Determinants of Adoption of Climate-Smart Agriculture Practices among Farmers in Sheema District, Western Uganda

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Abstract

With the rapid pace of climate change and its impact on food security and livelihoods, Climate-Smart Agriculture (CSA) is one strategy aiming to help farmers adopt more sustainable farming practices. This study examines the determinants of adoption of CSA practices by farmers in Sheema District in Western Uganda. Through 228 household surveys, we examined the influence of socio-demographic and institutional factors on adoption of climate smart agriculture practices using the multivariate probit model. Most of the farmers are aware of the CSA practices and are utilizing some strategies but have little understanding of how each contribute to the three pillars of CSA. The multivariate probit model results show that the adoption of CSA practices is significantly associated with gender, age, household size, land size, household income, access to agricultural credit and membership to a social group. It recognizes that there is need to; i) tailor appropriate and site-specific CSA practices, and ii) critically analyze the challenges farmers face to have a better understanding of the necessary steps to take that will benefit them and facilitate adoption.

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Keywords: Climate smart, smallholders, agriculture, adoption

Introduction and Problem Statement

Agriculture is Uganda's main economic sector, accounting for 27% of Gross Domestic Product (GDP) and employing 73% of the labor force (Uganda Bureau of Statistics, 2023), and continues to be a fundamental instrument for securing a livelihood. Currently, the sector is suffering from adverse impacts of climate change affecting the livelihood and resilience of smallholder farmers: who depend on rain-fed agriculture for their livelihood (Nsubuga & Rautenbach, 2018; Oriangi et al., 2020), a case in point occurring in 2016 when the agriculture sector experienced significant crop losses at the farm level, mainly due to climate-induced shocks, leaving several smallholder farmers and their families' food insecure with significant asset loses, reducing their adaptive capacities to the future climate change shocks (World Bank, 2018).

One of the strategies for increasing agricultural production in this era of climate change is the development and use of modern technologies (FAO, 2010; World Bank Group et al., 2015) since they can promote and enhance efficient and sustainable utilization of land and water resources by smallholder farmers, and boost resilience capacities against the noxious effects of climate-induced hazards hence calling for a strong emphasis on the adoption of Climate-Smart Agriculture (Palombi & Sessa, 2013). Climate-Smart Agriculture (CSA) refers to the agriculture that sustainably increases productivity, enhances resilience (adaptation), reduces greenhouse gas emission (mitigation) where possible, and enhances the achievement of national food security and development goals (Palombi & Sessa, 2013). CSA has several potential options including; changes in agronomic practices that are suitable to local climatic, socioeconomic, and cultural conditions; adoption of new technologies (fertilizer, water, and energy-use efficient technologies) and the use of relevant information (based agro-advisories and weather-index based insurance) at the farm level, to manage moderate to severe climate-risks in agriculture (FAO, 2010; Palombi & Sessa, 2013; World Bank Group et al., 2015).

According to Caffrey et al. (2013), crop diversification, small-scale irrigation, permanent planting basins, green manuring, conservation agriculture (rotations, intercropping, mulching and reduced tillage) and agroforestry are among the most common climate-smart practices being promoted in the country to improve productivity, food availability and resilience to climate hazards. These CSA practices predominantly used by small-scale farmers whose primary goal is to increase crop productivity, are location specific and knowledge-intensive (Palombi & Sessa, 2013). To a large extent, the adoption of these practices by farmers is a function of (i) farmer characteristics such as age, experience, and education, (ii) institutional factors such as access to input markets, credit and extension services, (iii) awareness or exposure to the practice, (iv) knowledge of the extension agents, and (v) the diffusion methods used by the extension agents (Rupan et al., 2018).

According to International Center for Tropical Agriculture-CIAT, Bureau for Food Security- BFS, and United States Agency for International Development-USAID (2017), the three selected CSA practices (cover cropping, mulching, and composting) in Table 1 are key for ensuring food security in Uganda.

