Effects of Climate Smart Agricultural Technologies on Household Food Security in Zanzibar

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ABSTRACT

The reported study sought to determine the factors that influence adoption and effects of Climate Smart Agricultural (CSA) technologies on household food security in Zanzibar. Data was collected using semi-structured questionnaire from a sample of 260 smallholder farmers. The first objective is to determine CSA technologies available; second objective is to determine factors influencing adoption and extent of adoption of CSA technologies and third objective is to assess the effects of CSA technologies on household food security in Zanzibar. The analysis was done using descriptive statistics, Heckman two-step model, and the endogenous switching probit model. Analysis of the average treatment effects was also used. The descriptive analysis showed majority of farmers (57%) were adopters compared to non-adopters (43%). The results also reveal that irrigation infrastructure, system of rice intensification, alternate wetting and drying, and rainwater harvesting are the common practices and technologies used by the majority of farmers. The results reveal that the majority of the households (72%) were food secure, though the average Household Dietary Diversity Score (HDDS) was 6.77. The Heckman two-step regression results showed that the factors that significantly influence the adoption of CSAs are age, education level, land size, farming experience, land tenure, farm income, rice yield and credit. The endogenous switching model analysis showed that the adopter farmers are more likely to be food secure compared to non-adopters. Further, the results revealed that five variables (marital status, household size, land size, rice output and education) were adequate to explain the observed increase in household food security. Although not significant, results reveal that female-headed households are more likely to fall into food insecurity. Policies that increase availability and adoptability of CSA technologies can ensure that farmers increase yield, farm income, and enhance household food security.

1. INTRODUCTION

1.1 Background

Achieving food security is the second Sustainable Development Goal (SDGs) of the United Nations and one of the objectives of the Zanzibar government (RGoZ, 2008a). It is a long-lasting and persisting problem faced by the poor population the majority of which are smallholder farmers in Zanzibar. About 9.3 percent of Zanzibar population lives below food poverty line. The problem is common in rural areas where 76.5 percent of the population is extremely poor and unable to meet their basic consumption need (RGoZ, 2020b). Majority of them are smallholder farmers with agriculture as the major economic activity.

Zanzibar economy depends on climate sensitive activities, particularly agriculture, tourism and fishing. The economy of Zanzibar and the livelihoods of the people are therefore very dependent on weather and the variability of climate. The islands are also affected by the regional patterns of extreme weather, which lead to major events such as floods, droughts and storms. Over the last decade, Zanzibar has experienced an extreme climate variability, particularly temperature rising, complex change of rainfall and increasing wind speed. This led to saltwater intrusion in agricultural land, prolonged dry spell and floods, which make the land used for agricultural activities to be unproductive (Omar, 2019) and that, smallholder farmers are vulnerable to climate shocks (Tesfaye *et al.,* 2017).

On the other hand, the scarcity of production land is a central issue in Zanzibar. The total usable land available to smallholder farmers is 186,240 ha. About 49% agricultural households are reported to have insufficient land with average land holding size of 0.25 ha to 2.7 ha in Zanzibar (URT, 2021). Therefore, there is a need to intensify agricultural production and productivity.

One of the goals of any agricultural development programme or strategy is to improve the welfare of rural households. This goal can be achieved by, among other things, increasing agricultural productivity of the farmers. This is possible if the appropriate modern agricultural technologies or innovation are properly developed, transferred and disseminated to farmers to extend and intensify their production (Ayele and Admassie, 2009).

It is widely acknowledged that agricultural technologies play a fundamental role in fostering a Green Revolution, which significantly impact agriculture productivity improvement and poverty reduction (Nakano and Kajisa, 2012). It is believed that the adoption of climate-smart agricultural (CSA) technologies could have a positive impact on the livelihood of poor farmers (Tesfaye *et al.,* 2017). However, little is known about how far CSA technologies have diffused and what their impact is on productivity and household food security in Africa in general, and Zanzibar in particular. While the farming communities are responding to these challenges, there is an intensive need for scaling-up adoption of appropriate interventions that can help increase crop yields and resilience to climate change (Tesfaye *et al.,* 2017).

In Zanzibar, agriculture is important for achieving the development goals of alleviating poverty and improving food security. The agriculture sector employs over 40% of the total population (RGoZ, 2020c) and mostly represents smallholder farmers. About 51.8 percent of the household engage in agriculture, which sustains the majority of the population through both cash income as well as food security (WKUMM, 2022). Stimulating agricultural growth, and, thus, improving food security, primarily depends on the adoption of improved agricultural technologies (Khonje et al, 2015), including climate smart technologies.

Rice is the staple food in Zanzibar, and so improving rice production is one of the most important strategies for improving household food security and welfare in Zanzibar. At present, the annual rice production is 30,353 tons while the area under rice cultivation is 28,172.4 (RGoZ, 2022d), which indicates low rice intensification. However, improved technologies developed by the national and international agricultural research centres very often fail to get adopted by smallholder farmers (Morris et al., 1999), partly because farmers have different needs. They require diverse technologies with multiple traits. This depends on technology traits or attributes, which are the performance characteristics that include both the production tendency and the consumption traits or attributes of the product. That is, farmers encounter difficulties in obtaining smart technologies that meet their specific choices.

At present, between 25% and 34% of households in Zanzibar have used at least one of the climate-smart management practices and technologies on their farms. The adoption level of CSA technologies and practices ranges between 9.7% and 46.7%. However, adoption rates vary by practice. For instance, livestock diversity, crop diversity, application of chemical fertilizers, agroforestry and irrigation are 9.7%, 23.6%, 28.1%, 31.8% and 46.7%, respectively (Kurgat *et al.*, 2020).

1.2 Problem Statement and Justifications

Addressing food security among smallholder farmers in Zanzibar has become a paramount issue in a country where majority of the population depends on climate sensitive activities and largely exposed to food insecurity with a small land holding size average range of between 0.25 ha and 2.7 ha. Food insecurity is due to low agricultural productivity caused by climate change variability, limited agricultural land and low adoption of productivity-enhancing technologies. Climate change has adversely affected agricultural land, making it less productive, ruining crop quality, reducing yield and killing plants.

To overcome the challenges, Climate Smart Agricultural technologies was developed and promoted by Zanzibar Government to increase crops production and productivity, increase income and attain food security among smallholder farmers. However, its impact on these areas is not known and no effort had been made to evaluate the type of CSA technologies available, factors that influence adoption and the extent to which these technologies have been adopted and their effects on food security. At present, several studies have examined only the impact of modern varieties on productivity, income and aggregate welfare measures (Kijima et al., 2008; Acheampong and Owusu, 2015), and that little is known on CSA technologies. Despite the government's efforts to address the issue of food insecurity, the problem remains persistent. This study, therefore, intended to examine the impact of the CSA technologies on households and its implications on food security in Zanzibar.

1.3 Research Questions

(a) What CSA technologies are available in Zanzibar?
(b) What factors influence adoption and the extent of adoption of CSA technologies in Zanzibar?
(c) What are the effects of CSA technologies on household food security in Zanzibar?

1.4 Objectives of the Study

1.4.1 Main objective:

To examine the effects of climate smart agricultural technologies on household food security in Zanzibar

1.4.2 Specific objectives:

(a) To identify the CSA technologies available in Zanzibar,
(b) To determine factors that influence and extent of adoption of CSA technologies, and
(c) To assess the effects of CSA technologies on household food security.

1.5 Significance of the Study

The study is important in the following ways:

(a) It will provide useful information that enables understanding of the appropriate feedback from farmers,
(b) it will help refine the efforts of generation and dissemination of technology,

(c) it will assess the effectiveness of a strategy of technology transfer,

(d) it will strengthen the flow of information between researchers and extension service providers on the one hand, and research and policymakers on the other,

(e) it will generate useful information that will inform policymakers and planners towards formulating appropriate policies and strategies for climate- sensitive technologies for agriculture development to attain food security,

(f) it will be used as a reference for further studies by students, researchers and policy makers, and

(g) it will contribute to documenting the impact of technology generation and promotion.

2. LITERATURE REVIEW

2.1 Climate Smart Agricultural Technologies

Climate-smart agriculture (CSA) can be defined as agriculture that increases productivity, improves resilience, and mitigates climate change (Kurgat *et al.*, 2020). Lipper *et al.*, (2014) define CSA as an approach to agricultural development that aims to address the intertwined challenges of food security and climate change. The approach increases agricultural productivity to support equitable increase in farm incomes, food security, and development; adapting and building resilience of food systems to climate change; and reducing greenhouse (GHG) emissions from agriculture. Interventions ranging from climate information services to field management have the potential to achieve these goals (Kurgat *et al.*, 2020).

