ADOPTION OF CLIMATE SMART AGRICULTURE TECHNOLOGIES BY SMALLHOLDER MAIZE FARMERS IN MANAFWA DISTRICT, EASTERN UGANDA

HAMFERY ROBERT MAFUMO

S19M43/017

A DISSERTATION SUBMITTED TO THE FACULTY OF AGRICULTURAL SCIENCES IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF MASTER OF SCIENCE IN AGRICULTURE AND RURAL DEVELOPMENT OF UGANDA CHRISTIAN UNIVERSITY

April, 2024

UGANDA CHRISTIAN UNIVERSITY
A Centre of Excellence in the Heart of Africa

ABSTRACT

Globally, climate change is becoming a major threat to food security systems and sustainable development. This study aimed to assess the effects of Climate-Smart Agriculture (CSA) practices adopted by smallholder farmers on maize yields in Butiru sub-county, Manafwa district. It focused on identifying the existing CSA practices, determined factors influencing their adoption, and evaluated their effects on maize yield. The study hypothesized that CSA practices have no significant effect on maize yield. A cross-sectional design was employed; simple random sampling to select 298 maize farmers and semi-structured questionnaires were used to collect primary data. Data analysis was conducted using descriptive statistics and a Binary probity with STATA software. The results revealed that, the common CSA practices included: intercropping maize with legumes, use of improved maize varieties, and application of organic fertilizers implementation of crop barriers, terracing and agroforestry. Among these, intercropping maize crop with legumes ranked 1st and agroforestry ranked the least among the CSA practices used. Majority of farmers (55.37%) were male, mean age of respondents was 43.61 years. On average, farmers' households comprised six (6) members, the mean maize average was 2.297 acres and an average number of extension visits was 0.439 per month. The average size of farmer groups was 10 members. The Binary probit revealed that factors such as gender, age, participation in CSA training sessions, extension visits, household labor availability, education level, and access to credit significantly ($p>0.1$) influenced the adoption of CSA practices among smallholder farmers. Furthermore, CSA practices like intercropping ($P>0.03$), planted better quality maize seeds ($P> 0.04$), and use of decomposed manure ($p = 0.01$) had a significant effect on maize yield. In conclusion, the adoption of the improved maize planning technologies is influenced by factors such as sex, age, education, and extension visits. Training has helped in promoting the use of different improved technologies, with significant effects on maize yield seen in practices like intercropping, use of biological mature and the use of better-quality seeds. To enhance the adoption of improved technologies and improve crop productivity, it is recommended to develop farmer education programs that increase adoption, promote gender empowerment and youth involvement and improve access to financial credit for small-scale farmers.

DECLARATION

I, MAFUMO ROBERT HAMFREY hereby declare that this is my original work, is not plagiarized and has not been submitted to any other institution for any award.

.... 02/04/2023

Signature Date

APPROVAL

I certify that this work has been done under my direct supervision

.... 03/04/2024 ....

Namuwaya Sheila Date

(Supervisor)

ACKNOWLEDGEMENTS

The author is greatly indebted to persons who contributed immensely to this research project in terms of sacrificing their resources and expertise.

Firstly, sincere thanks to my lecturers at Uganda Christian University, Faculty Agricultural Sciences for being available. With gratitude, I acknowledge Ms. Sheila Namuwaya and Mr. Mutyaba Livingstone for the great guidance and above all, I thank Almighty God for being on my side all the time.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

LIST OF ABBREVIATIONS

CSA	Climate Smart Agriculture
FAO	Food and Agriculture Organization
GHGs	Green House Gasses
IMF	International Monetary Fund
IPCC	Intergovernmental Panel on Climate Change
LG	Local Government
MoFPED	Ministry of Finance Planning and Economic Development
NEMA	National Environment Management Authority
SSA	Sub-Saharan Africa
UboS	Uganda Bureau of Statistics

CHPATER ONE: INTRODUCTION

1.1. Background

Maize is the most widely produced cereal globally, with production estimated at 1,162 million metric tons (FAO, 2022). It serves as a critical staple crop for over 1.2 billion people in Sub-Saharan Africa, with more than 300 million Africans relying on maize as their primary food source (IPCC, 2019). In Africa, maize production stands at approximately 75 million tons, accounting for 7.5% of the global yield (World Bank, 2019). Nigeria leads as the largest maize producer on the continent with over 33 million tons, followed by South Africa, Egypt, and Ethiopia. Within East Africa, maize holds a crucial role as both a cereal crop and a staple food, particularly in vulnerable communities (FAO, 2018).

Maize has become one of Uganda's most key crops in the country, serving not only as staple food but also an important ingredient in efforts aimed at achieving food security, income generation, and animal feed. The crop contributes to over 50% of the national grain supply and about 20% of the country's Gross Domestic Product (FAOSTAT, 2018). The current estimated maize production in Uganda is 2.75 million tons, while Mt. Elgon, in Eastern Uganda, has a high yield in this area, estimated at 60,000 tons annually (Chemayek et al., 2021). In this area, there are more than 21,395 households engaged in agriculture, with the majority of them practicing maize cultivation (Mubangizi et al., 2018).

Climate-Smart Agriculture Practices comprise agricultural methods that are aimed at increasing crop productivity, improving crops' resilience to climate change, while at the same time reducing its impact. It is where CSA practices is most needed in the Elgon region, as its impact is felt significantly within the region. Key CSA practices involve irrigation, which offsets the erratic rainfall and prolonged drought spells even while adoption amongst small-scale farmers in the region remains very low. Therefore, conservation tillage, involving minimum soil disturbance, is very important in maintaining soil structure, reducing erosion, and improving water retention in such regions as Butiru Sub-county (FARA, 2022). Intercropping legumes with maize or other crops maximizes soil fertility and also serves as a kind of insurance against crop failure amidst harsh conditions. Song et al. (2019), Elgon Investment Profile (2019 & 2020), again, crop diversification is the alternative important practice, which consists of spreading risks and enhancing food security in climate variable regions. Adoption of improved seed varieties that are tolerant or resistant-for example, drought-tolerant and pest-resistant maize-also significantly enhances resilience against climate stressors (Okaka, 2020). In Butiru Sub-county, Manafwa district, about 30% of the smallholder maize farmers have adopted CSA practices toward mitigating the hammer on productivity due to climate impacts. Its low rate of adoption calls for specific, targeted interventions that would enable farmers within this area to improve these practices.

Such interventions in the use of improved farming technologies in Uganda include those by government agencies, international and local NGOs, research and development, and community-based initiatives (Okaka, 2020). The Ministry of Agriculture, Animal Industry, and Fisheries has been at the forefront in the dissemination process for improved seed varieties, soil conservation techniques, and extension services, especially in the Elgon area, aimed at enhancing maize production and climate resilience (MAAIF, 2019). Ukamaka et al., (2018). Asserts that in Manafwa there are specific initiatives adopted like the use of drought-tolerant varieties of maize and associated practices of soil conservation (Institutions such as the National Agricultural Research Organisation have played a crucial role in the development and dissemination of CSA technologies through the testing and demonstration of climate-resistant varieties of maize and CSA in Mt. Elgon (FAO, 2022). Additionally, numerous community-based initiatives, often funded through international donors, are focused on grassroots levels for the promotion of CSA through farmers' training, demonstration plots, and the supply of inputs for CSA (Ukamaka et al., 2018).

In spite of these interventions, the adoption of climate friendly technologies of farming in the Elgon area is still below optimum, especially in areas like Butiru Sub-county, which has been evidenced to have low yields of maize alongside climate variability and socio-economic and institutional challenges (Aslam, 2019). These can only be addressed through a complete understanding of the existing CSA practices and socio-economic and institutional factors that influence their adoption among maize farmers in the study area.

1.2. Problem Statement

Maize is the most important cereal crop and a staple food for more than 1.2 billion people in Sub-Saharan Africa, and more than 300 million Africans including Ugandans depend on maize as the main staple food crop (FAOSTAT, 2018). It’s a main staple food grown by over 21,395 households in Elgon region, of which 500 households are found in Butiru Sub-county (Mutanyagwa et al., 2018). However, there is increasingly decline in maize crop yields because of climate change (Mayanja, 2018). For instance, current reduction in yield is estimated at 35% from 60,000tonnes in 2019 to 21,000tonnes in 2020 (Elgon Investment Profile, 2019 & 2020). This is largely attributed to low adoption rate of Climate Smart Agriculture practices such as irrigation, tillage, intercropping, diversification, among others by maize farmers (Bashir et al., 2017). It's also reported that only 30% of the maize farmers in Butiru Sub-county have embraced the use of Climate Smart Agriculture practices to mitigate climate change and variability challenges which impact on maize production (Manafwa district annual report, 2019). The low adoption of Climate Smart Agricultural practices together with increasing trend in climate variability of prolonged drought, high temperatures and reduced precipitation have led to decline in maize productivity which has led to reduced yield and this has become a threat to household food security, nutrition and economic insecurity (Mutanyagwa et al., 2018). Additionally, socio-economic and institutional factors also affect production of maize crop and these factors include characteristics of farmers like farmer's age, education level, gender and household characteristics such as the family size, land size, culture and norms, location and determine crop production and variations in farm yields (Guzman and Javier Santos, 2018). These socio-economic and institutional factors also affect the adoption or rejection of innovations and or CSA practices (Marenya and Barrett, 2017). Let alone the adoption practices by farmers in a given locality (Mutanyagwa et al., 2018).

Presently there is no study done in Elgon area to document the available Climate Smart Agriculture practices how socio-economic and institutional factors determine the use of CSA Technologies among maize farmers in Butiru sub-county. Therefore, there is urgent need to assess CSA practices and the socio-economic and institutional factors that influence the use and adoption of CSA practice among maize farmers in Manafwa district.

1.3. Objectives of the Study

1.3.1. Main Objective

To assess the effect of adoption of Climate Smart Agriculture technologies on Maize Yield among Smallholder growers in Butiru Sub-county, Manafwa district.

1.3.2. Specific Objectives

1. To examine the existing Climate Smart Agriculture practices among maize farmers in Butiru sub-county, Manafwa district.

2. To establish the factors influencing the use of Climate Smart Agriculture practices among maize farmers in Butiru sub-county, Manafwa district.

3. To assess the effect of Climate Smart Agricultural practices on the maize yield among the smallholder maize farmers in Butiru sub-county, Manafwa district.

1.4. Research Hypotheses

H_{O1}. There is no significant effect of the existing Climate Smart Agriculture practices among maize farmers in Butiru sub-county, Manafwa district.

H_{O2}. There is no significant effect of the factors that influence the use of Climate Smart Agriculture practices among maize farmers in Butiru sub-county, Manafwa district.

H_{O3}. There is no significant effect of Climate Smart Agricultural practices on the maize yield among the smallholder maize farmers in Butiru sub-county, Manafwa district.

1.5. Justification of the Study

Maize is the most important cereal crop and a staple food for over 1.2 billion people in sub-Saharan Africa, with more than 300 million Africans, including many Ugandans, relying on maize as a primary food source (Tesfaye et al., 2019). In Uganda, maize accounts for over 50% of the national grain supply, but climate change has threatened its productivity, reducing production by 35% from the usual 60,000 tonnes annually (Song et al., 2019; Elgon Investment Profile, 2019 & 2020). The Mt. Elgon region, including Manafwa district, is particularly vulnerable to climate change impacts, leading to declines in maize yields. This has exacerbated issues of household food insecurity and income instability (Kaizzi, 2019).

In Manafwa district, agriculture is the dominant economic activity, with over 21,395 households involved in farming. Maize is the primary crop, with an annual production of 7,920 tonnes per hectare (Kaizzi, 2019). However, the region's reliance on rain-fed agriculture makes smallholder maize farmers particularly susceptible to climate variability. The resulting decrease in maize productivity has led to food insecurity, income shortages, and broader socio-economic challenges for farming households (Mutanyagwa et al., 2018).

Maize crops in Butiru Sub-county are grown both for household consumption and commercial sales. However, high vulnerability to climate change makes it difficult for farmers to provide for their families; hence, this affects the functionality in terms of meeting basic needs such as healthcare and education.