Table 1

Smartness Assessment for Climate Smart Agriculture Practices

CSA practice	Contribution to three of the CSA pillars (*increased productivity*, *adaptation* to climate change, and *mitigation* of climate change)
Use of cover crops	*Productivity:* Water conservation and use for organic fertilizer results in improved yields. *Adaptation:* Protection of the soil against the impacts of raindrops; to keep the soil shaded, and conserve moisture content hence reduced vulnerability to erosion. Allelopathic effect on weeds; breaking of disease cycles; trap crops attract pests away from the crop of value or used to attract natural predators of pests. *Mitigation:* Cover crops increase soil carbon sequestration; reduce fertilizer use after legume cover crops; extract plant-available nitrogen unused by the preceding crop, thereby reducing N_2O emissions. GHG mitigation potential is 0.51-1.45 tCO_2-eq/ha/yr (Recha et al., 2014).
Mulching	*Productivity:* Improve the productivity of the land (i.e. crop yields) by making conditions more favorable for plant growth, i.e. conserving soil moisture, improving soil fertility, and reducing soil erosion. *Adaptation:* Promotes soil and water conservation during dry seasons. Increases soil organic matter hence soil fertility. *Mitigation:* Maintains and improves soil carbon stocks and soil organic matter content. GHG mitigation potential of mulching is 0.02-1.42 tCO_2-eq/ha/yr (Recha et al., 2014).
Composting	*Productivity*: Compost manure improves productivity and produces greater crop yield. *Adaptation*: Improve soil fertility; increases soil moisture and soil cover, as well as reducing soil loss. *Mitigation:* Handling manure in the solid form suppresses CH_4 emissions. Covering liquid manure reduces N_2O emissions. Reduce the need for fertilizer, which decreases greenhouse gas emissions. GHG mitigation potential of composting is 0.02-1.42 tCO_2-eq/ha/yr. (Recha et al., 2014).

Source: CIAT and BFS/USAID (2017).

Specifically, Sheema District is known for production of coffee and banana crops (MAAIF, 2015), which are highly vulnerable to climate variability and change due to their phenological characteristics (Caffrey et al., 2013). Despite this, farmers' level of adoption of the selected practices (cover cropping, mulching, and composting) has been generally low; less than 30 percent (MAAIF, 2015). Low adoption may be attributed to lack of coordination between farmers, extension agents and other actors in the agricultural information system (Kakota et al., 2017), as most farmers still depend on traditional subsistence farming systems (MAAIF, 2015). In addition, the choice of adoption by most of farmers is influenced by financial capabilities and different contextual factors such as socio-demographic and institutional characteristics (Mwadzingeni et al., 2022). With a better understanding of the factors that influence the adoption of different CSA practices, appropriate pathways can be identified for use by the extension agents to increase the diffusion and adoption of CSA practices. This study contributes to ongoing efforts to promote the adoption of CSA practices in Uganda, which aim to increase productivity, build resilience against climate change (adaptation) and remove and reduce greenhouse gas emissions (mitigation).

Purpose and Objectives

This study examines factors that influence adoption of climate smart agriculture practices in Sheema District in Western Uganda. More specifically, the study objectives were to determine the influence of socio-demographic and institutional factors on farmers' adoption of 1) cover cropping, 2) composting, and 3) mulching as climate smart agriculture practices.

Theoretical Framework

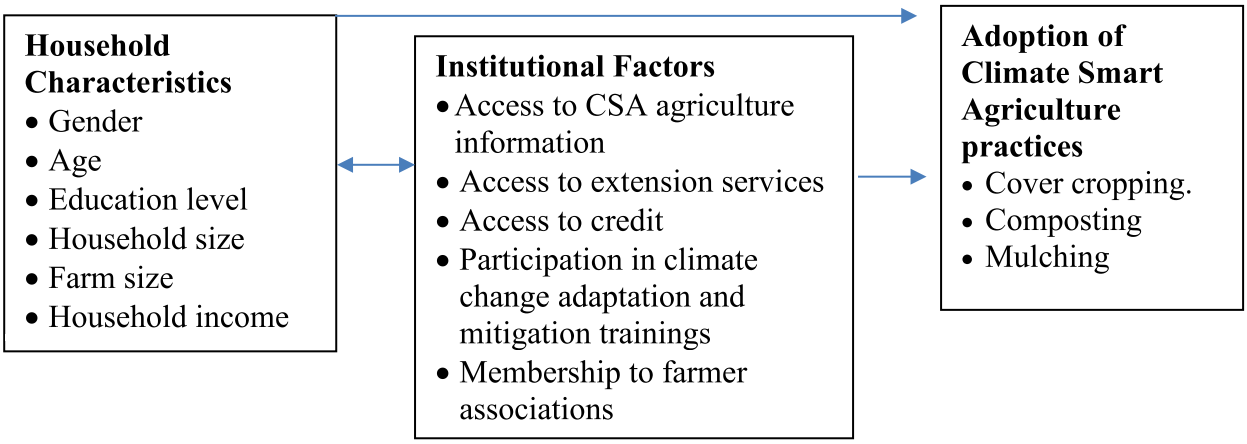
This paper is informed by the *theory of diffusion of innovation* (Rogers, 2003) and the expected maximum utility theory (Schoemaker, 1982). The *expected utility maximization theory* posits that an individual farmer will adopt a specific CSA practice on his or her farm if the expected utility from adoption of that innovation is greater than the expected utility from any other alternative practice, including the business as usual. The expected utility theory helps in supplementing the theory of diffusion of innovation by strengthening the decision to adopt or not to adopt CSA practice. The adoption of CSA practices is an essential component of economic growth (Perla & Tonetti, 2014) in this era of climate change.

