ADOPTION OF CLIMATE-SMART MAIZE VARIETIES AND ITS IMPACT ON HOUSEHOLD INCOME AMONG SMALL-SCALE FARMERS IN EMBU COUNTY, KENYA

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A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF MASTER OF SCIENCE IN AGRICULTURAL AND APPLIED ECONOMICS

DEPARTMENT OF AGRICULTURAL ECONOMICS

FACULTY OF AGRICULTURE

UNIVERSITY OF NAIROBI

September, 2021

Declaration

I declare that this thesis is my original work and has not been submitted for a degree in any university.

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Dedication

This thesis is dedicated to my wife Sylvia and my daughter Prudence.

Acknowledgement

I am grateful to God for the guidance, grace, strength, and protection to undertake and complete my studies. It has been a privilege to work under the supervision of; Prof. John Mburu and Dr. Felister M. Nzuve from the University of Nairobi, Dr. Stella Makokha, and Dr. Rosemary A. Emongor from Kenya Agricultural and Livestock Research Organization (KALRO). Thank you for your continued support, timely feedback, and support during this study. This work would not have been accomplished without your insightful feedback. My gratitude goes to the African Economic Research Consortium (AERC) and DAAD from Germany for sponsoring my studies and Kenya Agricultural and Livestock Research Organization (KALRO) through National Research Fund (NRF) for partially funding and facilitating the research work. I would also like to appreciate the entire University of Nairobi fraternity more so members of the academic staff for their valuable comments during seminar presentations. Special thanks go to Dr. Stella and Dr. Rosemary from KALRO for allowing me to be part of the research team under the project entitled "Assessing the Efficacy of Genetic Fingerprinting as Tool for Tracking Diffusion and adoption of maize varieties in Kenya" implemented by KALRO between 2019 and 2020. I am grateful for the support and perseverance of the data collection team, the input of the field guides, and respondents in Embu County for their cooperation and hospitality. My sincere thanks to my wife, Silvia Mwihaki, and the entire family for their love and unwavering support. Finally, I wish to thank my colleagues CMAAE class of 2017 from the University of Nairobi, you have been a fantastic team. I also wish to thank the colleagues I met at the shared facility at the University of Pretoria for their invaluable input in my stay at the facility. God bless you all.

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List of Abbreviations

AATF	African Agricultural Technology Foundation
AERC	African Economic Research Consortium
AGRA	Alliance for a Green Revolution in Africa
ATT	treatment effect on treated
ATU	treatment effect on untreated
CIMMYT	(International Maize and Wheat Improvement Center)
CO_2	carbon dioxide
CRE	random correlation effects
CSA	Climate-Smart Agriculture
CSMVs	climate-smart maize varieties
DAAD	Deutscher Akademischer Austauschdienst
DH	Double hurdle
DTMA	Drought Tolerant Maize for Africa
ESR	endogenous switching regression
FAO	Food and Agriculture Organization
FAOSTAT	Food and Agriculture Organization Statistics
FIML	full information maximum likelihood
GHG	Green House Gas
IITA	International Institute of Tropical Agriculture
IPCC	Intergovernmental panel on climate change
KALRO	Kenya Agricultural and Livestock Research Organization
KEPHIS	Kenya Plant Health Inspectorate Services
KNBS	Kenya National Bureau of Statistics
NO_2	nitrous oxide
ODK	Open Data Kit
OECD	Organization for Economic Cooperation and Development
OLS	Ordinary Least Square
OPVs	open-pollinated varieties
PSM	propensity score matching
RCT	Randomized control trial
RUM	random utility model
SSA)	Sub-Sahara Africa
STAK	Information Communication Technologies
TASAI	The African Seed Access Index
TH	Transitional Heterogeneity
USD	United State Dollar
VIF	Variance Inflation Factor

Abstract

Climate unpredictability and declining soil fertility affect agricultural production, especially in Sub-Sahara Africa thus threatening global food security. This has prompted the seed sector to introduce various varieties of climate-smart maize in Kenya and release them in the market. However, there is little empirical evidence on their adoption rate and impacts on household income for efficient formulation of policies aimed at reducing food insecurity and poverty level. Therefore, this study aimed at examining the adoption of climate-smart maize varieties and its impact on household income in Embu County, Kenya.

A multi-stage random sample of 550 maize farmers comprising of 346 adopters and 204 non-adopters of climate-smart maize varieties was used. Double hurdle model and endogenous switching regression model were used to analyze intensity of adoption and impact on household income respectively. The descriptive results indicated that adoption rate for climate-smart maize varieties was about 63 %. The results further indicated that land size, land ownership, size of the family, contact to extension officer, and previous yield had a significant influence on the intensity of adoption. The results on impact of adoption indicated that adoption of climate-smart maize varieties increased household income by 60 %. The results justify the need for creating awareness to ensure widespread adoption of climate-smart maize varieties both nationally and globally. In addition, adequate policies and development programs for promoting use of climate-smart maize varieties in Kenya should be directed towards input and output delivery, land under climate-smart maize varieties, extension service provision, affordable credit, education and age mechanism that are more effective and youth oriented initiatives.

Keywords: Adoption, climate-smart agriculture, climate-smart maize varieties, Double hurdle, Endogenous Switching Regression

CHAPTER ONE

INTRODUCTION

1.1 Background of the study

Agricultural productivity in Sub-Sahara Africa (SSA) is highly dependent on favorable climate and other genetic features of crops, livestock, forests, and soil characteristics. Agriculture thrives well when the aspects of climate are predictable at optimal conditions. Global food safety is highly threatened by the impact of climate unpredictability and a decline in soil fertility as it affects agricultural production substantially (Wheeler & von Braun, 2013). Agriculture is depicted as both a subject and an object in arguments about global climate change. It is a subject since it contributes to greenhouse gas (GHG) emissions, which are considered to be the main reasons for global changes in climate. Forestry, agriculture, and other land uses are estimated to emit about 24% of the global Anthropogenic GHG (IPCC, 2014). GHG emissions are anticipated to grow considerably up to 30% by 2050 (FAO, 2013).

On the other hand, climate change affects agriculture. Climate change is characterized by an increased temperature, volatility in both amount and onset of rainfall, and frequency of extreme floods and droughts. Yields are negatively affected by these changes, which add more difficulties for small-scale tropical farmers to continue growing particular food crops such as maize (Thornton & Lipper, 2014). These changes could see more small-scale farmers in Africa pushed into a new level of hunger and poverty in the near future especially in SSA (Thornton & Lipper, 2014).

Agricultural production in SSA is mainly rain-fed. In SSA, about 90% of the food consumed is produced under rain-fed conditions; hence drought is highlighted to be one of the significant causes of reduction in maize productivity and food insecure among small-scale producers (Shiferaw *et al*., 2011). Maize yield is predicted to decrease by 39.3% due to the manifestation of mid-droughts, especially in the producing maize areas (Daryanto *et al*., 2016). Production of staple foods such as maize decreases over time due to climatic change. Mitigation measures need to be developed to tackle food shortages as the population increases. The population of Africa is projected to grow from the current 800 million people to 1.5 billion people by 2050. On the other hand, Kenya's population is expected to grow from 47.5 million people up to 95 million people by 2050, according to the 2019 census (KNBS 2019). This growth in population will result in increased demand for food (AGRA, 2014).

To meet the growing demand for food and improving smallholder producers' livelihoods, there's a need for adoption of mitigating factors to climatic change, including changes in the agriculture sector (AGRA, 2014). One of the promising ways identified to address the effects and causes of changes in climate, is climate smart agriculture (CSA). The concept of CSA is defined as agriculture that instantaneously increases output, improves climate resilience, and mitigating greenhouse gas(GHG) emissions , which was first coined at the Conference on "Food security, Agriculture and change in "Climate " in 2010 (FAO, 2010). It is also defined as Integrated crop-livestock farming, agroforestry, conservative agricultural practices such as intercropping and residue management, stress-tolerant crop varieties usage such as drought-resistant maize varieties, advisories of meteorological weather, and index-based insurance (FAO,2010).

The population of Kenya is projected to increase to 95 million people from 47.5 million people by 2050 if the current growth rate continues (KNBS, 2019). Rapid population growth will increase food demand, particularly for maize since maize is a primary staple food in Kenya. Maize account for 68% of daily per capita cereal consumption and 42% of dietary energy intake (FAO, 2012). In Kenya, 75% of maize producers are smallholder farmers, and the rest comprises large scale farmers (Tegemeo, 2013). Over the last decades, annual average maize production was about 2.9 million tons, with the uppermost output recorded in 2012 at 3.6 million tons (Kamau & Otieno, 2013). Consumption of maize is far higher than production at 3.9 million tons annually, leaving a shortfall that is mostly met by importation and food aid. Increasing agricultural productivity without an increase in the land under maize is through the adoption of new farming technologies since there is a shortage of arable land due to increased population and urbanization (Minten & Barrett, 2008).

Crop development and developing high yielding and stress-tolerant varieties is a critical part of tackling maize deficits and food insecurity (Shiferaw *et al.* 2011). Through this notion, maize breeding programs are reflected as an achievement story in Kenya (Smale *et al.*, 2014). According to the African seed access index (TASAI) report in 2019, they deduced that about 98 maize varieties were produced between 2015 and 2017(Waithaka *et al*. 2019). Among them, 66% of maize variety produced were climate-smart varieties exceptionally drought-tolerant maize varieties.

According to TASAI report a variety qualified to be climate-smart if it meets at least one or two criteria of climate-smart variety qualities that are, early maturity or tolerance to extreme weather conditions (Waithaka *et al*., 2019). African Agricultural Technology Foundation (AATF) and CIMMYT collaborated to breed most of the drought-tolerant maize varieties under the drought tolerant maize for Africa (DTMA) program. However, an increase in the number of hybrid maize varieties within three years, especially climate-smart maize varieties, has not corresponded to an improvement in maize yield, and there has been a stagnation in both output and productivity growth (FAOSTAT, 2015). This mismatch is partially attributed to the marginal adoption of improved production technologies, unpredictable weather, poor agricultural practices, and costly inputs (Ogada *et al.*, 2014).

1.2 Statement of the Problem

The deficit in maize production will increase each year as Kenya's population and demand for maize increase if there is no increase in maize production. Improved maize varieties suited to climatic change, together with improved soil management, can be used as a strategy to enhance maize productivity, especially in Kenya, where soils are depleted of crucial nutrients. Soil depletion increases due to populace pressures which make practices such as traditional fallow less practical and limited use of inorganic fertilizer due to high prices (Salat & Swallow, 2018). Breeding of maize varieties which are stress tolerant such as drought-tolerant maize could help farmers respond to the adverse impact of climate variability in Africa (Cairns *et al*., 2013).

Climate-smart maize varieties, especially drought-tolerant maize types, have been regarded as part of the answer to sustaining production of maize, more so und er small scale production systems (Bänziger *et al*., 2006). Drought-tolerant maize varieties are estimated to produce 30% of their potential yield after suffering water stress for six weeks before and during flowering and grain-filling (Magorokosho *et al*., 2009). The three climate-smart maize varieties propagated by CIMMTY and KALRO are DUMA 43, DH0, and KDV (Berre *et al*., 2016). The climate-smart maize varieties are known to exhibit drought tolerance and high yields, especially in dry highland climatic conditions such as Embu South (CIMMTY, 2013). Climate-smart maize varieties, especially drought-tolerant maize, offer insurance to small-scale farmers over dry spells and ensures an excellent maize yield under trivial drought environments.

Despite the perceived benefits of climate-smart maize varieties and considerable efforts to encourage farmers to invest in them by National and International Organizations worldwide, the rate of adoption among small scale farmers is still low (Lunduka *et al*., 2019). This scenario is also observed in Kenya. Despite the promotion of improved DT maize varieties and efforts put in place to promote numerous novel soil management technologies, the rate of adoption of these endorsed measures is considered negligible (Oruko *et al*., 2016). The low adoption rate of improved climate-smart maize is evidenced by continued constraint to improving maize production among small scale farmers who are majority producers of maize in Kenya, amounting to 75 % of total maize produced (FAOSTAT, 2015). While at least 40 DT maize varieties have been released in Kenya since 2007, maize productivity and farmers' income have not increased (Kariuki, 2015). Ex-ante evaluation of the decision to adopt stress-tolerant maize varieties has anticipated a positive impact on yield increasing return to the farmer (La Rovere *et al*., 2014). Even though this is true, there is inadequate evidence on the effects of climate-smart maize varieties adoption rate on farmers' household income in Kenya. Therefore, to increase both maize production and farmers' household income, it is necessary to design auspicious pro-poor strategies promising to stimulate their adoption. Designing these strategies requires understanding the limitations that condition farmers' behavior regarding the adoption of these varieties and related practices and consequently, the impact on farmers' income.

1.4 Objectives

1.4.1 Main objective

To assess the adoption of climate-smart maize varieties and its impact on household income amongst small-scale farmers in Embu County.

1.4.2 Specific objectives

1. To characterize adoption of climate-smart maize varieties grown in Embu County
2. To evaluate the factors influencing the intensity of adoption of climate-smart maize varieties.
3. To determine the impact of the adoption of climate-smart maize varieties on household income.

1.5 Research Questions and Hypotheses

On objectives one, the following research questions will be addressed;

1. What are the type of climate-smart maize varieties grown by farmers?
2. What is the adoption level of climate-smart maize varieties?

For Objectives 2 and 3, the following hypotheses will be tested:

1. Socio-economic factors, institutional factors, and varietal attributes do not affect the intensity of adopting climate-smart maize varieties in Embu County
2. The adoption of climate-smart maize varieties has no significant impact on the household income of small-scale farmers in Embu County

1.3 Justification of the Study

In Kenya, food insecurity has become a worrying development problem. One of the Government's Big Four Agenda pillars is to reduce hunger to all citizens by improving the productivity of primary staple foods, including maize. According to Gitonga & Hugo (2016), when farmers adopted hybrid seeds they reduced the food insecurity index by a score of 6.6 in Kenya. It also increases the duration of the sufficient supply of household food by one month. Although a low rate of adoption is experienced, there is a high probability of improving productivity, hence improving food security through increased adoption rates among small-scale farmers.

This study will be crucial in determining and promoting awareness and adoption rate of climate-smart maize varieties among small scale farmers in Embu County to assist them in mitigating the effect of climatic change. The study will contribute to enhancing productivity in Embu County and assist in achieving the Big Four Agenda of Kenya Government, aimed at reducing the number of food insecure individuals by half. The results of this study will contribute in improving agricultural productivity, which is in line with vision 2030 and Sustainable development goals number 1, 2, and 13 of ending hunger, reducing poverty and combating climate change and its impact.

By understanding the farming household's adoption patterns of climate-smart maize varieties, extension programs can be planned. Agricultural policymakers will be able to develop programs that will address issues that determine the adoption of climate-smart maize varieties in Embu County and Kenya. The findings will complement the existing knowledge available as a guide to researchers in developing agricultural technologies that are farmer demand-driven and localized to their farming conditions. The research institutions; such as Kenya Agricultural and Livestock Research Organization (KALRO), will benefit from empirical results on the degree of diffusion and adoption of climate-smart maize varieties, hence informed future research activities.

CHAPTER TWO

LITERATURE REVIEW

2.1 Literature review

In chapter two, the literature on food security, an overview of production of maize, and agricultural technologies adoption are reviewed. The chapter explores farmers' adoption behavior of climate-smart maize varieties and the impact of adopting these varieties on their welfare, exposing the gaps therein. The chapter also contains the analytical models to be used and the theoretical framework guiding this study.

2.2 Food security

In Sub-Saharan Africa (SSA) majority of the populace depend on agriculture for their livelihoods. Sub-Sahara Africa (SSA) has the highest prevalence of undernourishment despite rapid economic growth over the last decade, where out of every nine people, one is chronically hungry (FAO, 2018). FAO (2018) documented that the number of people affected by undernourishment rose from 804 million to 821 million between 2016 and 2017. Reducing poverty and food insecurity in SSA requires sustainable agricultural production (World Bank, 2017).

2.3 An overview of Maize production

In the world, maize production, on average, stands at 785 million tons annually, where 6.5% of the total maize produced come from Africa. Maize consumption and industrial use, such as animal feed and biofuel production, are expected to rise to 30 million tons from 14 million (FAO, 2018). Maize production in SSA accounts for 96% of total maize produced in Africa, out of which 90% of maize produced comes from the top 20 producing countries where Kenya is among them (FAOSTAT, 2015). Land use for maize cultivation has increased substantially across SSA regions since 1961(FAOSTAT, 2015). Maize forms a higher percentage of consumed calories in about 22 countries in the world diet, where 16 are in Africa (Nuss and Tanumihardjo, 2011). In Southern and Eastern Africa, maize contributes to almost half of the total calories consumed, while in West Africa, it constitutes one-fifth of all calories consumed. Maize yield in West Africa, East Africa and South Africa averages at 1.7t/ha,1.5t/ha and 1.1t/ha respectively (Smale *et al.,* 2011). Many nitrogen-use efficient maize varieties and drought-tolerant varieties have been introduced and scaled-up in most African countries that show noteworthy improvement in productivity and potential impacts on food security (Kostandini *et al*., 2015).