It is this understanding that can, by the adoption and use of the CSA practices, vastly improve maize productivity in the region. Some of the key factors influencing adoption include a farmer's age, education, household size, and resource availability. Full maize production potential in Butiru Sub-county, Manafwa district will be attained when a thorough assessment of the current utilization of CSA practices, and socio-economic variables that affect adoption is availed.

1.6. Significance of the Study

The following stakeholders derived importance from the study:

Farmers: The study documented the level of adoption and categories of CSA practices among maize farmers, hence informing local agricultural authorities. This information is important for district production and marketing departments in proper planning, especially in the dissemination of new technologies, innovations, knowledge, and information to the smallholder maize farmers.

District Agricultural Extension Staff: The findings equip the agricultural extension practitioners with knowledge of socio-economic and institutional factors influencing the utilization of Climate friendly technologies by farmers producing maize in the region. With this information, the extension officers will thus be able to design programs that suit the needs of the farmers in better ways, which could result in improved adoption of climate-smart practices.

Policy Makers: The study examines the different socio-economic and institutional factors affecting the adoption of CSA practices in maize production, important for policymakers in the formulation of supportive policies and statutory instruments meant to foster agricultural development by way of the wide diffusion of CSA practices in maize farming. Examples are technocrats from the Ministry of Agriculture and the Climate department.

Researchers and Academicians: The study highlights gaps in research related to climate-smart agriculture, helping researchers and academics identify areas for further exploration. This could lead to new innovations in CSA practices that mitigate climate change effects and improve maize productivity.

1.7. Scope and Limitations of the Study

It targeted the adoption of CSA practices by smallholder maize farmers in Butiru Sub-County, Manafwa district, and the resulting impacts on maize yields. The research was limited to one-time household survey between March and May 2023. The area targeted for this study was because of the high number of small-scale farmers whose main source of income is maize production. It was, however, limited to only one maize production season, which, arguably, may also limit the generalization of results to other seasons and regions.

1.8 Operational Definitions

Climate-Smart Agricultural Practices: For the purpose of this study, CSA practices are defined as those interventions by producers that help in mitigating the production and accumulation of greenhouse gas emissions, promote viable food production, and contribute toward wider development goals (FAO, 2010). These approaches seek to enhance resilience to climate change; they enhance productivity and reduce environmental impacts (Jain et al., 2021).

Food Security: It is regarded as a condition whereby people at all times have access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life. (Abegunde et al., 2019).

Smallholder Farmers: refers to an individual or family who owns or manages a small plot of land dedicated to agricultural production (Kang et al., 2019). These farmers use small-scale farming methods.

1.9. Conceptual Framework

This presents the relationship between independent variable and dependent variable. The independent variable comprises of Technologies attributes like Maize seed variety used, Socio-economic factors like gender, age, off farm income, farming experience, farm size, and education level and Institutional and market factors like extension contact, number of trainings, credit access, target market, and group membership, the dependent variable Maize Yield and looks at factors like Use of terraces, Inter-cropping with legumes, use of improved maize varieties, planting in maize in trees and Use of crop barriers and the moderating variable comprises of the government policy.

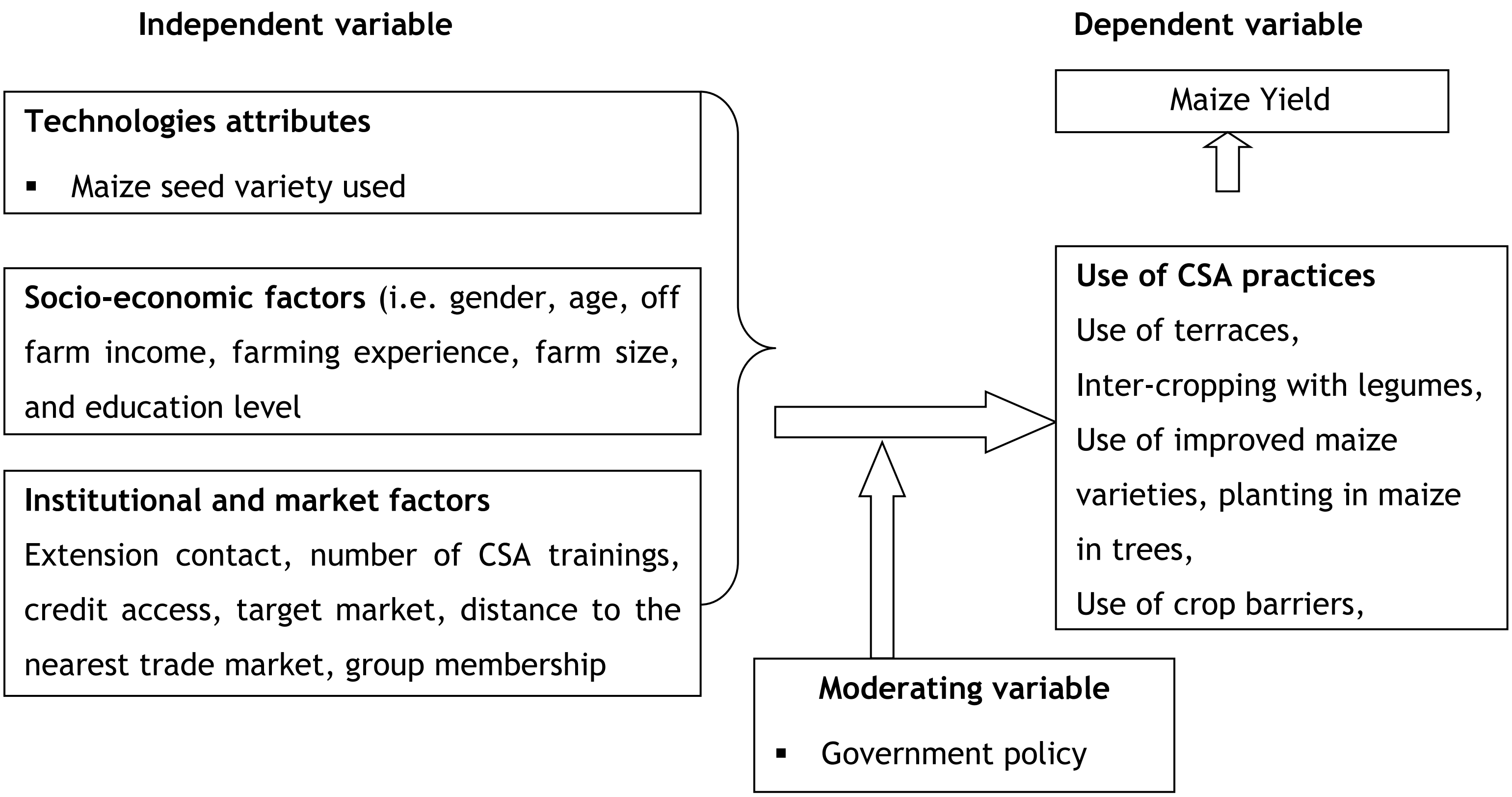

Figure 1: *Conceptual frame work framework relating technology attributes, socioeconomic, institutional and market factors to adoption of CSA practices in Manafwa district.*

Source: Modified based on Mthethwa et al., (2022).

CHAPTER TWO: LITERATURE REVIEW

2.1: The existing Climate Smart Agriculture practices among maize farmers

Some of the commonly adopted CSA practices among maize farmers include measures on water conservation, control of soil erosion, and use of improved planting materials, improved maize varieties, and trees integrated within maize fields (Abrishambaf et al., 2020). Other practices include efficient organic fertilizers use, implementation of crop barriers, intercropping of legumes, and the use of terraces. Regarding water management, water is an important factor in crop production, and good practices in water management often multiply yields many times over. For example, smart management of water, such as through sprinkler irrigation systems, can enhance agricultural yield by approximately 50% (Jain et al., 2021). The factors that contribute to storage of water in the soils include rainfall, soil depth, and texture in particular clay content, and structure (Libohova et al., 2018).

Soil management is beneficial influences on the condition of the soil through improvements in structure, porosity, aeration, and bulk density reduction (Abrishambaf et al., 2020). This promotes the process of water infiltration into, and storage within, the soil, enabling the plants to have more available water, (Abegunde et al., 2019). These practices enhance rainfall efficiency, which in turn increases maize productivity while reducing soil erosion, dispersion of soil particles, and risks of waterlogging and salinity in dry regions (Abegunde et al., 2019). Besides, properly developed drainage systems allow for the prevention of losses of crops and salinization of soils in waterlogged areas of fields (Liao et al., 2021).

Soil erosion is one of the most common but at the same time dangerous types of land degradation (Blanco et al., 2019). Intensive rainfall can lead to severe erosion of soil on cultivated lands with moderate to steep slopes, with areas receiving high runoff rates and an inadequate vegetative cover (Fenta et al., 2019). Furthermore, it has also been identified that tillage-induced soil erosion is among the leading reasons for massive soil carbon loss and soil displacement in upland landscape regions (Lindstrom, 2021). Even on gentle slopes, alkaline soils are likely to experience dispersion or crusting, which enhances the likelihood of soil erosion (Aslam, 2019). Minimum or zero-tillage practices along with optimum soil cover-for example, cover crops, residues, and mulch-can reduce runoff and consequent soil erosion as much as by an order of magnitude (FAO, 2019). Soil erosion on more prospective slopes can be reduced through planting on the contour across the slope, adopting improved soil and water conservation techniques for runoff capture, infiltration enhancement, such as terracing, earth bunding, and tied ridges, while constructing grassed waterways to safely dispose excess water from the slopes (Bashir et al., 2019). Higher windstorms frequency can accelerate soil erosion, as the sand carried away by winds is likely to fall on the surfaces of productive land. Wind erosion reduction measures include improvement of vegetation cover with drought-resistant varieties and planting of windbreaks across prevailing winds, (Aslam, 2019). There is a dire need for improved seeds at farm level, they are important in increasing productivity and enhancing production (Keller et al., 2019). Jain et al., 2021), defines that no good crop yield can be achieved with poor quality seeds. The national, regional, and international plant breeding programs have targeted the development of crop varieties that would withstand climate change-related events and use resources more efficiently to minimize the impact of agriculture on the greater environment (Keller et al., 2019).

Trees protect maize crops from winds by acting as windbreaks and provide shade to reduce heat stress-particularly important with rising temperatures in many regions due to climate change (Hossain et al. 2020). These tree roots also contribute to the soil structure by reducing erosion and enhancing water infiltration, two very important constituents in retaining soil health where rainfall patterns have commenced deviating. In fact, Garrity et al. (2019) and Kiptot et al. (2018) found that agroforestry systems that included maize showed higher yields and overall agricultural productivity. The organic matter added to the soil by the trees aids in nutrient cycling, thereby enhancing fertility of soil and sustaining maize production for a long time.

Several studies, as undertaken by Hossain et al. (2020), Adedeji et al. (2019), and Zhou et al. (2019), articulate that the use of organic fertilizers is a climate-smart option. These fertilizers promote soil health, assure higher maize yields, and contribute to reduced greenhouse gas emissions, which in turn ensure climate-resilient and sustainable maize production. Efficient organic fertilization would go a long way towards optimizing productivity with the minimum environmental footprint from agriculture. Hossain et al. Review provides valuable insight into the benefits of using organic fertilizers in maize production.

This study has highlighted the fact that organic fertilizers not only increase maize yields but do so at a considerably reduced level of greenhouse gas emissions, mainly nitrous oxide. Organic fertilizers will enhance nutrient management approaches leading to a healthy and resilient soil system (Adedeji et al. (2019). This environmentally friendly alternative to chemical fertilizers enhances soil fertility, thereby enabling sustainable farming of maize. A field experiment conducted by Adedeji et al. (2019), in the south-western part of Nigeria, proved that organic fertilizers performed better than their inorganic counterparts concerning sustaining maize productivity over a longer period and also maintaining soil health. Its findings indicated that organic fertilizers reduced leaching and increased the nutrient retention while simultaneously building up the content of soil organic matter, especially under tropical conditions when the ability to retain soil fertility is seriously difficult. Improved yields in maize will be witnessed by farmers upon the use of organic fertilizers; this will contribute to more robust, resilient agricultural ecosystems with fewer environmental concerns associated with the use of synthetic fertilizers.

