Socio-economic Factors Influencing Adoption of Climate Smart Agriculture Among Maize Smallholder Farmers in Kalambo District, Tanzania

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https://dx.doi.org/10.4314/ajasss.v7i2.8

Abstract
Climate Smart Agriculture (CSA) has the potential to improve production, reduce food security and reduce the impacts of climate change. However, the adoption of CSA in maize production is still very low in Kalambo District. The study was conducted to assess socio-economic determinants of CSA adoption by smallholder maize farmers. Specifically, the study was conducted to assess the socio-economic characteristics of smallholder maize farmers and analyse socio-economic determinants of smallholder maize farmers' adoption of CSA. The study employed a cross-sectional research design, and multistage sampling technique was employed to select Rukwa Region, Kalambo district, wards and villages. A sample size of 395 respondents was determined by using Yamane's formula, and a household survey questionnaire was used to collect data using a household questionnaire. The study adopted quantitative techniques whereby data were analysed descriptively and inferentially; for the latter, binary logistic regression was done. The results indicated that four variables, education, household size, access to information about CSA, and maize farming experience, out of ten variables which were entered in the model, were significant predictors of adoption of CSA by smallholder maize farmers ($p < 0.05$). It is concluded that the four socio-economic factors are the ones that mainly influence smallholder maize farmers to adopt or not to adopt CSA. It is recommended that, in order to increase the number of smallholder farmers adopting CSA, extension officers should create awareness among smallholder maize farmers about maize CSA in order for them to make an informed decision to adopt it. Also, smallholder maize farmers should be trained on CSA technologies for maize farming as education has been proven to enhance their chances of adopting CSA.

Keywords: *CSA, Adoption, Innovation*

1.0 INTRODUCTION

The agricultural sector is the engine of economic growth in most developing countries as it contributes to GDP, employment, and production of raw materials for the industrial sector, among other things. In Tanzania, the sector accounts for 29.1% of the GDP, 65.5% of employment, 65% of raw materials to the industrial sector, and 30% of export earnings (URT, 2021). Despite the importance of agriculture to economic growth, its growth rate during the early 2020s in Tanzania failed to achieve the national target of 10%; hence, poverty reduction is also lagging behind set targets (World Bank, 2019). The slow growth of the agricultural sector is partly due to the fact that smallholder farmers, who make a large population of farmers mainly depend on rain for their agricultural production which is prone to various impacts of climate change, resulting in low agricultural production (Senyolo, 2020).

Although climate change is a major threat to agricultural production, economic growth, and food security in developing countries, Climate-Smart Agriculture (CSA) has been pointed out as a critical solution in addressing climate change impacts (Shani *et al.*, 2024). According to Machete *et al.* (2024), CSA is a strategy to support agricultural systems globally while enhancing agricultural resilience to climate change to mitigate its adverse effects and guarantee global food security through creative financing policies and practices. Previous studies related to this one have indicated that CSA reduces challenges and risks imposed by climate change (Harvey *et al.*, 2023). In South Africa, studies by Senyolo *et al*. (2021) indicated that CSA contributed to increased agricultural productivity, food security, and income due to adaptation and enhanced resilience of agriculture to climate change and reduced GHG emissions. Empirical literature indicates that, in Malawi, six types of CSA practices were introduced through an agricultural sector-wide approach support programme in twelve districts (Shani *et al*., 2024). These initiatives increased production by 20%. Other previous studies in Kenya indicated that CSA practices contributed to increased income generation activities as well as carbon sequestration (Wanjira *et al.*, 2022).

Similarly, Studies by Makate et al. (2018) and Kimaro *et al*. (2019) reported that, in Tanzania and Zimbabwe, crop diversity improved crop productivity, income from crops, and household dietary diversity scores, and also increased crop resilience and biodiversity on farm, improved soil fertility, and controlled pests and diseases. In Ethiopia, adoption of CSA technologies resulted in increased agricultural production by 22%, compared to non-adopters (Negera *et al*., 2022). Furthermore, studies by Kimaro (2019) showed that adoption of CSA improved maize production, increased resilience/adaptation to climate change, and offered mitigation benefits in Tanzania. The empirical evidence reviewed vividly indicates that CSA adoption can contribute to improving agricultural production and productivity. However, its adoption is low.