In addition to food consumption, agricultural commodities such as maize are used as a feedstock for biofuel production. Maize contributes to about 17% of the total content in the manufacture of ethanol between 2014 and 2016. Share utilization of maize on biofuel grew from 4% to 18% in 2011 in SSA (OECD/FAO, 2017). Maize and protein meals accounted for about 58 % of total feed consumption in 2014-2016 (OECD/FAO, 2017). Cultivation of Maize is done on close to 30 million Ha of land and is the most significant cereal crop in most African communities since it supports around 300 million people in the continent (Fisher et al., 2015). Although it's cultivated in a large area, it is adversely affected by drought (Fisher *et al*., 2015). Maize yields are estimated to reduce by 39.3% due to the manifestation of mid-droughts, especially in maize-producing areas (Daryanto *et al*., 2016).

In Kenya, Food security remains a distant goal, where 43% of the country's population is food insecure, and about 46% live below the poverty line. Kenya has gone from being food self-sufficient in 1961 to import-dependent, which is brought about by high population growth and low investment in the agricultural production of staple food crops. The decrease in maize production in Kenya, illustrates the most significant problems of food insecurity and poverty (Kariuki, 2015). Smallholder farmers who are 98 % of the 3.5 million producers of maize with annual maize production of 3.4 million tons have rarely met domestic consumption needs. The country has partially relied on official and unofficial imports from Tanzania and Uganda to meet the maize shortage.

Maize production in Kenya accounts for approximately 80% of the total grain volume output. Maize production is estimated to be done by 3 million smallholder farmers in the country where production is expected to be about 37 to 40 million bags per year compared with the required 42 million bags annually to feed the nation (Alessandro *et al.,* 2015). The small scale farmers in Kenya contribute to about 70% of the total output of maize. They provide roughly to a third of the total marketed maize while consuming 60% of the total maize produced (Alessandro *et al.,* 2015). Maize produced in Kenya is not sufficient as the consumption surpass the output; hence, 58% of small scale producers are net buyers of maize (Kirimi *et al*., 2011). Large-scale commercial farmers in the country who contribute an average of 30% of total production and operate on overage of 20 hectares or more produce the remaining 30% of marketed maize (Kirimi *et al*., 2011). These commercial farmers are known as the best adopters of hybrid seeds and mechanization and the use of fertilizers. The production is significantly lower among smallholders yield since they forgo investment in improved production practices and inorganic fertilizers (Smale and Olwande 2014).

Kenya maize production is mainly reliant on rainfall; hence, it is susceptible to drought, thus causing year-to-year fluctuations in harvest. From the early 1980s, average maize yields increased with about 10 % and has been declining to the mid-1990s up to now (Alessandro *et al.,* 2015). This increase in production in the 1990s was driven by growth in land area under cultivation by 40%. La Rovere *et al.* (2014) estimated that 19.5% of maize production in Kenya takes place in areas with high rainfall unpredictability rated with a likelihood of crop failure of 40 to 100%. These regions' average yield is around 1.08 tons/ha while the national average is 1.62tons/ha. These production trends contribute to a higher level of production erraticism, amplifying Kenya's maize structural deficit further. As the purchase of inputs such as fertilizers and improved seeds enhances production, the adoption of these inputs has not been sufficient to maintain the increasing demand for food and higher yields as achieved 30 years ago (Alessandro *et al.,* 2015).

According to the Kenya National Bureau of Statistics (KNBS), (2018), production of maize in Kenya dropped to 35.4 million bags in 2017 from 37.8 million bags in 2016. The drought experienced in large parts of the maize producing region attributed to lower yields, hence the declines in production, leading to substantial importation of maize to bridge the deficit. In the same report, they deduced that marketed maize dropped from 265,800 tons in 2016 to 239,200 tons in 2017. With the decreasing volume of maize sold, the earning from marketed maize increased to 8.5 billion Ksh in 2017 from 7.9 billion Ksh in 2016 due to the increased price of marketed maize (KNBS, 2018). The volume of marketed maize decreased over the period because of the lower production rate of maize, which was primarily brought by prolonged drought in the country and infestation with fall armyworm in some areas. This led to a rise in maize importation by more than eight-fold from 149,000 tons to 1,328,000 tons in 2017, which translated to the increase of imported maize more than tenfold from 3.6 billion Ksh in 2016 40.3 billion Ksh in 2017. In 2017 maize imported from Mexico accounted for 90.4 % of the total maize imported in Kenya, while 7.7 billion Ksh is the value of imported maize from South Africa, accounting for19.1 % of the total expenditure of the imports in 2017(KNBS,2018). From this report, it is clear that the low production of maize in Kenya is leading to less development since most of the income is spent on purchasing an essential commodity, which is a staple food for 80 % of the Kenyan population.

According to Intergovernmental panel on climate change (IPCC) their assessment reports indicated that many countries will face an increase in average temperature, recurrent heatwaves, desertification, heavy precipitation periods and more stressed water resources (IPCC,2014).In this case, climate change and variability manifest itself in the form of higher average temperature than usual, altered precipitation patterns and intensity, increase in floods, and extreme events of droughts (Field & Barros, 2014). Agricultural yields are negatively affected by these changes, making it more challenging for small-scale farmers in the tropics to continue farming particular food crops such as maize, which is perceived as the leading staple food in many African countries.

Sub-Sahara Africa is the most affected since it is predicted that there will be an increase in temperature and erratic rainfall by 2050 (Tesfaye *et al.,* 2015). The overall temperature in SSA is foreseen to rise by 2.1 to 3.6°C by 2050 (Cairns *et al*., 2013). The rise in temperature is expected to have enormous effects on maize productivity and, consequently, food security and livelihoods of smallholder farmers (Lobell *et al*., 2011). There is a reduction of 10-25% yield due to occasional drought stress, where about 25 % of maize production suffers from occasional drought, leading to a loss of 50% of the maize yield (Fisher *et al*., 2015). Under rain-fed agriculture, crop production is highly reliant on weather and climate (Herrero *et al*., 2010). A decrease in soil moisture, an increase in salinity and acidity, and groundwater depletion, may lead to loss of arable land (Kandji, 2006). Food security in developing countries, especially in SSA, has been affected considerably by rainfall variability and drought shock induced by climatic change (Wossen *et al*., 2016). The economic crisis will continue to be enormous as frequent drought continues to occur since it has the likelihood of causing a severe crisis of food insecurity, malnutrition, and hunger. If it continues, it will create a long term continuous poverty trap to smallholder farmers because of their inadequate adaptability capacity (Bryan *et al*., 2013).

2.4 The concept of adoption of improved technology

Adoption can be categorized into two, namely aggregate or individual adoption. Personal adoption is where the farmer's decision to acquire new technology into the production process is a one-person decision. Aggregate adoption is the procedure of dissemination of new knowledge within a population or region. The technological change uptake process in agriculture is not constant at the farm level. This process is complex, and many socioeconomic factors govern it. Adoption is seen as a variable that represents a change in behavior undergone by farmers when adopting innovations and ideas in agriculture. The change in behavior is the desirable knowledge change, understanding, and capability of applying innovation information, changing feeding behavior, for example, in attitudes, interest, and changes in overall aptitudes and abilities. Economically, improved technology produces new returns compared to old technology, and the adoption of new technology increases farmer's yield and net returns (Muya, 2014).

Currently, when technology is introduced to smallholder farmers without other socioeconomic factors in consideration, it does not guarantee widespread uptake and efficient use alone. However, adoption is positively associated with age but negatively associated with landholding size and group participation factors (Chuchird *et al*., 2017). For effective deployment of technology, the satisfaction of particular technical, economic, and institutional environments is necessary. From the farmers' viewpoint, the new technology has to be economically viable and more profitable than the existing options. The new technology should be smooth technically and easy to manage by smallholders and adaptive to the area's sociocultural conditions (Chuchird *et al*., 2017).Similarly, top administrative support, comparable advantages, regulatory of the cultural environment, innovativeness and knowledge of the farmer have a substantial relationship with the adoption of new technology (AlBar & Hogue, 2019).

2.5 Research gap

2.5.1 The concept of adoption of climate-smart maize varieties

Adoption of improved drought-tolerant and other stress-tolerant maize varieties by the farmers can go a long way to reducing weather-induced production risks. Still, farmers should also be invigorated to invest in other input and practices which are yield-enhancing (Alessandro *et al.*, 2015). These input and practices could help in lowering the country's persistent maize production variability, which in turn could improve the Kenyan food security situations (Alessandro *et al.*, 2015).

Farmer adoption depends on access to these improved maize varieties. New drought-resistant and early maturity varieties are finding their way to the market as maize seed research in Kenya are continuously ongoing. Bill and Melinda Gates Foundation which funded the Drought Tolerant Maize for Africa (DTMA) Project to support the development and dissemination of locally adapted varieties of maize in Kenya and several other countries in Africa which are tolerant to drought and have high yields. Through this project, sixty hybrids maize varieties which are tolerant to drought and 57 open-pollinated maize varieties were made available by project participants to the smallholder farmers from 2007 to 2012. Efforts such as those should be supported further and scaled if there is to be an increase in maize productivity in Kenya (Alessandro *et al.*, 2015). The International Wheat and Maize Improvement Center reported that the germplasm of maize that is tolerant to drought developed in collaboration with IITA for Africa allows a 40% increase in yield over commercial varieties when subjected to severe stress an equivalent harvest under optimum cropping conditions (Cenacchi & Koo 2013). New varieties and hybrids are not only drought tolerance but also have desired qualities such as significant disease resistance trait (such grey leaf spot, maize streak virus, and *Turcicum* leaf blight) and superior cooking quality. Even with these advances, adoption rate of Kenya's maize farmers' remain low due to the scanty availability of seed and awareness of the farmers (Alessandro *et al.*, 2015). Availability of seed at the right place, at the right time, and at affordable prices will impact the adoption of a given variety. To incentivize new investments in seed multiplication, marketing, and training services, together with initiatives to propagate farmer demand, new ways are needed to strengthen supply of seed networks and improve access by farmers'.

2.5.2 Impact of adoption of climate-smart maize varieties

Drought has become more severe and prolonged due to climatic change (Hyman *et al*., 2008). Increase in drought can cause austere food crisis and sustained long-term poverty traps to farmers since most smallholder farmers has a limited adaptive capacity (Bryan *et al*., 2013). One of the most significant food crops in Africa is maize and is adversely affected by drought. Around 40% of areas where maize is cultivated in Africa face occasional drought stress, which results in loss of yield of about 10-25% (Fisher *et al*., 2015). Climate change leads to increased drought time, which leads to a decline of maize production by 22% in SSA (Schlenker and Lobell, 2010).As already suggested by Daryanto *et al*. (2016) the occurrence of drought reduces maize yield by 39.2%, especially at the asexual and productive growth phase for maize, reducing farmers' income over time.

The development of climate-smart crop varieties, especially stress-tolerant maize varieties, has been achieved as an adaptive strategy in this situation. This led to the initiation of drought-tolerant maize for Africa project, which aimed at developing and deploying maize varieties that were tolerant to drought in zones where there was variation in rainfall patterns and climatic conditions (Wossen *et al.*, 2017). Drought-tolerant maize varieties exhibited the ability to tolerate drought and had a higher yield than other commercial hybrids (CIMMYT, 2013). According to Setimela *et al*., (2014), drought-tolerant maize germplasm produces 40% more output under drought conditions than other commercial varieties.

Additionally, ex-ante economic analyses suggest that if small-scale farmers extensively adopt drought-tolerant maize, it can offer them a sizeable welfare change through improved production and reduced risk (Kostandini *et al*., 2009). Thus the uptake of stress-tolerant maize varieties in SSA can produce about USD 362 to USD 590 million on both producers and consumers in cumulative benefits (Kostandini *et al*., 2009). According to Lunduka *et al*. (2017), a family that cultivated stress-tolerant maize varieties had 247kg per acre more maize than those who did not cultivate Stress-tolerant maize varieties. This increase was estimated to generate USD 240 per ha more for those families that grew maize varieties that are drought tolerant compared to those that did not. Although ex-ante analyses of climate-smart varieties such as drought-tolerant maize varieties adoption performed by various authors such as, (Kostandini *et al*., 2009; La Rovere et al., 2014; Fisher *et al*. 2015; Holden & Fisher (2015), and Kassie *et al*., 2013) in SSA has predicted a positive impact on yield potential and the returns to the household, Ex-post empirical evidence on the impact of adoption of climate-smart maize varieties on household income in Kenya is deficient.

2.6 Review of the analytical models

2.6.1 Specification of Econometric model for adoption of agricultural technology and intensity.

Diverse models are used to analyze the determinants of technological adoption by various researchers (Beshir *et al*, 2014). According to Berhanu & Swinton (2003), decisions can be made jointly or independently on whether to adopt and how much to adopt. For the two-stage analysis, the Tobit model has been popularly used. The decision on whether to adopt or not and how much to take is anticipated to be jointly made by the farmer, which means that the factors influencing the two-level of choice are expected to be similar. Conversely, the adoption decision may well herald intensity of using decision where the explanatory variables in the two stages may be different. The second stage parameters can freely vary from those in stage one in the Double hurdle (DH) model (Asfaw *et al*., 2011). In the Tobit model, the explanatory variables appear in both equations, wherein the DH model can appear either in both equations or in either of them and also, the variables may have contrasting effects in both equations as indicated by several empirical studies (Beshir *et al*., 2012).

In the double-hurdle model, for each decision process, a different latent variable is used to model it. The Double-hurdle model was initially formulated by Cragg (1971) and has been applied in numerous studies. The model assumes that the farmer make two chronological decisions concerning adoption and extent of use or application of a given technology. In most cases, when the problems ascend from selection bias of the sample and the discrete of the non-negative nature of the outcome equation, the DH model is Applied (ELiya *et al*. 2019). Application of Double hurdle model has been made in different empirical studies to evaluate the adoption decision and rate of adoption of a given technology by various authors such as Teklewod *et al.*, (2006), Asfaw *et al.*, (2011), Beshir *et al.*, (2012), Beshir *et al.*, (2014), Yigezu *et al.*, (2018) and Eliya *et al.* (2019). Thus in this study, to analyze the issues influencing the likelihood of adopting and the extent of use of climate-smart maize varieties in Runyenyes sub-county Embu county in Kenya, the double hurdle model was used.

2.6.2 Adoption impact of climate-smart maize varieties on household income to small scale farmers in Embu County

The adoption of agricultural innovation and technologies impact is examined using two prominent research designs: observation approach and experimental research. The innovative design uses comparison and treatment groups presumed to be selected randomly so that the outcome variable is not correlated with adoption (Ogundari & Balarinwa, 2018). Randomized control trial (RCT) is an example of experimental design. By comparing potential outcomes of adopters and non-adopters, the impact of agricultural technology adoption can easily be determined when using an RCT approach. (Heinrich & Lopez, 2009).

Most studies are usually observational; hence, when RCT is applied, there are some barriers and expenses which may be prohibitive to give the desired outcome. Impediments may occur due to non-randomness of comparison and treatment groups in observational studies, which brings a problem of selection biasness. This problem affects the dependability of the predicted impact, which may significantly affect policy formulation (Caliendo, 2006). Due to difficulty of selection bias, potential participant into a non-experimental treatment and control groups is not equal which makes it very difficult to compare results between these two groups due to the biasness coming from the behavioral difference between those who adopted and non-adopters (Abdulai & Huffman, 2014). Therefore, the adoption decision of agricultural technology may be driven by both observed and unobserved characteristics. Additionally, it is not trivial to estimate the impact of adopting technology based on non- experimental observations since to observe the outcome of those who adopted in case they did not adopt is not possible (Amare *et al*., 2012).

To address the issue of bias selection in a non-experimental scenario, different econometric approaches are used, such as instrumental variables regression and Heckman models (Ogundari & Balarinwa, 2018). Some studies have applied single econometric models such as Tobit, fixed-effect models, and random correlation effects (CRE) to control unobserved heterogeneity (Hamazakaza *et al*., 2013; Smale & Mason, 2014). These traditional instrumental variables assume that the outcome variable of the adoption impact can be denoted as a simple parallel shift (Shiferaw *et al*., 2014). Using a single model to address selection bias will give you inconsistent results. The estimates will not be robust enough since every model has its own limitations, which cannot be independently corrected (Khonje *et al*., 2015).

Heckman models include propensity score matching (PSM) and endogenous switching regression model (ESR). Propensity score matching assumes that there are no unobserved differences among the non-adopters and adopters but only looks on observable characteristics. It assumes that participation is independent of explanatory variables' outcome conditions, which is not valid if there are unobserved outcomes affecting participation. PSM also expects that the outcome coefficient to be the same between the non-adopters and adopters, but recent empirical studies have proven this to be not the case (Di Falco *et al*., 2011; Asfaw *et al*., 2012; Teklewold *et al*., 2013; Shiferaw *et al*., 2014). This expectation may cause bias estimation, which may lead to inconsistency and bias policy recommendations.

