production yield, the greater the resulting productivity [27-29]. The productivity obtained by rice farmers in Telang Makmur Village, who implemented 3 planting seasons to face the challenges of climate change, can be seen in Table 8.

Table 8. Productivity in rice farming

Description	Planting Season 1	Planting Season 2	Planting Season 3	Average (year)
Production (kg)	10,076	5,439	85	33,505
Land Area (ha)	2	2	2	2
Productivity (kg/ha)	5,038	2.7195	42.5	16,753

Based on Table 8, it is stated that farmers produce three harvests per year, although not all farmers participate in the third planting season due to several factors, one of which is climate conditions. In terms of productivity across the three planting seasons, the highest yield is achieved in the first planting season, with an average of 5,038 kg/ha. Meanwhile, the average annual productivity across the three planting seasons in Telang Makmur Village is 42.5kg/ha.

Table 9. Productivity level

Description	Criteria (Kg/ha)	Percentage (%)
Low Productivity	2,000-4,299	27
Medium Productivity	4,300-6,599	56
High Productivity	6,600-9,000	17
Total		100

The productivity level of most farmers falls within the medium category presented in Table 9, with productivity ranging between 4,300 and 6,599kg/ha. This productivity is influenced by both total production and land area. When production yields are low, productivity decreases accordingly, and vice versa. In Telang Makmur Village, the lowest recorded productivity is 2,000kg/ha, while the highest reaches 18,000kg/ha.

3.5 Validation of the measurement model

The analysis employed a quantitative approach utilizing SEM. The measurement scale was validated based on quality criteria, including reliability and construct validity, to assess internal consistency and convergent validity. Model evaluation was conducted using indicators such as Cronbach's alpha, the composite reliability index (CRI), and the average variance extracted (AVE).

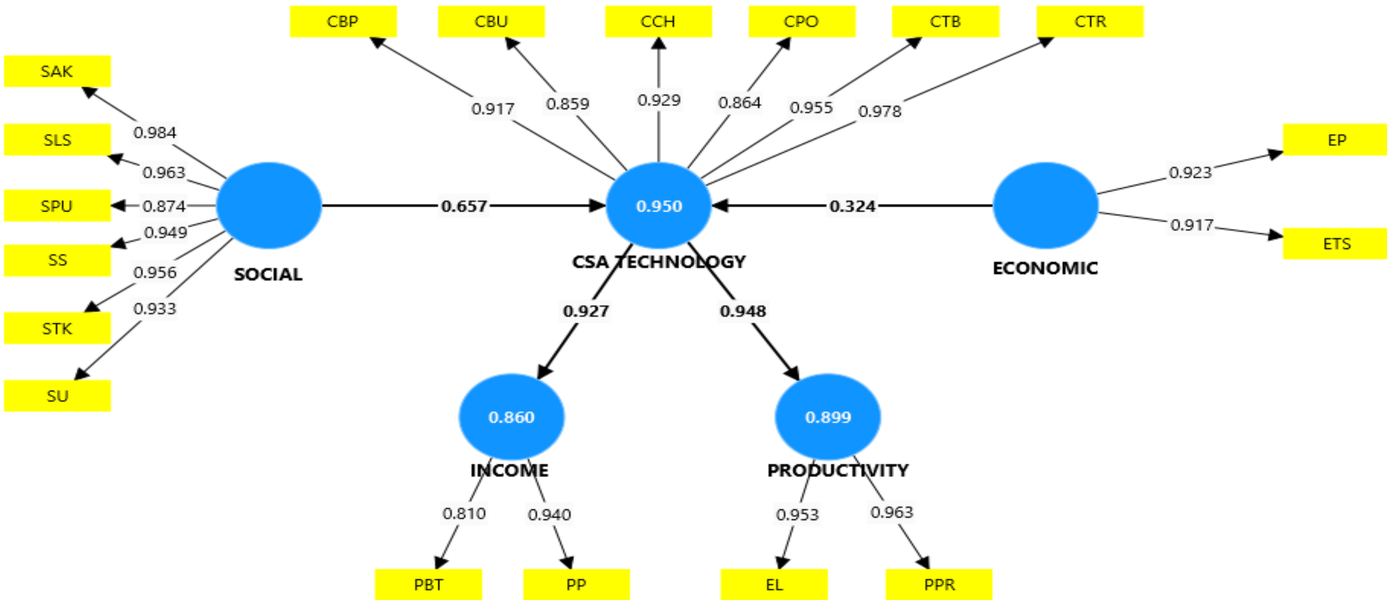

Figure 2. Path analysis (outer model)

