https://doi.org/10.58548/2023jaep11.4160

# Adoption of Multiple Climate Smart Agricultural Practices in Mbeya and Songwe Regions in Tanzania

# Abiud Bongole

The University of Dodoma, Department of Economics, P.O. Box 1208 Dodoma, Tanzania. Email: abiud.january@udom.ac.tz

Abstract: Climate change is the leading global problem which affects agricultural development and household food security. Climate-smart agriculture (CSA) is one of the approaches developed by FAO to address the impact of climate change through increasing agriculture productivity, improving adaptation to climate change, and mitigating greenhouse gases emission. However, the CSA practices usage by farmers is still low in developing countries, Tanzania inclusive. To understand the challenges in the use of CSA practises, an analysis which combines multivariate and ordered probit models were employed to analyse the decisions to use and the intensity to use the six CSA practices (i.e., drought-tolerant maize seed, crop rotation, organic manure, intercropping, irrigation, and residue retention) frequently practised in the study area. The study sampled 1443 farming households from two regions (Mbeya and Songwe) in the Southern Highlands of Tanzania. The results show that farming households are using CSA practises as complements. The results are essential in designing combinations of CSA practices. The study also found that the gender of the head of the household, geographical location, and plot ownership are essential determinants of the use of the type and number of CSA practices. It is recommended that agriculture experts should carefully design combinations of CSA practices for the aim of increasing agricultural productivity, resilience to climate change, mitigation of greenhouse gases, and improvement of food security.

Keywords: Climate-Smart Agriculture Practices, Multivariate Probit Model

JEL classification: C35, D63, I33

# **1.0 Introduction**

The major problem facing agriculture production is climate change as there is a gradual change in temperature, rainfall pattern, greenhouse gas emissions, and an increase of extreme weather phenomena adversely affecting agriculture (Mbow et al., 2019; FAO, 2018). In Sub-Saharan Africa, smallholder farmers depend on agriculture as a source of food and income-generating activities. However, the sector is highly affected by climate change with negative consequences on crop production and hence food insecurity (Azumah et al., 2020; FAO, 2014). For instance, Nwaobiala and Nottidge (2013) predicted that productivity in SSA countries will be negatively affected by climate change by 10–20% or even up to 50% by 2050.

In Tanzania, 80 per cent of the population depends on agriculture for their livelihood, therefore, it is also affected by climate change (Hulme et al., 2001; Tumbo et al., 2010). Climate change projections show a likely increase in average temperature of 0.8 to 1.8°C by the 2040s, evenly

distributed across Tanzania. By the 2090s, projected warming is in the range of 1.6 to 5.0°C across the country (Maliondo et al., 2012). The mean number of days with temperatures over 30°C is projected to increase from roughly ten days per year to 80 by the 2040s. Rainfall projections are broadly consistent in indicating increases in annual rainfall (Hulme et al., 2001; Tumbo et al., 2010). Rapid climate change poses a significant threat to the country's agricultural production and food security if urgent action is not taken. Rowhani et al. (2011), predicted that, by 2050, the yield of staple crops such as maize, rice, and sorghum will decrease by 13%, 7.6%, and 8.8%, respectively.

In order to rescue this productivity challenge, smallholder farmers need to adopt climate-smart agriculture practices. These may include promoting the cultivation of climate-resistant crop varieties, adopting sustainable farming practices, enhancing water management techniques, investing in research and development, providing climate information to farmers, and establishing supportive policies at the national and international levels. Taking these measures can strengthen agricultural resilience and contribute to safeguarding food security for the country's population in the face of a changing climate. Given the situation, efforts have been made to develop and promote agricultural technologies that can help smallholder farmers improve productivity, particularly those in vulnerable areas, and overcome challenges related to climate change (Lipper & Zilberman 2018). Climate-smart agriculture (CSA) was proposed by Food and Agriculture Organization (FAO) as one of the promising approaches to improving agriculture productivity and income, increasing climate change adaptation, and mitigating greenhouse gases (Lipper et al., 2014; FAO, 2010).

Food and Agriculture Organization (FAO) has identified several CSA practices, such as residue retention, irrigation methods, reduced tillage, organic manure, intercropping, organic fertilisers, and cover crops (Muzangwa et al., 2017). However, the usage of these practices in developing counties in farming households has been mediocre as the usage varies due to differences among farmers, context, riskiness, conflict with farmers' resources, and the perceived benefits (Mupangwa et al., 2021). In addition, usage of these practices varies from one location to another due to the differences in bio-physical, socioeconomic, and cultural factors (Ngaiwi et al., 2023).

Adopting CSA practices will benefit farmers financially by increasing yields, boosting food security and economic growth, and enhancing farmer welfare. Additionally, consumers who eat organic food without chemical contamination will benefit from CSA practices. However, there is a paradox amid this appealing narrative: while proponents describe CSA practices as being indisputably helpful for farmers, adoption has remained shockingly low in many poor countries, despite ongoing efforts to encourage CSA practices adoption. When taken singly or in combination, these practices can produce two or all three CSA advantages (FAO, 2010). It has been noted that smallholder farmers find it difficult to adopt and implement CSA practices, even though CSA practices are a well-documented and recognised methods to improve agricultural productivity. Consequently, it is essential to have a thorough understanding of the factors that influence farmers' adoption of CSA practices to help them become more climate change-resilient and advance effective CSA practices in the agricultural sector.

In addition, factors that have been empirically studied in the past in a variety of developing countries that influence farmers' adoption of CSA practices include age, gender, marital status, education, household size, access to agricultural extension services, access to input and output markets, number of occupations, crop diversity, plot size, farming experience, land ownership, membership in farmer organisations, and access to loans (Kimaro et al., 2019; Kurgat.,2020). According to these studies, usage decisions are typically location-specific and influenced by various relevant factors. However, farmers' willingness to use CSA practices varies significantly due to cultural awareness, resource endowments, preferences, and socioeconomic factors. Smallholder farmers also use CSA practices in isolation or in combination to address specific conditions and strategies (Vera et al., 2017). However, the majority of these studies only examined one practice without considering the fact that farming households might apply CSA practices separately or in combination with other CSA practices. Therefore, little is known about the multiple uses of CSA practices in Tanzania, particularly in Mbeya and Songwe Regions.

Teklewold et al. (2013) assert that CSA practices in combination could create a sustainable agricultural system resistant to climate change and other elements that limit agricultural production. Crop rotation, intercropping, irrigation, organic manure, drought-tolerant maize seeds, and residue retention are among the CSA practices considered in this study. To understand the challenges in the use of the multiple CSA practices, multivariate and ordered probit models were employed to analyse the decisions to use and the intensity to use the multiple CSA practices.

The study seeks to add to the limited literature on determinants of usage of CSA practices where household characteristics, plot characteristics, institutional characteristics, and resource constraints were considered. The specific objective of the study was to examine the usage and the intensity of using multiple CSA practices in the Southern Highlands of Tanzania. This study relied on four contributions: first, the study used a comprehensive household-level survey recently conducted on food crops (maize, paddy, beans and soya beans) farming systems in Mbeya and Songwe Regions; second, the study employed methods which consider the interdependence between CSA practices and joint analysis of the usage decision. Several CSA practices were considered, such as crop rotation, irrigation, drought-tolerant maize seeds, residue retention, intercropping, and organic manure.