To avoid working with biased estimation, the recommended model by other researchers such as Di Falco *et al*., 2011; Teklewold *et al*., 2013; Shiferaw *et al*., 2014 which takes care of both observed and unobserved difference between the comparison groups is Endogenous Switching Regression model. Through estimation of two separate equations that is one for the adopter and the other one for non-adopters, ESR relaxes the assumption of a single equation model of a simple parallel shift. Doing this, allowed the researcher to calculate the unobserved outcome of adopters if they did not adopt by predicting the outcome of non-adopters. Different authors have applied this model (Lokshin & Sajaia, 2004; Di Falco *et al*., 2011; Shiferaw *et al*., 2014; Khonje *et al*., 2015; Wossen *et al*., 2017; Wakesa *et al*., 2018) to generate empirical results. Thus in this study to minimize the selection bias, binary ESR treatment effects approach was adopted to control for both observed and unobserved heterogeneity during the analyzes of the impact of adoption of climate-smart maize varieties on the household income of small scale farmers in Runyenjes sub-county Embu county.

2.7 Theoretical framework

The study employed the random utility model (RUM). The decision to adopt is responsible behavior towards new technology or innovation by an individual. The decision an individual makes is influenced by the expected utility from adoption or non-adoption of the technology. RUM make into an assumption that the decision-maker is a rational economic agent who has perfect discrimination capability to make a given choice with the highest satisfaction from the choice set (Greene, 2003). Therefore adoption decision is made when the net return or utility from the adopted climate-smart maize variety is perceived to outweigh the actual net benefit if the technology is not selected. Observation of the households' actions is through the selection they make while the utility achieved from the chosen variety is unobserved.

In this study, the expected utility of the present value of agricultural returns and condition on the adoption of yield-enhancing inputs such as climate-smart seed represent farmer's preference. The expected utility for the household is specified as a function of climate-smart seed (z_{ik}), other technical factors and social-economic characteristics of the household (τ_i) (equation I)

$$\pi_{ik} = \bar{\pi}(z_{ik}, \tau_i) + \varepsilon(z_{ik}, \tau_i) = x_{ik}\theta + \varepsilon_{ik},\ k = 1,2;\ i = 1,...,n, \text{......................I}$$

where the deterministic factor of the utility function is $\bar{\pi}(z_{ik}, \tau_i)$, $\varepsilon(z_{ik}, \tau_i)$ is the stochastic element of the utility function which represent the unobserved attributes that affect technology choice, heterogeneity in tastes and measurement errors; x_{ik} is a matrix of covariates, z_{ik}, and τ_i; θ is the vector of parameters.

The farmer thus planted the climate-smart maize seed if the expected returns from using them are higher than those generated from traditional seed varieties. The binary choice model of adoption of improved seed is thus specified in equation (II):

$$y_i = I\{\pi_{i1} - \pi_{i0} > 0\} = I\{x_{i1}\theta + \varepsilon_{i1} - x_{i0}\theta + \varepsilon_{i0} > 0\} = I\{x_i\theta + u_i\} \text{...............II}$$

Where: $u_i = \varepsilon_{i1} - \varepsilon_{i0}$ is random error term with zero mean and θ is defined up to some scalar normalization.

CHAPTER THREE

METHODOLOGY

3.1 Conceptual framework

Technological adoption such as climate-smart agriculture and instructional innovations that intensify land use is induced by the change in population, land pressure, and demand for agricultural products (Mercer, 2004). Changes in weather patterns, reduced rainfall, increased food insecurity, and degree of possible misclassification bias in adoption estimates derived from farmer recall data, have prompted the researchers in the present study to look at the rate of uptake of climate-smart maize varieties and the impact of adoption of these varieties on household income. Adoption is perceived to be dependent on socioeconomic factors and socio-cultural parameters of the smallholder farmers and the varietal attribute of the given technology as shown in Figure 3.1 on conceptual framework (Babasanya *et al*., 2013). Farmers express their preferences for a specific composition of production attributes of different varieties presented to them according to which maximizes their utility (Edmeades *et al*., 2008). Therefore factors that affect the adoption of climate-smart maize varieties and the degree of possible misclassification bias in adoption estimates derived from farmer recall data was conceptualized into a framework (Figure 3.1) to include varietal attributes of a given variety adopted, socioeconomic factors of the farmers and the institutional factors influencing their decision. These factors are also imagined to affect the impact of adoption, together with the adoption rate and production inputs such as land. Specific varietal traits in this context are high yielding, early maturity, drought tolerance, diseases and pest resistance. Socioeconomic factors are the education level of household head, age, size of household and land size owned by the family. The institution factors are credit access, contact with extension officers or agricultural training, group membership, and market access.

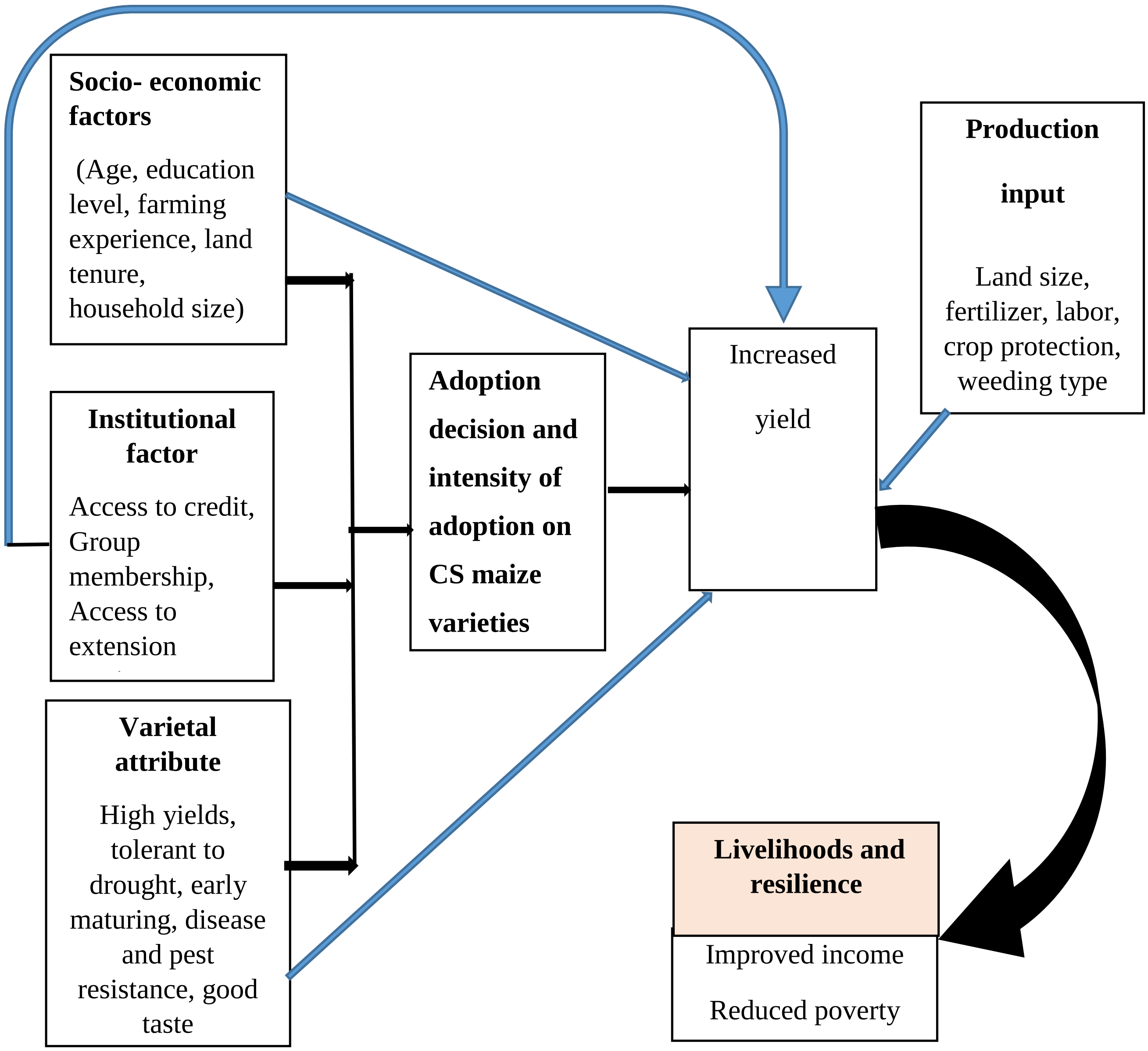

Figure 3.1 conceptual framework of climate-smart maize varieties and drivers of its intensity and impact of intensity on household income.

Source: Author's conceptualization

3.2 Study area

The survey took place in Embu County. Embu County lies 120 kilometers northeast of Nairobi. The County borders, County of Machakos to the South, Kitui County to the West, Kirinyaga County to the East, Murang'a County to the Southwest and Tharaka Nithi County to the North. According to the 2019 census, the population of Embu County was about 608,599 (KNBS, 2019). Embu is located approximately between latitude 008' and 00 50' south and longitude 370 3' and 370 9'east. Highlands, lowlands, and slopes characterize Embu County, and it rises from about 515m above sea level (a. s. l) from East at the basin of the River Tana to 5,199m Southwest at the top of Mt. Kenya. Embu County displays the typical agro-ecological profile of the windward side of Mt. Kenya from wet and cold upper zones to hot and dry lower zones in the Tana River Basin (Embu County Government plan, 2013).

The agro-ecology of the chosen study area is influenced heavily by Mount Kenya and Nyandarua Ranges with abundant and well-drained, dark reddish-brown, deep and friable clay with humic topsoil (Jaetzold *et al*., 2007). This type of soil is well suited for tea, coffee, maize, beans, and bananas growing. Due to its proximity to Mt Kenya, the county's temperatures are likely to be an average of between 9°C - 28°C. The county receives considerable rainfall with an average rainfall of 1206mm yearly. Between March and July is the wettest season, whereas the hottest season is experienced between January and mid-March. The main driver of the county economy is agriculture, where over 70% of the population are smallholder farmers. Prominent cultivated food crops in the county are maize, beans, pigeon peas, and peas, where maize and beans are grown as either intercrops or mono-crops. The average farm size ranged between 2-2.8 ha per household by 2002(Ouma *et al*., 2002).

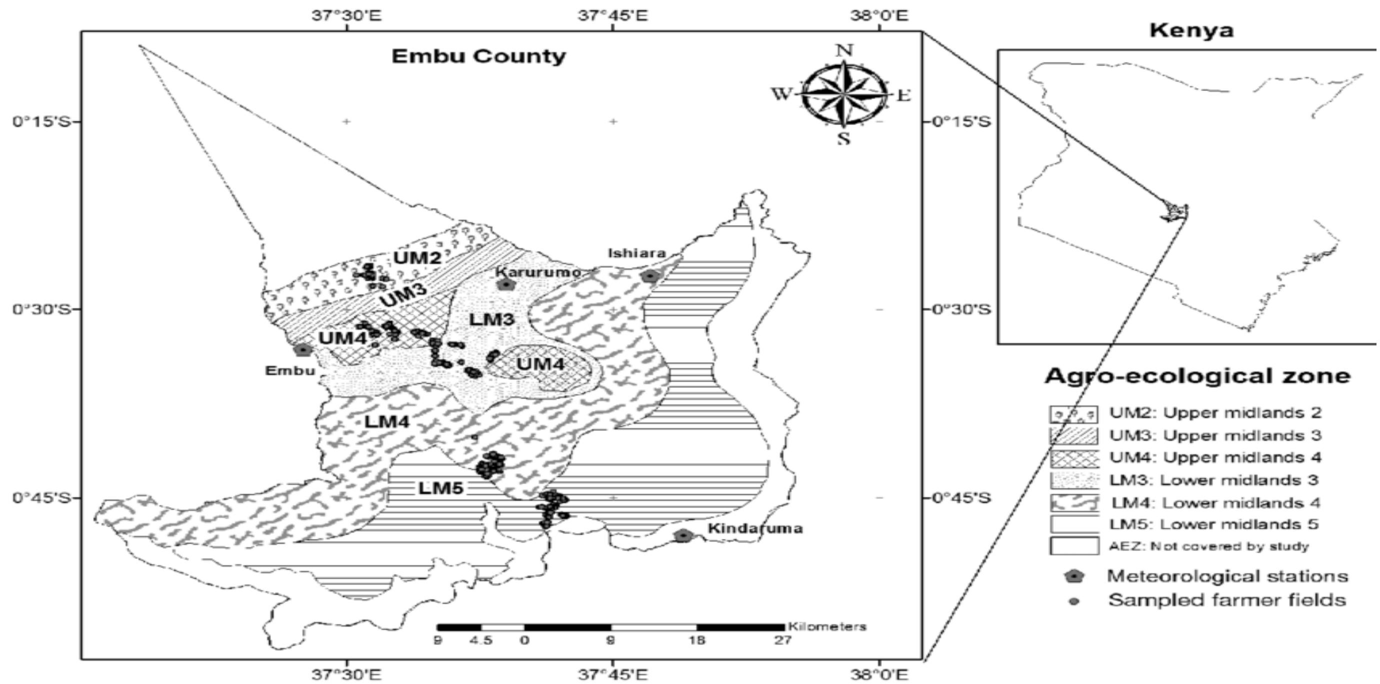

Figure 3.2: Map of Embu County

Source: The County Government of Embu (2013-2017)

3.3 Research Design and sampling procedure

This study embraced the use of survey design in a natural research setting. The research design adopted enabled the study of different groups of the population dispersed over the vast geographical area of Embu County, Runyenjes sub-county concentrated in different sub-locations forming three Agro-ecological zones, through a multistage sampling approach (Bartlett *et al*., 2001; Taherdoost, 2016).

3.3.1 Sampling procedure

This study used multistage sampling procedures. In the first stage, Embu County was purposively selected because it was the chosen study area by the project. Runyenjes sub-county was chosen since it represents other counties in a region where maize is an important crop. Also, it has the representative of the perceived agro-ecological zones targeted by the project that is lower midlands 3, upper midland 3, and upper midland 2. It has different agro-ecological zones that give room for growing different maize varieties ranging from hybrid maize, open-pollinated varieties (OPVs), and local varieties. The study area mainly comprises of small scale farmers who were the target group of the study. The second stage was a stratified sampling of Kyeni South Ward sub-locations, which were chosen as there was heterogeneity in demographic distribution. Major landmarks such as the chief's camp were identified within the ward. In which from the all-weather road the study collected primary data from the farmers. Systematic random sampling was used to select participants where the random sampling procedure was that the study interviewed every 3rd household on the opposite side of the transect from the previous homestead.

3.3.2 Sample size determination

The study used a stratified random sampling method (Alreck and Settle, 1985) to obtain data from the seven sub-locations of Kyeni South in Runyenjes Sub-county Embu County. These sub-locations are Kasafari, Karurumo, Kariru, Kathanjuri, Nyagari, Kathungari, and Kigumo sub-location, which formed three Agro-ecological zones as shown in table 1. These Agro-ecological zones are; Lower midlands, where three sub-locations comprising Kasafari, Karurumo, and Kariru sub-locations were sampled. The upper midlands 3 constituting Nyagari and Kathanjuri sub-location and Upper midlands two, which included Kathunguri and Kigumo sub-location. These Agro-ecological zones formed 3-stratas where stratification was based on the three zones' topographical and ecological demarcation. From the table 1 below, each zone was formed one homogenous stratum. From the sample of 550 farmers obtained, the strata sample proportion procedure was used to draw a proportional sample from every stratum to have an optimal distribution from each stratum (Mugenda and Mugenda, 1999).

Strata sample proportion=Sample established /total population in selected area

Therefore 550/ 27438= 0.020

Table 1: Strata sample computation

Stratum(sub-locations)	Population in each stratum	Strata sample prop*pop in each stratum	Sample in each stratum(sub-location)
Kasafari	4383	0.020* 4283	87
Kariru	4000	0.020* 4000	80
Karurumo	3720	0.020* 3720	74
Nyagari	4146	0.020* 4146	83
Kathunjuri	3574	0.020* 3574	72
Kathunguri	4429	0.020* 4429	88
Kigumo	3286	0.020* 3286	66
Total	**27,438**		**550**

Kreycia and Morgan (1970) formula was used to determine the sample size. The formula is generally used to compute a sample size from a specified finite population (P). The sample size was within a margin error of 0.05 and within a confidence level of 95%. The formula of the finite population is as shown below;

$$s = (x^2Np(1-p))/d^2\ (N-1)\ + x^2\ p(1-p)$$

Where S = size of the sample, X= standard variate at a given level of confidence, p = sample proportion (assumed to be 0.5 since this would provide the maximum sample size), N = the size of population and d = accepted error (the precision). Using Equation 1 with N=27,438, d =4%, X=1.96 (as per the table of the area under the standard curve for the given confidence level of 95%) so preferred sample size will be 587 farmers. Obtained as follows

$\frac{1.96^2 \times 27438 \times 0.5(1-0.5)}{0.04^2 \times (27438-1) + [1.96^2 \times 0.5(1-0.5)]} = 587.42$ Which is approximated to be 587 farmers.