Therefore, the theory of diffusions of innovation postulates diffusion of innovations is influenced by the characteristics of innovators, the innovation itself and the communication channels used to disseminate the innovations (Rogers, 2003). Based on Rogers' theory, the characteristics of innovators match the household factors (gender, age and education level of a farmer, household size, farm size, and household income) in the study. The characteristics of innovation as posited by the theory of innovation matches the CSA practices (i.e., cover cropping, composting, and mulching). The communication channels used to disseminate innovations match the component of institutional factors that facilitate the spread of innovations like access to CSA information, access to agricultural extension services, access to agricultural credit, participation in climate change adaptation and mitigation trainings, and membership to a farmer association. The underlying rationale to adopt a CSA practice lies in first making farmers aware of the options and technology required with the practice. (Kabunga et al., 2012; FAO, 2013). The adoption of CSA practices takes place within a socio-cultural environment and requires key capital inputs such as labor, finances, produced and social capital (FAO, 2013). Better organization and allocation of the various forms of capital enhances the efficiency, which is important for the adoption and diffusion of interventions to achieve increased productivity, adaptation to, and mitigation of climate change among smallholder farmers in any farming system (Mutoko et al., 2014). Effective partnerships and collaboration with other interested organizations is another avenue that can generate substantial synergy to accelerate the adoption rate of the promoted CSA practices (Odongo, 2010).

The conceptual framework shown in Figure 1 is derived from the theory of diffusion of innovation. The conceptual framework considers both household and institutional factors to have a bearing on the adoption of climate smart agriculture practices 1) cover cropping, 2) composting, and 3) mulching.

Figure 1

The conceptual framework



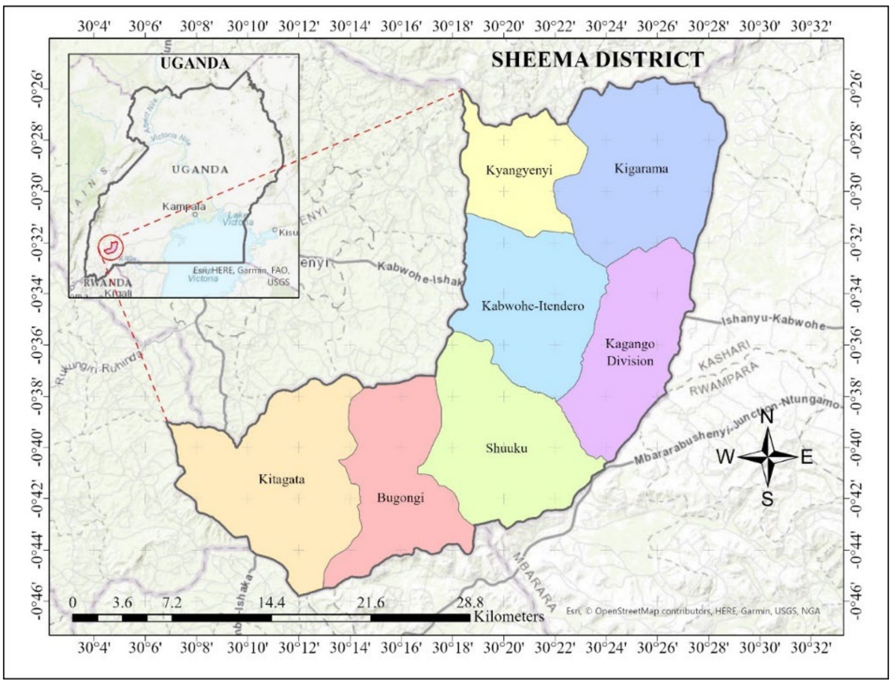
Adopted, with slight adjustments from Ngaruiya & Scheffran (2016).

Methods

The study was conducted in Sheema District of Western Uganda (See Figure 2). The district is divided into seven sub-counties; - Bugongi, Kabwohe-Itendero, Kagango, Kigarama, Kitagata, Kyangyenyi, and Shuuku; and lies between 00 32S, 30 26E, at an altitude of 1500 meters above sea level, and with a total area of 699.1km² (Uganda Bureau of Statistics, 2023).