Understanding the interrelationship between sets of CSA practices is crucial for the ongoing debate on whether farm households should use CSA practices in isolation or the package. This will assist policy-makers and agricultural extension agents in putting strategies that promote CSA practices to farmers. Third, the study concentrated on the importance of household, plot, and institutional characteristics to determine the probability and intensity of usage of CSA practices. Fourth, this study extends the concentration from the probability of usage decision to the extent of usage as measured by the number of CSA practices used. The following section (section 2) presents the analytical and conceptual framework. Section 3 presents the methodology of the study, and section 4 presents the results and discussions. Section 5 presents the conclusion and policy implications.

### 2.0 Analytical and Conceptual Framework

The probit and logit models are typically employed in many studies to examine factors that affect the adoption of CSA practices. The probit and the logit models are univariate models that use a single equation for each practice. The shortcomings of these models, however, are that they cannot account for the fact that farming households are more likely to practise more than one practice based on their experiences and benefits obtained from each practice (Teklewold et al., 2013; Muriithi et al., 2018). They also fail to take interdependence into account when multiple practices are employed. Farming households use practices as a complement or substitute, but the probit and logit models cannot determine this. The multivariate probit model (MVP) can be used to address these flaws. This model can account for the concurrent use of multiple CSA practices. It can also account for the correlation among disturbance terms resulting from the relationship between the practices.

### 2.1 A Multivariate Probit Model (MVP)

Farming households can use a combination of CSA practices to tackle climate change and other production constraints (Kassie et al., 2013). The use of one CSA practice, however, may impact another because some CSA practices are not mutually exclusive. Univariate modelling may therefore leave out important economic information when interdependent and concurrent decisions are made (Kassie et al., 2013). Therefore, considering possible complementarities and substitutability between the CSA practices used, an MVP can be an appropriate model (Greene, 2003). However, univariate models are not adequate to account for complementarities between practices. For example, many farmers who use irrigation may also use drought-tolerant maize seeds; nevertheless, unless the researchers analyse this effect, they will not be able to understand the factors that enhance the use of drought-tolerant maize seeds by farming households.

Theoretically, a CSA practice is more likely to be used by farming households if its utility exceeds that of the alternative practice. Let consider a  $i^{th}$  farming household (i = 1, 2, ..., N) decide to use the  $j^{th}$  CSA practices (j represents the use of intercropping ( $I_{cr}$ ), irrigation ( $I_r$ ), organic manure ( $O_m$ ), crop rotation ( $C_r$ ), drought resistant maize seeds ( $D_s$ ), and residue retention ( $R_r$ ). Let  $U_0$  and  $U_1$  represent the advantages of using CSA practices and conventional agricultural practices, respectively.

A farming household can decide to use the  $j^{th}$  CSA practices if the net benefit  $(y_{ij}^*)$  is higher  $(B_{ij}^* = U_j^* - U_0 > 0)$ . Therefore, the net benefit is a latent variable  $(y_{ij}^*)$ , which can be determined by the observed farming household, plot, institutional characteristics, and resource constraints  $(X_i)$  and the error term  $(\varepsilon_i)$  as shown below:

Equation 2 illustrates how the unobserved characteristics in equation1 can be changed into observed binary outcomes for each CSA practice employed by farming households.

The error terms in an MVP model jointly follow a multivariate normal distribution with zero conditional mean and variance normalised to unity with the possibility of using multiple CSA practices, i.e.  $\mu_{C_r}, \mu_{I_r}, \mu_{I_{cr}}, \mu_{O_m}, \mu_{R_r}, \mu_{D_s} \rightarrow^{MVN} (0, \Omega)$  and the covariance matrix (*X*) is given by:

$$\Omega = \begin{bmatrix} 1 & \rho_{C_{r}I_{r}} & \rho_{C_{r}I_{cr}} & \rho_{C_{r}O_{m}} & \rho_{C_{r}R_{r}} & \rho_{C_{r}D_{s}} \\ \rho_{I_{r}C_{r}} & 1 & \rho_{I_{r}I_{cr}} & \rho_{I_{r}O_{m}} & \rho_{I_{r}R_{r}} & \rho_{C_{r}D_{s}} \\ \rho_{I_{cr}C_{r}} & \rho_{I_{cr}I_{r}} & 1 & \rho_{I_{cr}O_{m}} & \rho_{I_{cr}R_{r}} & \rho_{I_{cr}D_{s}} \\ \rho_{O_{m}C_{r}} & \rho_{O_{m}I_{r}} & \rho_{O_{m}I_{cr}} & 1 & \rho_{O_{m}R_{r}} & \rho_{O_{m}D_{s}} \\ \rho_{R_{r}C_{r}} & \rho_{R_{r}I_{r}} & \rho_{R_{r}I_{cr}} & \rho_{R_{r}O_{m}} & 1 & \rho_{R_{r}D_{s}} \\ \rho_{D_{s}C_{r}} & \rho_{D_{s}I_{r}} & \rho_{D_{s}O_{m}} & \rho_{D_{s}R_{r}} & 1 \end{bmatrix}$$

$$(3)$$

The unobserved correlation between the stochastic components of the various types of CSA practices is represented by the off-diagonal elements in the covariance matrix. This assumption means that equation (2) gives an MVP model that jointly represents decisions to use a particular CSA practice. The specification with non-zero off-diagonal elements allow for correlation across the error terms of several latent equations, which are unobserved characteristics that affect the usage of alternative CSA practices.

#### 2.2 An Ordered Probit Model

The MVP model concerns the likelihood of using CSA practices. However, it cannot account for the distinction between farming households employing a single CSA practice and those employing several. It can be challenging to distinguish between users and non-users when identifying factors that affect the intensity of CSA practices (Wollni et al., 2010). Most farm households surveyed for this study used combinations of these practices rather than complete package on their farms. Therefore, it is not easy to quantify the intensity of usage of the CSA practices package. In order to overcome this problem, the study used the number of CSA practices as a dependent variable. That was the same as Wollni et al. (2010).

The number of CSA practices used in the study was used as a count variable. According to Wollni et al. (2010), the Poisson regression model is usually employed to analyse count data. This assumes that all events have equal chances of occurring. However, there may be a difference in application between the likelihood of using the first CSA practice and the likelihood of using a second practice. This is because, in the latter case, the farming household has already gained some experience and been exposed to information about that CSA practice.

As the numbers of CSA practices used were considered ordinal variables, the ordered probit model was employed in the estimations. Different latent variables were involved in the model for the frequency function of CSA practices ( $T^*$ ). As mentioned earlier, the  $i^{th}$  farm household (i = 1, ..., N) decides to use a certain number of CSA practices based on tmaximisation of an underlying utility function:

 $T_i^* = X_i' \alpha + \varepsilon_i.....(4)$ 

 $X_i$  represents a vector of household characteristics, plot/farm characteristics, institutional characteristics and resource constraints;  $\alpha$  stands for a vector of parameters to be estimated;

and  $\varepsilon_i$  is unobserved characteristics. Farming households can decide to use an additional CSA practice if the utility of using it is higher than that of not using it. According to McKelvey and Zavoina (1975), when the level of utility of individual farming household  $T_i^*$  is unobserved, then the observed level of CSApractices  $T_i$  is assumed to be related to the latent variable  $T_i^*$  in the following way:

 $T_i = j$  if and only if  $\mu_j \le T_j^* < \mu_{j+1}$  for  $j = 0, \dots, J$ 

*J* is the number of CSA practices used;  $\mu_{j+1}$  presents the estimated threshold levels. This equation states that if the number of CSA practices  $T_i$  is between  $\mu_0$  and  $\mu_{j+1}$ , the response to the question on the number of CSA practices used is equal to j ( $T_i = j$ ). The parameters  $\alpha$  and  $\mu$  are estimated using a maximum likelihood.