The obtained sample size was 587. However, due to resource constraints to meet all the respondents only a total of 561 respondents were interviewed. After data collection 6 questionnaires were discarded due to incomplete and poor responses. Therefore, the analysis was done for 550 respondents.

3.4 Data collection methods

The study used both primary data and secondary data. Collection of primary data was done using a structured questionnaire (see appendix). The semi-structured questionnaire was made and then administered to maize farmers in 30 to 40 minutes, which depended on the patterns, swiftness, comprehension, and respondent clarity. This exercise was carried out through face to face interviews with the farmer. This study used face-to-face interviews because they are considered resilient since they allow immediate follow-up and clarification, unlike other interviews (Mertens, 2014). Before the administering the questionnaire to the farmers, pre-testing was perpetrated to provide a chance to assess what questions are fit, which queries can be removed and which need to be supplemented. Pretesting enabled us to tell whether the questionnaire was very long, boring to the interviewee and whether the queries are simple to be understood by the farmers. Pretesting was carried out with other students to note any problematic words and whether there is a flow of questions, after which the questionnaire was revised. After pre-testing the questionnaire, it was entered in the ODK, a tool used in data collection for the efficient and safekeeping of the data. The questionnaire was pre-tested again after entering it in ODK with the Manyatta constituency farmers located around KALRO Embu offices, representing a similar characteristic as the pre-assumed population. Data was collected by trained enumerators. The collected primary data from farmers was supplemented with the secondary data. The study obtained secondary data from publications on climate-smart maize varieties such as stress-tolerant maize varieties and the adoption of new technologies. The secondary data were also extracted from Kenya Statistics from 2017/2019, the Ministry of Agriculture and Policy Brief obtained from the Embu County Agricultural Office.

3.5 Empirical Data Analysis

3.5.1 Characterization of adoption of climate-smart maize varieties

The study employed descriptive statistics, for instance, chi-square and T-test to characterize farmers' awareness of climate-smart maize varieties and current adoption of climate-smart maize varieties in Embu county, in terms of varietal attributes of given varieties and social-economic characteristics of the household.

3.5.2 Analyses of the determinants of adoption intensity of climate-smart maize variety.

Two definitions are used as the technology choice outcome on agricultural technology adoption in the literature (Yigezu *et al*., 2018). One is a binary measure. It takes the value of zero if no land is dedicated to climate-smart maize varieties and one if any area is dedicated to climate-smart maize varieties. The other one is adoption intensity, where in this study is expressed as the proportion of the total land where climate-smart maize variety is planted. Thus, examining the determinants of whether maize farmers adopt climate-smart maize varieties and the area over which it is adopted, an empirical model is used. The intensity of adoption was measured as the proportion of the area under which climate-smart maize variety was dedicated then used ration formula to linearize it to be a continues variable.

A double hurdle model proposed initially by Cragg (1971) was employed to analyze factors which affect the probability and intensity of use of climate-smart maize varieties. In double hurdle approach, the fundamental assumption is that farmers make two decisions. The first choice is to assign climate-smart maize variety an actual amount of land while the other one is the portion of the area to allocate, which is conditional on the decision made at first. The double hurdle model permitted the possibility of a different set of variables to affect the two decisions. This approach has an advantage in that it enabled the understanding of the characteristics of a group of farmers that would never adopt a given technology in our case the climate-smart maize varieties (Mignouna *et al*., 2011).

According to Green (2000), the double-hurdle model is a generalized parametric of the Tobit model. Two discrete stochastic procedures define the adoption decision and the adoption level of the technology. The adoption decision of the climate-smart maize is modelled as a binary function which is Probit, and the latent variable of a given household decision to use climate-smart maize varieties CSA_i^* is specified as;

$$CSA_i^* = \beta X_i + \mu_i \tag{1}$$

The Probit was estimated on the observed outcome as

$$\left.\begin{array}{l} CSA_i = 1 \text{ if } CSA_i^* > 0 \text{ and} \\ CSA_i = 0 \text{ if } CSA_i^* \leq 0 \end{array}\right\} \tag{2}$$

In the above equation CSA_i^* is a latent variable taking the value of 1 if the farmer decided to adopt climate-smart maize varieties and 0 if otherwise, X is a vector of explanatory variables that influenced farmers' adoption decision, a vector of parameters to be predicted is denoted by β while

μ is normally distributed error term with mean zero and constant variance. CSA_i is observed variable when the farmer makes a decision to adopt climate-smart maize technology.

The unobserved latent value of the desired area planted to CS maize varieties or latent variable of adoption intensity is A_i^* which can be specified as;

$$A_i^* = \acute{\alpha}\, Z_i + v_i \tag{3}$$

The study worked with an observed area that is A_i since A_i^* is a latent variable where;

$$\left.\begin{array}{l} A_i = A_i^* = \alpha\, Z_i + v_i \quad \text{if} \quad A_i^* > 0 \text{ and } \quad CSA_i^* > 0 \\ A_i = 0 \text{ otherwise} \end{array}\right\} \tag{4}$$

Where A_i was the observed share of land area where climate-smart maize varieties are planted (signifying the intensity or extent to adopt), Z is hypothesized to be the vector of explanatory variables affecting the extent of use of climate-smart maize varieties, $\acute{\alpha}$, was a vector of the parameter to be evaluated, where the error term is v_i.

v_i and μ_i are the error terms and are assumed to be independent of each other and are normally distributed with constant variance and mean which is zero which is distributed as;

$$\left.\begin{array}{l} \mu_i \sim N(0, 1) \\ v_i \sim N(0,1) \end{array}\right\} \tag{5}$$

Log-likelihood function of the double hurdle model is expressed as;

$$LogL = \sum_0 \ln\left\{1 - \emptyset(\beta_i X_i)\left(\frac{\alpha Z_i}{\sigma}\right)\right\} + \sum \ln\left\{\emptyset(B_i X_i)\frac{1}{\sigma}\emptyset\left[\frac{A_i - \alpha Z_i}{\sigma}\right]\right\} \tag{6}$$

The model is equal to a univariate Probit model: equations 1, 2, and the truncated regression model: equations 3, 4 combined under the independence assumption between the error terms U_i and Vi

(Cragg, 1997). Therefore, the sum of the Probit model and truncated regression is the log-likelihood of a double hurdle. A double hurdle hypothesis test was done against the Tobit model. Using the log-likelihood ratio test, a trial was done by estimating three regression models independently, which are; Tobit model, the Probit model, and the truncated regression. Tobit was used to measure how well our model fits by comparing the observed values in the dataset and predicted values based on the Tobit model (Long, 1997). The study used truncated regression to assess which of the observation not to include in the value of the dependent variable analysis (Greene, 2003). Probit was used to test whether the model fits by producing a variety of fit statistics (Hosmer & Lemeshow, 2000). Greene, (2003) formula was used to compute LR statistic.

$$ŕ = -2\{\ln L_T - (\ln L_p + \ln L_{TR})\} \sim x^2{}_k \qquad (7)$$

Where in both equations the number of independent variables is denoted by k, the Probit model likelihood is L_p, Tobit model likelihood is $L_{T,}$ and the truncated regression model likelihood is L_{TR}.

The hypothesis test was written as; Ho: $\lambda = \frac{\beta}{\sigma}$ and H_1: $\lambda \neq \frac{\beta}{\sigma}$

Thus study rejected the H_o on pre-specified significance level if $ŕ > x^2{}_k$

Empirical model specification

In this study the model specifying the adoption was expressed as;

$$Y_1 = B_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots\ldots\ldots\ldots\ldots + \beta_{13} X_{13} + \mu \qquad (8)$$

Y_1= (decision to adopt and intensity of adoption) ,X_i defined as X_1 =The age of household head (years), X_2 = household head level of schooling (years), X_3 = Farming capability (years), X_4 =

Size of the household (numbers), X_5 =off-farm income, X_6 = Size of the farm (Ha), X_7 = Credit access (1 if access, 0 otherwise), X_8 = access to extension services, X_9 = Distance to market , X_{10} = association into a group(1 if yes ,0 otherwise), X_{11} = Early maturity(3 – 4 months),X_{12} = Drought resistance, , X_{13}= high yielding(1 if yes, 0 otherwise), X_{14} = pest and disease resistance(1 if yes, 0 otherwise) ,μ= error term

3.4.3 Adoption impact of climate-smart maize varieties on household income

Information is needed on how much the adopters would have earned had they not accepted to plant new varieties and how much non-adopters would have earned if they had decided to adopt it. This information will be vital in addressing the objective of the impact of climate-smart maize variety on farmers' household income (Ngoma 2018). Lack of this information brings the problem of selection biasness since to observe the outcome of those who adopted in case they did not adopt is not possible (Amare *et al*., 2012). This biasness is also a problem of missing data since we cannot observe the same farmers when they adopted and not adopted at the same time (Ngoma 2018). Propensity score matching is less reliable due to unobservable characteristics of the farmers influencing self-selection into treatment; thus, the study employed Endogenous Switching Regression (ESR), where average treatment effect on treated (ATT) was used to measure this impact. The ATT estimates the average variance in upshots of adopters with and without a technology (Khonje *et al*., 2015).PSM is the most used method to compute ATT. However, it ignores the unobserved factors that influence the process of adoption. Thus, the best model to apply to this study is ESR to be able to avoid selection bias and unobserved heterogeneity of adopters and non-adopters (Wossen *et al*., 2017).

The study took two stage-treatment frameworks to model the impact of adopting climate-smart maize variety on household income outcome variables in ESR. The adoption decision of the climate-smart maize variety was the first one and was modeled and predicted by the use of Probit model equations 1 and 2. The assumption for using Probit in analyses of impact was that adoption decision was a dummy variable that is either you are adopter of climate-smart maize variety which was represented by 1 and 0 if otherwise. Ordinary Least Square (OLS) regression model with selectivity correlation was applied in stage two to analyze the correlation between the outcome variable with established dependent variables subject to adoption decision. The outcome regression equation function dependent on adoption was specified as an endogenous switching regime model in the following manner;

Regime 1: (Adopters): $Y_{1i} = \beta_1 X_{1i} + \varepsilon_{1i}$ if CSA = 1 (9a)

Regime 2 :(Non-adopters): $Y_{2i} = \beta_2 X_{2i} + \varepsilon_{2i}$ if CSA = 0 (9b)

In this study, the outcome variables (household income) was Y_1 for those who adopted and Y_2 non-adopters. Where X_{1i} and X_{2i} are exogenous covariates vectors, β_1 and β_2 were parameter vectors, and ε_{1i} and ε_{2i} were the error terms of the outcome variable. According to Shiferaw *et al.* (2014), in the adoption model for the ESR to be identified, explanatory variables are essential to have a selection instrument to add on those spontaneously created by non-linearity of the adoption selection model. These are the variables that affect the decision to adopt climate-smart maize varieties, which does not directly affect the outcome indicators (Wossen *et al*. 2017). The selection instruments were carefully chosen by executing a simple falsification test, which was used to validate the instruments selected (Di Falco *et al*., 2011). The variable was a valid choice instrument if it affected the adoption of climate-smart maize, but it did not affect the household income the output variable directly. The error terms in the equation one selected and the outcomes equation nine are presumed to have a trivariate standard distribution with covariance matrix and mean vector zero written as;

$$cov(\mu, \varepsilon_1, \varepsilon_2) = \begin{pmatrix} \sigma_\mu^2 & \sigma_{\mu 1} & \sigma_{\mu 2} \\ \sigma_{2\mu} & \sigma_1^2 & . \\ \sigma_{2\mu} & . & \sigma_2^2 \end{pmatrix} \quad (10)$$

Where σ_μ^2 = var(μ) , σ_1^2 = var(ε_1) , σ_2^2 = var (ε_2) , $\sigma_{\mu 1}$ = cov (μ,ε_1) and $\sigma_{\mu 2}$ = cov(μ,ε_2). σ_μ^2 Is valued up to a scale factor and is assumed to be equal to 1 and $cov(\varepsilon_1, \varepsilon_2)$ is not defined as y_1 and y_2 are not observed simultaneously (Maddalla, 1983).

The estimated values of the error terms ε_1 and ε_2 depending on the selection condition are non-zero; hence the prediction of β_1 and β_2 with OLS will give a biased estimate (Shiferaw *et al*., 2014). The predicted values of the error term ε_1 and ε_2 subject to the sample selection is not zero since the error term in the chosen Eq.1 is correlated with the error term of the outcome variable (income function) which create selection bias (Asfaw *et al*., 2012). The selection bias created was addressed by the use of ESR by predicting the inverse mills ratios (λ_{1i} and λ_{2i}) and covariance terms ($\sigma_{\mu 1}$ and $\sigma_{\mu 2}$) then including them as auxiliary regression in Eqs. 9. The bias is corrected as;

$$E\{\varepsilon_{i1}|CSA_i = 1\} = \sigma_{1i}\frac{\emptyset(\beta x_i)}{\theta[\beta x_i]} = \sigma_{1u}\lambda_{1i} \text{ And } E\{\varepsilon_{i1}|CSA_i = 0\} = -\sigma_{2i}\frac{\emptyset(\beta x_i)}{1-\theta(\beta x_i)} = \sigma_{2u}\lambda_{2i} \quad (11)$$

The absence of selection bias is rejected if $\sigma_{\mu 1}$ and $\sigma_{\mu 2}$ was significant after getting the inverse mills ratios, the ESR framework was used to calculate the average treatment effect of the untreated (ATU) and the treated (ATT) by matching the estimated values of non-adopters' outcomes and that of adopters in actual and counterfactual scenario. According to Shiferaw *et al.* (2014) and Khoja *et al*. (2015), the study computed the ATT and ATU as specified below:

Those who adopted with the adoption of CSMVs (observation in the sample)

$$E\{y_{i1}|CSA_i = 1; x\} = \beta_1 x_{1i} + \sigma_{1u}\lambda_{1i} \tag{12a}$$

Those who did not adopt without adoption (observation in the sample)

$$E\{y_{i2}|CSA_i = 0; x\} = \beta_2 x_{2i} + \sigma_{2u}\lambda_{2i} \tag{12b}$$

Those who adopted had they decided not to adopt (counterfactual)

$$E\{y_{i2}|CSA_i = 1; x\} = \beta_2 x_{1i} + \sigma_{2u}\lambda_{1i} \tag{12c}$$

Those who did not adopt had they decided to adopt (counterfactual)

$$E\{y_{i1}|CSA_i = 0; x\} = \beta_1 x_{2i} + \sigma_{1u}\lambda_{2i} \tag{12d}$$

Then we defined ATT that is the expected change in adopter's household income as the difference between 12a and 12c while the ATU that is the expected change in non-adopters' household income as the difference between 12d and 12b as follows;

$$\text{ATT} = E\{y_{i1}|CSA_i = 1; x\} - E\{y_{i2}|CSA_i = 1; x\} \tag{13}$$

$$\text{ATU} = E\{y_{i1}|CSA_i = 0; x\} - E\{y_{i2}|CSA_i = 0; x\} \tag{14}$$

The error term was presumed to be normally dispersed in the context of ESR while λ was the selection term which captured all probable effects of the difference in unobserved variables.

The climate-smart maize varieties which were considered in the study were drawn from KEPHIS national crop variety list which was updated on 2020.These varieties are shown on the Table 2 below:

Table 2: Climate-smart maize varieties from KEPHIS

Variety name	Official release name	Release year in Kenya	Owner /license	maintainer	Optimal altitude	Duration of growth (months)	Grain yield t-ha^{-1}
DK8031	Dk 8031	2003	Monsanto	Monsanto	900-1700	4-4.7	6-8
Decalb	Dk 777	2016	Monsanto Kenya ltd	Monsanto Inc	1400-1600	4-5	5-8
Duma 43	SC Duma 43	2004	Agriseedco ltd	SEEDCO Zambia	800-1800	4-5	6-7

Source; KEPHIS national crop variety list-Kenya (2020).

3.6 Measurement of variables

Table 3 presents the description and the measurement of both dependent and independent variables used in the double hurdle and endogenous switching regression model. The dependent variable of the Double hurdle model used in this study is the intensity of adoption of CSMVs among smallholder maize farmers in Embu, Kenya. It is derived by dividing the number of acres under CSMVs per household by the total maize acreage per household in the study .The dependent variable of the Endogenous switching regression model used in the study is the impact of adoption of CSMVs on household income among smallholder maize farmers in Embu County, Kenya. It is laborious and complex to measure income directly. In this study, measurement of household income is annual total income both farm and off-farm income. To achieve this, the households were asked to list the different sources of income obtained by the household then added together.