The study by (Kurgat *et al.*, 2020) outlines CSAs that includes crop and livestock diversity, irrigation, application of chemical fertilizers, and agroforestry. Likewise, for crops production systems, CSA practices include agroforestry, improved seed varieties (drought resistant and early maturing), cover cropping, in-situ rainwater harvesting, composting, intercropping (mostly with legumes), organic fertiliser, conservation agriculture, crop diversification and irrigation among others. For livestock-based production systems, CSA practices include in-situ fodder conservation, pasture management and water harvesting using small dams and wells. Traditional chicken breeds are usually kept for increasing household resilience, while integrated aquaculture systems are regarded as an effective household food security and alternative income source for many farmers. Some practices require high initial cost and present an opportunity for widespread adoption, while others require high initial capital investment. CSA practices and their expected benefits are also very site-specific. Therefore, scale-out strategies require careful consideration of socio-economic and environmental contexts (World Bank, 2017).

2.2 Factors that Influence Adoption of Agricultural Technologies

It is assumed that farmers weigh the consequences of adopting new innovations against their economic, technical and social feasibility when deciding about the given technology or innovation adoption. They evaluate social values or technical progress that is assumed to reflect the level of economic achievement in terms of incremental benefits of using a new technology. The decision of farmers to adopt or reject a technology at any time is assumed to be attributed to the combined effects of different factors associated with their objectives, opportunities and constraints (Ayele and Admassie2009).

In the study by Kurgat et al (2020), household size had a positive association with livestock diversity, the age of male-headed households less likely to uptake irrigation, while female-headed households were more likely to diversify their crop and livestock production and apply chemical fertilizers. Land ownership was positively associated with crop diversity and agroforestry and negatively associated with livestock diversity. Land size cultivated, access to off-farm income, livestock ownership and holdings positively influenced the diversity of livestock keeping. Households that use hired farm labour were more likely to use chemical fertilizers but avoid irrigating their farms. The study used a multivariate probit (MVP) model to determine factors influencing adoption of Climate-Smart Agriculture Technologies in Tanzania. The study observed only factors influencing adoption and remained mute on the extent of adoption of CSA technologies.

A study that employed Heckman two step model to examine the factors that influence the adoption and extent of adoption of the improved sweet potato varieties (ISVs) in Bungoma County Kenya indicated that education level, farming experience, sweet potato price, extension contact, training contact, group heterogeneity, household size, output, land tenure, number of livestock, group membership and credit amount were significantly found to influence the farmers' decision to adopt the improved sweet potato varieties at different significance levels (Wabwile, 2016). The study focused on ISVs only, which is a smaller portion of the new agricultural technologies, and that does not explain the factors that influence and extent of adoption of other agricultural technologies particularly CSA technologies.

Adoption and use intensity of improved cassava varieties in Zambia was found to be significantly influenced by access to extension services, access to credit, livestock, household size, and number of household members working as casual labourers and those who work on farm. The study suggested that increased access to institutional support services such as extension, credit, and input supply are a major part of efforts aimed at promoting the adoption of modern technologies (Khonje *et al.* 2015).

Adeola (2010) argued that socio-economic factors: education, contact with extension agent, farming experience and farm size were discovered to significantly influence the adoption of soil conservation measures among farmers in Oyo state, Nigeria. The analysis emphasized the need for considering the socio-economic environment of the farmers in designing appropriate soil conservation technologies to promote adoption.

The study (Mustapha, 2012) showed that poor extension services and lack of credit facilities were a major hindrance, while farming experience, educational level and information sources had positive influence on the adoption of improved soya bean production technologies by farmers in Nigeria. The study suggests that agricultural extension services with input support services should adequately be provided in the form of credit facilities among others.

Barungi *et al.,* (2013) determined the factors that influence the incidence and intensity of technology adoption in eastern Uganda. Collected data were analysed using descriptive statistics and double hurdle models. The study results indicated that increase in access to extension services, size of land owned, and diversity of farm tools owned by farmers can increase adoption of new technology.

The reviewed literature revealed unclear and mixed results from empirical analysis. Similar factors portrayed positive influence in one study and negative influence in the other studies.

2.3 Impact of Agricultural Technologies on Income and Food Security

There is scarce evidence of the relationship between the impact of agricultural technology adoption and household welfare in sub-Saharan Africa (Wabwile, 2016).

The study by Kimaro *et al.,* (2019) revealed that diversifying cropping practices, conservation agriculture and agroforestry in Tanzania significantly improved crop productivity, income from crops, and food security indicators, as measured by food consumption scores and household dietary diversity scores.

The study by Radeny *et al.,* (2018) revealed that farmers adopting multiple stress-tolerant crop varieties and improved small ruminant livestock breeds, had access to more types of food and accumulated more household assets than the non-adopting households. The adoption of improved multiple stress-tolerant crop varieties also increased household dietary diversity, increased asset index, and increased household income by more than doubled per adult. The study, therefore, concludes that adoption of crop and livestock-related CSA technologies and practices have a positive and significant impact on food security, asset index and income.

The study by Chidumu (2007) on the impact of OVOP (one village one product) on household food security found that household farm income and food security for OVOP beneficiaries was higher than their counterpart non-beneficiaries. The study recommends the expansion of the OVOP programme to target vulnerable groups.

The study by Wabwile (2016) on effect of improved sweet potato varieties (ISVs) on household food security in Bungoma county, Kenya showed that adoption of ISVs had a positive effect on farmer's household food security. The study used Endogenous Switching Probit Model for analysis. The study recommended strengthening extension services by the government, creating sustainable off-farm activities to diversify farm income and strengthening contractual agreements in marketing to assure farmers constant market for their produce to increase the probability of being food secure.

Estimates of treatment-effects models show that tissue culture banana adoption, combined with improved crop management reduces relative food insecurity in a significant way in Kenya (Kabunga *et al*., 2014). The study employed the Household Food Insecurity Access Scale (HFIAS) – a tool that has not been used for impact assessment before.

The study on impact of the Integrated Agricultural Research for Development (IAR4D) on Enhancing Smallholder Farmers Income and Food Security through Agricultural Research and Development in West Africa by Adeolu *et al*., (2013) revealed that IAR4D increased participants' income by about 13.9%, and improved food security by about

22.9%. The study used propensity score matching (PSM) and double-difference methods (DDM) to control for project placement and self-selection biases. The study concluded from the results that the IAR4D enhances the income and food security status of the participants.

Therefore, the adoption of CSA technologies at scale could achieve substantially improved food availability, while reducing the impacts of climate change.

3. METHODOLOGY

3.1 Data

3.1.1 Study area

The study was conducted in Kati and Magharibi ‘A’ Districts in Unguja, and Micheweni and Mkoani Districts in Pemba. The areas were intentionally chosen due to their high rice production and high incidence of food insecurity. The high production indicates the availability of food in the study areas, while the high incidence of food insecurity indicates limited access, utilization, and instability of food availability.

3.1.2 Sampling procedure

Multi-stage sampling method was used to select appropriate sample size. In this method, purposive sampling was used to select study areas, which are Kati and Magharibi ‘A’ Districts in Unguja, and Micheweni and Mkoani Districts in Pemba because of the high rice production, which indicates availability of food, and high incident of food insecurity, which indicates limited access and utilization of food varieties. Mchangani and Cheju villages from Kati District, Bumbwisudi and Kizimbani villages from Magharibi ‘A’ District, Micheweni and Ngwiya villages from Micheweni District, and Maotwe and Machigini villages from Mkoani District also were purposively selected. Purposive sampling was also used to select a sample from a population of smallholder farmers. The farmers in the area were then stratified into adopters and non-adopters of climate smart agricultural technologies. From each of the groups, farmers were selected proportionate to the size of the group using a systematic random sampling procedure.

The required sample size of 260 smallholder farmers was determined using the sample size formula by Yamane (Yamane, 1967; Israel, 2003). The formula was employed since the rice farmers’ population in Zanzibar is known.

$$n = \frac{N}{1+N(e)^2} \quad \text{.......................................} \ 1$$

Where n = sample size to be studied, N= Population size, which is 29,649 rice farmers, and e = margin of error 0.062 at 5% confidence level. This gives a sample size of 260 smallholder farmers.

3.1.3 Data collection method

In this study, farm level primary data was used. The data was collected in May 2023 based on 2021/22 cropping season. During the survey, a sample of 260 smallholder farmers was randomly interviewed using pre-tested semi-structured questionnaires administered to the farmers by trained enumerators. Information on socioeconomic, market and institutional factors was captured. The study also used secondary data collected from government reports and other documents, official government statistics website, statistics from official international organization, such as FAO and previous studies.

A STATA software programme was used for processing, analysis and presentation of the study data and findings.