Crop barriers refer to physical materials and structures that are installed to protect crops against environmental stressors Rondelli et al. (2019). This generally includes extreme weather conditions, pests, and frost. They have been largely shown to offer benefits to farmers in cases of climate change. These studies illustrated that crop barriers can indeed protect plants from bad weather; therefore, agriculture is more successful, with less damage to the frost, better reforestation, and higher yields for areas that may be prone to hailstorms. This approach allows farmers to continue being productive despite weather variability and enables the call for climate-smart approaches toward sustainable agricultural development.

Husson et al. (2019) proves the efficiency of crop barriers in protecting the young trees in reforestation areas against deer herbivory. The barriers ensure greater survival and allow successful reforestation by ensuring less damage from deer. For example, Rondelli et al. (2019), indicate that the agrotextiles used in orchards as frost protection barriers protect the apple trees and ensure better fruit productions. As evidenced by Liu et al. (2018), the use of a hail net increased the yield of spring maize and increased the economic benefit to farmers. These examples illustrate the key contribution of crop barriers that may be made in minimizing weather-related crop losses and enhancing profitability of farms, activities that are objectives of climate-smart agriculture. Along with weather-related impacts, crop barriers may form part of integrated pest management.

For instance, Dimou and Tsoukala (2019) present evidence to show that mesh screens can be another form of crop barrier that prevents the entry of aphids and minimizes the use of chemical insecticides. This crop protection method promotes healthier and more vigorous growth of crops while minimizing the ecological footprint related to pest control measures. Parra et al. (2020) review the potential of physical barriers in crops to impede the Mediterranean corn borer in corn. Enhanced crop protection using physical barriers can be integrated into the methods of the pest management system compatible with climate-smart agriculture, focusing on ecological balance. The intercropping systems also provide sustainable means through which the resilience of crops is improved and their productiveness increased. An intercropping of peas with maize, according to the work of Hauggaard-Nielsen et al. (2019), enhances the use of nitrogen efficiency and weed control. Peas are legumes and, as such, make extra nitrogen available to the maize plants from atmospheric nitrogen, hence less use of synthetic fertilizers and limits nitrogen runoff. This therefore optimizes resources utilized and at the same time minimizes environmental impacts while increasing productivity for the same crop, maize.

A few studies by Li et al. (2018), and Jain et al., 2021). successfully demonstrate terracing as one climate-smart agricultural practice in addressing the prevailing issues identified herein. Through terracing, soil erosion is retarded since it provides flat, level planting surfaces with the earthwork in line with the contours of the land (Rondelli et al, 2019). This contour farming method greatly reduces runoff, lessens erosion of the topsoil holding the nutrient-rich part important for maize nutrition, and hence largely prevents further degradation of the soil (Rondelli et al. 2019). Of these, Dabral et al. (2018) have identified the efficiency of the terracing system in reducing soil erosion and saving water in maize crops on sloping lands.

Li et al. (2018) indicated that terracing has played a crucial role in improving maize production on very erodible landscapes, such as China's Loess Plateau. Overall, terracing is a way of soil conservation and it reduces the amount of sediment loss so that the soils retain their integrity and maintain the crucial nutrients necessary for maize development. Terracing also promotes soil moisture availability during dry periods through increased infiltration and water retention, thereby enhancing maize crops' drought tolerance and thus ensuring regular yields. This therefore constitutes one of the many efficient climate-smart agriculture practices on sloping lands prone to soil degradation and variable rainfall. Forcella et al. (2019) discuss the use of terracing in high-value vegetable production systems, and identify it as a potential adaptation to climate change.

According to Adedeji et al. (2019), they assert that terracing, cover cropping and conservational tillage methods actually improve soil health and carbon storage, enhancing environmental sustainability and decreasing overall carbon footprint of agricultural activities. Application of such methods to maize production can thus give way to increased climate change resilience and sustainable land management. While literature available to date discusses CSA practices for most regions, the documentation of CSA practices among smallholder maize farmers in the Elgon region of Uganda is noticeably absent. This is inhibitive in understanding how the different CSA techniques such as terracing, intercropping, and organic fertilizer use are being adopted and optimized in this area. Given the susceptibility of this region to soil erosion, and variability in climatic conditions, assessment of the current practices of CSA amongst smallholder maize farmers in Elgon is very important for sustainable farming systems that can have more resilience.

2.2. Factors Influencing use of Climate Smart Agriculture practices in smallholder farming.

The adoption of climate-smart agricultural practices among farmers depends on several factors. These factors range from institutional elements through extension services to group membership, frequency of CSA training, credit accessibility, proximity to target market, distance to the nearest trading market, and other socio-economic influences such as gender, age, off-farm income, farming experience, farm size, and education.

Aswathy and Joseph (2020) applied a binary probit in an investigation into the determinants of cage fish farming adoption in India. The authors observed that the probabilities of adoption of CSA practices positively relate to occupation, family income, and access to farm information, training experience, and education. In turn, the variables family size, farming experience, perception of climate change, and group membership do not show any significant relationship. This is in agreement with a study by N'souvi et al. (2021) that shows that education contributes significantly to the adoption of climate friendly technologies among fish farmers in China at a 5% level of significance. However, this used binary probit is, to an extent limited since it assumes a binary nature of the outcome.

In another article, Tanti et al. (2022) analyzed how institutional factors affect smallholder farmers' adoption of technology using the Probit model in the case of India. The results showed that the model accounted for 69% of variance in the adoption behaviour with the following significant factors, access to extension services, information availability, labour use, and economic efficiency. In this regard, the present study consolidates the work of Oparinde et al. (2021), who reported education, off-farm income, age, household size, and credit accessibility as significant drivers of CSA adoption by fish farmers. However, this probit model has some weaknesses in assuming binary outcomes and does not take care of the cases where farmers do multiple CSA practices.

In this respect, Mantey et al. (2020) also found that some of the key factors that positively influenced adoption among the fish farmers in Ghana included availability of credit and access to extension services. One of the limitations of the Heckman model is that it is sensitive to violations of normality.

In a study on the adoption of selected climate-smart technologies among smallholder farmers in Kenya, Muriithi (2020) estimated the multinomial logit model. It was established that credit accessibility and off-farm income were the major factors that influence the level of adoption of CSA technologies. The study further noted that male-headed households were more likely to adopt CSA practices compared to the female-headed ones. Somewhat similarly, Adekola et al. (2022) propose that such policies by the government aim at enhancing the farmers' knowledge and improving information flow to adequately prepare them for fluctuating climatic conditions. Multinomial binary probit applies when individuals select one option from a list of mutually exclusive choices but assumes that the options chosen by different individuals are independent, hence failing to take into account the correlation across the choices. This, however, is a limiting factor in analysing the adoption of multiple CSA practices.

Amankwah and Quagrainie, (2019) have applied a double hurdle model to assess aquaculture feed adoption amongst smallholder farmers in Ghana. Their findings focused on various variables which affected the adoption decision and included years of schooling, fish farming training, availability of credit, fish farm size, total landholding, number of extension contacts, and water source. The marginal effects from the first hurdle obtained indicated that an additional extension contact and access to credit increased the probability of adoption by 5% and 18%, respectively. However, this model had focused on only one CSA practice. Thus, its applicability was found to be limited for CSA practice adoption. This study involved variety of CSA practices and more comprehensive policy recommendations.

Propensity Score Matching is quite a common methodology applied in many studies that involve group comparisons, especially in cases where randomization is not possible and there exists enough common support between groups. PSM calculates the conditional probability of a farmer participating in an intervention based on pre-participation characteristics.

The PSM is technique is applied in very handy when panel data is not available. Its application in impact assessment studies is based on its assumption that selection bias can be wholly explained by observable characteristics. Compared to other non-experimental methods of evaluation, one of the major advantages of the PSM approach is its handling of the problem of common support. It ensures that the treatment effects are estimated within the region where the overlap between the treated and control groups exists.

There is a substantial body of literature on climate-smart agricultural technologies around the world, but to date, very few studies have been carried out to understand the factors that affect the implementation of climate-smart agricultural practices by smallholder farmers in the Elgon region of Uganda.

2.3. Approaches that have been used to determine effects of Climate Smart Agriculture Practices.

In recent times, Climate-Smart Agriculture has gained the spotlight for its role in improving agricultural sustainability while building resilience against climate change.

Monitoring its impact requires methodologies of high order that can capture the complex interactions of CSA practices on agricultural systems and the environment. This literature review examines a number of methods used by researchers in the assessment of the outcomes of CSA practices, their advantages, and the limitations as evidenced in empirical applications.

2.3.1 Participatory approaches

Participatory methods of CSA involve the interaction of researchers and farmers and other stakeholders in the design, actual implementation, and assessment phases of CSA practices. Local knowledge and priorities are reflected in this approach, coproduced, and integrated into research and decision-making. Using participatory action research, for instance, Wilson et al. (2017) engaged smallholder farmers in co-developing and assessing climate-smart agricultural practices in East Africa.

Advantages of participatory approaches vary. They tend to ensure social learning and empowerment for farming communities, leading to ownership and commitment regarding CSA initiatives. Such an approach will better seek to provide insights and solutions that are contextually relevant since a diverse group is involved in its design, hence more likely to be adopted and sustained over longer periods than methods formulated without people's participation. Reviews include works by Thornton et al. (2019) and Wilson et al. (2017). Engagement with potential impacts and research users strengthens the credibility and applicability of research outcomes, incorporating knowledge and needs from those who shall be most affected by changed CSA practices.

However, there are several challenges with participatory approaches. They involve large capacity building, facilitation, and stakeholder coordination, which may consequently face limitations in time, funding, and expertise of participants or stakeholders involved in the process. Consensus building among various stakeholders may be problematic to achieve, as conflict or a compromise to manage such situations may influence the effectiveness of CSA interventions. However, in these approaches, qualitative insights and local knowledge are preferred over quantitative data and scientific rigor, thus raising a number of questions about the reliability and generalizability of findings (Thornton et al., 2019).

2.3.2 Quantitative Model

Quantitative modeling is one of the major methodologies for impact assessment within the improved farming techniques, this encompasses a full spectrum of approaches, from simple empirical models to complex integrated assessment frameworks. For example, regarding the assessment of the consequences of alternative practices on crop yield, carbon sequestration in the soil, and GHG emissions, dynamic simulation models have been used by scholars such as Smith et al. (2019). The biophysical processes are linked with socio-economic and institutional factors for the prediction of long-term impacts due to the adoption of CSA through varied agro-ecological zones by these models.

Many are the benefits accrued from quantitative modeling. It provides a procedural manner through which impacts under different scenarios can be investigated; hence, it enables scenario analysis and optimization. This approach clears up the interaction existing between climate variability, soil characteristics, and management practices, hence giving in-depth insight into the effects of CSA. Furthermore, the quantitative models can scale up the findings from the field experiments to a regional or global magnitude-a very useful guide for policymakers and other stakeholders.

However, quantitative modeling has its own deficiencies. Its accuracy greatly depends on quality data and the assumptions of the models used; therefore, it usually comes with its uncertainties and biases in the results. In addition, its considerable competence and accessibility at all levels may have a limiting effect, since the development and calibration require significant expertise and resources beyond the reach of many researchers and stakeholders.

2.4. Studies conducted on the effect of climate smart agricultural practices on crop yield.

Studies from various countries illustrate the effectiveness of Climate friendly technologies in enhancing yields, resilience, and sustainability for farmers. In Kenya, CSA methods like crop rotation, agroforestry, and drought-resistant crops increased maize yields and improved resilience to climate variability, boosting productivity and income for farmers who adopted multiple CSA techniques compared to those who did not (Ng'ang'a et al., 2021; Mungai et al., 2019).

In India, sustainable rice intensification, zero-tillage, and integrated nutrient management raised rice yields by 20-25% in Andhra Pradesh while reducing water and chemical inputs, thereby supporting ecosystem health (Jat et al., 2020). Ethiopia's Tigray region saw notable improvements in crop yields with soil and water conservation and drought-resistant seeds, helping farmers mitigate drought and soil erosion (Abate et al., 2022).