# **3.0 Methodology**

# 3.1 Data source

The study was carried out in Mbarali, Momba, Mbozi, and Mbeya Rural Districts in the Southern Highlands of Tanzania, where various food crops, such as maize, beans, soybeans, and paddy rice, are grown. The study area was chosen because various CSA practices were implemented by governmental and non-governmental organisations. These organisations aimed to increase productivity and income, improve resilience to climate change, and reduce greenhouse gas emissions. Some of the CSA practices introduced and implemented in the study area are intercropping, organic manure, residue retention, drought-tolerant maize seeds, crop rotation, and irrigation.

# **3.2 Sampling and Data Collection**

The study used cross-sectional data from a farm household survey in the Southern Highlands of Mbeya and Songwe in Tanzania. The survey was conducted by Sokoine University of Agriculture (SUA) and Wageningen University and Research Centre (WUR) in partnership with the Integrated Project to Improve Agricultural Productivity and Food Security in the Bread Basket area of Southern Highlands of Tanzania. The sample covered 1443 farm households where multistage sampling was used to select farmer organisations (FOs) from each district and households from each FO. In the first stage, four districts were purposively selected from Mbeya and Songwe Regions (i.e., two district from each region). Secondly, a total of 92 wards were identified, where 51 wards were randomly chosen from the selected district proportionally. Thirdly, Farmers' Organisations (FOs) were identified within each selected ward, and a proportionate random sampling method was used to select 1443 farming households from these FOs. A survey was conducted at the household level and a structured questionnaire was used to collect information. The questionnaires covered various aspects, such as household demographics, socio-economic characteristics, climate-smart agriculture practices, crop production and marketing, input usage, food consumption, and farm-specific characteristics.

# 3.3 Description of Dependent Variables

The farming households in the study area were interviewed to assess their climate change coping strategies over the past decade, and based on their farming experience, they reported adopting various Climate-Smart Agricultural (CSA) practices. The leading practices mentioned

were crop rotation, intercropping, irrigation, organic manure utilisation, residue retention, and use of drought-tolerant maize seeds, which were consistent with previous literature (Bolinder et al., 2020; Teklewold et al., 2019; Teixeira et al., 2018; Arslan, 2013; Masuka et al., 2017; Kpadonou et al., 2017). These practices were used as the dependent variables in the study. Table 1 present the descriptions and measures of the exogenous variables used.

Table1. Definition and	summary statistics	of variables in	the analysis
	summary statistics	UI VALIADICS III	the analysis

Variables	Description	Mean
Practises used (n = 1443)		
Crop rotation	% of households that have used the crop rotation	66.67
Irrigation	% of households that have used the irrigation	23.28
Drought-tolerant maize seeds	% of households that have used the DTMS	60.64
Residue retention	% of households that have used the residue retention	46.5
Organic Manure	% of households that have used the organic manure	36.94
Intercropping	% of households that have used the intercropping	33.96
The Household Characteristics	% of male household head	<u> 94 90</u>
Gender of the household head	% of male household head	04.09
Age of the household head	Age of the head of the household in years	50.3985
Marital status	% of married household head	0.82.05
Education of the household head	Years of education of the household head	6.1455
Education of the spouse	Years of education of the spouse	2.8974
Household size	Number of household members	5.3818
Age of the spouse	Age of the spouse	39.4338
Farming experience	Years of farm experience	22.0624
Number of occupations	Number of occupations of household head	2.2176
Geographical location		
Region	1= Songwe Region	0.4934
Farm Characteristics		
Farm size	Farm size in an acre	7.962
Soil fertility	1 = good soil fertility	47.5
Production diversity	Number of crops cultivated	2.8039
Soil erosion	1 = No soil erosion	0.3115
Farm distance	Farm distance from home, minutes	18.0589
Institutional Characteristics		
Number of group membership	1= More than one group membership	27.51
Extension services	1= Access to extension services	16.42
Distance to the extension offices	Extension office distance from home in minutes	23.6377
Distance to the local market	Market distance from home in minutes	62.2633
Household wealth		
Livestock ownership (TLU)	Livestock herd size (tropical livestock units; TLU)	1.7242
Logarithm of asset	The logarithm of Asset Index	13.1498
Farm ownership	1 = Own a farm	0.8579
The average number of plots cultivated	Number of plots	2.9381

In the study, adoption intensity, which represents the number of CSA practices adopted by the farming households, was measured and recorded in Appendix 1. The selection of independent and dependent variables was based on the existing literature on CSA practices adoption (Bolinder et al., 2020; Teklewold et al., 2019; Teixeira et al., 2018). The six CSA practices (crop rotation, intercropping, irrigation, organic manure utilisation, residue retention, and use of drought-tolerant maize seeds) were coded as one (1) if a farming household adopted a specific practice and zero (0) if they did not.

#### 3.5 Concerns in Estimations of the Econometric Models

Different factors determine the decision of farm households to use agriculture practices. Therefore, it is important to control them in estimating the MVP model (Kassie et al., 2013).

However, there is a possibility of a multicollinearity<sup>1</sup> problem when independent variables are added to the model.

# 4.0 Results and Discussion

# 4.1 Descriptive statistics

Concerning the profile of the sampled respondents (Table 1), the results showed that 84.89% of the sampled household heads were male and 15.11% were female. These results implied that many farmers in the study area were male. Additionally, the heads of the household spent an average of 6.1455 years schooling while their spouse spent an average of 2.8974 years schooling. The literacy level implied that most farming households in the study area could effectively comprehend new agricultural technologies, including CSA practices. The average age of the head of the household was 50.3985 years, while the spouse's age was 39.4338 years on average. This implies that farming households in the study area are in a productive age with high experience in food crop production. Kassie et al. (2013) holds that household heads at a productive age and high farming experiences can positively influence agricultural technology usage.

The distance from the homestead to the nearest market was 62.26 working minutes. The study found significant findings about the farming households in the study area. For example, the distance from the homestead to the farm was relatively short, with an average working distance of 18.06 minutes. The study also found the distance from homestead to the market to be a working distance of 62.26 minutes, implying that farmers have easy access to the potential buyers of the crops produced. The study found that the farming household visited in the study area are male-dominated, as evidenced by an 84.89 % share of male household heads with an average of 2.2 occupations and spent an average of 6.14 years schooling. The household size was 5.38 members, while the local market was 62.26 walking minutes away. The average tropical livestock unit (TLU) was 1.72, with an average of 3 plots cultivated in the previous season.

# 4.2 The Rate of using CSA practices

Table 2 shows the specific rate of using various CSA practices. The results show that usage rates ranged from 33.96% (intercropping) to 66.67% (crop rotation). The rates of using other practices are 60.64% for drought-tolerant maize seeds, and 46.5% for residue retention. The usage rate of organic manure, intercropping, and irrigation was 36.94, 33.96 and 23.28 %, respectively. The intensity of using these practices ranged between zero to six practices, which means that some farming households used up to six practices. In contrast, other households did not use any other practice. The findings are the same as the study by Kpadonou et al. (2017), which found that the use of CSA practices varies across socioeconomic settings of the households and the types of practices. The findings disclose that there is a need for the government and other agricultural practitioners to promote the usage of CSA practices to improve household income and food security. As such, understanding the major drivers and constraints to usage and intensity of using CSA practices is crucial to provide evidence-based policy-making for agricultural development in SSA.

<sup>&</sup>lt;sup>1</sup> According to Wooldridge, (2010) multicollinearity exists whenever two or more of the predictors in a regression model are moderately or highly correlated.

