RISK ATTITUDES AND ADOPTION OF CLIMATE SMART AGRICULTURAL TECHNOLOGIES AMONG SMALLHOLDER FARMERS IN THE NYANDO BASIN IN SOUTH-WESTERN KENYA.

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Declaration

This thesis is my original work and has not been submitted for the award of a degree in any other University.

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Approval

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Dedication

I dedicate this thesis to my parents, David Mwangangi and Francisca Ndunge, my wife, Lucia and my daughter, Sheryl and finally my siblings and friends who have earnestly supported me and encouraged me in this academic journey.

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List of Acronyms and Abbreviations

ASALs:-Arid and Semi-Arid Lands

BP:-Breusch-Pagan

CCAFS:- Climate Change Agriculture and Food Security

CRRA:- Coefficient of Relative Risk Aversion

CSA:-Climate Smart Agriculture

CSVs:-Climate Smart Villages

DMs:-Decision Makers

DOI:-Diffusion of Innovation

FHHs:-Female-headed households

GHGs:-Green House Gases

ILRI-International Livestock Research Institute

IPCC:- Intergovernmental Panel on Climate Change

MHHs-Male-headed households

MVP:-Multivariate Probit

OLS:-Ordinary Least Squares

OP:-Ordered Probit

PBC:-Planned Behavioral Control

PCA:-Principal Component Analysis

SDG:-Sustainable Development Goal

SIPs:-Sustainable Intensification Practices

SLM:-Sustainable Land Management

SN:-Subjective Norm

SSA:-Sub-Saharan Africa

TLU:-Tropical Livestock Unit

TPB:-Theory of Planned Behavior

VIFs:-Variance Inflation Factors

Abstract

Adverse climate change threatens livelihood security of rural households that depend mainly on on-farm income sources as it leads to depressed yields from both crop and livestock production. Climate smart agriculture innovations offer an avenue for farmers to concurrently build resilience to climate change and increase agricultural productivity. This study focused on risk attitudes and adoption of climate smart agricultural technologies among smallholder farmers in the Nyando basin in South-Western Kenya. . The specific objectives of the study were to assess Nyando basin farmers risk attitudes; determine the factors influencing livelihood diversification among Nyando households; and finally determine how Nyando basin farmers' risk attitudes and livelihood diversification influence their adoption of climate smart agricultural technologies. The study hypotheses were that Nyando smallholder farmers do not have a risk averse attitude; household head, household socioeconomic characteristics and institutional factors do not significantly influence Nyando households livelihood diversification; Nyando basin farmers risk attitudes and household livelihood diversification do not significantly influence the adoption of CSA technologies. The study utilized primary data collected from 122 randomly selected farm households in the contiguous Nyando basin stretching between Kisumu and Kericho counties. Farmers risk attitudes were elicited through a hypothetical risk experiment and the results of the experiment showed that Nyando basin farmers were moderately risk averse. The factors that influence Nyando households' livelihood diversification were modeled through a binary logit model. The results showed that the age of the household head, farmer training and social capital had a significant negative influence on livelihood diversification, household head education and the effect of floods significantly favored livelihood diversification. The study analyzed the effect of farmers' risk attitudes and household livelihood diversification on adoption of climate smart agricultural technologies through the multivariate probit and ordered probit models. Farmers' risk attitudes and livelihood diversification had a significant influence on probability of households adopting climate smart agricultural technologies. Other variables which had a significant influence on the decision of households to adopt climate smart agricultural technologies were gender of household head, wealth status of a household, distance to local markets, access to loans, farmer training, location and climate risks. The study recommends farmer training and farmer loan access to promote adoption of appropriate climate smart agricultural technologies. Targeted farmer training will help to promote livelihood diversification among Nyando basin rural households. Considering that farmers' risk attitudes significantly influence adoption of climate smart technologies, relevant stakeholders should work on providing appropriate insurance covers to encourage a greater adoption of agricultural technologies. Future research can incorporate plot analysis in analyzing the factors that influence the adoption of climate smart agricultural technologies in the Nyando basin region.