Despite the contribution of CSA to improving food security and increasing maize productivity in Kalambo District, adoption of CSA for maize production, especially “FUGA” innovation, is still very low (Kimaro *et al*., 2019). Empirical evidence indicates that several factors contribute to CSA adoption or non-adoption in Sub-Saharan Africa. The factors influencing adoption of CSA are diverse include household characteristics, farming systems, CSA technologies, household asset base, institutional factors, farm characteristics, access to information, access to credit, and cultural beliefs (Senyolo *et al*., 2021). This suggests that complex factors, which are context-specific as well as CSA technologies adopted, contribute to the adoption of CSA. Therefore, the study aimed to assess the socio-economic determinants of CSA among maize smallholder farmers in Kalambo District.

The paper would be useful to policymakers and other stakeholders interested in devising strategies for reducing climate change impacts among smallholder maize farmers. The socio-economic factors influencing the adoption of CSA are also paramount and must be studied to increase the number of maize farming households using CSA. The paper was guided by the “Technology Diffusion Theory,” which postulates that farmers with more education and large land size will have more knowledge on CSA and are more likely to adopt it rapidly (Khumalo *et al*., 2025). The theory postulates that adoption of CSA is influenced by many factors, including access to extension services, whereby the more the contacts between farmers and extension officers, the more the farmers get information, which increases their chances of adopting CSA for maize production. Likewise, maize farmers’ characteristics such as income, education, age, sex, marital status, household size, distance to market place, access to credit, maize farming experience, membership to self-help groups, and access to credit may influence CSA adoption (Asante *et al.*, 2024).

2.0 METHODOLOGY

The study was conducted in Kalambo District, Rukwa Region. The district was selected because it is among the four districts of Rukwa Region that rank high in terms of quantities of maize produced. The district was also selected because it has a higher number of smallholder maize farmers who have adopted Climate Smart Agriculture (CSA) technologies such as “FUGA” innovation (conservation tillage, cover cropping, and mulching during the dry season) compared to other districts in the region which have a low adoption rate. The study encompassed five wards, including Katazi, Mwimbi, Lyowa, Matai, and Kisumba. Ten villages were selected, including Kafukula, Ninga, Kateka, Matai, Singiwe, Chalaminwe, Majengo, Mwimbi, Kisumba, and Kasote. The villages were selected due to their high rank in terms of the number of smallholder farmers who had adopted CSA (FUGA) for maize production compared to other Villages in the five Wards.

The study employed a cross-sectional design with a quantitative approach in collecting data at a single point in time, allowing for simultaneous understanding and comparison of various population variables. A sample size of 395 smallholder maize farmers out of the population of 30,613 smallholder maize farmers was obtained by using Yamane's (1967) formula. The formula is as follows: $n = \mathrm{N}/(1 + (Ne^2)$ (Yamane, 1967),
where $\boldsymbol{n}$ = the sample size; $\boldsymbol{N}$ = the target population size and $\boldsymbol{e}$ = the level of precision, which is 0.05 at the 95% confidence interval. Therefore, $\mathrm{n} = 394.84 \approx \mathbf{395}$ maize smallholder farmers, i.e. $30{,}613/[1 + (30{,}613 * 0.05 * 0.05) = \frac{30{,}613}{77.5325} = 394.84087 \approx 395.$

The study employed quantitative data collection techniques using a structured questionnaire distributed to 395 respondents. The household survey questionnaire was first pre-tested and revised accordingly before actual data collection. Descriptive statistics (mean, standard deviation, frequency, and percentage) and inferential statistics were computed as part of data analysis. In inferential statistics, a binary logistic regression model was employed to analyse factors influencing smallholder maize farmers' adoption of CSA. The model was chosen due to the nature of the dependent variable (adoption of CSA), which was dichotomous. The binary logistic model was specified as follows:
$Logit\ (p_i) = log\ (p_i/1\text{-}p_i) = b_0 + b_1x_1 + b_2x_2 + \ldots + b_{12}x_{12} + \mu_i$ (Agresti and Finlay, 2009)

Where:
Logit (pi) = ln (odds (event), that is, the natural log of the odds of an event occurring
Pi = prob (event), that is, the probability that respondents will adopt CSA in maize farming.
$1\text{-}p_i$ = prob (non-event), that is, the probability that the respondents will not adopt CSA in maize farming.
b_0 = constant of the equation,
b_1 *to* b_{10} = coefficients of the predictor variables,
k = number of independent variables,
x_1 *to* x_{10} = independent variables entered in the model, which are specified in Table 1.