In the Philippines, conservation agriculture enabled rice and maize farmers to cut input costs and adapt to erratic rainfall, and drought-tolerant crop varieties helped maintain yield stability (Palao et al., 2021). Similarly, Zambia's Eastern Province recorded a 15-20% maize yield increase from CSA practices like conservation tillage and agroforestry, which improved soil fertility, moisture retention, and resilience to climate stress (Ngoma et al., 2016). These findings indicate that CSA practices are adaptable to various climates and agricultural systems, enhancing productivity and sustainability across maize and other crops worldwide.

2.5. Theoretical and Conceptual Framework

2.5.1. Theoretical Framework

The study assumes that small-scale farmers can improve their maize productivity and at the same time conserve the environment through the adoption of CSA practices. This study is based on the theory of random utility suggested by Ogola et al. (2021), assuming the farmer chose to adopt a given climate friendly technique on the basis of expected economic gain but maximizes utility. This therefore conceptualizes the utility derived from CSA practices as depending on various factors such as farm and farmer characteristics, besides institutional factors.

$U_{ji} = Di\alpha_i(Z_{ji}, F_{ji}) + \varepsilon_{ji} where(j = 1,0) and(i = 1,2.....n)$...................................... (1)

Since the utilities are random, the i_{th} farmer will choose alternative $j = 1$ conditional upon $U_{1i} > U_{0i}$ or if $y^* = U_{1i} - U_{0i} > 0$. The likelihood that $Y_i = 1$ (probability that a farmer applies *i*th CSA practice) can be written as a function of explanatory variables.

Where,

P_i , is the probability of i_{th} individual CSA method used by *j*th farmer.

$\varepsilon_i = \varepsilon_{1i} - \varepsilon_{0i}$, is a random disturbance term.

D is a cumulative distribution function for the random disturbance term evaluated at $X_i^1\beta$. The exact distribution of D depends on the distribution of the random error term. For instance, if the random disturbance term is normally distributed, then D is cumulative normal distribution (Phiri, 2007). Consequently, based on the assumed distribution of the random disturbance term, numerous qualitative choice models can be estimated (Seidl et al., 2011).

CHAPTER THREE: METHODOLOGY

3.1. Study Area

The study was carried out in Butiru Sub-County, Manafwa district, Uganda. This area was targeted on the basis of the high potential it offers toward food production, essentially maize, considering that the soil conditions are conducive, regardless of the challenges of soil degradation. Butiru Sub-County is made up of 5 parishes and 73 villages and is considered a main food supplier for the district and the entire Mount Elgon Sub-region at large (UBoS, 2020).

The area measures 36.8 km² with a population of 20,277 people. It has two rainy seasons, the first from March to June and the second from August to November according to UBOS, 2020. The rain falls within the range of 800 mm to 2200 mm annually; about 50% of this fall during the long rainy season, peaking in April, while about 25% falls during the short rain from September to October. Mean annual temperatures vary from 24°C to 30°C within the area.

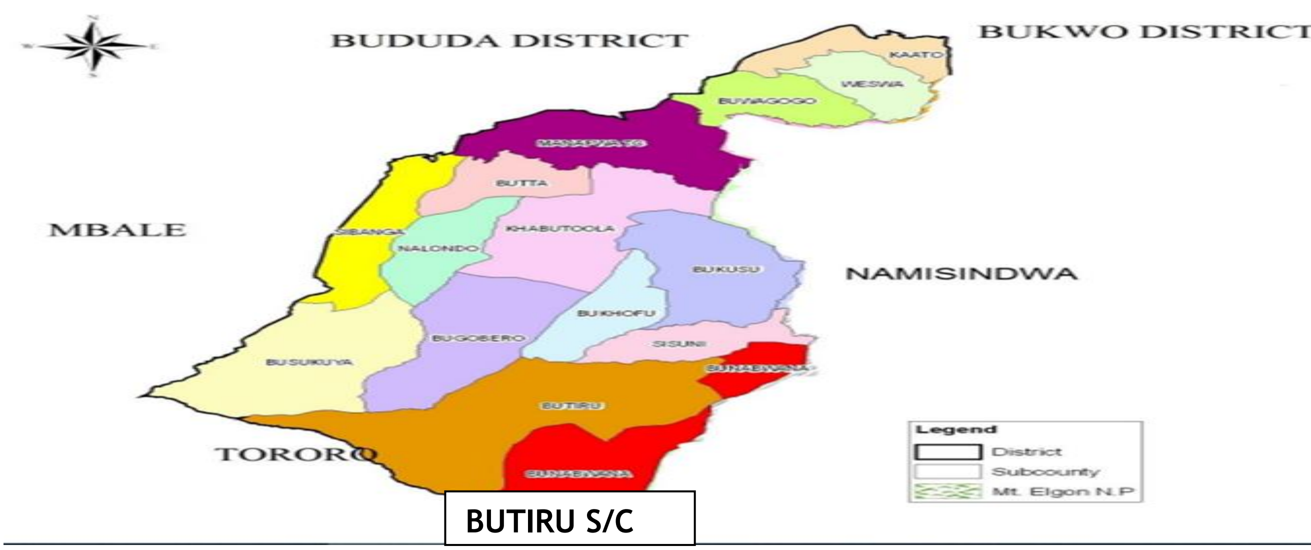

Figure 2: Map of Manafwa district showing study Area

The environment in Butiru Sub-County has faced related challenges, evidenced by a decline in the quality and quantity of natural biodiversity, soil erosion, and flooding that faces the area and threatens its food production. According to the district's integrated development plan, the irregular pattern of rain has disrupted land preparation and crop production, leading to reduced yields. There has also been recorded a significant reduction in water volumes at wetlands such as Lwemuna, Bunakhaima and Nasyanda.

3.2. Study Design

Designing a research requires organizing the conditions for gathering and analysing data that fit the purpose of the research. According to Kothari, 2003, this study therefore adopted a cross-sectional design, whereby the collection of data is made from a varied population at one single point in time. A cross-sectional study is one in which the researcher observes variation without manipulating any variable of interest. The research adopted a survey methodology with semi-structured questionnaires. Information on the pretested various parameters with the use of a questionnaire for data collection was categorized into thematic areas such as demographic characteristics, production systems, acreage of maize, and CSA practices use by maize farmers.

3.3. Sampling Techniques and Procedure

As defined by Enon (1995), a sampling technique refers to the methods used by researchers to choose a representative subset from the target population. This study employed both simple random and purposive sampling techniques, detailed as follows:

3.3.1 Purposive sampling

Purposive sampling involves deliberately selecting participants who can provide detailed insights into a particular theme, concept, or phenomenon (Tran et al., 2019). In this study, purposive sampling was used to choose the district and sub-county because they are prominent maize producers within the Elgon region.

3.3.2 Simple Random Sampling

Simple random sampling ensures that every respondent has an equal opportunity to be chosen for the study (Maria, 2001). In this study, simple random sampling was used to select households involved in maize farming. Specifically, the sampling was conducted in Butiru Sub-county across seven parishes (Buwopuwa, Bunakhaima, Bushakiro, Bumatanda, Makenya, Nasyanda, Bumwalye), and two villages were randomly chosen from each parish, resulting in a total of fourteen villages.

To select maize-growing households and villages, a lottery method was employed. Names of maize farmers were written on slips of paper and placed in a container, which was then mixed manually. Slips were drawn randomly to determine the sample group for each selected village. The village LC1 chairpersons, familiar with local maize farmers, assisted in this process. In each village, twenty-two maize farmers were randomly chosen. This approach ensured that every participant had an equal chance of being included in the study, allowing the researcher to accurately categorize farmers into two groups: those who adopted climate-smart practices and those who did not.

3.4. Sources of Data

3.4.1. Primary Data

The study relied solely on primary data, which was gathered through semi-structured interviews and focus group discussions using a validated questionnaire (see Appendix). The questionnaire was designed to capture various socio-economic parameters, including demographic information, maize production levels, farming practices, and existing climate-smart practices. The data collected from these tools was sourced directly from farmers.

3.5. Sample Size Determination

Sampling is a method of selecting participants from a target population to ensure that the selected sample accurately represents the entire population (Amin, 2005). In Butiru Sub-County, Manafwa district, there are 970 small-scale maize farmers (Mayanja, 2021). The study used Yamane's formula (1967:886) as shown below to determine the sample size.

$$n = \frac{970}{3.25}$$

$$= 298.46 \approx 298\, respondents$$

Therefore, the study considered 298 respondents

Different stages were considered in selecting the respondents. In Stage One, Butiru Sub-County was purposively selected due to its high food production potential within Manafwa district. Stage Two involved the purposive selection of five parishes within the sub-county. In Stage Three, a simple random sampling technique was used to select 298 farmers from a list provided by the Sub-County Extension Department. A pretested interview schedule was utilized for the face-to-face interviews conducted in the farmers' localities.

Data collected from these interviews was initially entered into an Excel spreadsheet and subsequently transferred to STATA version 15 for analysis. The statistical software facilitated the analysis for this study.

3.6 Data Collection Methods and Procedure

According to Bell (1999), the reliability of research results and the validity of conclusions depend on the appropriateness of the methodology and the quality of the data collected. In this study, a survey method was employed for data collection.

Semi-structured interviews were conducted using a validated questionnaire. This approach was chosen because it allowed for the development of a study instrument with both open and closed questions, providing flexibility to gather comprehensive information and insights from farmers. The questionnaire captured data on various demographic and socio-economic characteristics of the farmers, including age, gender, marital status, and education, awareness of CSA practices, farming experience, and whether they are subsistence or commercial farmers. Additionally, it gathered information on existing CSA practices in maize production, such as crop rotation, contour ploughing, and terracing.

To effectively collect data for each research objectives related to Climate Smart Agriculture practices among maize farmers in Butiru sub-county, Manafwa district, a survey method of data collection was employed as seen below.

1. Examine Existing Climate Smart Agriculture Practices (Objective 1)

Structured surveys questionnaires were designed to capture detailed information on specific CSA techniques such as intercropping, crop rotation, soil conservation methods, the use of drought-resistant maize varieties, agroforestry, etc. The questionnaire was distributed to a representative sample of maize farmers in Butiru sub-county, ensuring diversity across age, gender, and farming experience to capture a comprehensive picture of CSA practices currently in use. This method helped to identify the prevalence and variety of CSA methods adopted in the region.

2. Determine Factors Influencing the Use of Climate Smart Agriculture Practices (Objective 2).

To determine the factors influencing the use of Climate Smart Agriculture (CSA) practices, surveys questionnaires were administered to maize farmers to gather data on key influences such as access to information and training, availability of resources (e.g., seeds, fertilizers), socio-economic status, and perceived benefits of CSA. This approach helped to identify the primary drivers and challenges of the implementation of the CSA technology among the farmers in the region.

3. Assess the Effect of Climate Smart Agricultural Practices on Maize Yield (Objective 3).

Quantitative data was collected on maize yields both before and after the adoption of CSA practices which enabled an evaluation of changes over multiple growing seasons. Farmers provided data on their maize yields (measured in kg/ha), which helped in determining any observable impact attributable to the CSA practices. By comparing yields of farmers who have adopted CSA practices with those who have not, I was able to gain insight into the effectiveness of these practices.

3.7. Data Analysis

The collected data was first entered into an Excel sheet and then transferred to STATA version 14. It was in this statistical software package that the analysis for this study was performed.

To examine the existing CSA practices among maize farmers in Butiru Sub- County (Objective 1).

Descriptive statistics was performed to obtain; frequencies, percentages, means, standard deviations. Tables were drawn from percentage and means for continuous and categorical variables of the practices used by farmers in Butiru Sub-County.

To determine the factors influencing the use of CSA practices among the maize farmers (Objective 2).

The Binary probit model was adopted for this study due to its capacity to simultaneously evaluate the influence of socio-economic and institutional factors on the adoption of multiple CSA practices. The model allows for the correlation between the unobserved disturbances of different technologies used, acknowledging that the choice of one technology can be related to the choice of others.

While some studies have employed bivariate models to analyze the decision to use a particular practice (Aswathy & Joseph, 2020), these models fail to differentiate between multiple CSA practices that a farmer may undertake. Bivariate models are limited in their ability to handle multiple outcomes simultaneously. Other studies have used multinomial logit models (Murithi, 2020), which assume that the choice outcomes are mutually exclusive and independent of each other. This assumption can be problematic in scenarios where a household adopts more than one CSA practice. The multinomial logit model's assumption of independence among alternatives can lead to inaccuracies when multiple practices are not mutually exclusive.