Keywords: Climate smart agricultural technologies, multivariate and ordered probit models, adoption of agricultural technologies, livelihood diversification, Nyando basin.

CHAPTER ONE: INTRODUCTION

1.1 Background

As noted by Njoka *et al.* (2016), at least 80 percent of Kenya land mass is arid and semi-arid lands (ASALs). In Kenya; 14 counties are semi-arid while nine are arid out of the 47 administrative counties (Republic of Kenya, 2012; Njoka *et al.*, 2016). ASALs are vulnerable to adverse effects of climate change (World Bank & CIAT, 2015). Climate change exposes smallholder farmers to production risks in both crop and livestock farming (Hardaker *et al.*, 2015) and, therefore, there is a need to focus energies in implementing climate smart agricultural technologies in Kenya’s agricultural sector in the ASALs, especially at the production level. This will foster the mitigation of the adverse effects of climate change. Climate smart agriculture (CSA) is an approach of practicing agriculture in a sustainable way and it contributes to the realization of sustainable development goals (SDGs) (Palombi & Sessa, 2013). Aggarwal *et al.* (2018) asserted that CSA leads to increasing agricultural production through building resilience and adapting to climate change.

Through Climate Change, Agriculture and Food Security (CCAFS) program, experts and stakeholders have embraced a climate smart villages (CSVs) approach with an aim to promote agricultural technologies that enhance household food security and household income(Aggarwal *et al.*, 2018). The purpose of CSV approach is to collect evidence on the type of CSA technologies best suited to a given locality to aid policy makers in choosing the best course of action to respond to adverse climate change and offer insights to agricultural stakeholders at both local to global levels. The CSV approach incorporates five key components: i) national and subnational plans and policies, ii) farmers’ knowledge, iii) local and national level private and public institutions, iv) CSA technologies, and lastly, v) climate information services and insurance (Aggarwal *et al.*, 2018).

East Africa has particularly experienced extreme weather events, droughts and dry spells because of climate change. Agroforestry, water harvesting and improved small ruminants are the key climate smart technologies advocated and implemented to mitigate these climate risks (Aggarwal *et al.,* 2018). Nyando basin region is one of the CCAFS sites in Kenya and part of the larger CCAFS target regions in Eastern Africa (Aggarwal *et al.*, 2018; Bernier *et al.*, 2015).

Kinyangi *et al.* (2015) described Nyando basin as a region prone to adverse effects of climate change. The Nyando basin climate risks include decrease in rainfall frequency and increase in rainfall variability, a rise in frequency of droughts in the past decade compared to 20-30 years ago, increase in average temperatures and high frequency of storms and strong winds (Thorlakson, 2011). The average temperature increase and rainfall variability is consistent with the consequences of climate change in other parts of Kenya (Njoka *et al.*, 2016). Nyando basin has also experienced floods that have led to long-term negative farmland productivity as reported by affected farmers (Thorlakson, 2011).

According to Kinyangi *et al.* (2015), the CSV approach in Nyando basin particularly aimed at improving farmers' local knowledge of climate change and risks associated with climate change in the region. This in turn would help farmers build capacity to embrace CSA technologies that would enable them become resilient to adverse climate change in the region. CSA technologies are agricultural technologies meant to enable farmers cope with climate risks in farming and increase farm level productivity in a sustainable way(Mutenje *et al.*, 2019). CSA technologies are context specific agricultural technologies and the appropriateness of CSA technologies may differ by gender, region, age and cultural dimensions(Mwongera *et al.*, 2017)

The main CSA technologies for the Nyando basin region as promoted under the CCAFS program include crop residue mulching, minimum tillage, no till and water harvesting and irrigation. Other technologies include the adoption of improved seed varieties, terraces, ridges and bunds where applicable, efficient use of fertilizer, agroforestry and livestock management practices including rearing of improved stress-tolerant sheep and goat breeds (Bernier *et al.*, 2015; Karuku, 2018). The stress tolerant livestock species in the Nyando basin as promoted by CCAFS and International Livestock Research Institute (ILRI) include the Red Maasai sheep and the Galla goat (Kinyangi *et al.*, 2015).