Table 1: Measurement of Variable entered in the Binary Logistic Regression Model

Variable Definition	Unit of Measurement	Assumed Influence
X_1 = Age of the respondent	Years since birth	+
X_2 = Sex of the respondent	1 if male headed household, 0 if otherwise)	+
X_3 =Education of the respondent	Years of schooling (measured in years)	+
X_4 = Land size	Land size (measured in acres)	+
X_5 = Household size	Number of active people in the household	+
X_6 = Knowledge about CSA	1 = Have knowledge and 0 =otherwise	+
X_7 =Agricultural experience	Number of years in farming	+
X_8 = Access to credit	1 = Access, 0 = Otherwise	+
X_9 = Extension services	Frequency of extension contact	+
X_{10} = Marital status	1 if married, 0 if otherwise	+

3.0 RESULTS AND DISCUSSION

3.1 Socio-economic Characteristics of Respondents

The results indicated that 75% of the respondents were male, while 25% were female (Table 2). This suggests that CSA adoption was skewed towards men, as they had high interactions with extension officers. The mean age of the respondents was 35.56 years. This implies that most of the smallholder maize farmers were in the productive age range, which is crucial for the adoption of CSA innovations and technologies, which are sometimes labour-intensive.

Table 2: Households' Socio-economic Characteristics

Variable	Description	Mean or %
Sex	Male	75
	Female	25
Age	In years	35.56
Education	Years of schooling	7.89
Information about CSA	Yes	54
	No	46
Group membership	Yes	45
	No	55
Land size	In acres	11
Maize farming experience	In years	24
Access to extension services	Number of contacts with extension officers	5
Household size		5

The mean years of schooling were 8. This suggests that most smallholder maize farmers were literate enough to make reasonable decisions on CSA adoption. The results further indicate that the respondents had a mean of 5 contacts with extension officers. About 54% of the respondents had information about CSA, and a mean of 11 acres allocated for maize production.

3.2 Determinants of Smallholder Maize Farmers' Adoption of CSA

A binary logistic regression model was used to assess the factors influencing the adoption of CSA in Kalambo District, as indicated in Table 3. The results based on the model indicate that four variables, out of the ten variables that were entered in the model, were significant predictors of adoption of CSA by smallholder maize farmers ($p < 0.05$). Education was the highest predictor among these ten variables at ($p = 0.000$).

In addition to that, the results in Table 3 show that the Hosmer and Lemeshow Test had a Chi-Square statistic of 5.019 ($p = 0.562$). This suggests that the overall model effectively predicted the outcomes, as the Hosmer and Lemeshow test's Chi-square value was not statistically significant, as proposed by Field (2018). The Negelkerke pseudo R^2 statistic, which represents the adjusted Cox and Snell Pseudo R^2, was 0.547, which means that approximately 54.7% of the variability in smallholder maize farmers' adoption of CSA could be accounted for by the ten independent variables entered in the binary logistic model.

Moreover, the overall model exhibited good predictive power, as evidenced by the significant Omnibus Chi-Square statistic ($p = 0.000$). The Wald Statistic value for household age was among the variables entered into the model, registering a value of 17.386 and a significant statistical association at $p \leq 0.005$. Information about CSA followed as the second most influential variable, with a Wald statistic of 13.654 and a significant statistical relationship at $p \leq 0.001$. These findings suggest that information about CSA increases the likelihood of smallholder maize farmers adopting CSA.