# 4.3 Complementarity and Trade-off among CSA practices

The simultaneous usage of CSA practices shows a likelihood of correlation (interdependence) among the CSA practices. The study used the pair-wise correlation across the MVP residuals, and Table 2 shows the estimates. The result of the likelihood ratio test ( $Chi^2$  (15) = 63.9175;  $Prob > chi^2 = 0.000$ ) rejects the null hypothesis of zero covariance of the error terms across the equations. Table 2 shows that combinations of drought-tolerant maize seeds and crop rotation are positive and significant at 10%.

						Inter
	Crop			Residue		crop
	rotation	Irrigation	DTMS	retention	Organic Manure	ping
Crop rotation	1					
irrigation	-0.159**	1				
	(0.0697)					
DTMS	0.0915*	-0.0588	1			
	(0.0541)	(0.057)				
Residue						
retention	0.231***	-0.076	0.045	1		
	(0.0539)	(0.0541)	(0.0422)			
Organic Manure	0.192***	-0.068	0.107**	0.0666	1	
-	(0.0549)	(0.0587)	(0.0463)	(0.0435)		
Intercropping	0.0597	-0.0125	-0.0153	0.128***	0.130***	1
	(0.0549)	(0.057)	(0.0442)	(0.0426)	(0.0458)	

Table2:	Complementarities	and	Substitutability	of	CSA	practices:	Correlation
Coefficie	nt of the Error Term						

The Likelihood ratio test of rho21 = rho31 = rho41 = rho51 = rho61 = rho32 = rho42 = rho52 = rho62 = rho43 = rho53 = rho63 = rho64 = rho65 = 0:  $chi^2 (15) = 63.9175$  Prob > chi2 = 0.0000

Standard errors in parentheses

Combinations of residue retention and crop rotation, organic manure and crop rotation, intercropping and residue retention, intercropping and organic manure are significantly and positively associated at a significant level of 1%. In addition, the use of combinations of organic manure and drought-tolerant maize seeds is also positive and significant at 5%. This indicates that farming households consider these CSA practices as complements (i.e., farming households apply these technologies simultaneously). The complementary between CSA practices was similar to the finding of Kanyenji et al. (2020), who found that organic manure and intercropping complement each other in the farming system in western Kenya.

#### 4.4 Determinants of using CSA practices

Results of the MVP model estimated using the maximum likelihood method at the household level are shown in Appendix 1. Results show that the model fits the data since the Wald test shows Wald  $\chi^2$  (125) = 1052.48; Prob >  $\chi^2$  = 0.0000 of the null hypothesis, that all regression coefficients in each equation that are jointly equal to zero are rejected. This signifies the relevance of the model to account for the unobserved correlations across decisions to use a combination of CSA technologies. Additionally, the use of MVP was confirmed as the appropriate model in this study as the significance of the LR tests [Chi-Square ( $\chi^2 = 63.9175$ ,  $\rho = 0.000$ ). Therefore, we reject the hypothesis that the CSA technologies considered in this study (irrigation, organic manure, intercropping, crop rotation, drought tolerant maize seeds, and residue retention) are independent.

The results show that the gender of the head of the household positively and significantly influenced the usage of crop rotation, residue retention, and organic manure. This indicates that male household heads were more likely to use these practices compared to their counterpart female household head. The results are consistent with the study by Ngoma et al. (2015) and Mwangi and Kariuki (2015), who found that gender positively influenced the use of conservation agriculture practices.

Farm size positively influenced the usage of drought-tolerant maize seeds at a significant level of 5%. Farmers in rural Tanzania consider having large farms as a sign of wealth. So, farmers with large farms can afford to buy agricultural inputs, including drought-tolerant maize seeds. The age of the household head had a significant and positive effect on the use of irrigation at a significant level of 1%. This implies that aged people participated more in irrigation farming than youths in the study area. The low level of participation of youths in irrigation farming could be because they are not members of farmers' organisations such as Agricultural Marketing Cooperative Societies (AMCOS), which own the majority of irrigation schemes. However, the participation of aged people in irrigation farming could be an advantage in terms of social capital, as the majority are members of the AMCOS.

Farming households with more occupations have been revealed to have a positive link with the use of crop rotation, residue retention, organic manure, and intercropping. The positive effects of occupations on these practises suggest that farm households with many occupations are likely to intensify their spending to procure organic manure, hiring farm and other farm implements, as their engagement in different sources of income may overcome their financial barriers. The results are similar to that of Diiro (2013), who found that a number of occupations were positively associated with pesticide usage. The study by Danso-Abbeam et al. (2019) also found a positive effect of different sources of household income on the use of agro-chemicals. However, Kanyenji et al. (2020) found that farming households whose farming is the main occupation had an increased probability of using organic manure since its application is labour intensive. Thus, full-time farmers had more time at their disposal to transport and apply the manure on their plots.

The study found that agricultural extension services had a negative and significant effect on using irrigation practice. This implies that whether farming households have received extension services or not, they might not use a particular practice. Therefore, having contact with an extension agent for extension services was unimportant. The important thing is the decision to use an irrigation practice. The study did not meet the a priori expectation since agricultural extension is meant to influence practice uptake by farming households and promote cross-learning and experience sharing among farming households. Similarly, a study by Teklewold et al. (2017) finds that access to extension services has a negative and significant effect on using chemical fertilisers and improved seeds.

Furthermore, the study found a negative and significant association between access to agricultural extension services and residue retention. This might be caused by the opportunity cost of using crop residue such as maize or paddy residues for mulching or feeding animals. This was supported by Tey et al. (2014), who argued that for farming households which keep livestock, there is a possibility of the increased requirement of animal feed demand; as a result,

it leads to increased utilisation of crop residue as livestock feed instead of using them for mulching.

The study moreover found that farm size positively correlates with the usage of droughttolerant maize seeds. This means that farming households with large farm sizes aime to maximise profit and are risk-averse; therefore, they are likely to use the drought-tolerant seed to avoid risks related to climate change. In addition, farming households with large farms use their land to apply agricultural practices compared to smaller farms. The finding is consistent with the findings of Danso-Abbeam and Baiyegunh (2017), who found a positive association between farm size and the usage of pesticides and chemical fertilisers. Bezu et al. (2014) also found a positive relationship between farm size and the usage of improved maize variety.

The study found that the education level of the head of the household was found to have a positive and significant effect on the probability of using irrigation practice at a 1% level of significance. Household heads with higher education can use irrigation technologies as they might be more innovative and they can assess usage risks compared to their counterparts. Similar results were found by Ntshangase et al. (2018), who found the education level of the head of the household to be significantly and positively correlated with the use of zero tillage as a CSA practice at a 1 % significant level.

According to Kassie et al. (2013), the distance from home to the nearest market can be considered a proxy for market information. The study found a negative association with the use of irrigation. This suggests that access to the input and output market is imperative in enabling usage through assisting input and output transport, reducing the cost of the household's time and enabling more timely market information. Farming households with access to market are more likely to use irrigation because farming households in the study area with access to the markets were selling more of their crops that use irrigation, especially paddy in Mbarali District.

Asset ownership was found positive and significantly associated with the use of irrigation, drought-tolerant seeds, and residue retention. This is perhaps because better-off farming households may have the capacity to purchase drought-tolerant maize seed and other costs associated with irrigation usage. This finding agrees with that of Beyene et al. (2017), who found asset ownership to be correlated with the decision to use the number of CSA practices such as tree planting and intercropping.