Figure 1

Sheema District in Uganda



The district experiences bimodal rainfall from mid-November to Mid-May, with the annual rainfall ranging between 100 and 1300mm; the maximum temperature is 24ºC to 27ºC and a minimum is 13ºC to 16ºC. With a change in climate, the coffee and banana producing areas are reducing production and are expected to continue reducing production (Pachauri et al., 2014); thus, putting these farming communities at risk of suffering from climate change effects. Farmers keep livestock especially for dairy cattle under zero grazing and grow a variety of crops such as bananas (main food crop), coffee (main cash crop), cassava, sorghum, beans, groundnuts, and sweet potatoes. The selection of the study area was based on the representativeness in terms of biophysical characteristics, vulnerability to climate change, accessibility of the area and socio-economic activities, all of which clarified and informed the conclusions and recommendations.

The study employed a survey research design where data were collected from farmers between May and June 2019. The research design was chosen because it is a one-time research approach, and thus it is cost-effective in terms of time and financial resources. Western Uganda was purposively selected because the Government of Uganda with the support of the private sector had promoted the CSA practices in the region. Sheema District was also purposively selected because it was the pilot district for the training farmers in CSA practices in Western Uganda.

A sample size of 456 famers (228 CSA adopters and 228 non-adopters) that was constituted mainly of heads of households were selected using multi-stage, random and purposive sampling strategies. The first stratification considered seven sub counties of Sheema district namely, Bugongi, Kabwohe-Itendero Town Council, Kagango, Kigarama, Kitagata, Kyangyenyi, and Shuuku. Selection was in accordance with the Local Government decentralization policy of taking services closer to the local people to improve their participation in decision making. Five sub counties (Bugongi, Kabwohe-Itendero Town Council, Kigarama, Kitagata, and Shuuku) were randomly selected to participate in the study to give each sub county an equal opportunity for selection; thus, minimizing selection error.

The second level of stratification involved stratifying a sub county into a parish. A total of 20 parishes (four from each sub county) were randomly selected to give each parish an equal opportunity to participate and minimize selection bias. Furthermore, each parish was stratified into villages (third stratum), and four villages were randomly selected in each of the selected parishes. These villages are of almost the same size, with similar ethnic composition, and shared the same agro-ecosystem. Finally, at the village level, eight households (four for CSA adopters and four non-adopters) were randomly selected from the list of smallholder farmers who participated in CSA training at the sub county production office, which was the sampling frame for the study. The sub county local government leaders and agricultural production personnel were used as points of entry to households of smallholder farmers. At the household level, the head of a household was purposively selected to participate in the interview because of the principal role to make decisions on farming practices used. A sample size of farmers was arrived at based on Cochran's (1977) formula.

$$n_0 = \frac{Z^2 pq}{e^2} (1)$$

In this study, maximum variability, p = 0.5 was assumed. Also, a 95% confidence level and a 6.5% level of precision were considered. The resulting sample size calculated using equation was 228 respondents. The selected heads of the households, whether male or female was implicitly assumed to be the decision-makers in the selection of appropriate climate smart agriculture practices to adopt.

Quantitative data were collected using household surveys designed to capture individual household factors (gender, age, educational level, household size, farm size, and household income). The survey instrument gathered data on institutional factors of access to climate and climate smart agriculture information, access to extension services, access to financial credit, participation in climate change adaptation and mitigation training, and membership to a farmer association. In addition, the survey instrument collected data on three CSA practices (cover cropping, composting, and mulching).

The survey instrument was field tested for content validity by the thesis advisors from Haramaya University in Ethiopia and Kyambogo University in Uganda. Further, the reliability of the questionnaire was determined by administering a questionnaire to 15 farmers who were not included in the study population to avoid biased responses. The reliability was analyzed using Cronbach's alpha, with those items below 0.7 not used in the empirical analysis. The Cronbach's alpha indicated 0.83, and since the general rule of thumb is a Cronbach's alpha of 0.70 and above is good, 0.80 and above is better, and 0.90 and above is best, then the questionnaire was deemed reliable (Ursachi et al., 2015).

The R Software Version 4.4.0 was used to analyze data on the farmers' socio-demographic and institutional characteristics. To identify the factors that influence farmers' decision to adopt any of the three climate smart agriculture practices (cover cropping, composting, and mulching), a Multivariate Probit (MVP) regression model was used. The main advantage of this model is it allows the analysis of the potential correlation between unobserved disturbances (error terms) and the correlation between the adoption of each CSA practice (Mittal & Mehar, 2016; Mussida & Zanin, 2020). Accordingly, the correlation among the decisions to adopt different CSA practices may be due to technological complementarity or substitutability, in which case the estimates of simple binary logit or probit models can be biased and inefficient (Branca & Perelli, 2020; na et al., 2014). Thus, the study employed the MVP model, which was estimated using the mvProbit function from the mvProbit package (Henningsen, 2021).