3.1.4 Measurement of food security

Dietary diversity is a qualitative measure of food consumption that reflects household access to a variety of foods and is also a proxy for nutrient adequacy of the diet of individuals (FAO, 2011). It is usually measured as the count of the number of food items or food groups consumed over a predetermined period of time (Ruel *et al,* 2004).

Measures of dietary diversity based on the number of food groups consumed, rather than food items, are likely to more accurately reflect the diversity of macro and micronutrient intakes and can also be used to investigate dietary patterns (FAO,2011). Diets consisting of a limited number of food items, especially starchy staples, lacks the macro and micronutrient adequacy despite meeting calorie requirements.

This study measured food security status using indicators of food consumption, which is an outcome indicator of food availability, access, utilization and stability. This was done using 3 days recall for Household Dietary Diversity Score (HDDS). The household dietary diversity score (HDDS) is meant to reflect, in a snapshot form, the economic ability of a household to access a variety of foods (FAO, 2011). Dietary diversity, defined as the number of different foods or food groups eaten over a reference time period without regard to the frequency of consumption was used to assess quality of food intake. The HDDS used in this study was based on the food groups proposed by FANTA (2006). The food groups considered are as follows: Cereals, Roots and tubers, Vegetables, Fruits, Meats, Eggs, Milk and milk products, Fish and seafood, Legumes/nuts/seeds, Oil and fats, Sweets, and spices/condiments/beverages.

A food group was counted only once, regardless of the number of times it was consumed over the last three days, the selected reference period. This means that the HDDS ranged from a minimum of zero to a maximum of 12. A high HDDS reflects a diverse diet and suggests food security, while a low HDDS is indicative of food insecurity. HDDS is an attractive proxy indicator because obtaining these data is relatively straightforward, it is associated with several nutrition indicators, such as birth weight, child anthropometric status, haemoglobin concentrations and protein adequacy. A more diversified diet is highly correlated with such food security indicators as household per capita consumption (FAO, 2011).

To distinguish between different levels of food security, the following cut-off values were set for the HDDS. Households consuming less than 6 food groups were considered food insecure; those consuming 6 to 12 food groups were food secure. A shorter recall period indicates a risk of missing foods served habitually but infrequently at the household level or it overestimates the consumption if the survey is done over those special days, and that, it does not reflect a typical diet. Since the target group is smallholder farmers, the information on dietary diversity was gathered prior to the harvest as it indicates a period of greatest food shortage. Likewise, eating outside home is not very common in the area; the study prefers gathering information at household level.

3.2 Theoretical Framework

The study assumed that there is potential for the households adopting the climate smart agricultural technologies to increase their income and food security due to increased rice yield, thus impacting positively on their livelihoods. The study assumed that farmers make choices of what crop to grow and which technologies to adopt with the aim of maximizing their expected utility. The decision to adopt the CSA technologies is predicted by perceived utility, which is expected to be higher. Profit maximization framework was used to examine the decision to adopt or not (Pryanishnikov and Katarina, 2003). It is assumed that rice farmers will only adopt the CSA technologies if the expected net benefit from this option is significantly greater than is the case without it.

Assume that U_i and U_j represent a household's utility for the two choices, then the model is specified as;

$$U_i = \beta_n X_n + \varepsilon_i \text{ and } U_j = \beta_n X_n + \varepsilon_j \text{.......................... (2)}$$

Where U_i and U_j are perceived utilities of adopters and non-adopter's choices, respectively; X_n is the vector of explanatory variables that influence the perceived attractiveness of each choice; β_i and β_j are parameters to be estimated; and ε_i and ε_j are error terms assumed to be independently and identically distributed (Greene, 2008). In the case of CSAs technologies, if a household decides to use option i, then the expected utility from option i, is greater than the utility from option j, which is defined as;

$$U_{ni}(\beta_i X_n + \varepsilon_i) > U_{nj}(\beta_j X_n + \varepsilon_j))i\ddagger j \text{ .... (3)}$$

The probability that a farmer adopts CSA technologies and chooses option i, instead of j, is then defined as:

$$P(\mathrm{Y} = 1|X) = P(U_{ni} > U_{nj}) \text{ .... (4)}$$
$$P(\beta_i^* X_n + \varepsilon_i - \beta_j^* X_n + \varepsilon_j > 0|X) \text{ .... (5)}$$
$$P\beta_i^* X_n - \beta_j^* X_n + \beta_i - \beta_j > 0|X) \text{ .... (6)}$$
$$P(X^* X_n + \varepsilon^* > 0|X = F(\beta^* X_n)) \text{ .... (7)}$$

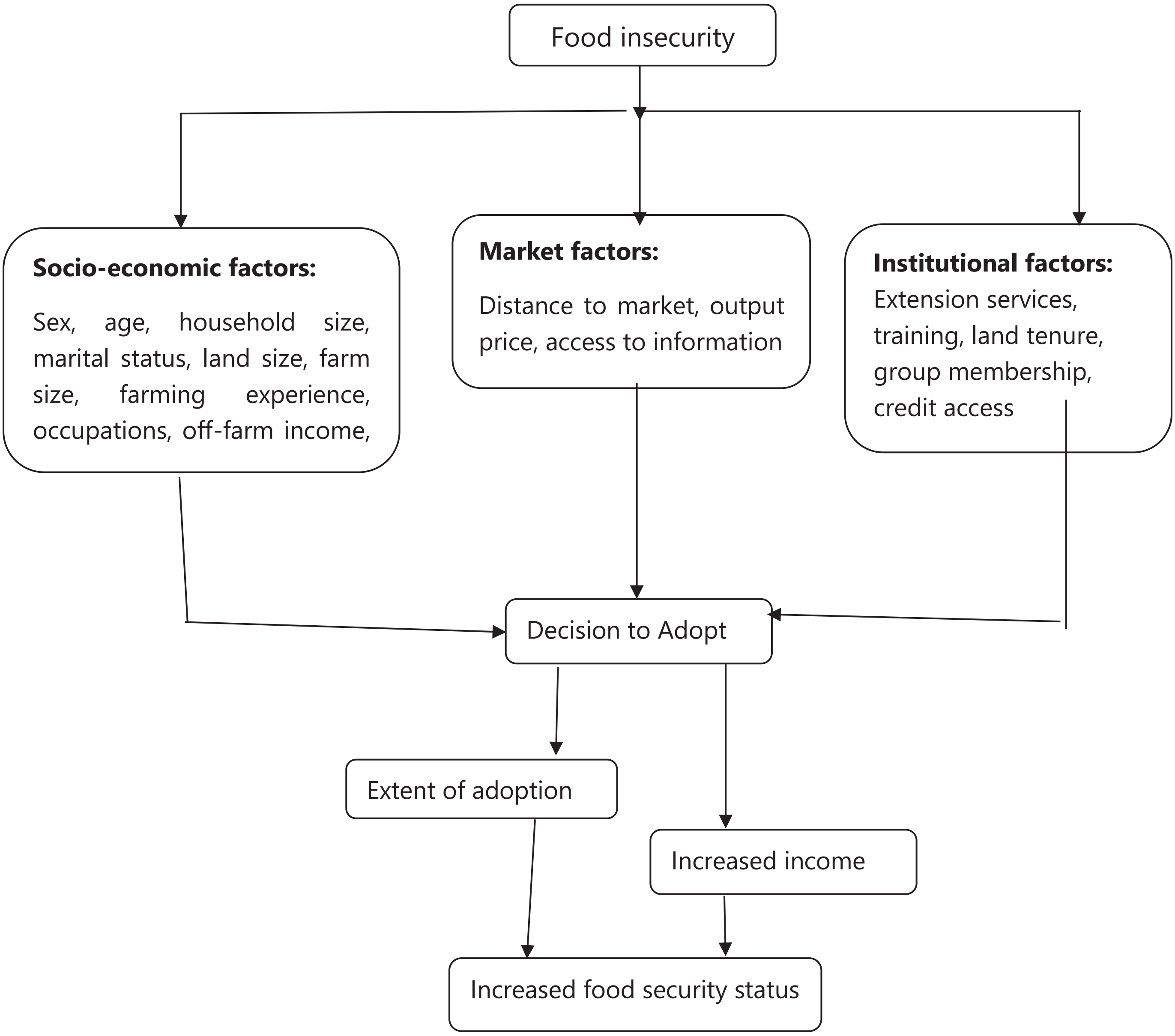
where P is a probability function,U_{ni}, U_{nj} represent a household's utility for the two choices, and X_n is the vector of explanatory variables that influence the perceived attractiveness of each choice, ε^*= $\varepsilon_i \varepsilon_j$ is a random disturbance term, β^*= $(\beta_i - \beta_j)$ is the net influence of the vector of independent variables influencing adoption of CSA, and $F(\beta^* X_n)$ is a cumulative distribution function of ε^* evaluated at $\beta^* X_n$. The exact distribution of F depends on the distribution of the random disturbance term ε^*. Depending on the assumed distribution that the random disturbance term follows, several qualitative choice models can be estimated (Greene, 2008). This theoretical framework emphasizes any household decision on the alternative.