Kurgat *et al.* (2020) noted that there are potential trade-offs and complementarity in the adoption of varied climate smart agricultural technologies among farmers in Tanzania. This shows that farmers perceive some climate smart agricultural technologies as substitutes while others as complements. Zakaria *et al.* (2020) insisted that farmers in the ASALs have to take the advantage of adopting several CSA technologies in order to improve their resilience against climate change. Since there are multiple climate smart agricultural technologies promoted in the Nyando basin, farmers in the region stand to benefit from exploiting the synergies in the adoption of multiple CSA technologies.

Crentsil *et al.* (2018) and Hardaker *et al.* (2015) stated that the adoption of new agricultural technologies among smallholder farmers is a risky undertaking due to the additional resources required. The need for additional resources exposes smallholder farmers to financial risk when faced with the decision of whether or not to adopt agricultural technologies(Komarek *et al.*, 2020). Nyando basin smallholder farmers are exposed to the financial risk involved in allocating additional financial resources in the adoption of appropriate CSA technologies. Financial risk emerges particularly from the fact that famers may choose to rely on credit financing to acquire new agricultural technologies (Komarek *et al.*, 2020).

Farmers fall into three risk attitudes as shown in literature; risk averse, risk neutral or risk loving attitudes (Hurley, 2010). Farmers' risk attitudes may influence their behavior in allocating resources to various farm operations and in the adoption of varied farm technologies For instance, Hill (2009) found that risk averse poor Ugandan farmers allocated less labor towards coffee production. Crentsil *et al.* (2018) found that risk averse Ghanaian farmers were more likely to adopt three aquaculture technologies. Similarly, Shimamoto *et al.* (2018) found that risk averse Cambodian farmers were more likely to adopt the use of moisture meters as a post-harvest technology. Contrary, Ambali *et al.* (2019) found that risk loving Nigerian farmers were more likely to adopt a high yielding rice variety. These studies show that farmers' risk attitudes influence on adoption of varied farm technologies differ by locality and the technologies in question.

The main livelihood source of Nyando basin residents is rain-fed subsistence agriculture, which includes rearing local cattle breeds and growing food crops such as maize and sorghum (Aggarwal *et al.*, 2018; Kinyangi *et al.*, 2015). A majority of agricultural households in Nyando basin do not produce enough food from their farms for own consumption (Kinyangi *et al.*, 2015). Kinyangi *et al.* (2015) noted that more than 75 percent of households in Nyando face at least one hunger month per annum. Connolly-Boutin Smit (2016) noted that livelihood diversification from on-farm sources is a main strategy to cope with unreliable on-farm income occasioned by adverse climate change in Sub-Saharan Africa (SSA). Rural smallholder households in SSA affected adversely by climate change can be able to earn income from having diversified livelihoods in order to cater for their financial needs. More income sources may translate to more likelihood of farmers adopting appropriate CSA if they manage to overcome the financial constraints hindering technology adoption.

1.2 Statement of the problem

Adoption of farm level climate smart agricultural technologies is one of the avenues through which smallholder farmers can become resilient against adverse climate change.

Adoption of CSA technologies has been analyzed mainly through two approaches; piecemeal adoption in univariate analysis or multiple adoption in joint analysis. Aryal *et al.* (2018) analyzed the multiple adoption of a bundle of CSA technologies in India by using a multivariate probit model and found farmers adopted the technologies in a joint manner; farmers adopted some technologies as substitutes and other technologies as complements. Shikuku *et al.* (2017) used binary probit model and Bernier *et al.* (2015) used the Heckman two stage selection model to analyze the piecemeal adoption of CSA technologies by farmers in the Nyando basin. Teklewold *et al.* (2013) argued that it is important to consider cross-technology correlation effects in joint technology adoption analysis to avoid generating biased estimates when analyzing the piecemeal adoption of technologies in univariate analysis. There is limited empirical knowledge in literature on the possible cross-technology correlation effects in the adoption of various CSA technologies by Nyando basin farmers.