The analysis was based on the expected utility maximization of adoption of a specific CSA practice by a farmer if the expected utility from adoption (U_{ij}^{*}) was greater than the expected utility from any other alternative practice, including the business as usual (i.e., not adopting any climate smart agriculture practice) (U_{ij}),

$$Y_{ji}^{*} = U_{ij}^{*} - U_{ij} > 0 \quad (2)$$

Where, Y_{ji}^{*} is the net benefit (latent variable) the farmer receives from adopting j^{th} climate smart agriculture practices. In the MVP model, there are multiple binary dependent variables (Y_{ji}), and multiple latent variables (Y_{ji}^{*}) (Sileshi et al., 2019). However, in this study, the MVP model consisted of three binary choice equations; cover cropping (Y_1), composting (Y_2) mulching (Y_3). Consequently, the model assumed that each binary observed variable takes a value 1 if, and only if, the continuous latent variable is greater than zero:

$$Y_{ji}^{*} = X_{ji}\beta_{ji} + \varepsilon_{ji} \quad (3)$$

Where Y_{ji}^{*} is a latent variable that captured the unobserved preferences associated with the choice of three CSA practices and is influenced by observed characteristics (X_{ji}) and unobserved characteristics captured by the stochastic error term (ε_{ji}). Using the indicator function, the unobserved preferences in equation (3) translated into the observed binary outcome equation for each choice as follows:

$$Y_{ji} = \{^{1}_{0} \quad ^{if\ Y_{ji}^{*}>0}_{otherwise} \quad (j = Y_1, Y_2 Y_3) \qquad (4)$$

In a multivariate model, where the choice to adopt several CSA practices in response to climate change is possible, the error terms jointly follow a Multivariate Normal

Distribution (MVN) with zero conditional mean and variance normalized to unity (for identification of the parameters) where:

$$[\mu_{y_1}, \mu_{y_2}, \mu_{y_3}] \sim MVN(0, \Omega) \qquad (5)$$

And the symmetric covariance matrix Ω is given by:

$$\Omega = \begin{bmatrix} 1 & \rho_{y_1 y_2} & \rho_{y_1 y_3} \\ \rho_{y_2 y_1} & 1 & \rho_{y_2 y_3} \\ \rho_{y_3 y_1} & \rho_{y_3 y_2} & 1 \end{bmatrix} \qquad (6)$$

Of particular interest were off-diagonal elements in the covariance matrix, which represent the unobserved correlation between the stochastic components of the different types of CSA practices. This assumption means equation (6) generated a multivariate probit model that jointly represented the decision to choose a particular CSA practice. This specification with non-zero off-diagonal elements allowed for correlation across error terms of several latent equations, which represented unobserved characteristics that affect the choice of alternative climate smart agriculture practice.

Following the form used by Hemmert et al. (2018), the log-likelihood function associated with a sample outcome is then given by:

$$ln\, L = \sum_{i=1}^{N} \omega_i \, ln\, \Phi\, (\mu_i, \Omega) \qquad (7)$$

Where ω_i is an optional weight for observation i, and Φ is the multivariate standard normal distribution with arguments μ_i and Ω, where μ_i can be denoted as:

$$\mu = (k_{i1}\beta_1 X_{i1}, k_{i2}\beta_2 X_{i2}, k_{i3}\beta_3 X_{i3}), \text{ while } \Omega_{ik} = 1 \text{ for } j = k \cdots\cdots\cdots\cdots\cdots\cdots (8)$$

And

$$\Omega_{jk} = \Omega_{kj} = (k_{ij} k_{ik} \rho_{jk} \text{ for } j \neq k, k = 1,2,3 \ \cdots \text{ with } k_{ik} = 2y_{ik} - 1 \cdots\cdots\cdots\cdots (9)$$

Results

Socio-demographic Characteristics

The farmers were asked to provide basic demographic information, including age, gender, education level, household size, household income, and land size, as well as institutional factors like access to climate information, access to extension services, participation in climate change adaptation and mitigation trainings and membership to farmer associations, as summarized in Table 2.