Table 3: Description of expected sign of the explanatory variables

Variable Name	**Variable description**	**Unit of Measurement**	**signs**
Dependent variables			
Intensity	Acres of maize under CSMVs divided by the total acreage of the household	Proportion	+
Household income	Annual total income	Continuous(Ksh)	+
Independent variables			
Age	Age of household head in years	Years	+/-
Gender	Gender of the household head	1= male ,0= female	
Education level	Number of years spent in school	Years	+
Farm experience	Number of years farmer farmed maize	Years	+
Household size	Number of persons in the household	Continuous	+
Land size	Size of land owned by a farmer	Hectares	+
Off-farm income	Annual income outside the farm	Continuous	+
Extension service	Farmer contact with extension officer in the past one year	(1=yes; 0 = otherwise)	+
Group membership	Membership to a farmers group	(1= yes; 0 = otherwise)	+
Credit access	Farmers access to any form of credit	(1 = yes ; 0 = otherwise)	+
Distance to market	Distance from farmer household to market	Continuous (KMs)	+
High yielding	Variety is perceived to be high yielding	(1 = yes ; 0 = otherwise)	+
Early maturity	The variety is perceived to mature early	(1=yes; 0 =otherwise)	+
Pest and diseases resistance	The variety is perceived to be resistance to pest and diseases	(1 = yes; 0 = otherwise)	+
Drought tolerance	The variety is perceived to have ability to maintains its biomass production during arid or drought conditions	(1= yes; 0 = otherwise)	+

The household head age: Age of the farmer may have a negative or a positive effect on the decision to adopt of the farmer and the extent of adopting new technology (Gbegeh and Akubuilo, 2013). Older farmers are more conservative towards new technology and are more risk-averse compared to young farmers. Additionally, farmers who are old have more farming experience than younger farmers; thus, they assess modern technologies better hence the high likelihood to adopt than young farmers (Adesine and Forson, 1995). Yirga *et al*. (2015) found out that age of the farmers had a substantial favorable effect on the adoption decision of improved wheat varieties in the Ethiopia Highlands while Larochele *et al*. (2016) found conflicting results where age was negatively affecting the adoption of shyushya improved bush bean variety in Rwanda.

The farmer's education level: This was the highest level of education measured as a continuous variable. Education is human capital and is expected to increase the possibility of acceptance of new ideas. It also enables the farmer to intellectualize and access appropriate information e to decide on a given innovation (Owuor and Bebe, 2012). Thus farmers with advanced education levels were expected to have more ability to accept new technologies. Hence in this study, the level of education is hypothesized to be positively affecting the adoption decision and the magnitude of adopting climate-smart maize varieties. Timu *et al*. (2014) deduced that the increase in education level had a positive sign on the decision to adopt Gadam improved sorghum variety in Kenya.

Farming experience: Farmer's experience in farming was hypothesized to influence the adoption rate of climate-smart varieties positively. Farming experience improves farmers' know how on numerous management techniques and how to apply them with existing data on climatic circumstances.

Household size: According to Teklewold *et al*. (2013), the number of family members in the farming house is a proxy to available labor, which may positively affect the decision to adopt the new technology since available labor force reduces labor limitations. Alternatively, large family size could contribute to constrained households resource allocation limiting investment in new technologies, thus reducing the likelihood of adopting climate-smart maize varieties. For instance, Odhiambo *et al*. (2018) found that the size of the household had a substantial positive influence on selecting new cassava varieties. However, in contrast, Abele *et al.* (2007) found out that household size had a negative impact on the adoption and extent of adopting improved cassava varieties in Uganda.

Land size: land size indicated the land size owned by the household. Quantity of the land owned by a given farmer was anticipated to positively influence the adoption and rate of adopting climate-smart maize varieties. As land size increases, it increases the household opportunity to utilize climate-smart maize variety. Ghimire *et al*. (2015) found out that in Nepal, maize production increased as the land allocated to improved maize varieties increased.

Contact to extension services: This was the contact of extension agent with the farmer over the past one year before the survey. The farmer's connection with the extension agent was categorized as a dummy variable where if a farmer had accessed extension services was 1 and 0 otherwise. Farmers who interact with extension officers are expected to know more about new technology and better farm management. Hence contact with extension agents had a positive influence on the adoption rate of climate-smart varieties. Yirga *et al*. (2015), in Ethiopia, found out access to extension services had a positive relationship with adoption behaviors.

Membership to farmers' group: This is where a farmer belongs to one of the farming groups or associations. Group membership of a farmer was hypothesized to positively affect the farmer's decision on adoption and rate to adopt. Farmer clutches the working group as a boulevard of advisory services and unconventional learning ground (Rowley and Cooke, 2014).In Rwanda, it was found that group membership of farmers increased the farmers' probability of adopting improved bean varieties(Larochelle *et al*. (2016).

Access to credit: This is where a farmer had access to any form of credit services. Access to credit by a member was hypothesized to positively affect the farmer's adoption decision and intensity to adopt climate-smart maize varieties. Those farmers who can access credit have a high likelihood of adopting new technologies since they will have resources to purchase the required agricultural practices. For example, Jari (2009) deduced that those farmers who preferred more formal marketing channels are those who had access to credit facilities.

High yield at maturity: High yield attribute of the variety is the ability of climate-smart maize varieties to giver high output compared to other maize varieties. It was a perception measurement of the farmer's expectation after adopting an array that was: 1 if the farmer perceives the variety was to give high output and 0 otherwise. Varieties of maize, which are high yielding, were likely to be adopted since they will increase farmers' production and subsequently, food security and household income. Also, Idrisa *et al.* in 2012 found out that soybeans' yield had a strong influence on the decision to adoption and intensity to adopt improved soybean varieties.

Early maturity period: Early maturity attribute of a given variety was a perception by farmers that specific climate-smart maize variety would mature early than other varieties they adopt the variety. The first maturity trait of a given cultivar is seen to have a positive effect on adoption.

Odhiambo *et al*. (2018) found out that cassava variety that had early maturity traits increase its probability of approval by the cassava farmers in Kenya.

Resistance to pest and diseases: Resistance to disease and pest is an attribute of a given variety and was measured as a dummy variable. If farmers perceive that a given variety was resistance to pest and diseases was coded 1 and 0 otherwise. New pests and diseases have been cropping up and affecting maize production, such as fall armyworm, which is very expensive to treat for a small-scale maize farmer. Thus any maize variety with pest and disease resistance will positively affect farmers' decision to adopt it. Acheampong and Owusu (2015) found out that pest and disease resistance is an essential trait to cassava farmers.

Drought tolerant attribute: Climate-smart maize variety ability to withstand drought is projected to have a positive effect on the farmers' adoption decision, which was measured as a dummy variable. Odhiambo *et al*. (2018), on their study on cassava in Kenya, found out that cassava varieties with high tolerance to drought had positive and significant impact on farmers' decision to adopt it.

Taste of given variety: If the farmers perceive a given variety to have a desirable taste, they were to adopt it, and it took a value of 1 if they utilize it and 0 if they don't. The taste attribute is postulated to have a positive influence adaption of climate-smart maize variety. Farmers would prefer a variety that has a good taste since most of the small scale farmers do both subsistence farming and cash crop hence need some yields for household consumption. Otieno *et al.* (2011) found out that pigeon pea, which had a good taste, was adopted more by farmers than others.

3.4.4 Econometric models Diagnostic Tests

The model diagnostic tests were performed to test the correlation among variables (multicollinearity) and the relationship between random terms across observations in the survey data (Heteroscedasticity) before running the models.

Test for multicollinearity

Multicollinearity is the state in which independent variables are closely correlated to each other, which can skew results. The study used Variance Inflation Factor (VIF) and Pearson correlation matrix test to test for the presence of multicollinearity among the explanatory variables used in the analysis. If there is a multicollinearity presence among independent variables, it can result in high standard errors, change in magnitude, and signs of the coefficients in the regression analysis (Muema *et al*. 2018). The VIF test was carried out after running an artificial Ordinary Least Square regression to test for multicollinearity, according to Gujarati and Porter, (2004). The VIF was followed by running Pearson's correlation to affirm the VIF results where the accepted range is from 0.00 to 0.45. (Attached results in appendix 1 and 2).

Test for heteroscedasticity

When the error term varies across the observations where the conditional variance of Yi increases with an increase in explanatory variables X, it means there is heteroscedasticity (Gujarat, 2003), leading to an inefficient estimator. The study used the Breusch-pagan test to test heteroscedasticity (Baum *et al*., 2003). The regression model was run then *hettest* was run on STATA Version 15. (Attached results in appendix 3).

CHAPTER 4:

RESULTS AND DISCUSSION

4.1 Socio-demographic characteristics of the respondents

The results from Table 4 shows the socio-economics and institutional factors of the respondents' which were used in the analyses to assess the intensity of adoption and impact of adoption. From table 4, 72% of the households who practiced maize farming in the study area are headed by men, while female-headed households were 28%. The result concurs with Chimoita *et al*. (2017) and Korir *et al*. (2015), who found out that most of the households in Embu County are headed by males by 79% and 88% respectively. The household head age ranged from 23 to 95 years with a mean of 57.1 years, which indicates an aging maize farmers' population who are faced with labor constraints for managing maize farming. However, the average number of years of maize growing was 27 years depicting that farmers in the study area had grown maize a long time, to appreciate the losses in production brought about by changing climatic conditions.

Among the interviewed farmers, 92.2% of them were above the age of 35 years. This age is above the age of a person considered as a youth according to the Kenyan constitution (2010), which shows limited involvement of youth in agriculture. This finding is supported by Filmer and fox (World Bank's (2014)) report, which concluded that the majority of the Kenyan population are youths who rarely engage in agricultural practices. The average household size was 4 persons per household, which corresponded with the 2018 Kenya Nation Bureau of Statistics (KNBS) on a human index, which reported an average of 5 people in a rural household (KNBS, 2018).

The household size is associated with the vulnerability of a household to climate-related shock since larger household sizes are more vulnerable to climate-related shocks (Nkondze *et al*., 2013). The average years of education were 8 years, which shows that majority of the farmers had attained the primary level of education. This result is consistent with the World Bank report (2004), which stated that the primary school enrollment rate in Kenya was 87%. This result imply a high illiteracy level, which may hinder adequate access to climate-smart agriculture information hence lowering the level of adoption of given climate-smart strategies to improve farmers' production.

The average land size was 1 hectare per household, consistent with the national average landholding of 0.8 hectares for small scale farming in Embu County (Embu County Integrated Development plan 2013). The smaller acreage was due to an increasing population in the county, specifically in the high agricultural productive areas, which continues to exert more pressure on arable land and other natural resources (Embu County Integrated Development plan 2013).In terms of institution factors, 37% of the farmers had access to an extension officer, while 59% of the farmers were members of any given agricultural group(s). Similarly, 26% of the farmers received credit during the period of the survey season that is 2018/2019. The results indicated that most of the farmers could not access these institutional services more so extension services and credit facilities. The study noted that the minimum number of extension officers in the county can be contributing to the problem of farmers to access extension services.

From the study it is evidence that there was a significant statistical mean difference in term of the household head age between those who adopted and non-adopters. This difference is minimal and indicates that the age of those who adopted and non-adopters on average was above 50 years. Old age is associated with risk-averse farmers, hence not readily adopting new technologies (Yirga *et al*. (2015).There is a statistical significant difference in off-farm income between those who adopted and those who did not adopt, where it is high among adopters. This difference signifies that high off-farm income made it possible for the adopters to be inquisitive and try new technologies. Even though on average, farmers' access or contact to extension services was low at

35%, there was a significant difference between the two groups where the adopters had more access to extension facilities.

Extension services access or being in contact with extension officers during the production period of a given crop is a proxy of awareness and subsequent adoption of new technology in our case climate-smart maize varieties (Odhiambo *et al*., 2018). In respect to group membership by the farmers, it was deduced that there was a statistical significant difference between those who adopted and non-adopters, where most adopters were under a given association. Group membership is seen as a way to build social capital, which improves information and resource sharing and sometimes can act as a source of subsidizing credit for members (Seebens, 2011).

There was a significant difference in access to credit services between the two groups, where those who adopted had more access to credit services. Those farmers who can access credit have a high likelihood of adopting new technologies since they will have resources to purchase the required agricultural practices. The results on the education level, size of household, land size and market distance had no significant difference amongst those who adopted and non-adopters.

Table 4: Socio-economic characteristics of surveyed households

Variables	***Pooled mean(Std Dev)***	***Adopters mean (n=346)***	***Non-adopters mean(n=204)***	***t-value***
The household head age(years)	57.1 (14.50)	56.3(14.20)	58.41(15.00)	1.7261*
The household head level of education (years)	8.1(0.16)	8.2(0.19)	7.9(0.28)	-0.9907
Number of years farmer farmed maize	26.7(15.43)	25.9(15.43)	27.90(16.70)	1.4017
Number of household in the house in 2019	4.2(0.08)	4.2(0.10)	4.0(0.13)	-1.5115
Land size owned by the farmer in acres	2.5(0.10)	2.4(0.10)	2.6(0.19)	0.3560
Distance between the respondent farm to the nearest input market in KMs	3.8(0.30)	3.8(0.44)	3.66(0.30)	-0.2494
Log of off-farm income	7.2(0.23)	7.6(0.28)	6.6(0.38)	-2.0800**
Variables	**Percentage of farmers**			**א 2 –value**
The household head gender	(M)= 72	62.9	37.1	-3.1205***
	(F)=28	63	37	-4.9701***
Access to extension services in the past one year(yes)	37.5	76.7	23.3	-6.0273***
Farmers belonging to a group or association(yes)	59.3	65	35	-5.1977***
Farmer access to any form of credit facilities	25.8	83.1	16.9	-6.5780***

*Note: levels of statistical significance, *** =1%, ** = 5%, * = 10%.*

Source: Survey Data(2019)

4.2 Characterization of adoption of maize produced in Embu County.

4.2.1 Farmers awareness and adoption of climate-smart maize varieties.

Table 5 shows farmers' level of awareness and adoption level of climate-smart maize varieties by farmers in Embu County. The results show that besides the awareness of the climate-smart maize varieties being high at 86%, the adoption rate is 63%. These results show that even though farmers are aware of the improved climate-smart maize varieties, some percentage of the farmers don't adopt them. These results were consistent with other studies done in the region. For instance, a study by Ouma *et al*. (2002) showed that improved maize varieties' adoption rate was at 75% in 1997. The rate had reduced by the year 1999, according to a study conducted by (CIMMYT) in 2003, which concluded that only 65% of the farmers had adopted improved maize varieties in Embu county, which was Embu District by then (Doss *et al*., 2003).

The study carried out by Ogada *et al*., (2014) found out that the rate of adoption of improved maize varieties was at 65% in the midlands ecological zones in the year 2007. This result compares well with the results of this study, which shows that the rate of adoption of improved climate-smart maize varieties was 63%, which is also lower compared to previous studies even though there are very many varieties produced by the seed sector of Kenya. This result can deduce that the adoption levels of improved crop varieties and the associated management practices by smallholder maize farmers are still low and not commensurate with the corresponding efforts to promote the same.

Table 5: Farmers awareness and rate of adoption of climate-smart maize varieties

Climate-smart varieties	**% of the farmers aware of the varieties (n=550)**	**% of the farmers growing the varieties(Adopted) (n=550)**
Duma43, Decalp and Dk 8031	86.4	62.9

Source: Survey Data(2019)

4.2.2 Farmers' awareness level and adoption rate of different maize varieties

Table 6 shows the farmers' awareness level and percentage of adoption of different varieties of maize grown in Embu County by small scale farmers. The results indicate that besides introducing climate-smart maize varieties such as DK 8031, Decalp, Duma 43, and others in the region, other improved maize varieties such as pioneer, H614D, Katumani and H51are still grown. While quite number of farmers are still growing local varieties such as *kiembu*. Decalp was the most widely known climate-smart maize variety followed by DK 8031 and Duma 43. About 21% of the farmers were aware of the local varieties such as *kiembu*.

In terms of adoption Duma, 43 was the most adopted climate-smart maize variety at (54.7%), followed by Decalp at (4.7%) and DK 8031 at (3.5%). Even though Duma 43 was less known compared to others, it is widely adopted among the farmers. This is because it matures early, resistant to diseases and pest and tolerant to extreme drought compared to other climate-smart maize varieties. Most of the farmers adopted Duma 43 due to its excellent taste when cooked hence most farmers adopted it for both home consumption and commercial purposes. These findings were consistent with those of Muli *et al*. (2017). They noted that Duma 43 was more superior in terms of drought tolerance than other varieties, hence indicating a higher grain yield than other varieties under drought-stressed conditions.

It was noted that the local varieties such as *kiembu* were grown by about 26.0% of the farmers. This is because *kiembu* is resistant to disease, has good taste when cooked and drought resistance. Summarily, the higher rate of adoption of climate-smart maize varieties compared to local varieties in the area reflects the superiority of their traits over the local varieties hence need to promote their awareness to improve their adoption rate since it's still low and not commensurate with the effort put into promoting these varieties by different players.

Table 6: Farmers level of awareness and adoption rate of maize varieties

Maize varieties	**% of the farmers aware of the varieties (n=550)**	**% of the farmers growing the varieties(adopted) (n=550)**
DK 8031 (1=yes)	94.7	3.5
Decalb (1=yes)	96.2	4.7
Duma 43 (1=yes)	85.1	54.7
Kiembu (1=yes)	22.8	26.4
Others (1=yes)	94.9	10.7

Source: Survey data (2019)

4.2.3 Source of planting material

The results from Figure 4.1 showed that the majority of adopters (91%) and only 38% of non-adopters sourced their maize seeds from the agro vet. Sourcing maize seed from an agro vet is the recommended method by Kenya Plant Health Inspectorate Services (KEPHIS). Since they will certify the seeds for planting to caution farmers from buying counterfeit maize seeds. About 35% of the non-adopters did seeds recycling. Most of them were traditional and local maize seeds like *kiembu*, while only 1% of adopters sourced their seeds from the previous harvest.