Hardaker *et al.* (2015) pointed out that models that incorporate risk as determinant of technology adoption predict better farmers' behavior than models that ignore risk. Bernier *et al.* (2015) recommended analyzing how risk influences the adoption of terraces, inorganic fertilizer and drought tolerant livestock breeds in the Nyando basin. There is limited knowledge in literature on how risk influences the adoption of CSA technologies among Nyando basin smallholder farmers.

Teshager Abeje *et al.* (2019) pointed out that there is a possible empirical link between livelihood diversification and adoption of agricultural technologies. Using ordered probit (OP) model Teshager Abeje *et al.* (2019) found that livelihood diversification had a significant inverse relationship with the intensity of adoption of sustainable land management practices among Ethiopian households. This study sought to determine whether there was any significant empirical link between livelihood diversification and intensity of adoption of CSA technologies among Nyando basin households. Bernier *et al.* (2015) explored only the link between off-farm income and the adoption of individual CSA technologies but not on the intensity of adoption of CSA technologies.

Loison, (2015) noted that livelihood diversification is a strategy for households to either cope under worsening agricultural environments or improve their welfare under stable agricultural environments by deliberately pursuing diverse income generating activities. Gebru *et al.* (2018) and Mackenzie *et al.* (2017) used the multinomial logit model while Kassie *et al.* (2017) used the binary logit model and found that household socio-economic characteristics, household wealth and institutional factors are some of the factors that have a significant influence on household livelihood diversification in SSA. However, there is little empirical evidence in literature on the factors that significantly influence the decision of Nyando basin households' to diversify their livelihood sources.

Therefore, this study was conducted; firstly, to contribute knowledge to the identified knowledge gaps in literature in order to guide relevant policy reform. Secondly to analyze how Nyando farmers' risk preferences and livelihood diversification influence the likelihood and intensity of adoption of CSA technologies in the Nyando basin

1.3 Objectives of the study

1.3.1 Overall objective

To study risk attitudes and adoption of climate smart agricultural technologies among smallholder farmers in the Nyando basin in South-Western Kenya

1.3.2 Specific objectives

i. To assess risk attitudes of Nyando basin smallholder farmers
ii. To determine factors influencing diversification of livelihood strategies among Nyando households

iii. To determine how Nyando basin farmers' risk attitudes and livelihood diversification influence their adoption of CSA technologies

1.4 Research hypotheses

i. Nyando basin smallholder farmers do not have a risk averse attitude

ii. Household head socioeconomic characteristics, household resources and institutional factors do not significantly affect diversification of livelihoods among Nyando households.

iii. Nyando basin farmers' risk attitudes and household livelihood diversification do not significantly influence the adoption of CSA technologies.

1.5 Justification

Diversification of livelihood strategies can potentially have an influence on adoption of agricultural technologies including CSA technologies among agricultural households. Diversification of livelihood strategies influences the liquidity that farmers have to be able to finance investment in key agricultural technologies (Hailu *et al.*, 2014). It is imperative to understand how diversification of livelihoods among Nyando basin households influences their adoption of key CSA technologies. Diversification of livelihoods also enables households build resilience against adverse climate change (Macoloo *et al.*, 2013). Diversification of livelihoods among smallholder farmers makes them less dependent on on-farm income sources, which can be affected adversely by unfavorable climate change. This study will contribute knowledge to existing literature on the factors influencing livelihood diversification among Nyando basin households for relevant policy recommendations.