The model overcomes addresses the assumption of independence of irrelevant alternatives and can handle cases where a farmer may adopt multiple CSA strategies simultaneously. The variables used in the model are based on previous studies and are designed to capture the influence of various economic and institutional factors that influence the use of improved technologies. Table 1 presents a description of these variables and their expected signs, derived from a review of the literature (Wang et al., 2019).

Specification of the Binary probit used

If there were three CSA practices under consideration (e.g., minimum tillage, crop rotation, and agroforestry), the binary probit model was specified as follows:

$Yi1*=Xiβ1+\epsilon i1$; $Yi2*=Xiβ2+\epsilon i2$; $Yi3*=Xiβ3+\epsilon i3$:

Where:

Yi1Yi1, Yi2Yi2, and Yi3Yi3 was the binary adoption decisions for minimum tillage, crop rotation, and agroforestry, respectively. $\epsilon i = (\epsilon i1, \epsilon i2, \epsilon i3)$ followed a trivariate normal distribution with mean zero and covariance matrix ΣΣ. This model allowed to understand not only the individual factors influencing each practice but also the potential correlations between the adoptions of different CSA practices.

Table 1: Description of variables in the probit model

Variables	**Description**	**Expected signs**
Dependent		
Use of CSA	Type of CSA practice used by a maize farmer Vs yield	
Explanatory Variables		
Age	Age of the farmers in years	+/-
Gender	Sex of farmers 1=male and 0=female	+/-
Education level	Number of years of schooling	-
Experience	Farming experience in years	-
Farm size	Farm size in acres	-
No contact with Extension worker	No. of contacts with extension agents	-
Off Farm Income	Participation in off-farm activities	+
Training on CSA	Number of training on CSA practices	-
Credit access	Access to credit 1= yes,0= otherwise	+/-
Maize production	Kgs of maize harvested/acre.	+
Maize seed varieties used	0=Hybrid, 1=local variety	+

Determining the effect of Climate Smart Agriculture practices on maize yield (Objective 3). In the first step, a probability model for participation in an intervention is estimated to calculate the probability or propensity scores of participations for each observation. In this case, any standard probability model such as logit or probit can be used (Rajeev et al., 2019). Because it is difficult to determine that the random error term has a normal distribution *a priori*, a binary probit was used in this study to generate propensity scores for farmer participation in maize production using the climate friendly technology. The binary probit was also preferred over others because of its consistency in parameter estimates owing to its logistic distribution (Baker, 2019; Revallion, 2019). In the second step, each participant is matched to a non-participant with similar propensity score value in order to estimate the ATE for the treated group (Caliendo and Kopeinig, 2018).

Rosenbaum and Rubin (1983) define the propensity score as the probability of receiving a treatment given pre-treatment characteristics. This is expressed as:

$(X) \equiv Pr\ \{Y = 1|X\} = E\{Y|X$ .... (3.1)

Where $Y = \{0, 1\}$ is a binary variable indicating whether a farmer uses a CSA practice (1=Yes; or 0=No), *X* is the multidimensional vector of pre-treatment characteristics of a household and *P*(*X*) is the propensity score. To estimate the effect CSA practice in maize production, the average treatment effect on the treated (ATT) after matching was calculated. The ATT estimation assumes that the distribution of outcome variables for the control group is the same as the counterfactual in the treatment group. The expected value of ATT is defined as the difference between expected outcome values with and without treatment for individuals who actually participated in the treatment (Baker and Ichino, 2018).

Thus, the ATT is estimated as follows:

$\{Y_{1i} - Y_{0i} | D_i = 1\}$

$= \{E\{Y_{1i} - Y_{0i} | D_i = 1, p(X_i)\}$

$= \{E\{Y_{1i} | D_i = 1, p(X_i)\} - E\{Y_{0i} | D_i = 0\}, p(X_i) | D_i = 1\}$ (3.2)

Where the anticipated is over the distribution of (X_i) $|D_i = 1$; *i* denotes the household, with 1i and *0i* as the possible results in the two counter factual situations of action and non-action respectively and *D* is the action group pointer.

Model specifications used

We evaluated specific CSA practices and their effect on maize yield, we included variables such as:

X1: Use of drought-tolerant seeds (1 = Yes, 0 = No)

X2X2: Conservation tillage practices (1 = Yes, 0 = No)

X3X3: Agroforestry practices (1 = Yes, 0 = No)

X4X4: Irrigation (1 = Yes, 0 = No)

The model estimated how these factors affect the likelihood of achieving higher maize yield. Each coefficient β represented the change in the log-odds of high maize yield for a one-unit change in the corresponding variable. To interpret the effect of a unit, change in XiXi on the probability P(Y=1), computed the marginal effects as:

$\partial P(Y=1) / \partial Xi = P(Y=1) \cdot (1-P(Y=1) \cdot \beta i$

This expression gave the change in probability of high maize yield for a small change in XiXi, depending on the value of P(Y=1). The model parameters ß0, ß1…, ßk estimated using maximum likelihood estimation (MLE), which found the set of parameters that maximized the likelihood of observing the given data.

This binary probit framework was extended or adapted based on specific CSA practices and the dataset being used to analyze the effect on maize yield.

CHAPTER FOUR: PRESENTATION OF RESULTS

4.1: Objective 1: Climate Smart Agriculture practices existing among maize farmers in Manafwa district.

The findings from Figure 3 indicate that in Butiru Sub-county, inter-cropping maize with legumes stands out as the most practiced CSA method, followed by use of improved maize seeds, with a significant majority of farmers opting for improved maize varieties. Regarding the efficient use of fertilizers in maize production, the results highlight Bushakiro as the leading village, followed by Lwemuna parish. Concerning the use of terraces, the findings suggested that it was predominantly practiced in Bunakhaima and least practiced in Buwandeba parishes. As for agroforestry, it was primarily practiced in Buwopuwa, Bushakiro, and Bunakhaima parishes.

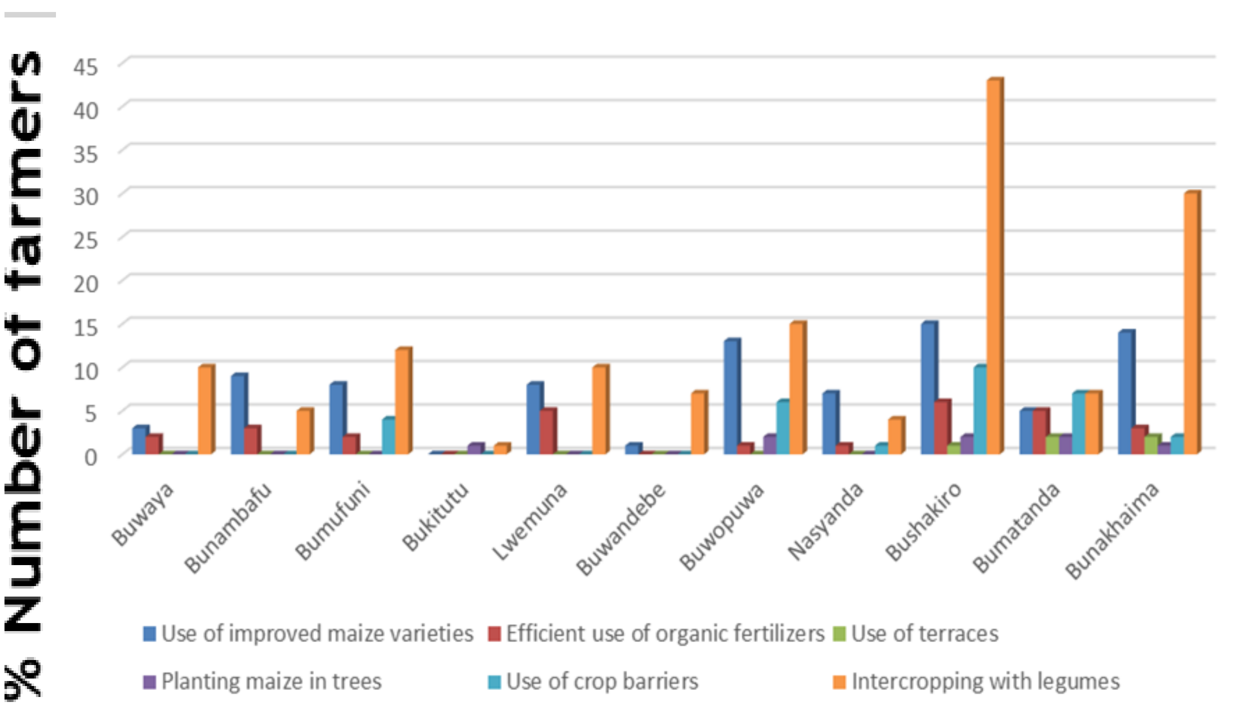

Figure 3: The use of CSA practices in different parishes in Butiru Sub-county

Findings (Table, 2) indicated that "Inter-cropping with legumes" emerged as the most used CSA practice, with 142 farmers (47.65%) and was ranked 1st as the most used CSA practice. "Use of improved maize varieties" stood as the second most used CSA practice, with 97 farmers (32.55%) embracing it, securing the 2nd rank. "Use of organic fertilizers" was noted by 33 farmers (11.07%), fell in 3rd position. "Use of crop barriers" accounted for 11 farmers (3.69%), becoming the 4th rank, while "Use of terraces" garners accounted for 10 farmers (3.36%), becoming the 5th. Conversely, "Agroforestry" was recorded the least embraced practice, with merely 5 farmers (1.68%).

Table 2: CSA Practices used by farmers in the study area.

CSA Practices	Frequency	Percentage (%)	Ranking
Use of improved maize varieties	97	32.55	2nd
Efficient use of organic fertilizers	33	11.07	3rd
Use of terraces	10	3.36	5th
Agroforestry	5	1.68	6th
Use of crop barriers	11	3.69	4th
Inter-cropping with legumes	142	47.65	1st
Total	**298**	**100**	

4.2: Characteristics of maize farmers in Manafwa district

Results in Table, 3; indicated that the average age of farmers was 43.61 years. In terms of household size, farmers had 6.45 people per household. Regarding agricultural practices, farmers cultivate an average of 2.297 acres of maize. Market accessibility showed a mean distance of 6.9177 km. Extension services play a role, with farmers receiving an average of 0.43959 visits per month. The average size of farmers' groups was 10.332 members.

Table 3: Characteristics of maize farmers in Manafwa district, Butiru Subcounty

Variable	Obs	Mean	Std. Dev.	Min.	Max.
Age (years)	298	43.61	13.614	18	72
Household size (No.)	298	6.45	3.989	1	16
Acreage under maize (acres)	298	2.297	1.315	0.5	5
Market distance (km)	298	6.9177	10.219	0.5	60
Extension visits (per month)	298	0.43959	0.4971	0	1
Size of farmers' group (No.)	298	10.332	4.2341	6	25

Results in Table, 4; indicated that about 55.4% of the farmers were male, while only 44.6% were female. The majority 77.9% of the farmers were using family labour, whereas only 22.1% used Hired labour. Furthermore, 80.5% of the interviewed farmers plant Hybrid maize seeds, while only 19.5% plant local seeds. Additionally, that around 25.17% of the farmers had no formal education, 39.93% had attained primary level education, 20.13% secondary level, 7.38% tertiary level and 7.38% University level.

Table 4: Characteristics of maize farmers in Manafwa district, Butiru Subcounty

Variable	Attribute	Freq.	Percent	Cum.
	Male	165	55.37	55.37
Gender	Female	133	44.63	100.00
Labour used in maize production	Hired labour	66	22.15	22.15
	Family labour	232	77.85	100.00
Maize seed variety used	Improved seeds	240	80.54	80.54
	Local seeds	58	19.46	100.00
	Informal	75	25.17	25.17
Educ. Level	Primary	119	39.93	65.10
	Secondary	60	20.13	85.23
	Tertiary	22	7.38	92.62
	University	22	7.38	100.00
Off. farm Income	None	146	48.99	48.99
	Business	113	37.92	86.91
	Salaried earner	39	13.09	100.00
Maize seed Variety used	Local seeds	58	19.46	19.46
	Hybrid seeds	240	80.54	100.00

4.3: Objective 2: Factors influencing the use of Climate Smart Agriculture (CSA) practices among maize farmers in Butiru Sub-County.