This model specifically illustrates the causal relationships between latent variables, both endogenous and exogenous, as presented in Figure 2, along with the associated indicators or measurements for each variable. Outer model testing is conducted to assess the reliability and validity of the indicators employed.

3.6 Results of confirmatory factor analysis (CFA)

Based on the results of the outer loading analysis presented in Table 10, all indicators for each construct exhibit outer loading values above 0.70, indicating that the criteria for convergent validity have been met. This finding demonstrates that all indicators consistently and significantly represent their respective latent constructs. The CSA Technology construct comprises six indicators with outer loading values ranging from 0.859 to 0.978, suggesting a very strong contribution of the indicators in explaining the construct. Similarly, the Productivity construct, measured by Land Area (EL) and Production (PPR), shows high validity, with outer loading values of 0.953 and 0.963, respectively. The Economic construct is represented by the Income (EP) and Side Income (ETS) indicators, with outer loading values of 0.923 and 0.917, respectively. The Income construct is measured by Total Cost (PBT) and Revenue (PP), with outer loading values of 0.810 and 0.940, respectively; although Total Cost (PBT) has the lowest value, it remains within the acceptable validity threshold. Meanwhile, the Social construct is represented by seven indicators with outer loading values ranging from 0.874 to 0.984. Among these, the Number of Family Members (SAK) and Number of Family Dependents (STK) indicators, with outer loading values of 0.984 and 0.956, respectively, exhibit the highest measurement strength within the construct.

The Cronbach's alpha values for all variables, presented in Table 10, exceed 0.7, which is the minimum threshold indicating good internal reliability. The highest Cronbach's alpha value is observed for the Social construct (0.975), while the lowest is found for the Income construct (0.719); both values remain within acceptable limits. Additionally, the Composite Reliability (CR) values, based on both the rho_a and rho_c estimates, consistently exceed 0.8 across all constructs, further confirming strong internal consistency of the indicators in measuring their respective latent variables. Moreover, the Average Variance Extracted (AVE) values for all constructs are above the minimum acceptable threshold of 0.5, with the highest AVE observed for the Productivity construct (0.918) and the lowest for the Income construct (0.770). These results indicate that the majority of the variance in the indicators is successfully explained by their respective constructs, thus confirming that convergent validity has been achieved.

Table 10. Measurement model and scale reliability

Variable	Item	Item Description	Outer Loadings	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
CSA Technology	CBP	Pump and biopores system	0.917	0.962	0.965	0.970	0.843
	CBU	Superior variety seedlings	0.859				
	CCH	Combine harvester	0.929				
	CPO	Organic fertilization	0.864				
	CTB	Tabela system	0.955				
	CTR	Tractor	0.978				
Social	SAK	Number of family members	0.984	0.975	0.977	0.980	0.891
	SL	Year of schooling	0.963				
	SPU	Farming experience	0.874				
	SS	Tribe	0.949				
	STK	Number of dependents family	0.956				
	SU	Age	0.933				
Economic	EP	Income	0.923	0.819	0.820	0.917	0.846
	ETS	Side income	0.917				
Income	PBT	Total cost	0.810	0.719	0.868	0.869	0.770
	PP	Receipt	0.940				
Productivity	EL	Land area	0.953	0.911	0.919	0.957	0.918
	PPR	Production	0.963				