Farmers owing to their risk preferences may end up adopting agricultural technologies in varied ways. Mao *et al.* (2017) noted that farmers' risk attitudes influences their technology adoption decisions, in that, high-risk averse farmers will invest less in technologies as well as be less likely to adopt new technologies. This current study aimed at first assessing Nyando basin farmers risk attitudes and secondly determined whether these risk attitudes play a role in determining adoption of key CSA technologies among Nyando basin households. Information on farmers' risk preferences is crucial to policy makers in cases where there is a need to roll out appropriate insurance covers tailor made to farmer unique circumstances. Jin *et al.* (2016) found that farmers' risk aversion positively influenced the probability of farmers purchasing agricultural insurance.

Nyando basin is one of the CCAFS sites in East Africa that are particularly prone to the adverse effects of climate change. This study was particularly crucial in adding knowledge to existing literature on the factors that influence the adoption of CSA technologies in the Nyando basin as per the sustainable development goal (SDG) number 13 on climate action (Blanc, 2015). It is important to policy makers to address factors that slow the uptake of CSA technologies through policy interventions. Relevant stakeholders working with Nyando basin farmers will benefit from the findings of this study to be able to align appropriately their development and capacity building incentives as they combat climate change in the region.

1.6 Limitations of the study

This study analyzed how Nyando basin farmers' degree of risk aversion influenced their adoption of CSA technologies. Nyando basin farmers' degree of loss aversion could potentially have influenced their decision to adopt the CSA technologies. This study did not factor in how Nyando basin farmers' degree of loss aversion influenced their adoption of varied CSA technologies considered in this study.

CHAPTER TWO: LITERATURE REVIEW

2.1 Climate Smart Agriculture and Agricultural Innovations

CSA as a concept encompasses achieving food security in a sustainable way within a framework of responding to climate change. CSA in itself does not aim to redefine sustainable agriculture but promotes agricultural production within the framework of sustainable development in the face of climate change (Lipper & Zilberman, 2018). Meybeck and Gitz (2013) emphasized that CSA is not new agricultural technologies but a new approach to manage the needed changes in agriculture to achieve food security in the face of climate change. CSA aims to achieve three goals, i)reduce and eliminate greenhouse gas (GHG) emissions, ii)improve food security in a sustainable manner via increasing agricultural productivity and incomes and iii)adapting and building resilience to climate change (Lipper & Zilberman, 2018; Palombi & Sessa, 2013). CSA developed out of the need for agriculture to adapt to climate change and concurrently contribute to climate change mitigation while at the same time promoting food security (Meybeck & Gitz, 2013)

Climate change as defined by the Intergovernmental Panel on Climate Change (IPCC) refers to the persistent change in the average properties of climate that occur over a significant period of time, typically decades or more (IPCC, 2012). IPCC (2012) noted that either natural processes or persistent human activities might cause climate change. Trenberth (2018) noted the key human activities leading to climate change are deforestation and the burning of fossil fuels. The anticipated effects of climate change that are likely to have an adverse effect on agricultural production among farmers in SSA include; increased frequency and intensity of extreme weather events, change of rainfall patterns, high average temperatures, variability in rainfall patterns and temperatures and water scarcity(Asfaw & Branca, 2018; Meybeck & Gitz, 2013).

Zilberman *et al.* (2018) emphasized that there are three kinds of innovations required in agriculture to deal with climate change. They include institutional, technological and managerial innovations. Technological and managerial innovations are both applicable at a micro level at the farm and macro level requiring a farm system approach while institutional innovations are majorly applicable at a macro level (Zilberman *et al.*, 2018). Technological innovations entail the agricultural production technologies used by farmers that include the type of inputs to use in crop production and livestock types and breeds to rear. Managerial innovations involve the best practices that can be embraced by farmers to combine inputs efficiently to produce desired agricultural products. Institutional innovations are the rules and regulations that guide the conduct of agricultural value chain players from production, transportation, processing, marketing and consumption.