The location variable (region) was positive and significantly connected with the farming household's decision to use crop rotation, drought-tolerant maize seeds, residue retention and organic manure. This means that farming households in Songwe Region use these practices more than their counterparts in Mbeya Region. This might be because Songwe Region receives more interventions on various CSA technologies provided by non-governmental organisations such as AGRA, ADP- Mbozi, and One-Acre fund, which are more based in Songwe Region than in Mbeya Region. Similarly, the study by Donkoh et al. (2019) found the Brong-Ahafo region variable to be positive and significantly connected with the use of pesticides but negatively and significantly connected with the use of chemical fertilisers. Land ownership showed a positive impact on the usage of crop rotation and organic manure. This suggests that

farming households are likely to use these practices on their owned plots. This implies that rent on a farm or a plot is associated with poor agricultural practices (Gray & Kevane, 2001).

# 4.5 Factors Explaining the Intensity of CSA practices Usage

Farming households in the study area have used multiple CSA practices, but the usage intensity differs. The study employed an ordered probit model to explain determinants of CSA practices' usage intensity. Farming households can use a specific CSA practice based on their needs. For example, farming households in drought areas like Mbarali District can opt to use irrigation than areas with high rainfall, like Mbozi and Mbeya Rural Districts. Likewise, farming households that kept different livestock types might use farm yard manure compared to their counterparts.

Therefore, Appendix 2 presents the marginal effects of the outcome variables where farming households which did not use any practice were given the value of 0, then the value of 1, 2, 3, 4, 5 and 6 were given for the households used one, two, three, four, five, and six CSA practices, respectively. The chi<sup>2</sup> statistics for the ordered probit model is statistically highly significant (LR chi<sup>2</sup> (34) = 1519.24; Prob > chi<sup>2</sup> = 0.000) and rejects the null hypothesis (all slope coefficients equal to zero).

The results from Appendix 2 show that the independent variables vary over the different intensity levels. It shows that farming households with higher production diversity have the probability of using at least three, four, five or six CSA practices at percentages higher by 3.25, 7.35, 3.19, and 0.31 points, respectively. Farming households can diversify their production by employing different CSA practices compatible with temperature or rainfall variability to take advantage of beneficial climate conditions. This result is similar to the study by Teklewold et al. (2019), which found that farming household diversifies their production system to reduce the risks of climate change and diversity in Ethiopia.

The study found the probability of using three, four, five, and six practices is higher by 1.59, 3.57, 1.55, and 0.15 % age points, respectively in households with many occupations compared to those with few occupations. This implies that household heads with many occupations used more CSA practices because they were not facing financial constraints, which could hinder them from investing in multiple CSA practices. However, this finding conflicts to that of Oumer and Burton (2018), who showed that number of occupations significantly decreased the intensity of using more than two practices by 14%. The coefficient for the gender of the household's head was significantly positive. Farming households headed by men have the probability of using five and six by 1.76 and 0.16 % higher than farming households headed by females.

Membership in more than one farmer organisations also has a link with the intensity of the usage of CSA practices. The study found that the probability of using two, three, four, five, and six practices is higher by 3.51, 1.54, 4.19, 1.93, and 0.2% age points, respectively for the household head joined in more than one farmer organisations compared to the farming household head joined only in one farmer organisation.

This is because, being a member of many organisations can help members to get different knowledge about the effect of climate change and variability, which leads them to use multiple CSA practices to reduce the increasing risks and reduce consequences of climate change and variability. The study is the same as the study by Teklewold et al. (2019), which found that membership in farmer organisations increased the intensity of CSA practices used by farming households in Ethiopia. The number of cultivated plots by the farming households in the previous season preceding the survey shows a positive relationship with the number of CSA practices used. Some variables, such as the distance from the agricultural extension office and local market distance from home, have shown a negative effect on the number of the practices used. Geographical location also has an association with the number of CSA practices used.

Farming households in Songwe Region have the probability of using three, four, five, and six by 1.16, 2.64, 1.15, and 0.11 % higher than farming households in Mbeya Region. The findings of this study support other literature which conclude that farming households in developing countries, Tanzania being inclusive, are usually adapted to climate risks by using multiple adaptation practices (Shiferaw et al., 2009). Farms/plots' ownership influences the intensity of CSA practices, where the probability of using two, three, four, and five practices is higher by 2.31, 1.25, 2.84 and 1.23 % age points, respectively, compared to farming households which rented in farms/plots for agricultural production. The result is related to the work of Teklewold et al. (2019) in their study of the usage of CSA in the Nile Basin of Ethiopia.

The study found that the education of the spouse, tropical livestock unit, plot size, household size, soil erosion, access to market, soil fertility and access to extension services and age, marital status, the education of the household head were insignificantly related to the intensity of usage of CSA practices in our study area. This is consistent with some studies, such as Oladimeji et al. (2020), which found the household size insignificant in the usage of conservation practices. The finding is different from the findings of Aryal et al. (2018), who found that the age of the head of the household, credit, and farmer organisation membership significantly influenced the intensity of usage of soil conservation practices.

# 5.0 Conclusion and policy implications

A cross-sectional study data was obtained from 1443 farming households in the Southern Highlands of Tanzania, where the factors determining the usage and intensity of using CSA practices were examined. The multivariate probit model (MVP) was employed to examine the usage of multiple CSA practices. In contrast, the ordered probit (OP) was employed to examine the factors influencing the intensity of using different CSA practices. Understanding constraints and supporting factors for using CSA practices helps in designing and formulating extension messages and agricultural policies that can accelerate the dissemination of CSA practices. The study found that the intensity of using these CSA practices considered in this study is also very low. More than 70 % of farming households use only one to three practices, indicating that a vital potential still exists to improve the specific usage rates and the intensity of using CSA practices. Policymakers must target practices with lower usage rates and provide farming households with further incentives towards intensifying their use. The study found that the farm households are using CSA practices as complements; therefore, government and nonorganisations dealing with agriculture development must consider governmental complementarities among these CSA practices and promote them to farming households. In

addition, the complementarities among the CSA practices can have vital policy implications. For example, a policy amendment that impacts one practice can have an impact on the use of other practices. Therefore, these complementarities can be used to define an appropriate combination of CSA practices used in specific areas.

The findings confirmed that wealthier farming households, particularly those with access to household assets and plot/farm ownership, are more likely to use these practices. Policies that enable farming households to secure their land for cultivation as a motivation for using multiple CSA practices should be considered. Furthermore, the study highlighted the contribution of the gender of the household head on the use of CSA practices. This calls for the policymakers to target female-headed households that showed lower incentives in intensifying CSA practices, possibly because of their limited control over labour and land assets. The promotion of CSA practice, primarily organic manure, is essential to reduce the need for synthetic fertilisers. Therefore, any practices such as organic manure that increase N use efficiency can substantially reduce emissions from agriculture. Our analysis shows that the gender of the household head, livestock ownership, asset ownership, production diversity, and occupation are positively associated with the decision to use organic manure. As suggested by Sapkota et al. (2019), policymakers need to set up alternative pathways for agricultural development to achieve highyield, low-emission targets in agricultural production. Setting up such an alternative pathway needs to consider several factors, including the type of agricultural technology/practices and the socio-economic and human behavioural dimensions.

Access to markets and extension services and other information sources are crucial in increasing CSA usage intensity. Therefore, focusing on policies and plans that improve market access and the quality of extension services is important. Dissemination of CSA knowledge and its role in climate risk mitigation is critical to promote it. More CSA training for farmers, government extension staff working at the local level, and the use of communication tools to share and promote knowledge on CSA use to combat the global challenge of climate change are essential. Understanding barriers and enabling conditions to CSA usage helps in designing and formulating extension messages and agricultural policies that can accelerate CSA dissemination and help safeguard agricultural production and food security in Tanzania.

# Acknowledgement

The author acknowledges the Sokoine University of Agriculture and the Integrated Project to increase agriculture productivity in the Southern Highlands of Tanzania. I also thank paddy, maize, soy bean and common beans farming households from Mbeya and Songwe Regions in the Southern Highlands of Tanzania for participating in the survey.