It can also be noted that about 38% of the non-adopters sourced their seeds from the agro vet. The percentage of non-adopter farmers who were growing improved maize varieties like pioneers, not necessarily climate-smart maize varieties. It can be noted that non-adopters sourced most of their seeds locally, which is (56%) either own seeds from the previous harvest or buying or borrowing from their neighbors. According to the respondents, this was brought about by the fact that these local varieties like *kiembu* had some desirable traits like drought resistance, pest and disease resistance, matures early, and sweet taste when cooked. Thus this could be reasons why local varieties were still prevalent in the region irrespective of introduction of improved maize varieties by seed sector Kenya.

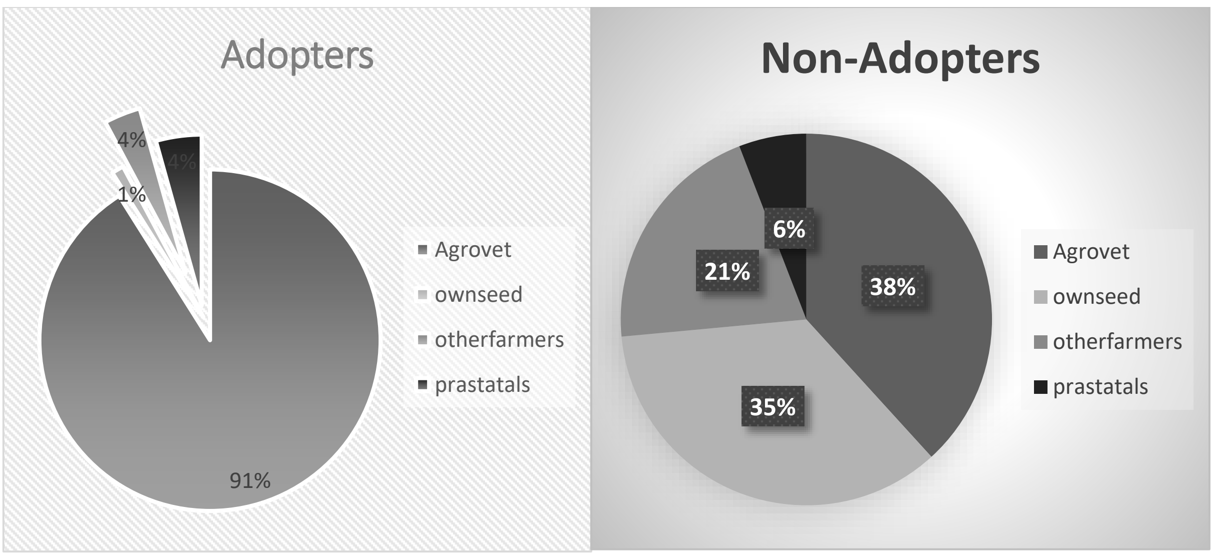

Figure 4.1: Sources of planting materials

Source: Survey Data (2019).

4.2.4 Varietal attribute contributing to adoption of given variety

The results in Table 7 show perceived varietal attributes contributing to adoption of a given variety. The varietal attribute were drawn from KEPHIS directorate as they have documented these varietal attribute according to a given variety since they are the inspectors of all seeds in Kenya. Concerning yield of a given maize variety, all improved maize varieties were perceived to be high yielding compared to the local variety. The DK 8031 variety was the most popular in terms of yield potential followed by PH 3253 which is a KALRO produced variety even though it's not climate-smart maize variety. In terms of the maturity period, most of the farmers interviewed said that Duma 43 had the shortest maturity period followed by DK 8031 among the improved climate-smart maize varieties.

A significant number of farmers perceived local variety, *kiembu*, to be high yielding and early maturity. Regarding the resistance to disease and pest, other improved maize varieties, which are not climate-smart varieties such as H514, were more resistant, followed by the local variety, which is *kiembu*. Dk 8031 was more tolerant of drought, followed by Duma 43 compared to other varieties. Notably, despite their popularity of improved maize varieties in production attributes, local variety, *kiembu*, had the best taste; hence it was mostly preferred by many farmers for household consumption. Overall, the improved maize varieties were perceived as superior in production attributes such as yield and pest and disease resistance. In contrast, local varieties were better in the maturity period and taste.

The results further explain that climate-smart maize varieties were adopted mainly due to their yield, drought tolerance, short maturity period, and resistance to pests and diseases. The results showed that in terms of yielding attributes, about 100%, 81%, and 77% of the interviewed farmers adopted DK 8031, Decalp, and Duma 43 varieties, respectively. Farmers' response to the drought tolerance was 68% for DK 8031, followed by Duma 43 with a 65% response rate and lastly Decalp with 39%. In terms of the short maturity period, about 67% of the interviewed farmers adopted Duma 43 due to its early maturity trait; 52% adopted DK 8031, and 39% adopted Decalp.

Resistance to pest and disease attributes contributed to about 84%, 79%, and 77% uptake of Duma 43, DK 8031, and Decalp maize varieties. Only a small percentage of the farmers adopted these climate-smart improved maize varieties due to the consumption attributes such as good taste since only 20% of the interviewed farmers adopted Duma 43.

Table 7: Varietal attributes contributing to adoption of given variety

Varietal attribute	***Improved varieties***					***Local variety***
	Climate-smart variety			***Non-climate-smart variety***		
	DK 8031	Decalp	Duma 43	Pioneer	Others	Kiembu
High yielding	100	80.7	76.7	95.2	68.2	58.6
Early maturity	52.6	38.5	67.4	42.9	36.4	60
Pest and disease resistance	79	76.9	84.1	81	90.9	90.7
Drought tolerance	68.4	38.5	65.5	35.7	40.9	54.3
Good taste	5.3	7.7	20.3	11.9	18.2	23.6

Source: Survey Data (2019).

4.3 Determinants of adoption and intensity of adoption of climate smart maize varieties

The results from the double hurdle model show the Probit model for the adoption decision and the truncated regression model for intensity of use of climate-smart maize varieties in the study area. In the second hurdle truncated regression model was used. All the zero values (those who did not adopt the climate-smart maize varieties (CSMVs)) from the selection model (first hurdle) were truncated, and only the positive values (proportion of land allocated for CSMVs) were included in the regression model. Table 8 presents the estimated coefficients' of Probit model and truncated regression model.

4.3.1 Factors influencing adoption of climate smart maize varieties

The results from Table 8 show that the household head's age was statistically significant at a 5% significant level with a negative relationship to adoption decision. As expected, the age was predicted to have either a positive or negative effect on adoption decision; hence, the negative relationship signified that as the farmer's age increased, the adoption probability reduced. The results showed that when years of the respondent age increases by one year, the probability of adoption of climate-smart maize varieties reduces by 0.008. This result infers that the older the respondents become, the lower the likelihood of adopting climate-smart maize varieties. Perhaps this could be brought by the fact that, as the farmers get old, they become risk-averse on new technologies introduced to them. It would also indicate that there are specific desirable attributes of the local maize varieties that older farmers don't want to abandon. The results are consistent with preceding studies such as Ghimire *et al*. (2015). They found out that age had a negative effect on the adoption of improved maize varieties, which was the case with Akinbode and Bamire (2015).

Contrary to the expected, the land size negatively influenced adoption of climate-smart maize varieties at a 10 % significant level, which contradicted our expected outcome of land size to the decision to adopt. The results indicate that an increase in land size with one unit decreased the likelihood of adopting the climate-smart maize varieties by 0.135. This result might be brought by the fact that, most of the respondents had a small landholding, with an average of 1 hectare divided according to the enterprises the farmer had. Also, according to Mwangi and Kariuki (2015), the smaller the size of the farm it may offer an incentive on decision to adopt technology, particularly in the case of an input-intensive innovation such as labor-intensive. Similar results were reported by (Beshir, 2014; Mwangi and Kariuki, 2015).

Land ownership or land tenure was having a positive impact on the likelihood of adopting climate-smart maize varieties at 1% significant level. The land ownership was a dummy variable where if a respondent owned land with title, it was 1 and 0 if otherwise. The results in this study indicate that if a farmer-owned land with title, it increased the farmer's probability of adopting the climate-smart maize varieties by 10.4%. The positive relationship is brought about by the fact that ownership of land emboldens the adoption of agricultural technology. This is because land ownership can safeguard flow of cash over time and enable liquidation of asset given transferable rights of land. It can also boost resources access such as credit, which can incentivize the decision to adopt technologies that require investments. These results were in line with other studies (Oostendorp and Zaal, 2012; Ali *et al*., 2012; Abdulai *et al*., 2011).

As hypothesized, off-farm income had a positive effect on the farmers' adoption decisions at a 5% significant level. The result implies that farming household who were undertaking off-farm activities were more probable to adopt climate-smart maize varieties. The results indicate that an increase in the off-farm income in one unit increases the possibility of adoption of climate-smart maize varieties by 0.6%. Off-farm income has a positive effect on adoption. Farm liquidity is enriched by off-farm income as it provides an alternative source of financing agricultural activities such as the purchase of farm inputs and meets labor costs involved in the cultivation of these climate-smart maize varieties. These results were consistent with other studies such as Muzari *et al*. (2012), who found that off-farm income expedites the decision to adopt high yielding and resilient adaptation practices.

As expected, according to the study, it is worth noting that the source of seed was positively influencing the probability of a farmer to adopt at 1% significant level. Sources of seed was a dummy variable where 1 was representing sourcing seeds from the certified agro vet dealer while 0 was other sources. The results indicated that if a farmer sourced their seeds from an agro vet, it increased their probability to adopt climate-smart maize variety by 62.3%. The result explains that purchasing the certified seeds was perceived to increase production since farming households in remote areas hardly get reliable sources of improved certified seeds, magnifying the importance of the availability of seed in the local area. The outcome was consistent with that of Ghimire *et al*. (2015).

As hypothesized, annual contact with the extension agent was positively significant at 1% and associated with the possibility of adopting climate-smart maize varieties. The availability of extension services signified an increase in the adoption rate of climate-smart maize varieties among farming households. The results indicate that if a farming household had a contact with an extension service provider in that farming year increased their chance of adopting the climate-smart maize varieties by 32.0%. This result shows that contact with extension agents is essential to enhance the rate of adoption. They popularize the innovation by providing the necessary information, knowledge, and appropriate special skills required for a given technology to enable farmers to apply the technology. The results were consistence with the finding of Maina *et al*. (2019), Wekesa *et al*. (2018), and Beshir *et al*. (2012).

The results show that being a member of a farmer group was positively significant at 1% and it was associated with the probability of adoption of climate-smart maize varieties as hypothesized. Farmer belonging to a farmer group increase the likelihood of adopting the climate-smart maize variety by 17.6%. Being a social group member provides farmers with a linkage to access facilities such as extension services and credit facilities, which are important ingredients of adopting new technology. Belonging to a social group enriches social capital that allow trust, ideas, and information exchange (Mignouna *et al*., 2011). Farmers who belong to a social group mug up from each other the usage and benefits of the new technology. As suggested by Uaiene *et al*. (2009), effect of social network are essential for personal decision making, and more so, in the agricultural innovations environment , farmers are able to share information and learn from each other.

Among the varietal attributes, all of them were significant and had a positive effect on decision to adopt as hypothesized. The results show that high yield attribute was significant at 5% and positively influenced farmers' probability of adopting climate-smart maize varieties. If a farmer perceives that yield attribute to be reasonable concerning a given variety, it increased the likelihood of farmer to adopt said variety by 13.3 %. This result suggests that farmers prefer those varieties which are high yielding to have high output with minimum input cost possible to generate a market surplus and increase their returns from maize production. This result was consistent with the finding of Rahman and Chima (2016), who found out that high yielding attributes positively influenced uptake of improved crop diversity among farmers in Nigeria. Also, Odhiambo *et al*. (2018) found out that high yielding attribute was significant and positively affecting farmers' decision to select improved cassava varieties in Kenya.

The maturity period was an important attribute considered in climate-smart varieties. According to the results, the early maturity attribute of a given variety was significant at 1% and positively influenced farmers' adoption decision of climate-smart maize varieties. The results show that if farmers perceive that a given climate-smart maize variety will mature early than other varieties, it increased their probability of adopting that variety by 15.4 %. The reason for farmers to select these varieties, which are early maturing, might be because of the many short rainy seasons nowadays than the expected time due to climatic change, which causes acute crop failure. These findings were consistent with that of Odhiambo *et al*. (2018).

Pest and disease resistance attribute was positively significant at 1% and associated with the possibility of adopting the climate-smart maize varieties. Any variety expected to be resistant to pests and diseases increased the likelihood of such variety being taken up by the farmer by 23.4

%. This attribute was essential to the farmers since it will reduce farmers' cost spent on purchasing chemicals to fight this menace brought by increased pests and diseases such as fall armyworm.

Finally, the drought tolerance attribute was significant at 5%, and positively influencing farmers' decision to adopt the climate-smart maize varieties. As expected, the drought tolerance attribute was found to increase the likelihood of using the climate-smart maize varieties by 10.5%. This attribute was essential to the farmers since it would caution them from extreme drought stress due to climatic change over time, causing crop failure. Frequency drought in the study area has brought severe crop failure over the years; thus, maize farmers preferred the variety that is perceived to be tolerant to drought. This finding was consistent with Fisher *et al*. (2015), who found out that maize varieties that were highly tolerant to drought had a significant effect on farmers' adoption decision. From the results it is evident that gender, household size, access to credit and yield of household in previous season no longer play role in adoption decision of new technologies.

Table 8: Determinants of adoption and intensity of adoption of climate-smart maize varieties

Model specification		Probit			Double- hurdle Truncated		
Variables	Coefficient	Robust Std. Err.	Marginal effects	P-values	Coefficient	p-values	Robust Std. Err.
Socio-economic factors							
Gender	-0.128	0.147	-0.051	0.386	-0.011	0.945	0.166
Age respondent	-0.009	0.005	-0.008 **	0.055	-0.013 **	0.028	0.006
Household size	-0.00009	0.036	0.03	0.998	0.090 **	0.048	0.046
Land size	-0.051	0.029	-0.135 *	0.078	0.464 ***	0.000	0.099
Land ownership	0.154	0.060	0.104***	0.009	0.137 **	0.084	0.079
Logoff-farm income	0.027	0.013	0.006 **	0.038	-0.026	0.160	0.019
Seed source	1.702	0.158	0.623***	0.000			
Previous yield	0.015	0.012	0.016	0.205	0.030 ***	0.008	0.011
Institutional factors							
Credit access	-0.108	0.233	-0.042	0.642	-0.002	0.990	0.196
Extension serv.	0.574	0.147	0.320***	0.000	0.309 **	0.043	0.152
Group membership	0.422	0.135	0.176**	0.002	0.050	0.743	0.153
Perceived attributes							
High yielding	0.346	0.148	0.134 **	0.020			
Early maturity	0.403	0.138	0.154 ***	0.004			
Pestdis.resistance	0.590	0.190	0.234 ***	0.002			
Drought tolerance	0.277	0.140	0.105 **	0.048			
Constant	-2.395	0.463		0.000	-0.700	0.196	0.541
	Model summary						
Log pseudo likelihood		-543.121					
Prob. > chi^2		0.0000					
Wald $chi^2(10)$		41.66					
Pseudo R^2		0.289					
Number of observations		550			346		

*Note: * , ** and * ** represents the significant levels at 10%, 5% and 1% levels respectively*

Source : Survey Data (2019)

4.3.2 Factors that are determining the use intensity of climate-smart maize varieties

From the results in Table 8, the truncated regression represents the results of the level of the adopting climate-smart maize varieties using the second step of the double hurdle model. As expected, the results show that the household size, land size, land ownership, extension services, and previous maize yield are significant and positively influence the intensity of adoption. Contrary to the expected household head age is significant and negatively influencing the extent of adopting climate-smart maize varieties. The results further show that gender of the household head, off-farm income of the farming household, access to credit, and being in a group or association had no significant influence on extent of adoption.

The results showed that the age of household head was statistically significant at a 1% significant level and negatively influenced the hectares of land under which climate-smart maize variety is cultivated. The result implies that as the respondent age increases with one year, the area allocated for climate-smart maize varieties become smaller by 0.013. This outcome is brought by the fact that old farmers have an experience of different enterprises, especially in the study area such as mango, macadamia, and banana farming. Thus they dedicated a large piece of land to other enterprises compared to climate-smart maize varieties. Older farmers have a conservative attitude towards the adoption of new technologies. Akinbode and Bamire (2015) attested to this finding when they observed that the age of the household head had a negative and significant influence on the intensity of adopting improved maize varieties in Nigeria.