Zilberman *et al.* (2018) also pointed out that the impacts of climate change across the globe are heterogeneous; this is mainly because climatic regions differ across the world. Meybeck and Gitz (2013) stated that climate change might lead to decreased agricultural productivity in the tropics but lead to increased agricultural productivity in high to mid latitudes regions. This will lead to diversity of innovations across the world needed to cope with climate change. Innovations are the avenues through which individual farmers, research scientists, local and national governments and world at large are able to embrace CSA in a practical manner.

Smallholder farmers in developing countries have a pivotal role to play in CSA adaptation by adopting relevant agricultural technologies. Agricultural technologies are a product of technological innovations in agriculture and are particularly accessible to small-scale farmers because they are applicable at a micro level by individual farmers (Zilberman *et al.*, 2018). When individual farmers adopt various appropriate agricultural technologies as a response to climate change, they will be embracing CSA. Some notable technologies that farmers can adopt at the micro farm level include stress –tolerant livestock and crops, on-farm storage and pest control technologies, sustainable land management (SLM) practices and lastly technologies that promote input use efficiency (Zilberman *et al.*, 2018).

2.2 Diversification of livelihoods and adoption of CSA technologies

Livelihood refers to households' and community's access to assets and other resources, capacity and capability to utilize the given assets and resources in productive activities as a source of living (Abdissa, 2017; Chambers & Conway, 1992; Sisay, 2010). This study adopted the definition given by Sisay (2010) to define diversification as a livelihood strategy that involves a household relying on off-farm income sources as opposed to on-farm sources. Off-farm activities can include wage employment, salaried employment and non-farm self-employment. One reason that rural households in developing countries diversify is to be able to cope with risks involved in relying on farming as a livelihood source (Gebru *et al.*, 2018). Adverse climate change threatens the livelihood security of rural households in SSA (Connolly-Boutin & Smit, 2016). Climate change makes it hard for rural households to depend optimally on agriculture as a source of income, which ultimately leads to food insecurity. An understanding of the factors that influence livelihood diversification among Nyando basin rural households will go a long way in promoting livelihood diversification in the region.

One key strategy to adapting to climate change is through the adoption of CSA innovations, especially agricultural technologies. The adoption of agricultural technologies by farmers requires financial resources (Zilberman *et al.*, 2018). Loison (2015) notes that livelihood diversification aims at increasing household income. Increased household income helps households overcome the financial constraint involved in adopting relevant agricultural technologies (Hailu *et al.*, 2014). Diversification of livelihoods can enable rural households in developing countries overcome their liquidity constraints in the adoption of CSA technologies.

2.3 Risk concept

Risk is a term closely related to uncertainty; both risk and uncertainty permeate everyday life. Hardaker *et al.* (2015) defined risk as uncertain consequences of what will happen after possible exposure to a given event while uncertainty is imperfect knowledge of whether a given event will occur. Hardaker *et al.* (2015) insisted that risk is not value-free, exposure to an event must affect something one values, for instance, the risk of investing in stocks and the share price drops (affecting one's financial position). Holton (2004) defined risk as ''*exposure to a proposition of which one is uncertain''*. Concina (2014), defined risk as the "*the effect of uncertainty on [the achievement of] objectives*". Risk involves a decision maker been exposed to an event with uncertain outcome, whereby the outcome affects the decision maker's objectives. Hardaker *et al.* (2015) highlight six types of risks present in agriculture. They include financial, institutional, production, personal, business and market risks.

Business risks encompass four of the risks: personal, institutional, price and production risks. Business risks are the risks facing a farm enterprise independent of its financing (Hardaker *et al.*, 2015). Financial risks are risks stemming from the nature of financing used to run a given farm business enterprise, particularly debt financing (Girdžiūtė, 2012; Komarek *et al.*, 2020). Institutional risks are risks as result of the change of the rules governing how farming is conducted within a country and even internationally. For instance, change in trade rules affecting agricultural products will certainly be a source of risk to various players in the agricultural value chain. One source of institutional risks is political risks that influence policy changes and the other source is sovereign risks resulting from the actions of foreign governments (Hardaker *et al.*, 2015).