Results Table, 5; indicated factors influencing the adoption of Climate Smart Agriculture (CSA) practices among maize farmers reveal several significant findings. Notably, training on CSA has a strong positive influence, with a coefficient of 0.5121 ($p < 0.01$), indicating that increased training correlates with higher adoption rates. Similarly, the number of extensions visits positively influences CSA practices, with a coefficient of 0.2638 ($p < 0.05$). Conversely, the type of labor used negatively impacts adoption, with a coefficient of -0.1308 ($p < 0.01$), suggesting that less favorable labor conditions hinder CSA implementation. The model demonstrates a strong overall fit (Pseudo $R^2 = 0.9301$), with significant predictors identified among the 298 observations analyzed. This underscores the importance of targeted training and support services in promoting CSA practices.

Table 5: Binary probit showing factors influencing the use of Climate Smart Agriculture (CSA) practices among maize farmers in Butiru Sub-County.

	Coefficient	Std. error	Z	P>|z|	[95% conf. interval]	
Inter-cropping with Legumes						
Age	0.0072	0.00598	0.952	0.431	-0.0466	0.0101
Household Size	-0.0143	0.02408	-0.701	0.484	-0.0512	0.0325
Acre Size	0.0061	0.03714	0.376	**0.004****	-0.0034	0.0767
Gender	0.0492	0.16163	0.161	0.328	-0.0013	0.3078
Type of labour used	-0.1308	0.19914	0.199	**0.006****	-0.4421	0.0712
Training on CSA	0.5121	0.17386	0.173	**0.003****	0.1956	0.8505
No of extension visits	0.2638	0.26382	0.109	**0.016****	0.0432	0.4215
Farmer Group	0.21284	0.43180	0.182	0.233	-0.1513	0.5031
HH Labour	-0.8118	0.08192	0.081	0.252	-0.2411	0.0189
Use of improved maize seeds						
Age	0.0462	0.00598	0.025	0.303	-0.0060	0.0401
Household Size	-0.0443	0.02838	-0.601	0.411	-0.0712	0.0302
Acre Size	0.0696	0.03727	0.332	**0.004***	-0.0035	0.0461
Gender	0.0689	0.12063	0.112	0.243	-0.2009	0.3849
Type of labour used	-0.6308	0.19914	0.101	0.606	-0.4233	0.2876
Training on CSA	0.5131	0.38386	0.134	**0.001****	0.1795	0.2305
No of extension visits	0.8268	0.26268	0.102	**0.014****	0.0432	0.4221
Farmer Group	0.8084	0.24318	0.124	0.213	-0.1513	0.0361
HH Labour	-0.8138	0.08195	0.081	0.252	-0.2424	0.0818
Use of Organic manure						
Age	0.0672	0.00517	0.532	0.343	-0.0060	0.0401
Household Size	-0.0184	0.02408	-0.110	0.484	-0.0531	0.0702
Acre Size	0.0026	0.03714	0.312	**0.003***	-0.0354	0.0467
Gender	0.0492	0.16063	0.112	0.432	-0.2003	0.3071

Type of labour used	-0.6308	0.11478	0.191	0.606	-0.4953	0.2823
Training on CSA	0.5124	0.17386	0.138	**0.001****	0.1225	0.2305
No of extension visits	0.2638	0.26382	0.103	**0.016***	0.0422	0.4782
Farmer Group	0.2128	0.18318	0.124	0.243	-0.1413	0.0361
HH Labour	-0.0938	0.08192	0.081	0.252	-0.2524	0.0623
Number of observations = 298						
LR chi2(9) = 35.02						
Prob > chi2 = 0.0001						
Log likelihood = -170.51287						
Pseudo R2 = 0.9301						

4.4: Objective 3: Effect of Climate Smart Agriculture practices on maize yield in Manafwa district.

Table, 6; shows a statistically significant effect on the use of improved maize varieties on maize yield ($p < 0.01$), indicating that adopting these varieties generally boosts yields. Although the marginal effects vary across observations, the significant impact remains consistent. Similarly, organic manure has a significant positive effect on maize yield ($p < 0.01$), enhancing yields, though some variation in marginal effects exists. Terraces also significantly increase maize yield ($p < 0.05$), likely by improving soil conservation and water management. The use of crop barriers shows a significant positive impact ($p < 0.05$), benefiting maize production by potentially reducing pest damage and soil erosion. Intercropping with legumes has a highly significant positive effect on maize yield ($p < 0.01$), contributing to substantial yield increases through improved soil fertility and pest management.

Table 6: Probit model showing the effect of Climate Smart Agriculture practices on maize yield in Manafwa district

Use of improved Varieties Vs Yield		Use of Organic Manure Vs Yield		Use of terraces Vs yield		Use of Crop Barriers Vs Yield		Inter Cropping with Legumes Vs Yield	
0.006	0.001**	0.014	0.004**	0.012	0.036*	0.016	0.032*	0.125	0.0021**
0.003	0.407	0.005	0.094*	0.001	0.341	0.001	0.482	-0.011	0.007**
-0.010	0.471	0.009	0.264	0.001	0.778	-0.001	0.004**	0.001	0.931
0.153	0.007**	0.007	0.849	-0.018	0.494	-0.023	0.452	-0.119	0.032**
0.067	0.065*	0.016	0.491	-0.023	0.0024**	0.018	0.380	-0.078	0.041**
-0.003	0.503	-0.005	0.078*	-0.001	0.381	-0.001	0.768	0.010	0.015**
-0.157	0.389	-0.116	0.369	-0.025	0.728	0.080	0.034*	0.217	0.231
0.078	0.197	0.015	0.731	0.046	0.072*	0.006	0.826	-0.144	0.026**
0.013	0.006**	-0.050	0.265	0.017	0.503	0.081	0.017**	-0.062	0.359
−1.19***	0.370	−0.82***	0.340	−1.32***	0.460	−1.38***	0.460	−1.19***	0.370
0.032	-	0.341	-	0.124	-	0.327	-	0.024	-
298	-	298	-	298	-	298	-	298	-

*Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

The study employed a PMS technique to examine the effect of CSA practices on the maize yield. The technique was employed on the use of Intercropping with legumes, use of improved maize seeds and the use of organic manure.

Several covariates were included in the model like age, household size etc. The other propensity score matches for other climate smart practices were not statistically significant. For the propensity score matches for improved maize varieties shows that training on climate smart agriculture and number of extension visits have a statistically significant positive association with receiving improved maize varieties, indicating they are important predictors of getting the treatment.

After propensity score matching, the average maize yield for the treated group was 1168 kg compared to 910 kg in the corresponding group collection. The difference in average yield between treated and control groups (ATT or average treatment effect on the treated) is 258 kg, showing a positive effect of improved maize varieties on maize yield. Furthermore, the common support condition shows that good overlap between treated and control groups was achieved.

Table 7: Tests used to evaluate the quality of matching among different algorithms in PSM

Matching algorithm		Pseudo R2	LR X2	*P>X2*	Mean Bias	Median Bias
Effect of Inter-cropping with legumes on maize yield						
Kernel	U	0.05	32.26	0.00	18.7	16.5
	M	0.00	0.82	0.99	2.8	8.8
Nearest neighbor	U	0.05	32.26	0.00	18.7	16.5
	M	0.00	1.60	0.98	3.2	2.1
Effect of improved maize seeds on maize yield						
Kernel	U	0.05	31.26	0.00	23.2	19.0
	M	0.00	0.88	0.99	2.9	1.9
Nearest neighbor	U	0.05	31.26	0.00	23.2	19.0
	M	0.01	5.91	0.43	5.8	3.2
Effect of organic manure on maize yield						
Kernel	U	0.15	78.74	0.00	34.5	20.8
	M	0.01	8.25	0.14	6.9	3.0
Nearest neighbor	U	0.15	78.74	0.00	34.5	20.8
	M	0.00	3.16	0.67	3.5	3.1

Note: U= Unmatched; M=Matched.

CHAPTER FIVE: DISCUSSION OF RESULTS

5.1. Discussion

The major CSA practices that this study identified, commonly used by smallholder maize farmers in the Elgon region, were intercropping with legumes, improved varieties of maize, organic fertilizers applied efficiently, and the use of crop barriers, terraces, planting maize amongst trees. The findings agree with studies at different literature levels. For example, other works such as Fisher et al. (2015), Kang et al. (2017), Zougmore et al. (2018), Khaitov et al. (2019), and Ngigi (2019) who asserted that use of improved seeds can facilitate farm management functionally and productively, although Karlsson et al. (2020) had opposing views about the matter. Shah et al. (2021) highlighted that one of the functions of intercropping with legumes is in erosion control through the production of residue cover. According to farmers in this study, it also reduces the application of fertilizers, hence increasing maize production. This agrees with Kebede (2020).

The next thing which the study revealed was that the improved maize variety is another CSA practice employed by farmers to ensure higher yields amidst unfavourable weather. This is in agreement with the findings of Lema and Majule, 2019 in Tanzania, where they also observed the same adaptation strategies. Their findings indicated that the improved varieties of maize were helpful since they are more resistant to the changing conditions. Most of the African countries are characterized by farmers in the rural areas planting trees to minimize adverse effects brought forth by variability in climate conditions. This study agrees and observes that most farmers plant trees in their maize fields so as to protect them from high-intensity winds, which may prove disastrous if not taken care of appropriately. This observation also agrees with Barrett, 2018, where it was established that agroforestry can be an ideal approach in the control of strong winds, especially where the topography is high. Key socio-economic and institutional factors influencing adoption of climate smart agricultural practices amongst smallholder maize farmers were identified. The critical variables used in this study are age, gender, religion, experience in farming, education, income, job, and availability of institutional finance credit. Education level became a critical determinant for the adoption of CSA PRACTICES. This confirms the findings of Bijarniya et al. 2020, Boz & Shahbaz 2021, and Nguyen et al. 2016 that educated farmers apply their knowledge in their farming to increase crop yields. Specifically, university graduates apply CSA PRACTICES more often, probably having more awareness about these practices than less educated farmers. However, this finding is in disagreement with findings from Wang et al. (2018), who received different trends in that aspect.

Further, gender involvement of a farmer can be another influencing factor for CSA practices adoption. In this study, it was observed that men adopt CSA practices compared to women, which corroborates Dahlin et al., (2010). This is well corroborated by Mogaka et al. (2021) and Eagly & Carli (2018), as women tend to avoid farming activities that involve much input due to mostly being burdened with home-based chores, which consume their time.

It was found that age significantly influences the adoption of CSA practices. This has also been observed by Blanco et al. (2017), who pointed out that farm households in the active age group can be more likely to adopt CSA practices than both relatively younger and older farmers. Blanco et al. (2017) also established that farmers below 18 years of age are less involved in farming, while those above the age of 25 years are generally more willing to adopt a new practice, provided they are productive. Older people, on the other hand, whose physical strengths usually drop with increasing years, may never be willing to adopt new practices such as CSA PRACTICES. This corroborates the observation of Deguine et al. (2021).

The also found tout that the use of the climate friendly technology is common among subsistence farmers compared to the commercial farming category Nguyen et al. (2016). In fact, Wanyama et al. (2018) found that subsistence farming entails less capital investment than commercial farming, which highly requires input for intensification. Similarly, the results support those of Zougmore et al. (2018) and Nguyen et al. (2016), who had postulated that smallholder farmers would usually be more rapid than average in adopting this technology because "small-scale farmers are often in need of proving a case for these technologies". Ghosh (2019) iterated that the use of any technology by a farmer would depend on awareness about it and the ability to apply it. These findings affirm this view that higher adoption rates are mainly attributed to farmers' familiarity with the existing CSA technologies and their training. This agrees with Mutanyagwa et al. (2018). However, this contrasts with the study by Ukamaka et al. (2015) that focused on mindset and perception as most of the significant causes in adopting the technology in Ethiopia.