The size of the family, which is an indicator of household labor availability, was statistically significant at 1% level and has a positive influence on use intensity of climate-smart maize varieties. This indicates that, as the respondent's household size increases with one member, the land size in hectares planted with climate-smart maize varieties increased by 0.09. Size of the household is taken as a proxy of available labor. Therefore, more land will be cultivated with climate-smart maize varieties since cheap labor will be available to take care of the crops. This study also posits that the larger the household, the higher the consumption and demand for food hence more pressure to ensure food security. When faced with food insecurity, large households will cultivate more hectares of land with climate-smart maize varieties since they perceive them to be high yielding and drought resistance hence increased production meeting their food demand. These findings are consistence with other studies (Odhiambo *et al*. 2018, Akinbode and Bamire, 2015; Idrisa *et al*. 2012).

The farm size of the respondent was significant at 1% and positively influencing the area allocation under climate-smart maize variety. This result implies that the large the size of the farm of the respondent, the more area is allocated for climate-smart maize varieties. Hence, if the farm size of the respondent's increases with one unit it leads to an increase in the area planted with climate-smart maize varieties by 0.464. As land size increases, it increases the household opportunity to utilize climate-smart maize variety. Ghimire *et al*. (2015) found out that in Nepal, maize production increased as the land allocated to improved maize varieties increased. This finding was also consistence with that of (Akinbode and Bamire 2015; Kabubo-Mariaura *et al*., .2010).

Land ownership had a positive influence on the area under climate-smart maize varieties and statistical significant at 5%. The result indicates that if a respondent has a secure land tenure, the more land area in hectares is dedicate to climate-smart maize varieties. Thus, if a respondent owned land with tittle, increased the land under climate-smart maize varieties by 13.7%. Land ownership is considered as an indicator of wealth and proxy for social status, which can improve resource access such as credit, which can incentivize and influence the intensity of use of climate-smart maize varieties. The result is consistence with that of (Ali *et al*., 2012 and Abdulai *et al*. 2011).

Access to extension services was statistically significant at 5% and had a positive effect on the intensity of adoption of climate-smart maize varieties. The result implies that as contact with an extension agent increased, it increased the intensity of the use of climate-smart maize variety by 30.9%. The household that had contact with extension agents was considered more enlightened about planting material and agronomic requirements of the new varieties hence appreciating the benefit of the new technology more than others. The frequent contact with extension agents shows there is the availability of reliable information sources, which will enhance the communication process and improve the intensity of use of improved technologies. Mignouna *et al*. (2011) found that extension service is one of the most agreed situations for creating awareness and building the necessary knowledge for using the new technology following the approach, which is most convenient for farmers.

The yield from the previous season is statistically significant at 1% and positively influencing the intensity of the use of climate-smart maize variety. The results show that if the harvest from the previous season when the farmer tried climate-smart variety was higher than before, they tried them, will lead the farmer to dedicate more land in hectares to climate-smart maize varieties on the current season. This result implies that the farmer will have gained confidence in the variety and have knowledge of the production requirement. Hence, they will dedicate more land to the climate-smart variety as they expect high yield, which will increase their returns.

4.4 Adoption impact of climate-smart maize varieties on household income

In this section, determinants of the decision to adopt the climate-smart maize varieties were first analyzed and then the impact of adopting these climate smart-maize varieties on the household income of small-scale farmers.

The results from Table 9 present the Endogenous Switching Regression model. Columns 2 and 3 represent the results for the adoption of climate-smart maize varieties from the selection equation of household income model, while columns 4, 5, 6, and 7 represent the outcome equations. Columns 4 and 5 represent the outcome equation for adopters, while 6 and 7 represent the outcome equation of non-adopters. The study included a set of explanatory variables such as household characteristics and institution factors to analyze the correlation between the adoption decision and household income.

The Endogenous Switching Regression model results assessed at FIML indicated that the predicted coefficient of correlation between the error terms of adoption decision of climate-smart maize varieties and household income function given by ρ^1, ρ^0 is significantly different from zero and negative. These results suggest that the adoption decision and the impact of adopting are both influenced by observed and unobserved factors. The significance of ρ^1, ρ^0 indicates a presence of self-selection bias in the decision to adopt climate-smart maize varieties, which justifies the use of the Endogenous Switching Regression model to correct self-selection bias. The negative correlation between adoption equation and household income outcome equation implies that adopters' household income is relatively higher than those of non-adopters. Furthermore, the transformed correlation (r^1 and r^2) in the systems equations are negative and significant. This result implies that those who adopted are better off when they adopted in terms of household income than if they did not adopt. It also shows that non-adopters are better off if they had adopted climate-smart maize varieties.

The results also show that, there is heterogeneity in the sample because of the differences in the household income equation's coefficients between the farming households that adopted and those did not adopt. Additionally, the likelihood ratio test for independence between the selection equation and the outcome equations is significant at 1%, indicating a dependence between the two system equations.

Table 9: ESR results for Adoption decision and Impact of Adoption on household income

Model specification	FIML Endogenous Switching Regression					
	Selection equation		Outcome equation			
	Adoption (1/0)		Adopters =1		Non-adopters = 0	
Variables	Coefficient	Robust Std.Err	Coefficient	Robust Std.Err	Coefficient	Robust Std.Err
Socio-economic factors						
Gender	0.388	0.196	0.278 *	0.163	0.197	0.334
Age	-0.024 ***	0.006	0.013 **	0.006	0.026 **	0.015
Education level	-0.037	0.023	0.063 ***	0.020	0.112 *	0.063
Household size	-0.006	0.041	-0.035	0.035	-0.002	0.082
Land size	0.010	0.033	-	-	-	-
Land ownership	0.250 ***	0.068	-	-	-	-
Land.un.maize	-0.086	0.089	0.337 ***	0.061	0.399 ***	0.137
Dist.to mkt	0.007	0.006	0.022 ***	0.003	0.045 **	0.019
Seed source	1.581 ***	0.187	-	-	-	-
Agronomic factors						
Fert. Application	1.164 ***	0.173	-0.255	0.178	-0.769 **	0.338
Mode of tillage	0.304 **	0.178	0.418 ***	0.129	0.070	0.326
Mode of weeding	0.669 ***	0.261	-0.227	0.226	-0.766 **	0.319
Crop protection	1.842 ***	0.225	-0.261	0.269	-0.537	0.356
Institutional factors						
Credit access	0.727 ***	0.184	-0.269 **	0.139	0.361	0.293
Extension serv.	0.369 ***	0.182				
Grp membership	0.206	0.158				
Perceived attributes						
High yielding	0.467 ***	0.174				
Early maturity	0.572 ***	0.170				
Pestdis.resistance	0.399 **	0.200				
Drought tolerance	0.464 ***	0.160				
Constant	-4.773 ***	0.734				
Model summary						
Number of observation		550	346		204	
Wald chi^2 (12)		131.69				
Prob > chi^2		0000				
Log pseudo likelihood		-1123.05				
r^1			-0.474 ***	0.240		
r^2					-0.495 ***	0.168
Rho_1			-0.442 **	0.194		
Rho_2					-0.458 ***	0.133
Wald test of independent eqns. :		chi2(1) = 12.91		prob > chi2 = 0.0003		

*Note: * , ** and * ** represents the significant levels at 10%, 5% and 1% levels respectively*

r^1r^2: Transformation of the correlation of the error terms in the adoption equation and outcome equation

ρ1ρ0: Correlation coefficient between error terms of the system equation

Source: Survey Data (2019

The estimates in the selection equation in Table 9 suggest that the main drivers of adoption decision of climate-smart maize varieties ranged from socioeconomic characteristics to varietal attributes. The respondent's age is significant at 1% and negatively influences farmers' decision to adopt climate-smart maize varieties. The result shows that as the respondent's age increased in years, it reduced the respondents' likelihood to adopt. These results substantiate findings in Kuntashula *et al*. (2014) and Ngoma *et al*. (2018).

Land ownership was statistically significant at 1% and positively influencing the decision to adopt. This result showed if a farming household-owned land, it increased the household likelihood of adoption. The result was consistent with that of Abdulai *et al*. (2011). Source of seed was positive and significant, suggesting that those farmers who sourced their seeds from the agro vet were more likely to adopt climate-smart maize varieties. This result would have been brought by the fact that when the farmer sources seeds from the certified agro vet, it is perceived as original, not counterfeit, which increases production hence increasing household income. The outcome was consistent with that of Ghimire *et al*. (2015).

According to agronomic factors applied by the farming household: fertilizer application, mode of tillage, crop protection, and mode of weeding were all significant and positively influencing the likelihood of farming households adopting climate-smart maize varieties as per the expectation. This result implies that if a farmer perceives that they will apply fertilizer and do crop protection on their maize such as pesticide application, it increased their probability of adopting the climate-smart maize varieties. In terms of mode of weeding and tillage, if a farming household perceives that they will plough their land and do hand weeding, it will increase their probability of adopting climate-smart maize varieties. The access to extension services was positive and significant, which indicated that farmers with contact to extension officers increased the probability of adoption. This result is consistence with that of Difalco *et al*. (2011); Kassie *et al*. (2015) and Maina *et al*. (2019), who found out that extension office availability increased the probability of a farmer to adopt new technologies.

The credit variable was significant at 1% and positive, indicating that farmers who could access credit services were more probable to adopt climate-smart maize varieties. This result implies that if a farmer's access formal credit since it will act as a source of financing production of adopted maize variety. This result was consistent with Abdulai *et al*. (2013) and Khanal *et al*. (2018), who found that credit access increased the probability of adopting new technologies. In terms of varietal attributes, which are high yielding, early maturity, drought resistance, and resistance to pest and disease were positive and significant, implying that if a farmer perceived that these varieties have these traits, it increased the likelihood of a farmer adopting them.

The results on the adoption impact on household income are presented in columns 4, 5 for those who adopted, and 6, 7 for those who did not adopt in Table 9. The ESR estimates of household income determinants between those who adopted and non-adopters are presented in Table 9. The Table 10 presents the estimates for the treatment effects and heterogeneity. The results in Table 9 show that the respondent age, education level, land under climate-smart maize production, and distance to the market were positive and significantly important factors in explaining higher household income in both farming households that adopted and those who did not adopt. However, the gender of the household head, fertilizer application, mode of tillage, mode of weeding, and access to credit appears to have a differentiated impact on the household income of those who adopted and non-adopters.

The results in column 4 in Table 9 indicate that gender of respondents and mode of tillage are significant and positively affecting household income among adopters. At the same time, access to credit has a negative and significant effect on adopters' household income. On the other hand, fertilizer application and mode of weeding in column 6 in Table 9 have a significant and negative effect on a household income of non-adopters.

The assessment of the main impact showing the expected household income under the actual and counterfactual conditions are presented on Table 10. The predicted household income from the Endogenous Switching Regression model is used to examine the gap of the mean household income between the adopters when they adopted and had they not adopted and non-adopters and the conditions if they adopted. Cell (a) and (b) denotes the expected household income observed from the sample for adopters and non-adopters, respectively. Cell (c) would represent the expected household income of those who adopted if they decided not to adopt while cell (d) exemplifies the expected household income of the non-adopters had they decided to adopt.

Table 10: Impact of climate-smart maize adoption on household income

Sub-samples	**Decision stages**		**Treatment Effect**
	To adopt	**Not to adopt**	
Log household income			
Farmers who adopted	(a) 10.861	(c) 9.138	(ATT)1.7221(0.029)***
Farmers who did not adopt	(d) 11.439	(b) 10.319	(ATU)1.1199(0.036)***
Heterogeneity effects	BH_1 = -0.578	BH_2 = -1.181	TH = 0.6022(0.046) ***

*Note: * , ** and * ** represents the significant levels at 10%, 5% and 1% levels respectively*

Source: Survey Data (2019)

The expected log household income of the farming households that adopted is about 10.861, while about 10.319 for the farming household that did not adopt. This result indicates that on average, the households that adopted the climate-smart maize varieties increased their household income by 0.54, which is 54% more than farming households that did not adopt. According to Difalco *et* *al.* (2011), this is a simple comparison that may be inadequate to compel the researcher to decide that, on average, the adopters of climate-smart maize varieties earned more than the farm households that did not adopt. Therefore, using the heterogeneity effects for accounting for counterfactuals ((c) and (d)).

On Table 10 the last column, the average treatment effects are presented indicating the impact of the adoption on household income. These treatment effects will account for any selection bias which may arise from the fact that those who adopted and non-adopters may be systematically different (Abdulai and Huffman, 2014). The Average treatment on the treated (ATT) is the difference between how much adopters earned (a) and what adopters would have earned had they not adopted (c). At the same time, ATU is the difference between how much those who did not adopt would have earned had they decided to adopt (d), and how much they earned without adoption, the actual estimate of non-adopters (b).

The results from the last column of Table 10 shows that ATT is statistically significant and positive, implying that, decision to adopt climate-smart maize variety increased household income by 172%. This result denotes that, adopters would lose an average log of 1.72 of the total household income if they had not adopted. The average treatment effect on untreated (ATU) results from the ESR, which is positive and statistically significant, indicates that those who did not adopt would have increased their household income by 112% had they decided to adopt climate-smart maize varieties. The difference between the ATT and ATU gives us the Transitional Heterogeneity (TH), which was 60.2%. The results imply that the adoption of climate-smart maize varieties increases adopters' household income by 60%. This result was consistent with the conclusion made by Khonje *et al*. (2015), who concluded that the decision to adopt improved maize varieties increased adopters' crop income. In their study in Zambia, Smale and Mason (2014) deduced that adopting hybrid maize varieties especially through subsidy increased household income.

The last row of Table 10 shows a positive and highly significant transitional heterogeneity (TH) for the outcome variable, which suggests that those who adopted and non-adopters were systematically different. Transitional heterogeneity estimates whether the effect of using CSMVs is larger or lesser for farmers that adopted CSMVs had they decided not adopt, or for farmers that did not adopt CSMVs had they decided to adopt (Ngoma *et al*., 2018). Positive TH in the study implies that the effect of the adoption of CSMVs is significantly higher for the farming household that adopted to those who did not adopt. This result was in conscience with Asfaw and Shiferaw, (2010). The significance of TH in the study implies that farmers who adopted would earn significantly more income than those who did not adopt in the counterfactual case (c). The positive TH shows that there are some essential sources of heterogeneity that make adopters better off and earn more than non-adopters regardless of adopting or not adopting climate-smart maize varieties. The result is in consistence with the finding of Di Falco et al. (2011), Khanal *et al*. (2018) and Quan *et al*. (2019).

CHAPTER 5. 0

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary

Climate-smart maize varieties are vital for ensuring food security and poverty eradication in Kenya, especially in areas faced by changing climatic conditions. Food security has been threatened by increasing drought caused by changing climate within the emerging drier part of eastern Kenya, especially the Embu region. This problem calls for interventions to tackle the menace and improve the production of major staple food such as maize in the region and the country. As such the seed sector has introduced various varieties of maize and released them in the market. However, there is little empirical insight on the adoption rate and the impact of the adoption on the household income to assist in reducing food insecurity and reduce poverty level among rural areas, especially in Embu County. Therefore, the study focused on examining the adoption of climate-smart maize varieties and their impact on household income in Embu County.

Three specific objectives guided the study: to characterize the adoption of climate-smart maize varieties, to evaluate the factors influencing the intensity of adoption of climate-smart maize varieties, and lastly, to analyze the impact of the adoption of climate-smart maize varieties on household income.

The study used the double hurdle regression model to assess the influences of the intensity of adoption and endogenous switching regression model to evaluate the impact of adoption on household income. The study used a multi-stage random sampling procedure to draw a sample of 550 respondents, and semi-structured questionnaire was used to collect primary data.

The results indicated that the rate of adoption of climate-smart maize varieties was 63%. The most common maize varieties grown in the area were Duma 43, DK 8031, Decalp, pioneer, and *kiembu*, a local variety. The majority of the farmers were aware of these varieties' existence in the study area, but only a small percentage of the farmers were growing a number of them. The results indicate that only 55%, 4% and 5% of the respondents were growing Duma 43, DK 8031 and Decalp respectively, whereas 26% of respondents were planting *kiembu*. The results revealed that in general, farmers perceived the climate-smart maize varieties to be high yielding, early maturity, resistance to pest and diseases, and drought resistance. Moreover, farmers perceived local varieties to be highly resistant to pests and diseases and having good taste compared to other improved varieties.

The double hurdle model results indicate that if a farmer-owned a land with a title, had an off-farm income, sourced seeds from an agro vet, had contact with extension agent, and was a member of any association group significantly increased the likelihood of choosing climate-smart maize varieties. Among the varietal attributes, high yielding, early maturity, tolerance to drought, and resistance to pest and diseases significantly increased the probability of selecting climate-smart maize varieties.

Additionally, as the age of the respondents' and the size of the land increased they had a significant and negative influence on the likelihood of using climate-smart maize varieties. The results in the model indicate that land size, land ownership, size of the respondent family, contact to extension officer, and previous yield significantly increased the likelihood of allocating more land under climate-smart maize variety production. However, as the respondent's age increased, it significantly reduced the intensity of the use of climate-smart maize varieties.