Market risks are the risks brought about by the uncertainty of the effects of price changes of farm inputs and outputs, as well as change in foreign currency exchange rates (Komarek *et al.*, 2020). Market risks are part of economic risks, which stem from the willingness of trading partners to honor their obligations (contractual risks), price controls and tax policy (Girdžiūtė, 2012). Personal risks are risks that stem from the personal circumstances of the farm workers and owners, which can be transmitted to affect the success of a farm enterprise (Girdžiūtė, 2012; Komarek *et al.*, 2020). For instance, poor managerial capability, farm workers' carelessness and idiosyncratic shocks affecting farm owners are sources of personal risks. Lastly, production risks are risks stemming from the fact that farming depends on unpredictable weather and biological processes (Girdžiūtė, 2012; Komarek *et al.*, 2020). Girdžiūtė (2012) points out that technology used by farmers is a source of production risk.

The subject on risk taking among farmers has received attention in developing countries. In studying risk among farmers, researchers essentially seek to measure the risk attitudes of farmers (Binswanger, 1980; de Brauw & Eozenou, 2014; Jin *et al.*, 2017; Liebenehm & Waibel, 2013).

2.3.1 Risk attitude and agricultural technology adoption

There are three notable approaches in literature that one can reliably use to infer the risk attitudes of individuals(Concina, 2014; Hardaker *et al.*, 2015). First approach is the use of risk premium (RP), which is the difference between the expected value (EV) of a prospect and its certainty equivalent (CE) (Chen, 2016). The RP of a risk-loving individual is negative (CE>EV) while a risk averse individual has a positive RP (CE<EV) and the RP of a risk neutral person is equal to zero (CE=EV) (Concina, 2014; Hardaker *et al.*, 2015). Second approach is to infer from the choice an individual makes between two risky prospects with equal expected value but varying variance. A risk-lover will choose the option with higher variability while a risk-averse individual will choose the option with lower variability and a risk-neutral individual will be indifferent between the options (Concina, 2014).

The third approach is the use of the shape of the utility function of wealth for an individual (Hardaker *et al.*, 2015; Varian, 2010). A risk-neutral person has a linear utility function (Varian, 2010). The utility function of a risk averse individual is a concave curve while that of a risk-loving individual is a convex curve (Chen, 2016). A risk averse individual prefers the expected value of his or her wealth rather than face a gamble. The expected utility of wealth of a risk-loving person is greater than his or her utility of the expected value of wealth while a risk neutral person is indifferent between the two (Varian, 2010). Alternatively, one can rely on the second order derivative of the utility function of wealth, $\mu^2(w)$ to deduce the risk preference of an individual (Hardaker *et al.*, 2015; Jian & Rehman, 2016). If $\mu^2(w)$ < 0, it means risk averse while if $\mu^2(w)$ > 0 means risk-lover and when $\mu^2(w)$ = 0 means risk-neutral (Binici *et al.*, 2003; Hardaker *et al.*, 2015).

Further, one can rely on the Arrow-Pratt measures of absolute risk aversion (r_a) and relative risk aversion (r_r) to infer the risk preference of an individual (Abdulkadri, 2003; Jian & Rehman, 2016). The Arrow-Pratt measures for r_a and r_r is the negative ratio of the second order derivative ($\mu^2(w)$) divided by the first order derivative ($\mu^1(w)$) for each measure respectively (Abdulkadri, 2003). The Arrow-Pratt measure is equal to zero for risk-indifferent individual, positive for risk averse individual and negative for a risk-lover (Binici *et al.*, 2003).

Hardaker *et al.* (2015) noted that the adoption of agricultural technologies by farmers might be a high-risk activity especially in instances whereby the adoption requires substantial capital outlay. For instance, adoption of stress-tolerant livestock and improved crop varieties will require farmers to use substantial financial resources unless they are receiving donor funding for the same. Adoption of technologies potentially affects the wealth status (inclusive of income streams) of farmers; famers face the risk of either increasing their wealth or diminishing it depending on the consequences of their actions. Many people inclusive of famers, are risk averse when faced with risk prospects that can significantly influence their wealth status (Hardaker *et al.*, 2015).