Table 3: Socio-economic Determinants of Smallholder Maize Farmers (n=395)

Variables	Coefficient (B)	S.E.	Wald	Sig.	Exp(B)
Household head years of schooling	0.068***	0.025	17.386	0.000	2.067
Household head age	0.282	0.320	3.345	0.11	2.321
Household head sex	-0.006	0.040	0.007	0.641	0.986
Group Membership	-0.329	0.224	0.568	0.431	0.736
Household size	1.534**	0.461	8.728	0.002	0.449
Household Marital Status	0.236	0.231	0.101	0.853	0.978
Household access to extension services	0.523	0.281	2.674	0.102	1.255
Access to information about CSA	0. 351**	0.018	13.654	0.038	1.341
Maize farming experience	0.004**	0.005	6.599	0.0013	0.879
Household land size	0.502	0.102	3.483	0.037	0.781

*Omnibus Tests of Model Coefficients (Chi-square = 135.512; Sig. = 0.000); Hosmer and Lemeshow Test (Chi-square = 5.019, Sig. = 0.562); Cox & Snell R Square = 0.356; Nagelkerke R Square = 0.547; *, ** and *** indicate levels of significance at the 5%, 1%, and 0.1% respectively.*

The results indicate that years of schooling was positive and statistically significant at the ≤ 0.01% level. This implies that, as the number of years in school of smallholder maize farmers increased by one year, the chances of CSA adoption increased by 2.067 times, as shown by the odds ratio that was 2.067. This positive influence of education is because, educational achievements contribute to enabling farmers to acquire the necessary skills and knowledge disseminated by extension officers. These results corroborate those by Alemayehu *et al*. (2024), Asante *et al*. (2024), Machete *et al.* (2024), and Mzingula *et al*. (2024), who reported that levels of adoption of CSA tend to increase with an increase in education level. Surprisingly, the results were inconsistent with previous findings by Pandeya *et al*. (2024), who reported that education level negatively and significantly influenced CSA practices adoption.

Similarly, the agricultural experience of smallholder maize farmers had a positive and significant influence on the chances of CSA adoption at the 5% level. For every year that a farmer gained experience, there was a 0.879 times likelihood that their decision to adopt CSA would increase, as shown by the odds ratio of 0.879. These results suggest that farmers with longer maize farming experience are more aware of climate change and are ready to adopt technologies that will help them reduce the risk posed by climate change. Similar results were reported by Abegunde *et al*. (2020), Negera *et al*. (2022), Olajide *et al*. (2023), and Mbanasor *et al*. (2024). However, Machete *et al*. (2024) reported negative relationship between farmers' farming experience and adoption of CSA in South Africa.

Moreover, access to information about CSA had a positive and statistically significant influence at the level of 5% on the chances of adoption of CSA by smallholder maize farmers. The results show that, when information about CSA increased by one unit, the chances of smallholder farmers adopting CSA increased by 1.341. These results imply that chances of CSA adoption depend on smallholder maize farmers' awareness of respective CSA innovations. These results are in line with those by Serote *et al*. (2021), Machete *et al*. 2024), and Petros *et al*. (2024). The results, surprisingly, differ from those of Shani *et al*. (2024), who reported that information about CSA had a negative significance relationship with adoption of CSA, as farmers were more aware of the risk posed by climate change but reluctant to adopt new technologies.

The coefficient of smallholder maize farmers' household size was found to be positive and statistically significant at the 5% level. This positive effect shows a positive relationship between farmers' household sizes and their chances of adopting CSA. As shown by the odds ratio of 1.534, one additional active member in the household would increase the likelihood of smallholder maize farmers adopting CSA by 1.534 times. These results are consistent with those reported by Mujeyi *et al.* (2021), Petros *et al*. (2024), and Khumalo *et al*. (2025). However, this result is inconsistent with findings of some previous studies, e.g., those reported by Machete *et al*. (2024) and Pandeya *et al*. (2024) who found an inverse relationship between household size and adoption decision among smallholder farmers.

4.0 CONCLUSIONS AND RECOMMENDATIONS

It is concluded that the four socio-economic factors, namely education, household size, access to information about CSA, and maize farming experiences, are the ones that mainly influence smallholder maize farmers to adopt or not to adopt CSA. It is recommended that, in order to increase the number of smallholder farmers adopting CSA, extension officers should create awareness among smallholder maize farmers about CSA in order for them to make an informed decision to adopt it. Also, smallholder maize farmers should be trained on CSA technologies for maize farming, as education has been proven to enhance their chances of adopting CSA.

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