3.3 Conceptual Framework

Conceptual framework serves as a simplification to the understanding of the relationship between the independent (explanatory) and dependent (explained) variables. A change in the independent or explanatory variable is expected to have a significant impact on the dependent variable. The dependent variable is countered by the independent variable.

Figure 1 shows the conceptual framework of the study. The adoption of CSA technologies is conceptualized to be influenced by farmers' socio-economic, market, and institutional factors, which also influence the extent of adoption. Adoption of CSA technologies is hypothesized to increase yield that can be sold to generate household income and achieve food security.

Figure 1: Conceptual framework



Source: Author

3.4 Empirical Model

3.4.1 Descriptive statistics.

Descriptive statistics was used to analyse objective one, which is CSA technologies available in Zanzibar. This was captured through quantitative and qualitative variables that are important in understanding the types of CSA technologies available and accessed by farmers. Percentage of various variables was obtained.

3.4.2 Heckman two step model

Heckman two step model was used to analyse objective two, which is about factors that influence adoption and extent of adoption of CSA technologies.

The model involves the unobservable decision to adopt and the observed degree or extent of adoption (Alene *et al*., 2009; Wabwile, 2016). In the second step, an additional regressor in the equation was included to correct for potential selection bias. This regressor is Inverse Mills Ratio (IMR). IMR is computed as:

$$\boldsymbol{\lambda} = \frac{\boldsymbol{\varphi}(\boldsymbol{h}(\boldsymbol{w}_{\boldsymbol{i},}\tilde{a}))}{\boldsymbol{\varphi}(\boldsymbol{w}_{\boldsymbol{i},}\tilde{a})} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (\mathbf{8})$$

Where, $\boldsymbol{\varphi}$ is the standard normal probability distribution function. The second stage equation is given by:

$$E = (\,Y_i/Z = 1) \; = f(x_i\,) + \boldsymbol{\lambda}\,\frac{\boldsymbol{\varphi}\left(\boldsymbol{h}(\boldsymbol{w}_{\boldsymbol{i},}\tilde{a})\right)}{\boldsymbol{\varphi}(\boldsymbol{w}_{\boldsymbol{i},}\tilde{a})} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.... (\mathbf{9})$$

Where *E* is the expectation operator, *Y* is the (continuous) proportion of land allocated on CSA technologies for crops production, *x* is a vector of independent variables affecting the extent of adopting CSA technologies, and β is the vector of the corresponding coefficients to be estimated

So Y_i can be expressed as following:

$Y_i^* \; = \beta' x_i \, + \, \gamma\boldsymbol{\lambda}_i + u_i$ -- --- (10)

Where $u_i \sim N(0, \sigma_u)$

Y_i^* is only observed for farmers who have adopted CSA technologies

(Z_i = 1), in which case $Y_i = Y_i^*$.

Heckman two step model

Step 1: Selection equation

$Y = \beta_0 + \; \beta_1 x_1 + \beta_2 x_2 + \; \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. + \beta_n x_n + \varepsilon$

$Y(0,1) = \beta_0 + \beta_1 age + \beta_2 Sex + \beta_3 Educ + \beta_4 Hhsize + \beta_5 Output + \beta_6 offFminc + \beta_7 Credit + \beta_8 Smtechprc + \beta_9 Train + \beta_{10} Extcont + \beta_{11} Landsz + \beta_{12} Livstck + \beta_{13} Farmexp + \beta_{14} Grpmbshp + \varepsilon$ .... (11a)

Step 2: Outcome equation

$$Y(Extadpt) = \beta_0 + \beta_1 age + \beta_2 Sex + \beta_3 Educ + \beta_4 Hhsize + \beta_5 Farmsz + \beta_6 offFminc + \beta_7 Credit + \beta_8 Farminc + \beta_9 Train + \beta_{10} Excont + \beta_{11} Grpheter + \beta_{12} Occup + \beta_{13} Lnwlth + \beta_{14} IMR + \varepsilon \quad \text{.............................. (11b)}$$

Table 1: Explanation of variables used in Heckman Two Step Procedure

Variables	Description of variables	Measurement
Dependent Variables		
Adopt	Adoption	Adoption of CSA technologies
Extadpt	Extent of adoption	Proportion of land allocated
Independent Variables		
Age	Age in years	Age of household head in years
Sex	Sex of household head	Dummy (1= Female, 0= No)
Educ	Education level	Farmers level of education
Hhsize	Household size	The size of household members
Output	Quantity of output	Kilogram (kg)
offFminc	Off farm income	Off farm income in TZS
Credit	Credit amount borrowed	Amount of credit borrowed in TZS
Smtechprc	Price CSA technology	TZS
Train	Training contact	Number of training attended by farmer
Extcont	Extension contact	Number of extensions contact with farmers
Landsz	Land size	Acre
Livstck	Livestock	Number of livestock owned by farmers
Farmexp	Farming experience	Number of years of farming
Farmsz	Farm size	Farm size in acres
Farminc	Income from farming	TZS
Grpmbshp	Group membership	Dummy (1= Yes, 2= Otherwise)
Grpheter	Group heterogeneity	Group heterogeneity Index
Occup	Occupation	Main occupation of farmer
Lnwlth	Wealth in TZS	Value of household assets in TZS

3.4.3 Endogenous switching probit model

In assessing the effect of CSA technologies on household food security, a model employed is the following: $F = P'X + \gamma I + \varepsilon$, Where F *is* the food security status of a certain household, X is a vector of exogenous household characteristics, and *I* is a dummy variable *(I* = 1 if the individual has adopted CSA, and 0 otherwise). However, this model is subject to misinterpretation because the adoption decision is voluntary, thus, resulting in the familiar problem of self-selectivity bias. If the adoption decision is based on individual self-selection, it is likely that CSA adopters have systematically different characteristics from non-adopters. This subsample different characteristics is econometrically problematic when unobserved characteristics are distributed differently across adopters and non-adopters. Thus, unobserved variables may influence both the adopters' decision and food security status, resulting in inconsistent estimates of the effect of CSA on household food security. A more general model for econometric analysis is the endogenous switching regression model (Dube and Ozkan, 2022).

Endogenous Switching Probit Model

This study aimed to provide empirical evidence on the effect of CSA technologies on household food security. Endogenous switching probit model was used to analyse objective three, which is about effects of CSA technologies on household food security. The model accounted for both observable and unobservable characteristics, thus, controlling for a 'hidden bias', which could arise when unobservable variables are not considered. Ignoring the endogeneity of adoption of CSA technologies would result in biased estimated parameters. To address the endogeneity problem, this study used the endogeneity switching probit model, which accounts for the correlation in the unobserved characteristics in the decision to adopt the CSA technologies and food security status, which is the outcome variable. Following Lokshin and Sajaia (2011), we consider a household with two binary outcome equations (whether food secure or not) and the criterion function *Ii* (binary variable of household adoption of CSA technologies) that determines the regime faced by the household. The potential values are represented as:

$$Ii = 1 \; if \; \gamma Zi + \mu > 0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (12a)$$

$$Ii = 0 \; if \; \gamma Zi + \mu \leq 0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (12b)$$

Regime 1: $Y_{1i}^* = \beta_1 X_{1i} + \varepsilon_{1i} I_i = 1 \; if \; (I_i^* > 0) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (13a)$

Regime 2: $Y_{0i}^* = \beta_0 X_{0i} + \varepsilon_{0i} I_i = 0 \; if \; otherwiswe \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (13b)$

Where Y_{1i}^* and Y_{0i}^* are latent variables (household food security status) that defines observed food security status Y_1 and Y_0 (whether the household is food secure or not, respectively), Z is a vector of exogenous variables determining adoption of CSA, X_i is a vector of exogenous variables determining food security status, γ and β are the vector of parameters estimated while μ_i, ε_{1i} and ε_{0i} are disturbance terms. Equation (12) is a probit specification for CSA use. The observed food security status Y_i is defined as $Y_i = Y_{1i}\, if\ I_i = 1$ and $Y_i = Y_{0i}\, if\ I_i = 0$. With the assumption of joint normal distribution of μ_i, ε_{1i} and ε_{0i} with mean of zero, the correlation matrix written as:

$$\Omega = \begin{pmatrix} 1 & \rho_0 & \rho_1 \\ & 1 & \rho_{10} \\ & & 1 \end{pmatrix} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(14)}$$