Table 2

Socio-demographic and Institutional Characteristics

Characteristic	Statistics			
Continuous variables	*Minimum*	*Maximum*	*Mean*	*SD*
Age (Years)	27.00	66.00	46.72	9.795
Land Size (Acres)	2.00	20.00	6.814	3.845
Household Income (USD per annum)	195.00	16,000	2407.68	1713.05
Household Size (Numbers)	3.00	11.00	5.88	1.66
Education Level (Number)	0	4	1.58	0.894
Categorical	*Frequency*	*Percentage*		p-value

			χ^2	
Gender (Male)	149	65.4	21.491	0.000***
Access to agricultural credit (Yes)	137	60.1	9.281	0.002***
Access to climate and CSA information (Yes)	69	30.3	35.526	0.000***
Access to extension services (Yes)	145	63.6	16.860	0.000***
Participation in climate change adaptation and mitigation training (Yes)	55	24.1	61.070	0.000***
Membership to a farmer association (Yes)	128	56.1	3.439	0.064

Table 2 indicates the mean age of the survey population was 46.7 years of age, was predominately male (65.4%), and had formal education (89%). The average land size owned by farmers was 6.814 acres, average annual household income was $2,407, a typical household had an average of 6 members (range 3-11), with half of whom worked mostly on the farm while the remaining household members were school-going children and adults engaged in other occupations such as teaching and business. Most farmers had access to agricultural credit (60.1%) and access to extension services (63.6%) delivered by the public extension workers stationed at sub-county level. More than half of the respondents (56.6%) belonged to at least one farmer association, and a few (30.3%) had access to CSA information. Only 24.1% of the farmers participated in climate change adaptation and mitigation trainings.

The Adoption of CSA Practices

The results of descriptive analysis show at least 70% of the households adopted at least one of the selected three climate smart agriculture practices as summarized in Table 3.

Table 3

Adoption of Climate Smart Agriculture Practices

Practice	Adopters		Non adopters			
	(N=228)	(%)	(N=228)	(%)	χ^2	p-value
Cover cropping	171	75.0	57	25.0	57.000	0.000***
Mulching	161	70.6	67	29.4	38.754	0.000***
Composting	193	84.6	35	15.4	109.491	0.000***

Table 3 shows that the most adopted CSA practice was composting (84.6%), cover cropping (75%), and mulching (70.6%), the number of adopters being significantly different from the non-adopters for all the three CSA practices. The simultaneity and interdependence among the adoption decisions of CSA practices is summarized in Figure 3.

Figure 2

Simultaneity and Interdependence among the Adoption Decisions of CSA Practices

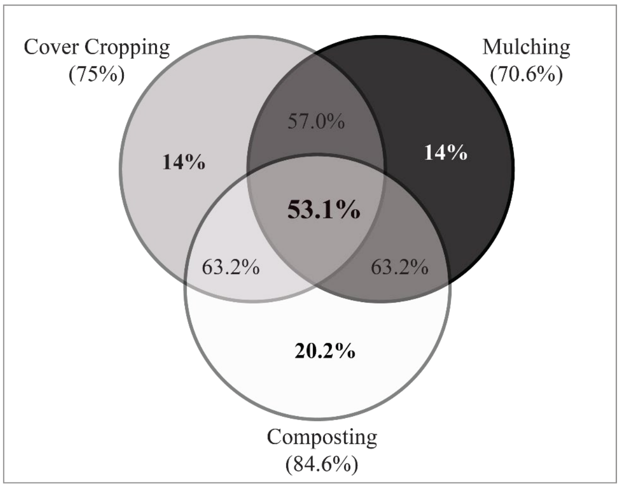


Figure 3 indicates 48.4% of the farmers adopted a single practice at a time on their farms: cover cropping (14.1%), mulching (14.1%) and composting (20.2%); while 61.2% adopted two CSA practices on their farms: cover cropping and composting (63.2%), composting and mulching (63.2%), mulching and cover cropping (57.1%), and only 53.1% of the farmers adopted all the three CSA practices. This indicates there is simultaneity and interdependence among the adoption decisions of CSA practices measures in the study area.

Results of Empirical Analysis

The factors that influence the adoption of the three climate smart agriculture practices, i.e. cover cropping, composting, and mulching were grouped into socio-demographic and institutional characteristics. The statistical relationships between the dependent variable (i.e. adoption of selected three CSA practices) and explanatory variables (i.e. socio-demographic and institutional characteristics) were estimated using the Multivariate Probit Regression Model.

Factors that Influence Farmers' Decision to Adopt Climate Smart Agriculture

Before interpreting the results, investigators determined the statistical validity of the model and interdependence of dependent variables. The model fit the data reasonably well (Wald Chi-squared = 186.30; $p = 0.000$). The correlation coefficients between cover cropping and mulching, cover cropping and composting, and mulching and composting were 31.4%, 3.65%, and 57.5% respectively. The positive sign indicated there were positive (complementarity) and interactive correlations between cover cropping and mulching, cover cropping and composting, and mulching and composting, as summarized in Table 4.