# References

- Arslan, H. (2013). Application of multivariate statistical techniques in the assessment of groundwater quality in seawater intrusion area in Bafra Plain, Turkey. *Environmental Monitoring and Assessment*, 185(3), 2439-2452.
- Aryal, J. P., Jat, M. L., Sapkota, T. B., Khatri-Chhetri, A., Kassie, M., & Maharjan, S. (2018). Adoption of multiple climate-smart agricultural practices in the Gangetic plains of Bihar, India. *International Journal of Climate Change Strategies and Management*. 10 (3), 407-427.

- Azumah, S. B., Adzawla, W., Donkoh, S. A., & Anani, P. Y. (2020). Effects of climate adaptation on households' livelihood vulnerability in South Tongu and Zabzugu districts of Ghana. *Climate and Development*, 1-12
- Beyene, A. D., Mekonnen, A., Kassie, M., Di Falco, S., & Bezabih, M. (2017). Determinants of adoption and impacts of Sustainable Land Management and Climate Smart Agricultural Practices (SLM-CSA): Panel data evidence from the Ethiopian highlands.
- Bezu, Sosina, Girma T. Kassie, Bekele Shiferaw, and Jacob Ricker-Gilbert. "Impact of improved maize adoption on welfare of farm households in Malawi: a panel data analysis." *World Development* 59 (2014): 120-131.
- Bolinder, M. A., Crotty, F., Elsen, A., Frac, M., Kismányoky, T., Lipiec, J., & Kätterer, T. (2020). The effect of crop residues, cover crops, manures and nitrogen fertilization on soil organic carbon changes in agroecosystems: A synthesis of reviews. *Mitigation and Adaptation Strategies for Global Change*, 25(6), 929-952.
- Danso-Abbeam, G., & Baiyegunhi, L. J. (2017). Adoption of agrochemical management practices among smallholder cocoa farmers in Ghana. African Journal of Science, Technology, Innovation and Development, 9(6), 717-728.
- Danso-Abbeam, G., Dagunga, G., & Ehiakpor, D. S. (2019). Adoption of Zai technology for soil fertility management: evidence from Upper East region, Ghana. *Journal of Economic Structures*, 8(1), 32.
- Diiro, G. M. (2013). Impact of off-farm income on agricultural technology adoption intensity and productivity. *Working paper (11), International Food Policy Research Institute*.
- Donkoh, S. A., Azumah, S. B., & Awuni, J. A. (2019). Adoption of improved agricultural technologies among rice farmers in Ghana: A multivariate probit approach. *Ghana Journal of Development Studies*, *16*(1), 46-67.
- Food and Agriculture Organization of the United Nations (FAO). (2010). *Climate-smart agriculture sourcebook*. Available from: http://www.fao.org/docrep/018/i3325e.pdf (Accessed 11/10/2022).
- Food and Agriculture Organization of the United Nations (FAO). (2018). The State of Food Security and Nutrition in the World: Building Climate Resilience for Food Security and Nutrition. Available from https://www.fao.org/3/I9553EN/i9553en.pdf (Accessed 11/7/2023).
- Food and Agriculture Organization of the United Nations (FAO). (2014). *FAO success stories* on climate-smart agriculture. Available from: http://www.fao.org/3/a-i3817e.pdf (Accessed 11/11/2017).
- Gray, L. C., & Kevane, M. (2001). Evolving tenure rights and agricultural intensification in southwestern Burkina Faso. *World Development*, 29(4), 573-587.
- Greene, W. H., & Hensher, D. A. (2003). A latent class model for discrete choice analysis: contrasts with mixed logit. Transportation Research Part B: Methodological, 37(8), 681-698.
- Kanyenji, G. M., Oluoch-Kosura, W., Onyango, C. M., & Karanja Ng'ang'a, S. (2020). Prospects and constraints in smallholder farmers' adoption of multiple soil carbon enhancing practices in Western Kenya. Heliyon, 6(3).
- Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F., & Mekuria, M. (2013). Adoption of interrelated sustainable agricultural practises in smallholder systems: Evidence from rural Tanzania. Technological Forecasting and Social Change, 80 (3), 525-540.

- Kimaro, F. D., Jumanne, S., Sindato, E. M., Kayange, N., & Chami, N. (2019). Prevalence and factors associated with renal dysfunction among children with sickle cell disease attending the sickle cell disease clinic at a tertiary hospital in Northwestern Tanzania. PloS one, 14(6).
- Kpadonou, R. A. B., Owiyo, T., Barbier, B., Denton, F., Rutabingwa, F., & Kiema, A. (2017). Advancing climate-smart-agriculture in developing drylands: Joint analysis of the adoption of multiple on-farm soil and water conservation technologies in West African Sahel. Land Use Policy, 61, 196-207.
- Kurgat, B. K., Lamanna, C., Kimaro, A. A., Namoi, N., Manda, L., & Rosenstock, T. S. (2020). Adoption of climate-smart agriculture technologies in Tanzania. Frontiers in Sustainable Food Systems, 4, 55.
- Lipper, L., & Zilberman, D. (2018). A short history of the evolution of the climate smart agriculture approach and its links to climate change and sustainable agriculture debates. Climate smart agriculture: Building resilience to climate change, 13-30.
- Lipper, L., Thornton, P., Campbell, B.M., Baedeker, T., Braimoh, A., Bwalya, M., ... Henry, K., (2014). Climate-smart agriculture for food security. Nature Climate Change., 4, 1068–1072.
- Maliondo, S. M. S., Mpeta, E. J., & Olson, J. (2012). Climate change and food security in Tanzania: An analysis of current knowledge and research gaps and recommendations for a research agenda. Ohio State University and Sokoine University of Agriculture: Columbus, OH, USA.
- Masuka, B., Atlin, G. N., Olsen, M., Magorokosho, C., Labuschagne, M., Crossa, J., and Macrobert, J. (2017). Gains in maize genetic improvement in Eastern and Southern Africa: I. CIMMYT hybrid breeding pipeline. Crop Science, 57(1), 168-179.
- Mbow, Cheikh, Cynthia E. Rosenzweig, Luis G. Barioni, Tim G. Benton, Mario Herrero, Murukesan Krishnapillai, Alexander C. Ruane et al. Food security. No. GSFC-E-DAA-TN78913. IPCC, 2020.
- McKelvey, R. D., & Zavoina, W. (1975). A statistical model for the analysis of ordinal level dependent variables. Journal of mathematical sociology, 4(1), 103-120.
- Mupangwa, W., Nyagumbo, I., Liben, F., Chipindu, L., Craufurd, P., & Mkuhlani, S. (2021). Maize yields from rotation and intercropping systems with different legumes under conservation agriculture in contrasting agro-ecologies. Agriculture, ecosystems & environment, 306, 107170.
- Muriithi, B. W., Menale, K., Diiro, G., & Muricho, G. (2018). Does gender matter in the adoption of push-pull pest management and other sustainable agricultural practises? Evidence from Western Kenya. Food security, 10(2), 253-272.
- Muzangwa, L., Mnkeni, P. N. S., & Chiduza, C. (2017). Assessment of conservation agriculture practices by smallholder farmers in the Eastern Cape Province of South Africa. Agronomy, 7(3), 46.
- Mwangi, M., & Kariuki, S. (2015). Factors determining usage of new agricultural practise by smallholder farmers in developing countries. Journal of Economics and sustainable development, 6(5), 208 -216
- Ngaiwi, M. E., Molua, E. L., Sonwa, D. J., Meliko, M. O., Bomdzele, E. J., Ayuk, J. E., ... & Latala, M. M. (2023). Do farmers' socioeconomic status determine the adoption of

conservation agriculture? Empirical evidence from Eastern and Southern Regions of Cameroon. Scientific African, 19, e01498.