3.7 Results of SEM

The analysis results presented in Table 11 indicate that the relationship between the CSA Technology variable and income has a path coefficient of 0.927, with a t-statistic of 190.377 and a p-value of 0.000. This result demonstrates that the relationship is highly statistically significant at the 0.05 significance level. Similarly, the relationship between CSA Technology and productivity also shows a highly significant effect, with a path coefficient of 0.948, a *t-statistic* of 93.883, and a *p-value* of 0.000. These findings suggest that CSA Technology has a strong direct influence on both income and productivity. In contrast, the relationship between Economic factors and CSA Technology shows a path coefficient of 0.324, a t-statistic of 1.606, and a p-value of 0.108. Since the p-value exceeds 0.05, this relationship is not statistically significant, indicating that economic factors do not directly affect the adoption of CSA Technology within this model. Conversely, the relationship between Social factors and CSA Technology is significant, with a path coefficient of 0.657, a t-statistic of 3.284, and a p-value of 0.001, suggesting that social factors play a crucial role in promoting CSA Technology adoption. Overall, these results confirm that CSA Technology is a key variable strongly influencing outcomes such as income and productivity, with social factors also playing a significant supporting role.

Table 11. Assessment results of SEM

Path	Path Coefficient	Mean	Standard Deviation	*t* Statistics	*P* Values
CSA TECHNOLOGY->INCOME	0.927	0.929	0.005	190.377	0.000
CSA TECHNOLOGY->PRODUCTIVITY	0.948	0.948	0.010	93.883	0.000
ECONOMIC->CSA TECHNOLOGY	0.324	0.342	0.202	1.606	0.108
SOCIAL->CSA TECHNOLOGY	0.657	0.639	0.200	3.284	0.001

3.8 Socio-economic factors of CSA technology adoption

This finding suggests that the social factors, which consist of four indicators—age, years of schooling [30, 31], farming experience [32, 33], and the number of family dependents [34], influence farmers' decisions to adopt CSA technology in response to climate challenges in Telang Makmur Village. For example, farmers with more years of formal education tend to have higher levels of knowledge and understanding, making it easier for them to comprehend new technologies and accept innovations that contribute to the sustainability of their agricultural practices.

The economic factors examined in this study include cultivation area and side income. The results suggest that these economic variables do not significantly influence farmers' decisions to adopt CSA technology on their farms in Telang Makmur Village. However, when analyzed individually, the land area indicator appears to have a potential influence on farmers' decisions to adopt CSA technology. Farmers with larger land areas often require technological assistance to support and streamline their agricultural processes, which aligns with previous research [35]. Despite this, the overall influence of economic factors on CSA adoption was found to be statistically insignificant in this study [36, 37]. Farmers' reluctance to adopt new technologies, despite potential long-term benefits, is often rooted in their focus on short-term economic security and the proven profitability of traditional practices. This hesitance is compounded by perceived risks and indirect profitability associated with new technologies. The research papers provided offer insights into the factors influencing this reluctance and suggest strategies to encourage the adoption of innovative agricultural practices in line with [38, 39]. Even when economic factors allow, farmers with lower or more stable incomes tend to be more cautious in adopting new technologies due to fear of the risk of failure. They feel that changing their farming methods risks the sustainability of their farming business, so they prefer to stick with proven methods even though they have the economic capacity [40, 41].

3.9 The Impact of CSA technology on income

The technology indicators utilized by farmers include tractors, superior variety seeds [42], tabela system, organic fertilization, pump and biopore systems [43], and combine harvesters. These technologies have been shown to contribute to increased farmer income in Telang Makmur Village, consistent with previous research [44-46]. By adopting these technologies, farmers can save time throughout various stages of the agricultural process, which enhances efficiency. In addition, they can increase production yields. For example, the use of superior variety seeds, which are of high quality, enables plants to grow optimally and withstand pests and weather disturbances. Combine harvesters are also employed during the harvesting process to minimize losses due to scattered grain, thereby reducing post-harvest losses. These findings align with previous studies [47, 48]. Overall, the implementation of these technologies positively impacts farmers' income, as improved grain quality and higher production volumes lead to better selling prices and, consequently, increased income.