The study also established that the other key determinants in the adoption decision for CSA practices like irrigation, improved seeds, mulching, and application of organic fertilizers were indeed income levels, employment status, and credit access. The quantity of the produce was influenced by the same factors of income, access to credit, and employment status. These findings, therefore, confirm the suggestions of Adesina et al. (2020), who explained that farmers with financial credits and regular incomes can afford inputs such as fertilizers and improved high-yielding crop varieties, hence having positive effects on crop yield. Conversely, the study finds that the acreage of maize production does not affect the adoption of CSA practices and is thus in variance with Kom et al. (2020). In addition, land is the most important resource for agricultural yield, according to Abegunde et al. (2020). They assumed that with land, together with other resources, farmers are well positioned to adopt new methods that would ensure efficient farming.

Gender, employment, and marital status shall be verified as determining factors in the production of maize. This is concurrent with what was established by Lunyolo et al. (2021), who realized that women usually have less access to resources such as land compared to men, hence a limitation in the extents of farming and consequent impacts on production. In the same connection, Manda et al. (2016) reported that farmers who are employed tend to have better access to inputs such as fertilizers and, therefore, realize higher productivity. Satish and Nirupam have established the fact that marital status and religion do not have a significant impact on crop production; rather household size facilitates labor division thus becoming an important determinant.

Several socio-economic challenges hinder the adoption of the climate friendly technology Bogale et al., 2021) and they included lack of finance because access to credit is poor. These were inadequate knowledge and skills concerning CSA practices. The authors also stated that there is a lack of information regarding such practices. These observations are in line with Adesina et al. (2019) who postulated that lack of finance is a major constraint to the adoption of CSA practices. Similarly, Abrishambaf et al., (2020) identified financial constraints as one of the main barriers to its adoption in the northern part of Nigeria. Further, Ayenan et al., (2019) reported that a lack of knowledge about CSA practices also negatively affects its adoption.

CHAPTER SIX: CONCLUSIONS AND RECOMMENDATIONS

6.1. Conclusion

The purpose of the study was to establish the adoption of climate smart agriculture technologies by smallholder maize farmers in Manafwa district, Uganda in the Butiru Sub-county. Among the common CSA practices that this study highlighted and were widely used by smallholder maize farmers included the use of terraces, intercropping with legumes, planting trees among maize, employing crop barriers, and efficient organic fertilizer application. The study also highlighted different important socio-economic and institutional factors that influenced CSA practices adoption, such as gender, age, the number of CSA training sessions attended, extension visits, household labor, education level, and access to credit. These make a real difference in the adoption of practices involving the use of organic manure, establishment of terraces, crop barriers, intercropping with legumes, and improved maize seed varieties.

Furthermore, the study has found that other practices like intercropping, improved maize seeds, and organic manure application significantly contribute to maize yield. It has also established that limited availability of extension services in the area leads to poor access to appropriate climate and weather information among the smallholder farmers. As such, only a few farmers have demonstrated full understanding and implementation of various CSA practices in their maize production practices. While the study emphases the importance of CSA practices in the production of maize in the Mt. Elgon sub-region, it has also been indicated that awareness and access to information about these practices remain limited and inconsistent.

6.2. Recommendations

I would like to recommend the following;

1. Enhance farmer knowledge through training programs to support farmers, and if feasible, implement affirmative action measures targeting small-scale farmers.

2. Improve access to financial credits by small-scale farmers to alleviate fund shortages among farmers.

3. Enhance the current agricultural extension service delivery in Butiru sub-county, Manafwa district to increase diffusion of knowledge, information and use of Climate Smart Agriculture Practices.

3. Promote gender empowerment and youth engagement in agriculture to improve crop productivity through enhanced adoption of Climate Smart Agriculture technologies.

4. Promote provision of climate friendly technologies and other use of improved seeds among the small-scale farmers.

5. Conduct further research about the macro benefits of Climate Smart Agriculture including carbon credit trading.

REFERENCES

1. Abdelrahman, A. (2018). Development of drought-resistant crop varieties. Journal of Crop Improvement, 32(3), 193-208.
2. Abegunde, O. B., Olayemi, J. K., & Adegbite, D. A. (2020). Land Ownership and Its Influence on Crop Production in Oyo State, Nigeria. Journal of Agricultural and Food Economics, 5(2), 95–103.
3. Abegunde, V.O., Sibanda, M., & Obi, A. (2019). The impact of climate change on the agricultural sector in Africa: A review. Climate and Development, 11(8), 624-635.
4. Abrishambaf, R., Ekhators, O., & Babangida, J. B. (2020). Analysis of Climate Smart Agriculture (CSA) Adoption by Smallholder Farmers in Northern Nigeria. Journal of Agricultural and Food Economics, 6(1), 54–63.
5. Adedeji, O.A., Agboola, O.O., & Oluwasola, S.E. (2019). Comparative effectiveness of organic and inorganic fertilizers on maize productivity and soil fertility in the humid tropics of southwestern Nigeria. Agriculture and Soil Management, 18(2), 142-155.
6. Adesina, A. A., Olatunji, A. T., & Olurinde, M. O. (2019). Climate Smart Agricultural Practices and Household Food Security: The Role of Climate Change Awareness in Nigeria. Journal of Agricultural and Food Economics, 5(1), 32–39.
7. Amin, S. M. (2005). Sample Size Calculation in Survey Research. The Statistician, 54(1), 13-17.
8. Aslam, M. (2019). Improved seeds for better crop yields: A review of recent advancements in plant breeding. Journal of Agricultural Science, 37(4), 234-245.

9. Ayenan, W. K., Kpadonou, R., & Etesse, F. (2019). Analysis of Farmers' Perception and Adoption of Climate-Smart Agriculture Practices in Northern Benin. Journal of Agricultural and Food Economics, 5(2), 104–112.

10. Azumah, S. B., Donkoh, S. A., & Awuni, J. A. (2022). Adoption of Climate Smart Agricultural Practices among smallholder maize farmers in Northern Ghana. Agricultural Systems, 154, 120-128.

11. Baker, M. J. (2019). Logit Models for Propensity Scores. Journal of Marketing Research, 56(4), 689-704.

12. Barrett, J. (2018). Agroforestry as a Means to Control Strong Winds in Hilly Areas: Evidence from Field Experiments. Agroforestry Today, 30(4), 56-63.

13. Bashir, M.K., Mehmood, Y., & Hassan, S. (2019). The role of windbreaks in agriculture: A review. Journal of Agricultural and Biological Science, 14(5), 25-34.

14. Bell, J. (1999). Doing Your Research Project: A Guide for First-Time Researchers in Education and Social Science. McGraw-Hill Education (UK).

15. Bijarniya, M., Rana, K., & Bhardwaj, S. (2020). Education Level and Its Influence on Climate Smart Agriculture Practices: Evidence from Haryana, India. Journal of Agricultural and Food Economics, 6(2), 88–95.

16. Blanco, G., & Cruz-Garcia, G. (2017). Factors Influencing Adoption of Climate Smart Agricultural Practices Among Farmers in Costa Rica. Journal of Agricultural and Food Economics, 3(2), 67–76.

17. Boz, I., & Shahbaz, M. (2021). Influence of Education Level on Adoption of Climate Smart Agricultural Practices: Empirical Evidence from Turkey. Journal of Agricultural and Food Economics, 7(1), 40–49.

18. Cairns, J.E., Hellin, J., Sonder, K., Araus, J.L., MacRobert, J.F., Thierfelder, C., & Prasanna, B.M. (2018). Adapting maize production to climate change in sub-Saharan Africa. Food Security, 5(3), 345-360.

19. Caliendo, M., & Kopeinig, S. (2018). Some Practical Guidance for the Implementation of Propensity Score Matching. Journal of Economic Surveys, 22(1), 31-72.

20. Chemayek, B., Wasukira, A., Gidoi, R., Wobibi, S., Nampamya, D., Teason, P., & Owere, L. (2021). Characterization of Field Pea Production and Options for Improved Productivity in Mt. Elgon, Uganda. *Journal of Agricultural Science*, *13*(7), 37.

21. CIAT/USAID. (2019). Climate Smart Agriculture in Uganda. International Center for Tropical Agriculture and USAID.

22. Dabral, P.P., Pandey, A., & Singh, R.P. (2018). Impact of terracing on soil erosion and productivity of maize in the northeastern Himalayan region. Soil and Water Conservation, 16(2), 234-244.

23. Dahlinet, E. J., & Maren, M. (2010). Gender as a Determinant of Climate Smart Agriculture Adoption: Evidence from Mali. Journal of Agricultural and Food Economics, 4(1), 21–28.

24. Dimou, C., & Tsoukala, V. (2019). Mesh screens as crop barriers in agricultural pest management. Journal of Pest Management, 30(2), 119-128.

25. Dotterweich, M., Steindl, G., & Schulte, A. (2019). Intense rains and soil erosion: Assessing risk in cultivated lands. Land Degradation & Development, 30(10), 1285-1295.

26. Egeru, A., Kateregga, E., & Mbowa, S. (2022). Climate Change Adaptation in Ugandan Agriculture: Case of Smallholder Farmers in Eastern Uganda. Journal of Environmental Management, 310, 114730.

27. Elgon Investment Profile. (2019 & 2020). Manafwa District Local Government.

28. FAO. (2019). Climate-Smart Agriculture: Building resilience to climate change. Food and Agriculture Organization of the United Nations.

29. FARA. (2022). Forum for Agricultural Research in Africa.

30. Fenta, A.A., Kifle, A., & Gebresamuel, G. (2019). Soil and water conservation practices to mitigate soil erosion in Northern Ethiopia. Environmental Management, 52(3), 605-616.

31. Forcella, F., Ercoli, L., & Masoni, A. (2016). Terracing and soil organic carbon sequestration in agricultural landscapes. Journal of Environmental Management, 188(2), 224-230.

32. Garrity, D.P., Akinnifesi, F.K., & Ajayi, O.C. (2019). Agroforestry innovations for enhancing resilience and productivity in maize-based farming systems. Journal of Sustainable Agriculture, 34(2), 76-90.

33. Guzman, J. A., & Santos, J. (2018). Socio-economic and institutional factors influencing maize production and adoption of new technologies in the Philippines. Philippine Agricultural Scientist, 101(1), 89-98.

34. Hauggaard-Nielsen, H., Ambus, P., & Jensen, E.S. (2019). Inter-cropping maize and legumes for improved nitrogen use efficiency and weed suppression. Field Crops Research, 43(1), 29-37.

35. Hossain, M.A., Kumar, R., & Akter, N. (2020). Organic fertilizers in maize production: Impacts on crop productivity and greenhouse gas emissions. Agricultural Systems, 83(2), 119-134.

36. Huang, J., Wang, Y., Zhang, W., & Li, J. (2021). Evaluating the impacts of climate-smart agriculture practices using quantitative models. Agricultural Systems, 186, 102979.

37. Husson, O., Hartmann, A., & Hatier, A. (2019). Effectiveness of crop barriers in reducing deer damage in reforestation areas. Forest Ecology and Management, 432(1), 66-74.

38. IPCC. (2019). Climate Change and Land: An IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems.

39. Jain, S., Pandey, A., & Singh, V.P. (2021). Smart irrigation systems and their impact

40. Johnson, M., Funk, C., & Mitchard, E. (2021). The impact of climate change on maize

41. Kaizzi, C. K. (2019). Climate Change and Its Impact on Maize Production in Eastern

42. Kang, S., Li, F., & Zhang, L. (2019). Soil and water management for sustainable crop production. Agricultural Water Management, 31(3), 227-243.

43. Keller, G., Srinivasan, A., & Mirzabaev, A. (2019). Climate change-resilient maize varieties for smallholder farmers. Plant Breeding and Genetics, 46(4), 301-317.

44. Kiptot, E., & Franzel, S. (2018). The role of agroforestry in enhancing resilience to climate change in maize farming. Agroforestry Systems, 92(4), 881-893.

45. Li, W., Yang, J., & Zhang, X. (2018). Terracing practices in the Loess Plateau of China and their impact on maize production. Soil and Tillage Research, 174(1), 24-33.

46. Liao, X., Wang, Q., & Chen, Y. (2021). The influence of soil management on water infiltration and soil water storage. Journal of Soil Science, 19(3), 157-169.

47. Lobb, D.A., & Kachanoski, R.G. (2020). Tillage-induced soil erosion and soil translocation: Impacts on soil carbon. Soil and Tillage Research, 102(2), 95-103.