Table 4

Results of Multivariate Probit Model (MVP) for Choice of CSA Practices

Variable	Cover Cropping			Mulching			Composting		
	Coef.	Std. Err.	Pr(>|z|)	Coef.	Std. Err.	Pr(>|z|)	Coef.	Std. Err.	Pr(>|z|)
Intercept	0.3407	0.6338	0.591	-2.4276	0.6192	0.000*	3.9689	0.8390	0.000*
Gender	-1.0190	0.2394	0.000*	0.3990	0.2268	0.079	0.8591	0.2530	0.001*
Age	0.0156	0.0118	0.187	-0.0034	0.0122	0.776	-0.0742	0.0151	0.000*
Education Level	0.0464	0.0903	0.607	0.0836	0.1135	0.461	0.0754	0.1327	0.570
Land Size	0.1288	.04958	0.009*	0.0191	0.0389	0.623	-0.0227	0.0388	0.559
Household Income	0.0004	0.0001	0.009*	0.0002	0.0001	0.175	-0.0000	0.0000	0.665
Household Size	-0.2419	0.0799	0.002*	0.2332	0.0867	0.007*	-0.0580	0.0779	0.456
Access to Agricultural Credit	0.0264	0.2755	0.924	0.8426	0.2415	0.000*	1.3540	0.2867	0.000*
Access to Climate Information	-0.3853	0.3118	0.217	0.2429	0.3362	0.470	-0.0235	0.3827	0.951
Access to Extension Services	-0.4112	0.2761	0.136	0.1074	0.2602	0.680	0.2145	0.2935	0.465
Participation in CC Trainings	0.0112	0.3129	0.971	-0.3642	0.3630	0.316	-0.0752	0.4227	0.859
Membership to a Farmer association	0.7503	0.2196	0.001*	0.8770	0.2281	0.000*	-0.3707	0.2629	0.158

Note: * Indicates significance at 95% level.

The results of MVP model in Table 4 reveal the adoption of the three CSA practices had significant associations with varied socio-demographic and institutional characteristics of farmers. Out of the eleven (11) hypothesized variables, five (i.e., gender, land size, household income, household size and membership to a farmer association); three (i.e., household size, access to agricultural credit, and membership to a farmer association), and three (i.e., gender, age, and access to agricultural credit) have significance influence on the adoption of cover cropping, mulching, and composting respectively.

Gender had both a negative and positive relationship on the adoption of cover cropping and composting, significant at 0.1% and 1% levels respectively. Male farmers were found to be less likely to adopt the cover cropping practice and mitigate climate change effects compared to female farmers. Contrary, male farmers were also more likely to adopt the composting practice compared to female farmers. Age of the farmer had a negative relationship on the adoption of composting practice, and the relationship was significant at .05% level. Land size had a positive influence on the adoption of cover cropping, significant at .05% level. Household income had a positive influence on the adoption of cover cropping practice, significant .05% level. Household size had negative and positive influence on the adoption of cover cropping and mulching practices respectively, significant at .05% level. Access to agricultural credit had a positive relationship on the adoption of mulching and composting practices, and the relationship was significant at .05% level. Membership to a farmer association had a negative influence on the adoption of composting and the relationship was significant at .05% level.

Discussion/ Conclusion

Socio-demographic Factors

This paper is informed by the theory of diffusion of innovation (Rogers, 2003) and the expected maximum utility theory (Schoemaker, 1982). The expected utility maximization theory posits an individual farmer will adopt a specific CSA practice on his or her farm if the expected utility from adoption of that innovation is greater than the expected utility from any other alternative practice, including the business as usual. The adoption of CSA practices is an essential component of economic growth (Perla & Tonetti, 2014) in this era of climate change.

The respondents' mean age of 46.7 implies most farm households in the study area belong to the economically active age group and their technology adoption behavior is critical for the improvement of agricultural productivity and farm household welfare (Perla & Tonetti, 2014). The fact that most of the farmers were men could imply that most of the climate smart agriculture decisions tended to be tilted towards views, concerns, and opinions of men. This agrees with the findings of Jost et al. (2016) where women said men are the primary decision-makers for staple food crops because they seek to maximize profits, and men are the first to adopt new practices taught by extension service staff. The men then pass on the knowledge and information to the women, which indicates a potential pathway for diffusion of these practices (Rogers, 2003) as local extension services develop their programming.