3.10 The impact of CSA technology on productivity

The CSA technologies adopted by farmers include tractors, superior variety seeds, tablea system, organic fertilization, pump and biopore systems, and combine harvesters. These technologies contribute to increasing the productivity of rice farmers in Telang Makmur Village. Several examples illustrate the effects of these technologies. The use of superior seeds increases yields, as the seeds are more resilient to external disturbances, which aligns with the findings of previous research [49]. To maintain soil fertility and ensure adequate water supply during the dry season, farmers can utilize pump technology to draw water from the river. For land preparation, tractors are employed to save both time and labor costs. Additionally, the use of combine harvesters during the harvesting process helps minimize losses due to scattered grain.

4. CONCLUSION

The adoption of CSA technologies in Telang Makmur Village has demonstrated a significant positive impact on farmers' income and productivity. This finding aligns with the core objectives of CSA, which seek to sustainably increase agricultural productivity, enhance resilience to climate change, and reduce greenhouse gas emissions. Social factors, including the number of family members, years of schooling, farming experience, ethnicity, number of dependents, and age, were found to positively influence the level of CSA technology adoption. In contrast, economic factors such as income did not show a significant effect, suggesting that social motivations are more influential in driving adoption at the local level. Based on these results, the study recommends enhanced socialization, extension services, and technical training on CSA practices to strengthen farmers' adaptive capacity and raise community-level awareness of CSA benefits. Additionally, subsidies, incentives, and technological support are necessary to overcome barriers to adoption, particularly during the early stages of implementation. Further research is also needed to assess the long-term impacts of CSA adoption on food security, the sustainability of agricultural ecosystems, and the overall well-being of farmers.

Due to the limitation of this research, the future research could be directed toward several areas, including comparative studies across different farm typologies and longitudinal tracking of the impacts of CSA adoption.

REFERENCES

[1] Hidayah, R.F., Ghulamahdi, M., Lubis, I. (2024). Effect of ameliorant and actinobacteria on growth and production of soybean (Glycine max (L.(Merr)) with saturated soil culture and tidal land. Buletin Agrohorti, 12(2): 246-256. https://doi.org/10.29244/agrob.v12i2.54531

[2] Gribaldi, G., Nurlaili, N., Effendy, I. (2020) Harvest time management and fertilization of main plant nitrogen to the growth and yield of ratoon rice in tidal swampland: pengaturan waktu panen dan pemupukan nitrogen tanaman utama terhadap pertumbuhan dan hasil ratun padi pada lahan pasang surut. Agrosainstek: Jurnal Ilmu dan Teknologi Pertanian, 4(2): 121-128. https://doi.org/10.33019/agrosainstek.v4i2.131

[3] Kazemi Garajeh, M., Akbari, R., Aghaei Chaleshtori, S., Shenavaei Abbasi, M., Tramutoli, V., Lim, S., Sadeqi, A. (2024). A comprehensive assessment of climate change and anthropogenic effects on surface water resources in the Lake Urmia Basin, Iran. Remote Sensing, 16(11): 1960. https://doi.org/10.3390/rs16111960

[4] Asresu, A.T., Furlan, E., Horneman, F., Zennaro, F., Nguyen, N.D., Torresan, S., Critto, A., Marcomini, A. (2025). A systematic review of climate change impacts on water quality in transitional environments from a multi-hazard perspective. Estuarine, Coastal and Shelf Science, 109194. https://doi.org/10.1016/j.ecss.2025.109194

[5] Mathew, J., Echoh, D.U.A., Ibrahim, M.H. (2025). Paddy farmers' awareness and knowledge of agroforestry practices in Siburan, Sarawak. Urban Agriculture & Regional Food Systems, 10(1): e70011. https://doi.org/10.1002/uar2.70011

[6] Song, S., Goh, J.C., Tan, H.T. (2021). Is food security an illusion for cities? A system dynamics approach to assess disturbance in the urban food supply chain during pandemics. Agricultural Systems, 189: 103045. https://doi.org/10.1016/j.agsy.2020.103045

[7] Van Huong, N., Nguyet, B.T.M., Van Hung, H., Duc, H.M., Van Chuong, N., Tri, D.M., Van Hien, P. (2022). Economic impact of climate change on agriculture: A case of Vietnam. AgBioForum, 24(1): 1-12.