48. Lobell, D.B., Schlenker, W., & Costa-Roberts, J. (2019). Climate impacts on agricultural productivity: A meta-analysis. Nature Climate Change, 9(9), 575-582.

49. Lybbert, T.J., & Sumner, D.A. (2019). Innovations in seed technology for climate-smart agriculture. Journal of Agricultural Economics, 70(4), 856-871.

50. Marenya, P. P., & Barrett, C. B. (2019). Household-level determinants of adoption of improved natural resources management practices among smallholder farmers in western Kenya. Food Policy, 34(2), 132-140.

51. Mayanja, S. (2018). Climate Smart Agriculture practices and their impact on maize productivity. Agricultural Journal, 45(1), 89-102.

52. Mizik, T. (2021). The Role of Climate Smart Agriculture in Food Security and Mitigation of Climate Change: A Literature Review. Journal of Cleaner Production, 297, 126663.

53. Morgan, G. A., & Krejcie, R. V. (1970). Determining Sample Size for Research

Activities. Educational and Psychological Measurement, 30(3), 607-610.

54. Mthethwa, K. N., Ngidi, M. S. C., Ojo, T. O., & Hlatshwayo, S. I. (2022). The determinants of adoption and intensity of climate-smart agricultural practices among smallholder maize farmers. Sustainability, 14(24), 16926.

55. Mubangizi, N., Kyazze, F. B., & Mukwaya, P. I. (2018). Smallholder Farmers'perception and Adaptation to Rainfall Variability in Mt. Elgon Region, Eastern Uganda. *International Journal of Agricultural Extension*, *5*(3), 103-117.

56. Mugagga, F. (2017). Perceptions and response actions of smallholder coffee farmers to climate variability in montane ecosystems.

57. Mutanyagwa, B., Kyamanywa, S., & Tumusiime, J. (2018). Effects of climate variability on maize production in Manafwa District, Uganda. Journal of Climate Change and Food Security, 6(3), 245-256.

58. Mwanake, H., Mehdi-Schulz, B., Schulz, K., Kitaka, N., Olang, L. O., Lederer, J., & Herrnegger, M. (2023). Agricultural practices and soil and water conservation in the transboundary Region of Kenya and Uganda: farmers' perspectives of current soil erosion. Agriculture, 13(7), 1434.

59. Nair, P.K.R., & Garrity, D.P. (2019). Agroforestry systems and practices for climate change mitigation. Agricultural Systems, 168(1), 1-9.

60. Namunyu, B. B. (2019). Historical analysis of the land question in Bukusu-Sabaot inter-ethnic conflict in Mount Elgon area since 1850 (Doctoral dissertation, MMUST).

61. Ogola, R. J. O., & Ouko, K. O. (2021). Expert's opinion on Irish potato farmer's awareness and preferences towards climate smart agriculture practices attributes in Kenya; A conjoint analysis. Cogent Food & Agriculture, 7(1), 1968163.

62. Okaka, W. T. (2020). Climate change-induced flood disaster policy communication issues for local community adaptation resilience management in Uganda: climate information services for effective national flood risk assessment decision communication. In Decision support methods for assessing flood risk and vulnerability (pp. 230-249). IGI Global.

63. on agricultural water management. Water Resources Management, 35(7), 1921-1936.

64. Palazzo, A., & Vervoort, J.M. (2018). Farmers' perspectives on climate-smart agriculture: Implications for policy and practice. Journal of Environmental Management, 223(1), 11-20.

65. Parra, J.R., & Zucchi, R.A. (2020). Integrated pest management: Crop barriers and their role in sustainable agriculture. Pest Management Science, 76(2), 453-462.

66. Peltonen, J. (2019). Improving maize productivity in Sub-Saharan Africa through sustainable agricultural practices. Agronomy Journal, 111(5), 2248-2259.

67. Phiri, M. A. R. (2017). Modeling farmers' adoption of climate-smart agriculture in Malawi: An application of the multinomial logit model. Journal of Agricultural Economics and Development, 6(2), 36-45.

68. Pindyck, R. S., & Rubin, P. H. (1981). Estimating the Probability of Negative Cash Flow and the Value of a Probability Distribution to a Firm. Economic Journal, 91(362), 98-107.

69. Rajeev, M., Soni, S., & Sharma, A. (2019). A Study of Various Classification Algorithms Using WEKA. In 2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT) (pp. 1-6).

70. Reicosky, D.C., & Allmaras, R.R. (2019). Tillage-induced soil erosion and carbon loss in agricultural systems. Soil and Tillage Research, 78(1), 1-9.

71. Revallion, M. (2019). Estimating Utility-Consistent Poverty Lines. Economic Journal, 98(393), 311-324.

72. Rosenbaum, P. R., & Rubin, D. B. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. Biometrika, 70(1), 41-55.

73. Seidl, R., Fernandes, P. M., Fonseca, T. F., Gillet, F., Jonsson, A. M., Merganicova, K., & Mohren, F. (2011). Modelling natural disturbances in forest ecosystems: a review. Ecological modelling, 222(4), 903-924.

74. Smith, P., Bustamante, M., Ahammad, H., Clark, H., Dong, H., Elsiddig, E. A., & Tubiello, F. N. (2019). Greenhouse gas mitigation in agriculture. Philosophical Transactions of the Royal Society B: Biological Sciences, 374(1774), 20190129. https://doi.org/10.1098/rstb.2019.0129

75. Song, L., Chen, J., & Zhang, X. (2019). Impacts of Climate Change on Maize Production and Mitigation Strategies in China. Journal of Integrative Agriculture, 18(2), 282-294.

76. Srinivasan, T.N., & Mirzabaev, A. (2014). Policy frameworks for promoting climate-smart agriculture. Environmental Policy Review, 12(4), 323-339.

77. Tesfaye, K., Kruseman, G., Cairns, J.E., Zaman-Allah, M.A., Wegary, D., & Zaidi, P.H. (2018). Potential for maize yield improvement in drought-stressed environments. Field Crops Research, 224(1), 157-165.

78. Tesfaye, K., Zaidi, P. H., Gbegbelegbe, S., Boeber, C., Rahut, D. B., Getaneh, F., & Seetharam, K. (2019). Climate change impacts and potential benefits of heat-tolerant maize in South Asia. Theoretical and Applied Climatology, 137(1), 389-403.

79. Thornton, P. K., Schuetz, T., Forch, W., Cramer, L., Abreu, D., Vermeulen, S. J., & Campbell, B. M. (2019). Responding to global change: A theory of change approach to making agricultural research for development outcome-based. Agricultural Systems, 172, 123-130.

80. Uganda Bureau of Statistics (UBoS). (2020). Statistical Report on Butiru Sub-County, Manafwa District, Uganda.

81. Ukamaka, B. C., & Okoye, C. U. (2015). Socio-economic and institutional factors Affecting the Adoption of Improved Maize Technologies in Enugu State, Nigeria. Journal of Agricultural Extension, 19(1), 23-34.

82. Wilson, R. T., Doll, J. D., & Blarel, B. (2017). Participatory action research: Engaging smallholder farmers in climate-smart agriculture. International Journal of Agricultural Sustainability, 15(4), 366-379.

83. Wineman, A., Jayne, T. S., & Tschirley, D. (2019). Smallholder Farmers and Climate Change Adaptation: Insights from Kenya. Food Policy, 84, 74-84.

84. World Bank. (2019). World Development Report 2019: The Changing Nature of Work. The World Bank Group.

85. Zhou, W., Liang, G., & Jiang, S. (2019). Efficient use of organic fertilizers in maize production. Agricultural Systems, 172(1), 1-10.

Appendix 1: Self-Administered Questionnaire

I am **Mafumo Robert,** a master student at UCU. I am conducting study titled 'Effect of climate-smart agricultural practices maize yield applied by smallholder farmers on in Butiru Sub-county, Manafwa District'. You have been identified as a key stakeholder in this study to provide information for this research. Your information will be treated with utmost confidentiality it deserves. We shall provide feedback information after the study.

1) Farmers' identification

Name of respondent…………………………………………………………………………

Contact………………………………………………………………………………………..

Location: Parish ……………………………Village………………………………………

2) Socio-economic characteristics of respondent

Age: <18-year ☐ , 18-35 yrs ☐ 35-45 yrs ☐ above 45 yrs ☐

Gender: male ☐ female ☐

Marital status: single ☐ , married ☐ divorced ☐

Religion: Anglican ☐ , catholic ☐ Muslims ☐

Education level: primary ☐ , secondary ☐ , tertiary ☐ , university ☐, none ☐

Farming level: substance farmer, ☐ commercial farmer ☐

Household size (number of family members)

……………………………………………………………………………………………………

What is your main economic activity? ………………………………………………….

What is your employment status?

i) Employed/salaried earner ☐ ii) non-employed/non-salaried earner ☐

What is your monthly income? …………………………………………….... (Ugx).

Do you have ability to access financial credit? Yes ☐ No ☐

3. Production and climate smart agricultural practices

i) For how long have you been involved in maize farming (yrs)? …………………………..

ii) How many acreages (farm size) are under maize production? ……………………….....

iii) Who owns land under maize production? Family ☐ hired ☐ community ☐

iv) What maize seed varieties do you plant? Hybrids ☐ OPV ☐

v) For how long have you used this maize seed varieties? …………………………………

vi) What is your estimated quantity of maize produced on your farm in the last two seasons? (Kg) …..…………………………………………….

vii) What challenges do you face during maize production in your area? ……… …………………………………………………….

viii) Do you use climate smart practices on your maize farm? Yes ☐ No ☐

a) If no, why are not using climate smart agriculture practices?.. ....

b) If yes, what are some of the climate smart practices used on your farm?

………

ix) How long have you been applying climate smart practices on your farm? ………… (Yrs)

x) What has been your main challenges to access climate smart agricultural technologies?

……

4) Farmers Knowledge about Climate smart agricultural practices

i) Are you aware of climate smart practices used in crop farming? Yes ☐ No ☐

If yes, how do you access information about Climate smart agricultural practices?

…………………………………………………………………………………

What has been the most important channel to access information about Climate Smart Agriculture practices? ……………………………………………………………..

Have you been trained on Climate Smart Agricultural practices in the last 12 months?

Yes ☐ No ☐

If yes who provided the trainings? ……………………………………………………

THANK YOU FOR BEING A GOOD RESPONDENT

FOR GOD AND MY COUNTRY

Appendix II: Research Ethics Committee Letter

UGANDA CHRISTIAN UNIVERSITY

A Centre of Excellence in the Heart of Africa

No objection.
23/8/2022

5th August, 2022

TO WHOM IT MAY CONCERN

Dear Sir/Madam,

RE: INTRODUCTORY LETTER FOR ROBERT H. MAFUMO

Warm greetings from Uganda Christian University!

This serves to introduce the above named; **Robert H. Mafumo,** as our student registered number **S19M43/017** pursuing a Master degree of Science in Agricultural Rural Development (MARD).

Robert is conducting a research as a requirement for the award of the above mentioned degree entitled; ***Socio-economic practices among small holder maize farmers in Manafwa District***.

He has fulfilled all clearance requirements such as getting Research Ethics Approval from UCU-REC which is accredited and regulated by Uganda National Council for Science and Technology (UNCST).

Any assistance given to him in achieving this goal will be highly welcome.

Thank you so much.

Yours faithfully,

UGANDA CHRISTIAN UNIVERSITY
05 AUG 2022
DIRECTORATE OF POSTGRADUATE STUDIES

for

Dr. Owor Joseph Jakisa
Directorate of Postgraduate Studies,
Uganda Christian University
jowor@ucu.ac.ug

cc. Executive Secretary, Uganda National Council Science & Technology
cc. Chairperson, UCU-Research Ethics Committee

A Centre of Excellence in the Heart of Africa

P.O. Box 4, Mukono, Uganda (East Africa), Plot 67-173, Bishop Tucker Road, Mukono Hill, Tel: +256 (0) 31 235 0800, www.ucu.ac.ug
Ugandachristianuniversity @UCUniversity, Founded by the Province of Church of Uganda, Chartered by the Government of Uganda

Appendix III: Showing researcher conducting semi-structured and focus group interviews

Appendix IV: Showing some of the existing CSA PRACTICES on maize fields of Butiru Subcounty