- Ngoma, H., Mason, N. M., & Sitko, N. J. (2015). Does minimum tillage with planting basins or ripping raise maize yields? Meso-panel data evidence from Zambia. Agriculture, Ecosystems & Environment, 212, 21-29.
- Ntshangase, N. L., Muroyiwa, B., & Sibanda, M. (2018). Farmers' perceptions and factors influencing the adoption of no-till conservation agriculture by small-scale farmers in Zashuke, KwaZulu-Natal Province. Sustainability, 10(2), 555.
- Nwaobiala, C. U., & Nottidge, D. O. (2013). Effect of climatic variables on cassava farmers' production in Abia State, Nigeria. Nigerian Journal of Agriculture, Food and Environment, 9(4), 57-62.
- Oumer, A.M., & Burton, M. (2018). Drivers and synergies in the adoption of sustainable agricultural intensification practises: A dynamic perspective. In Proceedings of the 2018 Agricultural and Applied Economics Association Annual Meeting, Washington, DC, USA.
- Sapkota, T. B., Vetter, S. H., Jat, M. L., Sirohi, S., Shirsath, P. B., Singh, R., & Stirling, C. M. (2019). Cost-effective opportunities for climate change mitigation in Indian agriculture. Science of the Total Environment, 655, 1342-1354.
- Shiferaw, B. A., Okello, J., & Reddy, R. V. (2009). Adoption and adaptation of natural resource management innovations in smallholder agriculture: Reflections on key lessons and best practices. Environment, Development and Sustainability, 11(3), 601-619.
- Teixeira, E. I., de Ruiter, J., Ausseil, A. G., Daigneault, A., Johnstone, P., Holmes, A., ... Ewert,F. (2018). Adapting crop rotations to climate change in regional impact modelling assessments. Science of the Total Environment, 616, 785-795.
- Teklewold, H., Gebrehiwot, T., & Bezabih, M. (2019). Climate smart agricultural practices and gender differentiated nutrition outcome: Empirical evidence from Ethiopia. World Development, 122, 38-53.
- Teklewold, H., Kassie, M., Shiferaw, B., & Köhlin, G. (2013). Cropping system diversification, conservation tillage, and modern seed adoption in Ethiopia: Impacts on household income, agrochemical use and demand for labour. Ecological Economics, 93, 85-93.
- Teklewold, H., Mekonnen, A., Kohlin, G., & Di Falco, S. (2017). Does adoption of multiple climate smart practices improve farmers' climate resilience? Evidence from the Nile Basin of Ethiopia. Climate Change Economics, 8(01).
- Tey, Y. S., Li, E., Bruwer, J., Abdullah, A. M., Brindal, M., Radam, A., ... & Darham, S. (2014). The relative importance of factors influencing the adoption of sustainable agricultural practices: A factor approach for Malaysian vegetable farmers. Sustainability science, 9, 17-29.
- Tumbo, S.D., Mpeta, E., Tadross, M., Kahimba, F.C., Mbillinyi, B.P., & Mahoo, H.F. (2010). Application of self-organizing maps technique in downscaling climate change projections for Same, Tanzania. Physics and Chemistry of the Earth 35: 608–617.
- Vera, T. S., Wiliams, C. E., & Justin, C. O. (2017). Understanding the factors affecting adoption of subpackages of CSA in Southern Malawi.
- Wollni, M., Lee, D. R., & Thies, J. E. (2010). Conservation agriculture, organic marketing, and collective action in the Honduran hillsides. Agricultural Economics, 41(3:4), 373-384.

# Bongole, A. Appendix 1: Estimates of the MVP Model

Variables	Crop rotation		Irrigation		DTMS		Residue reten	tion	Organic manur	e	Intercropping	
variables	Coef.	Std Err.	Coef.	Std Err.	Coef.	Std Err.	Coef.	Std Err.	Coef.	Std Err	Coef.	Std Err.
Household Characteristics Gender of the household	5											
head	0.781***	0.2400	-0.267	0.2490	-0.109	0.1760	0.284*	0.1680	0.327*	0.1850	-0.0271	0.1780
Age of the household head	-0.00455	0.0063	0.0253***	0.0068	0.000140	0.0046	-0.000918	0.0044	0.00209	0.0049	0.00125	0.0047
Marital status Education of the	-0.238	0.2380	0.0705	0.2520	0.252	0.1660	-0.153	0.1570	-0.118	0.1730	-0.116	0.1700
household head	0.0120	0.0209	0.0827***	0.0224	-0.0114	0.0150	0.00155	0.0142	0.0107	0.0156	0.0193	0.0151
Education of the spouse	0.0299	0.0468	-0.00622	0.0511	0.0504	0.0324	-0.0268	0.0306	-0.0169	0.0337	0.0376	0.0318
Household size	-0.0365	0.0253	-0.0369	0.0273	0.0298*	0.0177	0.0138	0.0167	0.0154	0.0179	0.0302*	0.0177
Age of the spouse	0.000360	0.0055	0.00216	0.0059	-0.00566	0.0040	-0.00562	0.0039	-0.00145	0.0043	-0.000284	0.0040
Farming experience	0.00406	0.0051	-0.0147***	0.0054	-0.00461	0.0038	-0.00381	0.0037	0.00582	0.0040	0.00313	0.0038
Number of occupations	0.518***	0.0861	0.104	0.0876	-0.0401	0.0588	0.156***	0.0560	0.205***	0.0618	0.126**	0.0586
Farm Characteristics												
Farm size	-0.000574	0.0069	0.00505	0.0088	0.0112**	0.0048	-0.000465	0.0040	0.00223	0.0043	-0.00685	0.0049
Moderate soil fertility	0.00520	0.1050	-0.160	0.1110	0.0295	0.0726	0.0984	0.0690	-0.171**	0.0748	-0.00339	0.0725
Moderate soil erosion	-0.304***	0.1170	-0.404***	0.1340	0.0506	0.0801	-0.0489	0.0762	0.0893	0.0814	0.110	0.0794
Farm distance	0.00221	0.0036	-0.00846**	0.0035	-0.00452**	0.0021	0.00198	0.0020	-0.00664***	0.0023	-0.000484	0.0022
Production diversity	0.225***	0.0766	-0.00698	0.0707	0.0610	0.0505	-0.0675	0.0458	0.157***	0.0496	0.489***	0.0511
Geographical location												
Region	1.387***	0.1540	-7.830	142.2000	0.324***	0.0801	0.230***	0.0768	0.379***	0.0809	-0.0400	0.0808
Institutional Characteristi	cs											
Number of group membership	0.175	0.1330	0.333**	0.1330	-0.136*	0.0823	0.398***	0.0779	0.0816	0.0821	0.0146	0.0814
Access to extension	0.440	0.1.500	0.054.00	0.1050	0.1.10	0.1020		0.00.50	0.4.45	0.0000	0.0004	0.000.5
Services	-0.119	0.1580	-0.3/4**	0.1850	0.148	0.1020	-0.275***	0.0952	0.145	0.0998	-0.0224	0.0996
office	-0.00360**	0.0017	0.0196***	0.0021	-0.0109***	0.0013	0.00384***	0.0012	-0.00936***	0.0015	0.00100	0.0013
Distance to the market	-0.000524	0.0008	-0.00326***	0.0009	0.000178	0.0004	-0.000252	0.0005	-3.14e-05	0.0002	0.000232	0.0003
Household wealth												
Asset ownership	0.00837	0.0458	0.243***	0.0483	0.0794**	0.0317	0.0468	0.0298	0.124***	0.0330	-0.0179	0.0319
Farm ownership	0.223*	0.1280	-0.327**	0.1430	-0.00257	0.1050	0.0983	0.1000	0.275**	0.1170	0.0397	0.1070
Livestock ownership (TLU)	0.00489	0.0160	-0.00808	0.0164	0.00289	0.0121	0.00171	0.0116	0.0438***	0.0120	-0.0195	0.0144
Number of plots owed	0.119*	0.0703	-0.0588	0.0634	0.172***	0.0459	0.0201	0.0409	0.135***	0.0440	-0.111**	0.0444
Constant	-1.656**	0.6780	-4.259***	0.7240	-1.289***	0.4720	-1.087**	0.4530	-3.943***	0.5110	-1.926***	0.4830