Most farmers widely adopting composting, cover cropping, and mulching implies there is simultaneous and interdependence among the adoption decisions of the selected three CSA practices. Male farmers were less likely to adopt the cover cropping practice and mitigate climate change effects than female farmers. Gender roles and responsibilities within the local communities, where men are more involved in the growing of crops like perennials and high value crops like coffee and are more exposed to agricultural extension capacity building and trainings (Jost et al., 2016), could impact these decisions. It is possible that male farmers preferred practices that demand less labor and less disturbance of the root system compared to use of cover cropping that calls for opening of the soil, which in turn damages the coffee roots making it vulnerable to drought. Male farmers being more likely to adopt composting practices than female farmers could be attributed to a gender bias in flow of information about composting and the fact that women do not always get involved in labor-intensive activities. This finding agrees with research reported by (Suvedi et al., 2017) in their study of factors influencing adoption of improved seed varieties in the hills of rural Nepal.

Given that the age of a farmer had a negative influence on the adoption of composting practice, it implies older farmers are less likely to practice composting compared to younger farmers. Older farmers were less receptive to technologies that required more profound changes in traditional cultivation practices, as was the case with the findings of Sennuga et al. (2020) and Yokamo (2020). Farmers' volume of economic activities reduced as they aged and therefore, they may have been unable to pay for the CSA practices. Additionally, older farmers have accumulated years of experience in farming through experimentation and observations and may have found it difficult to leave such experiences for new practices that they may not seeing adding to the utility of their current system (Schoemaker, 1982).

Land size had a positive influence on the adoption of cover cropping, significant at .05% level which implied that farmers with large land sizes farmers were more likely to adopt cover cropping practice than those with small farm sizes. Since cover cropping does not require any specific equipment or initial investment, the positive effect of land size, which is related to the income level, is somewhat surprising. This evidence suggests farmers with large parcels of land could experiment with cover cropping. This finding agrees with Ruzzante et al. (2021) who found technologies, such as agricultural machinery, were adopted only by farmers with a minimum critical farm size that makes adoption profitable.

Household income had a positive relationship on the adoption of cover cropping practice, significant .05% level, which implies the higher the household income, the more the likelihood that a farmer will adopt cover cropping and mulching practices. This is possible because a high household income facilitates the procurement of for example, seeds for use in the cover cropping practice compared to households with small incomes that cannot afford such inputs.

Farmers with large household size were found to be less likely to practice cover cropping practice compared to farmers with small household size, a factor that could be attributed to fact that households that are large may be forced to divert part of their labor force to non-farm activities. On the other hand, household size had a positive relationship with the adoption of mulching practice could imply that farmers with large household size were more likely to practice mulching than farmers with small household size. Mulching is less labor-intensive, but larger amounts of labor would be available in large households, if not diverted to other non-farm activities.

Institutional Factors

The fact that access to agricultural credit had a positive relationship with the adoption of mulching and composting practices could imply that farmers with access to agricultural credit were more likely to adopt mulching and composting practices than farmers without access to agricultural credit. This could be attributed to the fact that good composting practice calls for digging of compost pits and procurement of covering sheets or construction of compost sheds that call for finances to invest in the use of the practices.

Membership to a farmer association had a negative relationship with the adoption of composting, which is contrary to most farmer associations in the local setting that promote collective group action, which increases awareness about climate change adaptation strategies because farmers share information and best practices at their periodic meetings. The negative relationship of membership to a farmer association to adoption of composting could be because most farmer groups tend to focus on land tillage and harvesting of the agricultural produce rather than soil management practices, the benefits of which may not easily recognized by the smallholder farmers.

In conclusion, the age of a farmer and membership to a farmer association constitute the most curtailing factors to the adoption of composting practices, thus farmers less adopt composting as a farming practices. Contrary, gender and household size tend to deflect and subdue the adoption of mulching because of cultural bias and financial costs involved in the use of the practice. The gender of a farmer and access to financial credit tend to enhance the adoption of composting. In addition, land size, household income, and access to financial credit tend to promote the adoption of cover cropping practice. Given that several of the factors influence adoption of cover cropping, mulching, and composting, it is important for agencies that promote CSA to deliberately consider socio-demographic factors when training farmers to encourage the adoption of such practices. Agricultural extension educators need to understand the socio-demographic and cultural attributes of a local farming community as they impact adoption of CSA practices. Ultimately, educators must clearly evidence to the farmer the benefits of change (Schoemaker, 1982) for implementation of these CSA practices (Rogers, 2003) to become more prevalent in the Sheema District of Uganda.

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