[8] De Pinto, A., Cenacchi, N., Kwon, H.Y., Koo, J., Dunston, S. (2020). Climate smart agriculture and global food-crop production. PloS One, 15(4): e0231764. https://doi.org/10.1371/journal.pone.0231764

[9] Li, W.Q., Han, X.X., Lin, Z.B., Rahman, A. (2024). Enhanced pest and disease detection in agriculture using deep learning-enabled drones. Acadlore Transactions on AI and Machine Learning, 3(1): 1-10. https://doi.org/10.56578/ataiml030101
[10] Okolie, C.C., Danso-Abbeam, G., Groupson-Paul, O., Ogundeji, A.A. (2022). Climate-Smart agriculture amidst climate change to enhance agricultural production: A bibliometric analysis. Land, 12(1): 50. https://doi.org/10.3390/land12010050
[11] Li, L., Awada, T., Shi, Y., Jin, V.L., Kaiser, M. (2025). Global greenhouse gas emissions from agriculture: Pathways to sustainable reductions. Global Change Biology, 31(1): e70015. https://doi.org/10.1111/gcb.70015
[12] Balo, S., Mahata, D. (2022). A review of climate-smart agriculture is a new approach to farming system. International Journal of Environment and Climate Change, 12(1): 2682-2692. https://doi.org/10.9734/ijecc/2022/v12i1131256
[13] Ngenoh, E., Kurgat, B.K., Bett, H.K., Kebede, S.W., Bokelmann, W. (2019). Determinants of the competitiveness of smallholder African indigenous vegetable farmers in high-value agro-food chains in Kenya: A multivariate probit regression analysis. Agricultural and Food Economics, 7: 1-17. https://doi.org/10.1186/s40100-019-0122-z
[14] Tadesse, B., Tilahun, Y., Bekele, T., Mekonen, G. (2021). Assessment of challenges of crop production and marketing in Bench-Sheko, Kaffa, Sheka, and West-Omo zones of southwest Ethiopia. Heliyon, 7(6): e07319. https://doi.org/10.1016/j.heliyon.2021.e07319
[15] Segnon, A.C., Zougmoré, R.B., Green, R., Ali, Z., Carr, T.W., Houessionon, P., M'boob, S., Scheelbeek, P.F. (2022). Climate change adaptation options to inform planning of agriculture and food systems in The Gambia: A systematic approach for stocktaking. Frontiers in Sustainable Food Systems, 6: 834867. https://doi.org/10.3389/fsufs.2022.834867
[16] Kurgat, B.K., Lamanna, C., Kimaro, A., Namoi, N., Manda, L., Rosenstock, T.S. (2020). Adoption of climate-smart agriculture technologies in Tanzania. Frontiers in Sustainable Food Systems, 4: 55. https://doi.org/10.3389/fsufs.2020.00055
[17] Amadu, F.O., McNamara, P.E., Miller, D.C. (2020). Understanding the adoption of climate-smart agriculture: A farm-level typology with empirical evidence from southern Malawi. World Development, 126: 104692. https://doi.org/10.1016/j.worlddev.2019.104692
[18] Zizinga, A., Kangalawe, R.Y., Ainslie, A., Tenywa, M.M., Majaliwa, J., Saronga, N.J., Amoako, E.E. (2017). Analysis of farmer’s choices for climate change adaptation practices in South-Western Uganda, 1980-2009. Climate, 5(4): 89. https://doi.org/10.3390/cli5040089
[19] Teklu, A., Simane, B., Bezabih, M. (2023). Multiple adoption of climate-smart agriculture innovation for agricultural sustainability: Empirical evidence from the Upper Blue Nile Highlands of Ethiopia. Climate Risk Management, 39: 100477. https://doi.org/10.1016/j.crm.2023.100477