Variables	Coef.	Std. Err.	$\Pr\left(\mathbf{Y}=0 \mathbf{X}\right)$	Std. Err.	$\Pr\left(\mathbf{Y}=1 \mathbf{X}\right)$	Std. Err.	$\Pr\left(\mathbf{Y}=2 \mathbf{X}\right)$	Std. Err.	$\Pr\left(\mathbf{Y}=3 \mathbf{X}\right)$	Std. Err.
Gender of the head of the household	0.2250	0.1367	-0.012	0.00843	-0.04334	0.0278	-0.0340*	0.01848	0.0252	0.0183
Age of the household head	0.0046	0.0036	0.000	0.00016	-0.00084	0.0007	-0.0008	0.0006	0.0004	0.0003
Marital status	-0.0271	0.1289	0.001	0.00566	0.004915	0.0234	0.0045	0.02146	-0.0024	0.0116
Farm experience	-0.0013	0.0030	0.000	0.00013	0.000231	0.0005	0.0002	0.00049	-0.0001	0.0003
Production diversity	0.3590**	0.0382	-0.0156***	0.00272	-0.0652***	0.0077	-0.0598***	0.0075	0.0323***	0.0051
Occupation	0.1742	0.0454	-0.0076***	0.00225	-0.0316***	0.0084	-0.0290***	0.0078	0.0157***	0.0045
Level of education of the head of the										
household	0.0144	0.0116	-0.001	0.00051	-0.00262	0.0021	-0.0024	0.00193	0.0013	0.0011
Level of education of the spouse	0.0129	0.0249	-0.001	0.0011	-0.00234	0.0045	-0.0021	0.00414	0.0012	0.0023
Household size	0.0208	0.0136	-0.001	0.00061	-0.00378	0.0025	-0.0035	0.00227	0.0019	0.0013
Age of the spouse	-0.0056*	0.0031	0.000	0.00014	0.0010*	0.0006	0.0009*	0.00052	-0.0005*	0.0003
Tropical Livestock Unit	0.0055	0.0094	0.000	0.00041	-0.001	0.0017	-0.0009	0.00156	0.0005	0.0009
Total plot size	0.0000	0.0032	0.000	0.00014	2.74E-06	0.0006	0.0000	0.00054	0.0000	0.0003
Geographical location	-0.1293**	0.0622	0.0056**	0.00282	-0.0234*	0.0114	-0.0215*	0.01042	0.0116**	0.0057
Soil fertility	-0.0088	0.0560	0.000	0.00246	0.001595	0.0102	0.0015	0.00932	-0.0008	0.0051
Soil erosion	-0.0225	0.0617	0.001	0.00276	0.004101	0.0113	0.0037	0.01018	-0.0021	0.0057
More membership	0.2029***	0.0632	-0.0081***	0.00259	-0.0354***	0.0107	0.0351***	0.01147	0.0154***	0.0044
Average farm distance	-0.0028*	0.0017	0.000	0.00008	0.000511	0.0003	0.001	0.00028	-0.0003	0.0002
Extension services	-0.0412	0.0769	0.002	0.00359	0.007573	0.0143	0.007	0.01245	-0.0039	0.0076
Distance to the extension office	-0.0028***	0.0010	0.000	0.00005	0.0005***	0.0002	0.0004***	0.00017	-0.0001***	0.0001
Access to market	-0.0001	0.0001	0.000	0	1.41E-05	0.0000	0.001	0.00002	0.0000	0.0000
Log of asset	0.1152***	0.0243	0.0051***	0.00127	-0.0209***	0.0046	-0.0192***	0.0042	0.0103***	0.0025
Plot ownership	0.1389*	0.0815	-0.0061*	0.00367	-0.02525	0.0149	0.0231*	0.01366	0.0125*	0.0075
Number of plots cultivated	0.0574*	0.0336	-0.0025*	0.00152	-0.01042	0.0061	-0.0096*	0.00564	0.0223	0.0052

Appendix 2: Estimates of the ordered probit model and marginal effects of key variable

#### Continue...

Variables	$\Pr\left(\mathbf{Y}=4 \mathbf{X}\right)$	Std. Err.	$\Pr\left(\mathbf{Y}=5 \mathbf{X}\right)$	Std. Err.	$\Pr\left(\mathbf{Y}=6 \mathbf{X}\right)$	Std. Err.
Gender of the head of the household	0.0446	0.026	0.0176*	0.0095	0.0016*	0.0009
Age of the household head	0.0009	0.001	0.0004	0.0003	0.0001	0.0000
Marital status of the household head	-0.0055	0.026	-0.0024	0.0114	-0.0002	0.0011
Farm experience	-0.0003	0.001	-0.0001	0.0003	0.0000	0.0000
Production diversity	0.0735***	0.009	0.0319***	0.0043	0.0031***	0.0011
Occupation	0.0357***	0.009	0.0155***	0.0042	0.0015**	0.0006
Level of education of the head of the household	0.0030	0.002	0.0013	0.0010	0.0001	0.0001
Education of the spouse	0.0026	0.005	0.0011	0.0022	0.0001	0.0002
Household size	0.0043	0.003	0.0018	0.0012	0.0002	0.0001
Age of the spouse	-0.0011*	0.001	-0.0005*	0.0003	0.0000	0.0000
Tropical Livestock Unit	0.0011	0.002	0.0005	0.0008	0.0000	0.0001
Total plot size	0.0000	0.001	-0.0001	0.0003	0.0000	0.0000

Geographical location	0.0264**	0.013	0.0115**	0.0056	0.0011*	0.0007
Soil fertility	-0.0018	0.011	-0.0008	0.0050	-0.0001	0.0005
Soil erosion	-0.0046	0.013	-0.0020	0.0054	-0.0002	0.0005
More membership	0.0419***	0.013	0.0193***	0.0067	0.0020**	0.0010
Average farm distance	-0.0006*	0.000	-0.0002*	0.0002	0.0000	0.0000
Extension services	-0.0084	0.016	-0.0036	0.0065	-0.0003	0.0006
Distance to the extension office	-0.0006***	0.000	0.0002***	0.0001	-0.0001**	0.0011
Access to market	0.0001	0.002	0.0011	0.0001	0.0021	0.0023
Asset ownership	0.0236***	0.005	0.0102***	0.0023	0.0010**	0.0004
Plot ownership	0.0284*	0.017	0.0123*	0.0073	0.0012	0.0008
Number of plots cultivated	0.0117*	0.007	0.0051*	0.0030	0.0005	0.0003
/cut1	1.477797	0.369582				
/cut2	2.510713	0.370806				
/cut3	3.391741	0.373057				
/cut4	4.325163	0.376861				
/cut5	5.258687	0.381774				
/cut6	6.351345	0.401489				