The full information endogenous switching regression model results show that agronomic factors in this study; fertilizer application, crop protection mode of tillage, and weeding increased the likelihood of adopting climate-smart maize varieties. The results indicated that the respondents' age, level of education of the respondents, land dedicated to climate-smart maize variety, and distance to the market had a significant and positive effect on the household income on those who adopted and non-adopters. The causal impact implication from FIML endogenous switching regression model suggests that adoption of climate-smart maize variety increased the household income by 60%.Farming households that adopted would have earned about 172% less household income if they did not adopt. Similarly, farming households' who did not adopt would have earned about 112% more if they had adopted. This result shows that farmers who adopted were better off in terms of household income compared to those who did not adopted.

5.2 Conclusion

The results show that most of the farmers were aware of the climate-smart maize varieties, but only about 63% had adopted them. The results from the study showed great potential for increasing household income through the adoption of climate-smart maize varieties. The study also looked at the viability of farmers' adoption and intensity of adopting climate-smart maize variety given the potential returns. Therefore, there is a need for widespread adoption to enable more people to benefit from these climate-smart maize varieties.

This widespread can be done by addressing the factors that affect the decision to adopt and those that influence the intensity of adopting climate-smart maize varieties. In terms of varietal attributes, all of them contribute to the adoption of climate-smart maize varieties. Age of the respondents negatively influenced both the adoption and intensity of adoption, implying that older farmers were skeptical about these varieties; hence youth were the most likely to adopt them. Therefore, strategies are needed to make maize enterprises more attractive to unemployed youths, which can be done through improved access to extension services.

Extension service was positively contributing to the decision to adopt and intensity of adoption of climate-smart maize varieties. Thus there is a need to strengthen support in the provision of extension service since only a minimum number of farmers had access to extension officer. Farmers who were in any form of association contributed them to adopt climate-smart maize varieties.

The amount of land the farming household had negatively influenced the adoption but positively contributed to the use intensity of the climate-smart maize varieties. Land tenure contributed positively to the choice of variety and the extent to which to utilize the climate-smart maize varieties. This because land acts as a security to acquire some of the needed credit to facilitate production cost hence being a considerate factor when adopting these varieties. As Ali *et al*. (2012) noted, owner-cultivators who had secured tenancy arrangements were more probable to do investment in measures that are soil-improving and productivity-enhancing than those on leased contracts in Pakistan.

On the adoption impact on household income, the results indicates that the adoption of climate-smart maize varieties increased household income by 60%. This increase can be interpreted in two ways: the adoption may increase household income through increased productivity, which farmers sell, and the income from maize sale contributes to household income. Secondly, the higher rate of adoption of climate-smart maize varieties is concomitant with increase in household food security if the farm household gets food from its production, hence not spending any income on food purchase, especially maize. The casual impact estimation from switching regression suggests that the adopters had significantly higher household income than those who did not adopt even after controlling for all confounding factors. Additionally, the results indicated that those farmers who did not adopt would have gained from the adoption of climate-smart maize varieties if they did adopt. Consequently, agricultural growth in order to reduce poverty and improve food security essentially depends on the adoption of climate-smart agricultural technologies such as climate-smart maize varieties. The results indicate that age and land under maize had a significant effect on decision to adopt and household income of those who adopted and non-adopters.

The results show education had a statistical significant and positive impact on the household income of those who adopted and non-adopters. Therefore, it draws attention to the importance of enhancing the farmer's education, particularly in rural areas. Distance to the market was significant and positively contributing to the household income of both adopters and those who did not adopt. Therefore, it indicates that easy to access into market and availability of market plays a key role in reduction of high transaction costs to farmers, which may affect their household income.

Credit access has a positive and significant contribution to the probability of adopting (CSMVs) but negatively influences the adopters' household income. Thus indicating the role of credit in allowing the farming households to facilitate the implementation of adoption of climate-smart maize varieties, but reducing adopters' income due to high-interest rates. The casual effect of the adoption of the climate-smart maize varieties had a positive and significant impact on household income which reaffirms the potential role of climate-smart agricultural technology in raising farm productivity and directly reducing poverty levels in rural areas through high household incomes.

5.3 Recommendation

The findings from this study suggest that more efforts and resources should be directed towards enabling the adoption of climate-smart maize varieties besides creating awareness. Hence, both government actors such as KALRO and non-government actors such as STAK should invest in linking farmers to different information sources to enable farmers to access quality varieties to promote adoption. The government should also direct the resource through KALRO towards breeding of more varieties that are tolerant to high temperatures, resistance to diseases and pests, fast-maturing, and high yielding, which are attributes desired by the farmers due to increasing climatic changes. Additionally, to promote their adoption, the seeds should be made available to farmers at affordable prices.

The age of a farmer in maize production contributes to the adoption, extent of use, and household income of those who adopted and non-adopters. Young farmers are more probable to adopt climate-smart maize varieties as age increases as the extent of use and income increases. This increase is due to other supporting factors, such as access to land. Therefore, strategies are needed to make maize enterprise more attractive to unemployed youths. The enterprise can be made more attractive by formulating policies that make youths access the production factors such as land, mostly held by older farmers. Although extension service is one way to promote youths venturing in agriculture, access to extension agents is very low, hence calling to the county government since agriculture is devolved to increase the number of extension officers in the region.

Access to extension services contributes to adoption, and therefore there is a need to strengthen support in the provision of extension services. The study recommends the county government and private sectors to come up with more innovative ways to disseminate information to farmers to increase the intensity of extension outreach to farmers. This outreach could be through incorporating Information Communication Technologies (ICTs) such as mobile phones, televisions, or radio, where almost every household has one in the dissemination of agricultural information, which can contribute greatly to increasing farmers’ access to information.

The finding shows that land is significant in deciding to adopt, the extent of the area to dedicate adopted variety, which contributes positively to the farmers' household income. Therefore, to improve the decision to adopt and production of climate-smart maize varieties, the county government of Embu needs to enhance land registration and adjudication to improve land tenancy. This registration will make more farmers have title deeds for their farms, thus improving their adoption rate, which will improve productivity and income level of small scale farmers. The findings show that the land's size has been decreasing over the years in the region due to population pressure on arable land. Thus, multi-stakeholders need to invest in capacity building on production intensification measures such as use fertilizers, crop protection, and use of high yielding varieties to increase output per unit area since it’s not possible to increase the land size among farmers.

There was a positive influence of access to credit on the endogenous switching model on adoption and negative impact on adopters’ household income. It suggested that policies that enhance access to affordable credit would go a long way toward adopting new climate-smart agricultural technologies and household income. Thus this can be done by taking corrective action between government institutions, financial institutions, and farm-driven strategies. Lending institutions such as commercial banks and micro-finance should work out strategies that will avail affordable credit to farmers by lowering interest rates and simplifying application bureaucracy.

The government and research institutions should develop innovative ways of assisting farmers in accessing credit. For example, coming up with mobile apps that will analyze farmer information such as production process make that information accessible to financial institutions to assess risk and develop loans such as farm drive mobile platform. The other strategy which can be used to reduce risk, which may hinder lenders from advancing loan to farmers is by the introduction of insurance cover for agricultural loans. Insurance cover has seen to improve the credit access by farmers as narrated by Mishra *et al*. (2018) on their policy brief on the innovation lab for assets and market access in Ghana. They found out that insured agricultural loans significantly increased credit access and adoption of farming technologies among small scale farmers.

Additionally, farmers should be encouraged to form farming groups to help them improve their social capital. Farming groups can act as a form of collateral to them to secure loans, especially small scale farmers without collateral. Finally, there is a need for policies that will be directed at improving the adoption of climate-smart maize varieties amongst the non-adopters through the provision of more competent and effective extension services, addressing land tenure system and price of related agronomic practices.

5.4 Suggestion for further research

Future research can focus on assessing the effectiveness of adoption rather than on household income. Since the adoption of climate-smart maize varieties needs the application of more chemical fertilizers, which may be expensive for a farmer to acquire. This may lead to deterioration of soil health, and farming may not be sustainable in the long run. Therefore, adoption may be expensive to implement and inconsistent with ecosystem balancing.

There were those varieties that farmers were planting there before, but they don’t do now. Future research can focus on dis-adoption and factors contributing to the dis-adoption of these maize varieties. The study call for future research to investigate whether insured loans can improve credit access to the farmers in Kenya.

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Appendices

Appendix 1: VIF results for explanatory variables used in both models

Variable	*VIF*	*1/VIF*
Age of respondent	1.22	0.817270
Previous yield	1.19	0.841956
Land size	1.16	0.861516
Land ownership	1.14	0.879856
Log of off-income	1.12	0.891153
Access to credit	1.09	0.918866
Tolerant to drought	1.09	0.920939
Group membership	1.08	0.923599
Access to extension services	1.08	0.927476
Early maturity	1.08	0.928064
Gender of the farmer	1.07	0.931536
High yield	1.06	0.942191
Size of the household	1.06	0.943147
Source of seeds	1.06	0.947184
Resistance to pest and diseases	1.03	0.966892
Mean VIF	1.10	

Source :**survey Data(2019)**

Appendix 2: Pearson correlation coefficients for multicollinearity test

	gende~01	age	hhsize	landsize	landow~p	accese~n	grpmem~r	previo~d	highyi~s	earlym~y	pestdi~t	drghtt~t	logoff~m	seedso~M	credit~s
gender_01	1.0000														
age	-0.0822	1.0000													
hhsize	0.1512	-0.0904	1.0000												
landsize	0.0627	0.1738	0.1122	1.0000											
landownship	-0.0735	0.2177	0.0487	0.2226	1.0000										
accesexten	0.0643	0.0222	0.0662	0.0328	0.0031	1.0000									
grpmember	-0.0511	-0.0497	0.0788	-0.0356	0.0165	0.1208	1.0000								
previousyi~d	0.0626	0.1347	0.0772	0.2590	0.1256	0.0197	-0.0549	1.0000							
highyields	0.0811	0.0493	0.0398	0.1171	-0.0099	0.1148	0.0432	0.1123	1.0000						
earlymatur~y	-0.0643	0.0035	-0.0225	-0.0791	-0.0481	0.0559	0.1790	-0.1460	-0.0654	1.0000					
pestdisrest	0.0265	-0.0656	0.0223	-0.0291	-0.0949	0.0142	0.0313	-0.0021	0.0213	-0.0101	1.0000				
drghttoler~t	-0.0772	-0.0641	0.0252	-0.0226	0.0822	-0.0370	0.0299	0.1443	-0.1114	0.0095	0.0117	1.0000			
logoffinco~m	0.1265	-0.2355	0.0484	-0.0955	-0.0540	-0.0081	0.0875	-0.1121	-0.0175	-0.0101	-0.0263	-0.0775	1.0000		
seedsource~M	0.0362	-0.0459	0.0889	0.0292	0.0687	0.1148	0.0432	0.1987	0.2512	-0.0325	-0.0127	0.1252	0.0195	1.0000	
creditacces	0.0493	0.0264	0.0176	0.0248	0.0389	0.0196	0.1089	0.0913	-0.0159	0.0320	0.0291	-0.0158	-0.0055	-0.0572	1.0000

Source: survey Data (2019)

Appendix 3: Test results for heteroscedasticity

The results presented below show there is presence of heteroscedasticity as chi2 of 21.14 was large and significant at 1%.To counter this problem the robust standard error terms were used in the subsequent analyses.

Appendix 4: Questionnaire

University of Nairobi

Adoption of Climate-Smart Maize Varieties and Its Impact on household income among Small-Scale Farmers in Embu County, Kenya

INTRODUCTION

Dear Sir/ Madam

The University of Nairobi, Department of Agricultural Economics is interested in conducting a research survey to assess Adoption of climate-smart maize varieties and its impact on the household income of small-scale farmers at Runyenjes.

The objective of the study is to assess the adoption of climate-smart maize variety and its impact on household income among small scale farmers. This will enable the involved stakeholders and policy formulation personnel to effectively address the reasons which are surrounding adoption of given varieties.

The information you provide will be treated with ultimate confidentiality and used for academic and policy purposes only. This interview will take at least 30 minutes and your dedication and time will be highly appreciated. I would like to begin the interview now.

The respondent must be an individual who normally makes farm decisions in the household. This must be the household head or the spouse.

Section A. Identification

A.1 Name of Respondent	|___________|	A.1a.Respondent's Cellphone number	|___________|
A.2 County	|___________|	A.3 Sub-County	|___________|
A.4 Ward	|___________|	A.5 Location	|___________|
A.6 Sub-location	|___________|	A.7 Village	|___________|
A.8 Household/ Respondent Code	|___________|	A.9 Date of Interview	|___________|

GPS Coordinates: Longitude|___________| Latitude |___________|

Section B. Household characteristics

B.1 Name of the Household Head	B.2 Sex of household head	B.3 Age of household head in years	B.4 Household size	B.5 Level of formal education of Household Head	B.6 Source of HH income (Estimated Amount per year)				
					B.6a Sale of crop produce	B.6b Sale of livestock/ livestock products	B.6c Off-farm employment	B.6d Business	B.6e Other (Specify)
	(1=Male,2 = Female)			(1= Primary ,2= Secondary, 3= college/university, 4=None)					

Section C. Land characteristics and production	
C.1 What is the total size of land available to the household in acres?	[__ __ __]
C.2 What is the type of land ownership? (1 = Owned with title , 2 = Hired , 3= Owned without title 4= Other, specify)	[__ __ __]
C.3 How many maize plots do you have?	[__ __]
C.4 What is the total size of all the land under maize production in acres?	[__ __]
C.5 What is the size of the main/major maize plot in acres	[__ __]
C.6 Have you ever received advice/training on maize production (1= Yes, 0= No)?	[__ __]
C7. If yes, where did you get the advice/training from? (1= Extension ,2= Agro dealers ,3 = Other farmers ,4= Media , 5= Research/Academic	[__ __]

Institutions, 6= NGOs ,7 = Agricultural Training Centre (ATC); 8= Others, specify)	
Maize crop management practices	
C.8 Which method of weeding do you use?(1= Hand weeding; 2= herbicides; 3=Other (Specify)),	[__ __]
C.9 Which type of tillage do you use?(1= Minimum tillage, 2= Ploughing)	[__ __]
C10. Do you use fertilizer in your main maize plot? 1= Yes, 0= No)	[__ __]
C.11 What is the type of fertilizer used? (1= Organic ,2 = inorganic ,3= None)	[__ __]
C.112 In case you use fertilizer, when do you apply (1= Basal; 2=Top dressing, 3= Both 1&2)	
C.13 Do you use crop protection on maize? (1= Yes, 0= No)	[__ __]
C.14 How many years have you been in maize farming?	[__ __]
C.15What is your estimated output of maize from the current main maize plot	[__ __]
C.16.Specify unit of weight for the estimated output from the main maize plot (1= 90kg bag , 2 = 50kg bag , 3= 20kg bucket (debe) ,4 = 2kg tin , 5= other (specify))	[__ __]
C.17 Does any member of your household belong to any social group? (1= Yes, 0= No)	[__ __]

Section D. Maize Variety Use

D.1 What is the name of the Maize Variet	D.2 Is the variety improve d?	D.3 Where did you get the seed from?	D.4 What are the two most important reasons why you grow or	D.4 If you used own save seed, selected,	D.5 Which other maize varieties do you know

y grown in the main maize plot this season? (Oct 2018-March 2019)			like this variety?				that can be grown in this area or are grown by your neighbors?
			1= = High yields =2= early maturing 3= Resistance to pests and diseases 4= Drought tolerant 5= Good taste 6= Fetches good prices 7= Good cookability 8= Others (specify)	D.4a When did you get the original seed of this variety? (Give year)	D.4b Where did you get the original seed of this variety?	D.4c What seed quality maintenance practices do you use?	
	(1= Yes, 0 = No)	(1= Agrovet inputs dealer,2= Seed company/cooperatives, 3= Local open market ,4= Other farmers ,5 = Own seed from previous season ,6 = Government ,7 = NGO; 7=other (specify)				(1= Seed cleaning before planting, 2= seed treatment ,3 = Rouging off-types ,4= Seed storage, 5=others, specify)	(codes for varieties ,to be provided)

Section E. Market factors

E.1 Do you have access to credit?	E.2 Do you produce maize for selling?	E.3 If no, why?	E.4 If yes, where do you sell the maize?	E.5 What is the distance to all weather road in km?	E.6 What is the distance to the main farm input market in km?	E.7 What are some of the constraints that do you face in maize production?	E.8 What are some of the constraints that you face in maize marketing?
(1= yes , 0= No)	(1= Yes , 0= No)	1= Not enough to sell 2=Not profitable 3= No good market 4= Land is small 5= Costly to farm a lot of maize 6= Other (specify)	(1= Local Market, 2 = Brokers ,3= NCPB, 4= Millers ,5=Neighbours, 6 = Institutions 7=At farm gate to local traders)			(1 = High cost of inputs, 2= Pests and diseases ,3 = Unpredictable weather, 4= Post harvest losses ,5 = Poor seed quality, 6= Poor fertilizer quality 7=Others (specify)	(1= Low prices ,2= Excess supply of maize,3= Post harvest losses ,4 =Unpredictable weather,5 = Low yields; 7= Long distance to market; 8=Other)