Where ρ_0 is the correlation between $\varepsilon_0$and μ, ρ_1 is the correlation between ε_1 and μ while ρ_{10}
is the correlation between ε_0 and ε_1. Consequently, the log likelihood function for the model is given by:

$$\begin{aligned} Ln\ (\xi\,) = & \sum_{ci\neq 0, Y_i\neq 0, \omega_i} \ln\{\emptyset_2(X_{1i}\,, \beta_1, Z_i\alpha, \rho_1)\} + \sum_{ci\neq 0, Y_i\neq 0, \omega_i} \ln\{\emptyset_2(-X_{1i}\,, \beta_1, Z_i\alpha, \rho_1)\} \\ & + \sum_{ci=0, Y_i\neq 0, \omega_i} \ln\{\emptyset_2(-X_{1i}\,, \beta_1, Z_i\alpha, \rho_1)\} \\ & + \sum_{ci=0, Y_i\neq 0, \omega_i} \ln\{\emptyset_2(-X_{1i}\,, \beta_1, -Z_i\alpha, \rho_1)\} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots . (15) \end{aligned}$$

Where ω_i is an optional weight for the i_{th} household and $\emptyset_2$ is cumulative function of bivariate normal distribution (Lokshin and Sajaia, 2011). Previous studies have used the switching probit regression model in social research (Ayuya et al., 2015; Floro and Swan, 2013; Gregory and Coleman-Jensen, 2013; Lokshin and Glinskaya, 2009; and Wabwile, 2016). The advantage of endogenous switching probit model specification in Equation (15) is the possibility of deriving probabilities in counterfactuals cases for household's food security status on adoption of CSA. Following Heckman, Aakvik, and Vytlacil (2000) and Lokshin and Sajaia (2011) two cases are defined as:

$$TT(X) = \Pr(Y_1 = 1|I = 1, X = x) - \Pr(Y_0 = 1|I = 1, X = x) = \frac{\emptyset_2(X_1\,\beta_1{,}Z\alpha{,}\rho_1 - \emptyset_2(X_0\,\beta_0{,}Z\alpha{,})}{F(Z\alpha)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(16a)}$$

$$TU(X) = \Pr(Y_1 = 1|I = 0, X = x) - \Pr(Y_0 = 1|I = 0, X = x) = \frac{\emptyset_2(X_1\,\beta_1 - Z\alpha - \rho_1 - \emptyset_2(X_0\,\beta_0 - Z\alpha - \rho_0)}{F(Z\alpha)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(16b)}$$

Where *F* is the cumulative function of the univariate normal distribution, Equation (16a) computes the effects of treatment on the treated (TT), which is the difference between the predicted probability of being food secure for adopters of CSA and the probability of being food insecure for non-adopters of CSA. Computing the average of TT(x) on households that have adopted the CSA, results in the average treatment effect on the treated (ATT). The effect of the treatment on the untreated (TU) was computed by Equation (16b), which is the expected effect on food security status if the non-adopter's households had adopted the CSAs. Computing the average of TU(x) of households that did not adopt the CSA results in average treatment effect on the untreated (ATU) (Heckman *et al*., 2000; Lokshin and Sajaia, 2011).

Table 2: Description of variables used in the Endogenous Switching Probit Model

Variables	Description of variables	Measurement
Dependent Variables		
FFS	Food Security Status	Food insecure = 0, Food secure = 1
Independent Variables		
Age	Age in years	Age of household head in years
Sex	Sex of household head	Dummy (1= Female, 0= No)
Educ	Education level	Farmers level of education
Hhsize	Household size	The size of household members
Output	Quantity of output	Kilogram (kg)
Credit	Credit amount borrowed	Amount of credit borrowed in TZS
Paddypr	Price of paddy	TZS
Train	Training contact	Number of trainings attended by farmer
Extcont	Extension contact	Number of extensions contact with farmers
Infsoc	Information source	Farmers main source of farm information
Landsz	Land size	Acre
Livstck	Livestock	Number of livestock owned by farmers
Farmexp	Farming experience	Number of years of farming
Riceld	Land under rice	Acres
Farminc	Income from farming	TZS
Grpmbshp	Group membership	Dummy (1= Yes, 2= Otherwise)
Occup	Occupation	Main occupation of farmer

Explanation of the main variable considered in the study:

Sex of household head: Female farmers are mostly forgotten in official agricultural statistics, while they play a core role in the agricultural system. Therefore, it is important to consider the degree to which a new technology or innovation reaches female farmers and how much they benefit from the CSA interventions. Women headed households are less likely to adopt a new technology or innovation because they are usually having less resources and less exposed to new information and ideas.

Age of farmers: Age can be a proxy for experience with farming. Farmer's age may influence adoption on several ways, and the direction of the influence is not clear and there are always mixed results from empirical analysis. Older farmers are more likely to adopt a new technology because of having more experience, resources and authority whereas younger farmers may to adopt a new technology, because they have had more schooling or exposed to new ideas than older generation.

Marital status of the household head: It is included because married households are able to make up rational decisions because of different ideas in the family compared to single, divorced or separated households. Therefore, knowing the role of marital status in influencing technology adoption is crucial.

Household size: May be a proxy for the labour availability within the farm household. Different technologies have different characteristics with respect to their labour requirement; some reduce the number of labours required for cultivation, while others significantly increase demand for it. In addition, rice farming is usually labour intensive and family labour are mostly used to replace expensive hired labour. The influence of household size on adoption studies is still unclear and always has mixed empirical results.

Education: Many adoption studies show the existence of some relationship between farmer's education level and new technology adoption. The more complex a technology is the more likely is that education will play a role. Usually, education improves access to information and new ideas and inputs make a farmer more receptive to technical advice from extension officers or more able to deal with technical recommendations that require a certain level of numeracy or literacy. On the other hand, educated farmers tend to divert from farming to high waged jobs. So, the influence of education on adoption studies is still unclear and have mixed results from empirical analysis.

Occupation of farmers: Farmer's activities may also be important factor on adoption studies. Farmers tend to engage in more than one activity aimed to raise their income that can be used to finance uptake of new technology. Higher wage works may make farmers less incentive to spend time on farming activity. The influence of occupation on adoption is undetermined.

Land size: It may be an important factor in a technology adoption. It is often assumed that farmers with larger land size will be more likely to adopt a new technology or innovation, especially if the technology requires an extra cash investment. It may also be that a certain threshold land size may be necessary before fully investment in a technology is worthwhile. Moreover, on larger farms, different managerial practices may be tried. On the other hand, some technologies may be appropriate for the intensive management characteristics of smaller farms.

Farming experience: Experience may influence adoption of technology in several ways. The direction is not clear. More experienced farmers may have already made-up rigid decisions on what they know about agricultural technologies and that tend to be conservative. On the other hand, farmers with many years of experience may be more receptive towards new upcoming agricultural innovation because of capital accumulation and adequate experience. The influence of experience on adoption is unclear.

Training: This variable may be proxy for farmer's awareness on CSA technologies. Mostly, farming appears to be an activity of unskilled people with low wages. Several capacity building programs and training have been made to raise farmer's skills and awareness on new technology. Provision of training based on the individual needs of each farmer will better improve extent of adoption. This analysis will help in knowing whether training made was either general or specific to farmer's needs.

Extension contacts: Extension officer serves as a tool for delivering information, create awareness and provision of technical advice to the farmers. It is often assumed that farmers who had frequent extension contact would easily adopt new technologies since they access information and knowledge about traits and benefits of improved varieties. Understanding how efficient extension service is important.

Group membership: It is included because group members can exchange ideas and learn about the traits and benefits of various new upcoming technologies. Members of the group also may easily organize and receive training on various agricultural technology issues that influence the adoption of the CSA technologies. Social capital and network are important in influencing diffusion of technology through exchange of information and facilitates timely inputs access.

Output: Rice output is an important factor for adoption studies. Yield is a direct measure of seeds performance and other CSA technologies, and a technology that promotes high yields stands to be adopted by farmers since high yield would raise output and subsequent gross earning.

Price of rice: It is included because it informs the farmers' decision to adopt new technology and impact on his decision to pay attention to the crop. The high quality and favourability of new technology in the market translates its high price than the local ones. This is common with farmers in that, with existence of a new profitable technology, farmers would want to adopt the new technology to cover up their cost of production and yield enough profit in the market. It is expected that this will influence adoption.

4. RESULTS AND DISCUSSION

4.1 Climate Smart Agricultural Technologies Available in Zanzibar

The results in Table 3 reveal that 57% of the farmers were adopters compared to 43% who were non-adopters. The results of weather smart technologies reveal that among adopters, 62% and 69% use seasonal weather forecast and agro-advisory services, respectively, compared to their counterpart non-adopters of which 37% and 30% use weather forecast and agro-advisory services, respectively. This was due to that majority of farmers own homestead assets, such as radio, which they use to access information including weather related information.

Table 3: Types of climate smart technologies.