[20] Martinez, J., Nam, C.C., Bell, M.M. (2020). On the contributions of incipient vortex circulation and environmental moisture to tropical cyclone expansion. Journal of Geophysical Research: Atmospheres, 125(21): e2020JD033324. https://doi.org/10.1029/2020JD033324
[21] Liu, Z., Ban, J., Hong, J.S., Kuo, Y.H. (2020). Multi-resolution incremental 4D-Var for WRF: Implementation and application at convective scale. Quarterly Journal of the Royal Meteorological Society, 146(733): 3661-3674. https://doi.org/10.1002/qj.3865
[22] Wang, D., Lin, Y., Chavas, D.R. (2022). Tropical cyclone potential size. Journal of the Atmospheric Sciences, 79(11): 3001-3025. https://doi.org/10.1175/JAS-D-21-0325.1
[23] Im, W., Khalid, S. (2020). Molecular simulations of gram-negative bacterial membranes come of age. Annual Review of Physical Chemistry, 71(1): 171-188. https://doi.org/10.1146/annurev-physchem-103019-033434
[24] Frey, M.E., Petersen, H.C., Gerke, O. (2020). Nonparametric limits of agreement for small to moderate sample sizes: A simulation study. Stats, 3(3): 343-355. https://doi.org/10.3390/stats3030022
[25] Khan, G.F., Sarstedt, M., Shiau, W.L., Hair, J.F., Ringle, C.M., Fritze, M.P. (2019). Methodological research on partial least squares structural equation modeling (PLS-SEM) An analysis based on social network approaches. Internet Research, 29(3): 407-429. https://doi.org/10.1108/IntR-12-2017-0509
[26] Benitez, J., Henseler, J., Castillo, A., Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. Information & Management, 57(2): 103168. https://doi.org/10.1016/j.im.2019.05.003
[27] Ayalew, H., Chamberlin, J., Newman, C., Abay, K.A., Kosmowski, F., Sida, T. (2024). Revisiting the size-productivity relationship with imperfect measures of production and plot size. American Journal of Agricultural Economics, 106(2): 595-619. https://doi.org/10.1111/ajae.12417
[28] Villoria, N. (2019). Consequences of agricultural total factor productivity growth for the sustainability of global farming: Accounting for direct and indirect land use effects. Environmental Research Letters, 14(12): 125002. https://doi.org/10.1088/1748-9326/ab4f57
[29] Yang, L., Wang, J., Feng, Y., Wu, Q. (2022). The impact of the regional differentiation of land supply on total factor productivity in China: From the perspective of total factor productivity decomposition. Land, 11(10): 1859. https://doi.org/10.3390/land11101859
[30] Musafiri, C.M., Macharia, J.M., Ng'etich, O.K., Kiboi, M.N., Okeyo, J., Shisanya, C.A., Okwuosa, E.A., Mugendi, D.N., Ngetich, F.K. (2020). Farming systems’ typologies analysis to inform agricultural greenhouse gas emissions potential from smallholder rain-fed farms in Kenya. Scientific African, 8: e00458. https://doi.org/10.1016/j.sciaf.2020.e00458
[31] Yogarajah, V., Weerasooriya, S.A. (2020). Associated farm and farmer-specific factors for climate-smart agriculture adaptation in the dry zone: A case from vavuniya, sri lanka. Sri Lankan Journal of Agricultural Economics, 21(1): 69. https://doi.org/10.4038/sjae.v21i1.4642
[32] Mujeyi, A., Mudhara, M., Mutenje, M. (2021). The impact of climate smart agriculture on household welfare