Types of climate smart technologies		%	
		Adopters	Non-adopters
Adoption		57	43
Weather smart	Seasonal weather forecast	62.41	37.59
	Agro-advisory services	69.88	30.12
	Climate analogues	0.86	0.14
Water smart	Rainwater harvesting	74.36	25.64
	Bund construction	62.50	37.50
	Alternate wetting and drying	85.33	14.67
	Soil erosion control	51.06	48.94
	Irrigation infrastructure	94.67	5.33
Crop smart	Improved variety	63.06	36.94
	Drought resistant variety	63.01	36.99
	Disease resistant variety	66.19	33.81
	Short matured variety	61.28	38.72
Carbon smart	Agroforestry	66.67	33.33
	Trees for fodder and forage	46.84	53.16
	Composting manure	59.83	40.17
Knowledge smart	Smart farms e.g. drones, soil sensor, automated greenhouse etc	0.00	0.00
	Collective action groups	59.40	40.60
	Farmer-to-farmer learning	56.63	43.37
	Crops rotation	49.69	50.31
	System of Rice Intensification (SRI)	80.39	19.61

The results of water smart technologies reveal, that 74%, 62%, 85%, 51% and 94% of adopters use rainwater harvesting, bund construction, alternate wetting and drying, soil erosion control, and irrigation infrastructure, respectively. On the other hand, only 25%, 37%, 14%, 48%, and 5% of non-adopters use rainwater harvesting, bund construction, alternate wetting and drying, soil erosion control, and irrigation infrastructure, respectively. This might be attributed to the fact that not all potential land for irrigation is irrigated and few dams for rainwater constructed, which create a gap of water access among farmers. Adopter farmers might be living close to the irrigation infrastructure and rainwater harvesting dams constructed by the Government to ease farmers access to water. Also, adopter farmers might have frequent contact with extension officers who are instrumental on providing technical advice to farmers on how to harvest and retain water in their farms.

Results on the crop smart technologies reveal that, among potential adopters, 63%, 63%, 66% and 61% use improved varieties, drought resistant, disease resistant and short matured varieties, respectively. On the contrary, 36% of potential non-adopters use improved variety, 36% use drought resistant, 33% use disease resistant, and 38% use varieties with short maturity, respectively. Seed development, multiplication and distribution is not sufficient to serve all farmers in Zanzibar. Therefore, adopter farmers might be in a better position to access information on availability and knowledge of crops smart technologies compared to non-adopters.

The results of carbon smart technologies reveal that, among the adopters, 46% use trees for fodder and forage, and 46% use composting manure, compared to non-adopters: 53% and 40% use trees for fodder and forage and composting manure, respectively.

Of the majority adopters of knowledge smart technologies: 59%, 56%, 49%, and 80% use collection action groups, farmers to farmer learning, crops rotation and system of rice intensification (SRI), respectively. On the contrary, 41% of non-adopters use collection action groups, 43% use farmer to farmer learning, 50% use crops rotation, and 19% use system of rice intensification (SRI).

4.2 Factors that Influence Adoption and Extent of Adoption of CSA Technologies

4.2.1 Factors influencing adoption of CSA technologies

To determine the factors influencing adoption of the climate smart agricultural (CSA) technologies, a probit model was estimated in the first step of the Heckman two step selection equations. The estimation procedure was chosen to account for the sample selection bias as proposed by Heckman (1979). Four variables (age, education, land size and farming experience) were significantly found to influence the farmers' decision to adopt the CSA at different significant levels. Age was significant at 5% level, while education, land size and farming experience were significant at 10% level. The Inverse Mills Ratio (IML/Lambda) term was significant and positive at (0.088), which suggests that the error term in the selection and outcome equation is positively correlated. This implies that unobserved factors that influence adoption of CSA are more likely to be associated with higher scores on the dependent variable.

Age of respondent negatively and significantly influenced adoption of climate smart agricultural technologies. This means that older farmers are less likely to adopt CSA technologies because most tasks in agriculture are very tedious and require active involvement. The likelihood of adoption would increase to the younger farmers as they get exposed to CSA technologies and become more aware of the benefits of adoption. Also, most of households that grow older tend to reduce the land holding sizes by giving out portions to be inherited by their children and grandchildren for cultivation as part of the customary land acquisition, which reduce the size of land available per household member and discourage CSA technologies adoption. This finding agrees with Wanjira *et al* (2022) and Ayele and Admassie (2009), where they conclude that older farmers are more likely to stop adopting the technology as their physical ability to participate actively in farming activities declines with increasing age. However, these results are inconsistent with Audu and Aye (2014) found that older respondents adopted new varieties more than young farmers.

Table 4: Heckman Twostep Selection Equation

Variable	**dy/dx**	**Std. Error.**	**P> $|Z|$**
Sex	0.2865	0.7001	0.682
Age	-0.7185	0.6347	0.007***
Marital status	0.9938	0.8224	0.227
Household size	0.1744	0.1628	0.284
Education	0.2915	0.5612	0.021**
Occupation	-0.1050	0.3004	0.727
Land size	-0.7451	0.3216	0.021**
Farming experience	0.0970	0.0399	0.015**
Training	-0.2414	0.8320	0.772
Extension contact	-0.1131	0.1880	0.548
Credit	0.9108	0.9453	0.335
Farm income	0.2471	0.3503	0.481
Yield	0.0860	0.0581	0.139
mills lambda	0.1574	0.2269	0.088*
Rho	-1.0000		
Sigma	0.1574		

*, **, ***: Significant at 10%, 5% and 1% level respectively

Education level of the household head was found to have a positive significant influence on the adoption of CSA technologies. The likelihood to adopt CSA technologies by farmers increases by 22% for every year increase in education level. This implies that as the education level increases, adoption of the climate smart agricultural technologies increases. This can be explained by the fact that educated farmers have greater awareness of the availability and benefits of new agricultural technologies. (Faturoti *et al*. 2006) suggested that education empowers individuals with technological skills and knowledge that will accelerate individual to adopt a new technology. These findings, however, are inconsistent with a study by Wabwile (2016), who found that education level have a negative significant influence on adoption of the improved sweet potato varieties because educated farmers are more likely to earn higher wages from off-farm work. They are expected to have a higher proportion of off-farm income to on-farm income given the same proportion of on and off farm work time. Therefore, it seems plausible if highly educated farmers, who are more reliant on off-farm income, have fewer incentives to spend time and effort on farming, including adoption of technology such as ISVs. Kangile (2015) found that education level does not to influence participation of members in input purchases including improved varieties. It is typically appearing that farmers with formal education are mostly youngster who are less likely to stay in farming business. In doing so, they tend to migrate to urban areas in search of jobs or engage themselves in other business.

The result found that land size negatively influenced the adoption of CSA technologies. The results can be explained by the fact that rice is labour intensive and labour cost could constitute a higher percentage of total production cost. Therefore, increase in land is associated with increased production cost, which discourage farmers from adopting new technologies. Also, majority of smallholder farming households fall below poverty line. They live without much willingness to absorb additional expenses including purchasing CSA technologies for additional acres. The result is inconsistent with the results from the study by Wanjira *et al* (2022) who argued that land positively influenced the adoption decision of climate smart maize varieties.

Farming experience was found to have a positive and significant influence on adoption of CSA technologies. The results show that the likelihood of CSA technologies adoption by farmers' increases by 9.7% for every additional increase in year of farming experience. This can be explained by the fact that farmers with many years of experience are more receptive towards new agricultural technologies due to adequate experience, capital accumulation and higher level of risk averseness towards new technologies. The results agree with those reported by Masuki *et al.,* (2003). These findings, however, are inconsistent with a study by Wabwile (2016) who found that farmers with many years of adoption have already made-up rigid decisions on what they know since they started adopting the technologies, so any changes on the technology can no longer change their understanding further.

4.2.2 Factors influencing extent of adoption of CSA technologies

To determine the factors influencing the extent of adoption of the CSA technologies, Ordinary Least Square (OLS) regression was estimated in the second step of the Heckman outcome equation. Six variables were significant at different levels: land size, land tenure, yield, and farm income were significant at 1%, access to credit and extension contact were significant at 5% and 10% level, respectively. The Inverse Mills Ratio estimated from the first equation was added to the second equation as an independent variable to capture the selection bias effect. The variable was found to be statistically significant at 5% level justifying existence of selection problem and the use of the model.

The analysis shows that the extent of adoption of CSA technologies increases with land size. This probably is because farmers with more plots of land may be able to allocate part of their land for the new technology and thus are more likely to adopt new technologies than those who have small farm size. Similarly, Mutanyagwa (2017) argued that land size could influence the use of improved maize seed varieties as farmer may portion a certain part of land for testing the newly certified improved seed varieties compared to people with small land sizes. Khonje *et al* (2015) argued that farmers can only allocate more land to improved varieties if they have enough land, and therefore those who own more land are expected to have a comparative advantage when it comes to adopting Improved Cassava Varieties.

Land tenure had a strong and positive significant influence on the extent of adoption of CSA technologies. The probability of adoption increased by 3.2%. This could be attributed to the fact that land ownership accords the farmers the right of usage, thus, creating incentive to the farmers to adopt new technologies. The findings are consistent with those of the study by Wabwile (2016), who argued that secure land provides farmers with full rights of land ownership and usage, thus, influencing the decision to adopt new technologies.

Table 5: The Heckman Two Step Outcome Equation

Variables	Coef.	Std. Err.	P>Z
Sex	-0.1134	0.2540	0.655
Age	0.1781	0.1168	0.127
Household size	0.0023	0.0284	0.933
Education	-0.1191	0.1034	0.250
Land size	0.6609	0.0509	0.003**
Land tenure	0.3279	0.0637	0.000***
Yield	0.1460	0.390	0.068*
Farm income	0.6601	0.1422	0.050**
Price	0.0004	0.0015	0.794
Occupation	-0.0170	0.0686	0.804
Credit	0.3459	0.1312	0.008***
Extension contacts	0.0900	0.0410	0.028**

*, **, ***: Significant at 10%, 5% and 1% level respectively

Output of rice was strong, positive, and significantly influenced the extent of adoption of CSA technologies. This might be attributed to the fact that yield is a direct measure of technology performance and, a technology that influences high yield stands to be adopted by the farmers since high yield would raise output and subsequently high earning and food security. In line with study by Ojiako *et al.* (2007), yield of soybean significantly influenced the adoption of improved soybean in Nigeria.

Farm income had a strong positive and significant influence on the extent of adoption of CSA technologies. This can be suggested by the fact that income from farming activities could be used to finance the uptake of new technologies. Wabwile (2016) argued that high farm income improves the capacity to adopt agricultural technologies.

Access to credit had a positive significant influence on the extent of adoption of CSA technologies. The tendency that farmers will adopt new innovations because some of them had access to credit from government funds, which would enable them to purchase farm inputs and pay for farm mechanization and labour. The availability of government soft loans could act as incentives given the fact that farmers have limited access to finance, which leads to increased probability of adoption. The findings are in line with the study by Arslan *et al.,* (2016), who found that farmers with access to credit are more likely to adopt practices that involve liquidity, such as improved seeds. The study supports the importance of extension services in providing information on both short-run and long-run benefits of all practices to farmers to improve productivity and adaptive capacity at the same time. Wanjira *et al* (2022) found that farm households that had access to credit are more likely to adopt climate smart maize varieties. This suggests that it is essential for farmers to access formal credit as it acts as a source of financing the production and the adoption of maize varieties.

Extension contact was found to have positive influence on the extent of adoption of CSA technologies. This indicates that farmers who have frequent contacts with extension officers had a higher probability of adopting the CSA technologies because extension officers create awareness on the benefits of new technologies to farmers. Also, contact with extension officers allow farmers to exchange ideas, experience, and makes it cheaper to source information, knowledge and skills that enable farmers to improve their livelihood. Consistent with a study by Ayele and Admassie (2009), on Adoption of Improved Technology in Ethiopia, found farmers' contact with extension agents came out to be positive and statistically significant indicating that farmers who had some kind of extension contact are strongly and positively motivated to adopt modern technology. Extension contact helps the smallholders to raise their awareness about the characterization and attributes of the technology use and impact.

4.3 Effects of CSA Technologies on Household Food Security

4.3.1 Determinants of food security status

To determine the effects of CSAs on food security status, the endogenous switching regression probit model was used for analysis. The endogenous switching probit model is identified by functional form (Lokshin and Sajaia, 2011; Gregory and Coleman-Jensen, 2013). Hence, the study used exclusion restriction methodology to improve on identification. The study used farmer to farmer extension and non-governmental extension as instruments. This study, however, is consistent and exclusive to studies such as Ayuya *et al.*, 2015, Asfaw *et al.*, (2012) and Negash and Swinen (2013), who used agricultural information sources as instruments in their studies. Table 6 presents tests that indicate the above variables as valid instruments. Sargan's test showed the correlation between the instruments excluding the error terms. Sargan's test was $Pr > \chi 2\ (10) = 0.6237$ and $Pr > \chi 2\ (1) = 0.4077$ showing that the excluded instruments were uncorrelated with the error terms.

The results of food security status reveals that 72% of the households were food secure compared to 28% who were food insecure. The average Household Dietary Diversity Score (HDDS) was 6.77.

Gender of household head, although was not significant, its coefficient shows that it could affect food security status negatively. Female headed household are more likely to be food insecure compared to male headed households. This could be explained by the fact that females have less resources, poor access to information and therefore unable to access climate smart technologies through the formal sources than male headed households and, hence, experience low yield and consequently low income and food insecurity. The insignificant difference between male and female headed households might be attributed to the fact that females have other means of accessing food for their households such as engaging in small business or entrepreneurship ventures, remittance from their relatives living in urban areas, from Government and Non-Government organizations. The study findings were in line with the study by Kumba (2015), who discovered the insignificant influence of gender of household head on food security.

Table 6: Validity of selected instruments used in the Endogenous Switching Probit Model.

Variables	Coeff.	Std. Error	P>$\|Z\|$
Farmer to farmer extension	-0.5062	0.3541	0.073*
Non-governmental extension	0.6818	0.3632	0.662
Constant	0.5954	0.3762	0.062*
Wald test	437.43		0.000***

Note: *, and ***: Significant at 1% and 10% level, respectively

The coefficient of marital status had positive and significant effect on food security at 10% level. The positive sign and significance of the estimated coefficient of marital status suggests that married farmers are more likely to have higher household food security compared to their counterparts: single or separated households. The suggested reason is that married households can make up rational decisions because of different ideas in the family including that of adopting CSA technologies. Also, married households indicate the availability of household labour, which reflects the human capital resources available to a household for agronomic activities. Therefore, households with large pools of labour are more likely to be food secure, as they can carry out farming activities on time. They can also commit large portion of land to food crops, which may result into increased crops yield and food security. This is also an indication that vulnerable groups of people in the study area, such as the widowed, are not actively participating in upcoming a new technology. The results are consistent with those from the study by Kumba (2015), who suggested that married household had a higher likelihood of being food secure because both the husband and wife contribute their labour and other resources to improve the household food security. Yusuf *et al.,* (2015) argued that married household heads have a higher incidence of food security compared to others because married household heads are likely to have larger households, which are engaged in income generating activities, therefore, contributing more to household income compared to households headed by either singles or widowed.

Table 7: Full Information Maximum Likelihood Estimates of the Switching Regression Model. (Dependent variable: Food Security Status)

	Adopter			**Non-adopter**		
Variables	**Coefficient**	**Std. Error.**	**P>$\|Z\|$**	**Coefficient**	**Std. Error.**	**P>$\|Z\|$**
Sex	-0.0139	0.0406	0.731	-0.0136	0.0368	0.711
Marital status	0.1130	0.0521	0.030**	0.0212	0.0380	0.576
Age	-0.0038	0.0267	0.884	-0.0137	0.0261	0.599
Household size	-0.1300	0.0082	0.000***	-0.1179	0.0084	0.000***
Occupation	0.0232	0.0232	0.317	-0.0378	0.0284	0.184
Education	0.0246	0.0266	0.356	0.0740	0.0239	0.002***
Land size	-0.0321	0.0136	0.018**	-0.0058	0.0142	0.682
Land tenure	0.0161	0.0106	0.130	-0.0055	0.0097	0.571
Credit	0.0413	0.0545	0.449	-0.0443	0.0774	0.567
Rice output	0.0115	0.0052	0.027**	0.0020	0.0007	0.004***
Income	0.2446	0.0065	0.218	0.1134	0.0038	0.921
Market distance	-0.0031	0.0040	0.446	0.0015	0.0027	0.571
Constant	1.1370	0.1732	0.000***	1.4888	0.1541	0.000***
ρ 0				-0.4800	0.3753	0.201
ρ 1	-2.6505	0.4763	0.000***			
LR test for indep. eqns: chi2 (2) = 12.30				Prob > chi2 = 0.0021***		

Note: **, ***: Significant at 5% and 1% level, respectively

Household size, not surprisingly, had a negative and significant effects on food security. The likelihood of being food insecure increased with an increase in household size. This implies that households with small household size are more likely to become food secure compared to households with large household size. Mango *et al* (2014) argued that household size represents the consumption-level needs of a household and shows the burden it faces to feed its members. Therefore, bigger households obviously have a higher 'burden to feed' and are, thus, more likely to be food insecure. Family size is more linked to family labour supply (Chidumu, 2007), as almost all farming activities in Zanzibar are not mechanized. Therefore, majority of households use family labour who are technically inefficient. This reduces farm yield, decreases surplus that could be saved to fill the seasonal gap or sold to the market to buy other food groups and, thus, increase the likelihood of being food secure.