in smallholder integrated crop-livestock farming systems: evidence from Zimbabwe. Agriculture & Food Security, 10: 1-15. https://doi.org/10.1186/s40066-020-00277-3

[33] Kangogo, D., Dentoni, D., Bijman, J. (2021). Adoption of climate-smart agriculture among smallholder farmers: Does farmer entrepreneurship matter? Land Use Policy, 109: 105666. https://doi.org/10.1016/j.landusepol.2021.105666

[34] Zheng, H., Ma, J., Yao, Z., Hu, F. (2022). How does social embeddedness affect farmers' adoption behavior of low-carbon agricultural technology? Evidence from Jiangsu province, China. Frontiers in Environmental Science, 10: 909803. https://doi.org/10.3389/fenvs.2022.909803

[35] Ajmal, T., Mohammed, F., Goodchild, M.S., Sudarsanan, J., Halse, S. (2024). Mitigating the impact of harmful algal blooms on aquaculture using technological interventions: Case study on a South African farm. Sustainability, 16(9): 3650. https://doi.org/10.3390/su16093650

[36] Xie, H., Huang, Y. (2021). Influencing factors of farmers' adoption of pro-environmental agricultural technologies in China: Meta-analysis. Land Use Policy, 109: 105622. https://doi.org/10.1016/j.landusepol.2021.105622

[37] Vasan, M., Yoganandan, G. (2024). Does the belief of farmers on land as God influence the adoption of smart farming technologies? Benchmarking: An International Journal, 31(7): 2338-2359. https://doi.org/10.1108/BIJ-10-2022-0645

[38] Yashabh, J., Prakash, Singh, G. (2024). Agronomy practices of rural farmers of SAS district of Punjab. International Journal of Research in Agronomy, 7(11S): 194-199. https://doi.org/10.33545/2618060x.2024.v7.i11sc.1967

[39] Nazarov, A., Kulikova, E., Molokova, E. (2024). Economic security through technological advancements in agriculture: A pathway to sustainable agro-industrial growth. In BIO Web of Conferences. EDP Sciences, 121: 02012. https://doi.org/10.1051/bioconf/202412102012

[40] Masere, T.P., Worth, S.H. (2022). Factors influencing adoption, innovation of new technology and decision-making by small-scale resource constrained farmers: The perspective of farmers in lower Gweru, Zimbabwe. African Journal of Food, Agriculture, Nutrition and Development, 22(3): 20013-20035. https://doi.org/10.18697/ajfand.108.20960

[41] Patil, V., Veettil, P.C. (2024). Farmers' risk attitude, agricultural technology adoption and impacts in Eastern India. Agriculture & Food Security, 13(1): 50. https://doi.org/10.1186/s40066-024-00497-x

[42] Mutenje, M.J., Farnworth, C.R., Stirling, C., Thierfelder, C., Mupangwa, W., Nyagumbo, I. (2019). A cost-benefit analysis of climate-smart agriculture options in Southern Africa: Balancing gender and technology. Ecological Economics, 163: 126-137. https://doi.org/10.1016/j.ecolecon.2019.05.013

[43] Imran, M.A., Ali, A., Ashfaq, M., Hassan, S., Culas, R., Ma, C. (2019). Impact of climate smart agriculture (CSA) through sustainable irrigation management on Resource use efficiency: A sustainable production alternative for cotton. Land Use Policy, 88: 104113. https://doi.org/10.1016/j.landusepol.2019.104113

[44] Nyang'au, J.O., Mohamed, J.H., Mango, N., Makate, C., Wangeci, A.N. (2021). Smallholder farmers' perception of climate change and adoption of climate smart agriculture practices in Masaba South Sub-county, Kisii, Kenya. Heliyon, 7(4): e06789. https://doi.org/10.1016/j.heliyon.2021.e06789

[45] Kassa, B.A., Abdi, A.T. (2022). Factors influencing the adoption of climate-smart agricultural practice by small-scale farming households in Wondo Genet, Southern Ethiopia. Sage Open, 12(3): 21582440221121604. https://doi.org/10.1177/21582440221121604

[46] Ngigi, M.W., Muange, E.N. (2022). Access to climate information services and climate-smart agriculture in Kenya: A gender-based analysis. Climatic Change, 174(3): 21. https://doi.org/10.1007/s10584-022-03445-5

[47] Malanon, H.G., Dela Cruz, R.S. (2023). Effects of rice combine harvester on postproduction losses and production costs: The case of Luzon, Philippines. Asian Journal of Agriculture and Food Sciences, 10(6). https://doi.org/10.24203/ajafs.v10i6.7100

[48] Wang, J.Z., Fang, X.F., Wang, F.Z., Liu, Y.C., Zhao, B. (2023). Study on the loss control system of wheat combine harvester. INMATEH-Agricultural Engineering, 69(1): 471-480. https://doi.org/10.35633/inmateh-69-44

[49] Ikhwan, R., Ar-Rozi, A.M., Suryadi, M., Ashari, A. (2024). Rice farmers' participation in the use of improved technology and its impact on productivity and income. BIO Web of Conferences, 119: 03004. https://doi.org/10.1051/bioconf/202411903004