The coefficient of education had a positive and significant influence on household food security among non-adopter farmers. The positive sign and significance of the estimated coefficient of education suggests that highly educated farmers (particularly non-adopters) are more likely to have higher household food security compared to their counterpart not/less educated farmers. The suggested reason is that non-adopters higher educated farmers are not full-time farmers, avail themselves to other economic activities and have broad opportunities of being employed in non-farm high wage jobs, which could be an additional source of income for food purchase. Also, educated farmers have high capacity of managing farm risk which causes increased farm household food security. However, empirical findings contradict the study by Awotide *et al.,* (2011), which indicates that education was negative and statistically significant; suggesting that education has a reducing effect on household income and food security. They suggested that the number of educated households in the rural areas engaged in full time farming is negligible; those that have a substantial number of years of education take farming as a secondary occupation with minimal commitment.

Land size significantly and negatively influenced household food security at 5% level. This could be explained to the fact that majority of farmers own a farmland without a tittle deed and that are not able to undertake risk or entrepreneurial ventures, such as adopting CSA technologies. These farmers must be sure on the good performance of the technologies before adopting them since many of them have no secure rights on their land. This reduces the crops productivity, which consequently leads to the decrease in food surplus that could be saved to fill the gap during off season or sold to earn extra income to buy other food groups. The study findings contradict with those findings by Kumba (2015), who suggested that as land size increases the likelihood of being food secure also increases among households. The reason could be that households with larger farms are able to diversify their agricultural activities to improve food security.

Rice output had a positive and significant influence on food security. This could be explained to the fact that increase in production leads to a substantial increase in food surplus that could be sold to earn extra income. The study results agree with those by Wabwile (2016) who suggested that increased and improved sweet potato yield lead to earn extra income among farm households that could be used by these households to buy other food groups and diversify household food diet.

The coefficient of income was positive and had insignificant influence on household food security. This might be attributed to the fact that, majority of farmers have rarely intended to sell their products beyond the farm or village market because they are not commercialized. They fail to participate in the emerging potential market because they are unable to intensify production, meet quality and ensure stability of supply. The study is consistent with the findings by Radeny *et al.*, (2018), which indicate the positive but insignificant effects of improved small ruminants' income and food security across the Climate Smart Villages.

4.3.2 Mean treatment effects on food security

The effect of adoption of CSA on food security is shown in Table 8. The values across the diagonals (in cell (a) and (d)) represent the mean values of adopters and non-adopters in the sample. The values in cell (b) and (c) are the counterfactual expected values. The average treatment effect on the treated (ATT) was 0.7103, which is the actual effect that adopters experience through adoption. This implies that among the adopters, their adoption of CSA led to a higher probability or more likelihood of being more food secure compared to the counterfactual case of not adopting the CSA. Hence, adoption of the CSA substantially improved the food security of the adopter households.

Table 8: Mean treatment effects on food security.

Treatment effects	**Decision stage**		
	Adopter (ATT)	**Non-adopter (ATU)**	**Average Treatment Effects (ATE)**
Adopter	(a) 0.7193 (0.0283)	(c) 0.5915 (0.4950)	0.7103 *
Non-adopter	(b) 0.5659 (0.4970)	(d) 0.0731 (0.0428)	0.7314

Note: *: Significant at 10% level. The standard errors are in parentheses

In addition, results also confirm the presence of variation and sorting based on comparative advantages (differences in food security status between the adopters and non-adopters caused by unobserved factors), the results can therefore be concluded for the entire population. The key interest is to understand what the effects of CSA on food security status on non-adopter households would be if they were to adopt CSA. The finding was as expected and is given by average treatment effect on the untreated (ATU) which shows that for non-adopter's food security would increase if they would adopt the CSA. However, positive and insignificant, these households are not likely to have better alternatives than the CSA and somehow, they do not live better, at least in terms of food security, by not adopting. Farmers with higher expected net returns do apply the technology and the one who has low expected net returns do not adopt and apply them. However, these findings are inconsistent with other studies' results (Wabwile, 2016), who found negative and insignificant results, indicating that non-adopter farmer's food security would decrease if they were to adopt new technologies. The negative and insignificant indicate these household probably have better alternatives than the improved sweet potato varieties and they are better, at least in terms of food security, by not adopting.

5. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The general objective of this study was to contribute towards food security by examining the contribution of the CSA technologies on household food security in Zanzibar – Tanzania. Specifically, the study was aimed to determine CSA technologies available in Zanzibar, to determine factors influencing adoption and extent of adoption of CSA technologies and the effects of CSA technologies on household food security. Data was collected and analysed using descriptive statistics, Heckman two step and endogenous switching probit model. Based on the findings as presented in chapter four, the following conclusions have been made: First, household socio-economic characteristics, market and institutional factors are very important in influencing the adoption of CSA and its effects on household food security. Further, irrigation infrastructure, system of rice intensification, alternate wetting and drying, and rainwater harvesting are used by majority of farmers.

Second, eight variables were found to be significant in influencing adoption and extent of adoption. Education level, farming experience, land tenure, farm income, rice yield, and credit access, were found to positively influence the level and extent of adoption, while only age and land size negatively and significantly affected adoption and extent of adoption. Age had a negative influence because older farmers tend to be conservative in their approach of doing things, whereas land size had a negative influence because of rice is far much labour intensive, which constitute higher production cost. Therefore, increase in rice land associated with increased production cost discourage farmers from adopting new technologies. The positive significance of education implies more skills and knowledge is gained with increase in level of education; land tenure implies land used as a security against the risk of crop failure; farming experience implies increased capital accumulation and improved level of risk averseness towards technologies; whereas, farm income implies extra income to buy other food groups, rice output implies surplus food that can be saved to fill seasonal gap or sold to earn extra income for buying other food groups; and credit access implies increased capital that could be used to purchase farm inputs and pay for farm mechanization for rice farming.

Third, five variables were significant in influencing the household food security. Marital status, education level of household head and rice output had a positive influence on the household food security, while household size and land size had a negative significant influence. The negative effect of household size implies that family size is more linked to family labour supply as almost all farming activities in Zanzibar are not mechanized. Therefore, majority of households use family labour who are technically inefficient. This increases the likelihood of being food insecure. The negative effects of land size imply that majority of farmers own farmlands without tittle deeds and that cannot undertake risk ventures, such as adopting CSA technologies and, therefore, likely to become food insecure. The positive insignificant influence of gender of household head implies that females have less resources, poor access to information and therefore unable to access CSA. Although not significant, female headed household are more likely to fall in food insecurity. The insignificant difference between male and female headed households might be because of women being engaged in other off farm small scale entrepreneurial ventures, support or remittance from relatives, Government, and Non-Governmental Organizations.

Fourth, CSA technologies increase food security significantly. However, the study found insignificancy of CSA on overall household income. This might be attributed to the fact that majority of farmers have rarely intended to sell their products beyond the farm or village market because they are not commercialized. Adoption of the CSA reduces food constraints as they can be practiced at periods of adverse climate conditions, harvested at the period of food shortages and can contribute to ease seasonal variations in food availability. In addition, adoption of the CSA improved access to other food groups and farm inputs for these households, which improves overall agricultural productivity.

Fifth, adopters gain significantly from adopting when compared to not adopters. Non-adopters, appear to do this because they would not benefit., as they consider to be better off without adopting the CSA.

The study enabled better understanding of what CSA technologies are available, key factors influencing their adoption and their effects on household food security. In so doing, it generated useful information for all institutions intending to develop or promote CSA technologies, as well as for those responsible for the development of agricultural sector in Zanzibar.

5.2 Recommendations

Based on the above conclusions and findings from the study, the following recommendations are made: -

First, age, education level, farming experience, land size and tenure, rice output, farm income, and credit access influence adoption of CSA. However, exploiting the full benefits of the technology in improving food security status will require increased investment in labour saving technologies and policy support for improving rice productivity through access to land with title deeds, improving farmers education with a special focus to aged farm households, better access to farm mechanization, assuring farmers constant market for their produce, and easing farmer’s constraints from accessing credits.

Second, marital status, household size, education, land size, and rice output are important drivers in determining food security status. It is therefore recommended to implement special programmes or initiatives to support vulnerable groups such as single, divorced or separated and less educated households. Also, provision of land with title deeds as suggested earlier, should go hand in hand with improving technical capacity of household members to become technically efficient. Although, farm income was not significant, this calls for the need to commercialize rice farming by intensifying production while assuring farmers constant market for their produce.

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