2.3.2 Elicitation of risk attitude

There are three common techniques in literature that researchers have used to elicit risk attitudes from research respondents; choice-list procedure, allocation procedure and ranking procedure (Loomes & Pogrebna, 2014). The choice-list procedure as applied in risk measurement involves a multiple price list in tabular form, a particular respondent works through the table and a researcher expects him to switch at some point between two sides of the table. The point of switching indicates a given respondent's risk attitude. The ranking procedure as used in assessing risk attitudes, involves a researcher giving a respondent a list of risk options for the respondent to pick his most preferred option. The risk attitude is identified in a respondent's desired balance between mean and variance in choices' values. Lastly, the allocation procedure as applied in risk measurement involves two steps. First, an interviewer gives a budget to a respondent and allows him to distribute the budget between state-contingent claims. Second, a respondent's chosen allocation with consideration of the rate of exchange between claims gives an indication of an individual's risk attitude (Loomes & Pogrebna, 2014).

This study used the Eckel and Grossman approach (Charness *et al.*, 2013), which is a form of the ranking procedure to elicit risk preferences of the research subjects. The subjects were presented with a list of six options that differ in expected values and variance. Respondents were expected to pick one of the options. Charness *et al.* (2013) noted that this procedure allows for the estimation of an implied risk aversion parameter while assuming that respondents exhibit a constant relative risk aversion utility function. In this study, the implied coefficient of relative risk aversion (CRRA) parameter interval corresponding to each gamble choice as used in Dave *et al.* (2010) was used for estimation of farmers' risk aversion level. The study employed the ranking procedure for two reasons. First, convenient to administer as part of a larger survey instrument, this is because the elicitation technique is easy for subjects to comprehend. Second, the Eckel and Grossman technique generates smaller noise and equal predictive accuracy as compared to a complex technique for subjects with supposedly low math skills as noted by Dave *et al.* (2010). Rural sub-Saharan Africa is marked by significant levels of adult illiteracy (Chikalipah, 2017). Due to the noted adult illiteracy in literature, the study assumed that the risk experiment subjects have low math abilities.

Risk measurement also differs from the context in question that is, measuring risk taking in general or risk taking for a particular context like farming. The response to a question on general risk taking gives the best predictor of the all-round risk attitude of an individual. However, the best predictor of the risk behavior of an individual in a given context is the response to risk-taking incorporating the particular given context(Dohmen *et al.*, 2011). In this study, the risk-taking behavior observed was within the financial context. The rationale behind considering the financial context was because investment in climate-smart technologies involves an aspect of financial outlays as capital. The risk-taking question that the respondents tackled incorporated the financial context.

De Brauw and Eozenou (2014) noted that while eliciting risk preferences, researchers could adopt hypothetical or real money at stake experimental games. The main limitation of the hypothetical money games is that they are not incentive compatible while real money at stake games are incentive compatible. The fact that hypothetical money games are not incentive compatible makes economists' doubt the validity of this procedure. However, a number of studies have nevertheless employed hypothetical experiments to measure risk preferences (Cotty *et al.*, 2018; de Brauw & Eozenou, 2014; Hill, 2009; Shimamoto *et al.*, 2018). Wik* *et al.* (2004) also noted there is insignificant difference in employing either incentivized or non-incentivized games in revealing a subject's risk attitude.

On the other hand, real money at stake lotteries are expensive to conduct with a large representative sample that hypothetical money lottery games achieve (Dohmen *et al.*, 2011). This study employed hypothetical money game due to insufficient funds, which would have made it impossible to include a large representative sample if an incentivized experiment was to be considered instead.

2.4 Theories on Agricultural Technology Adoption

Adoption of CSA technologies by smallholder farmers is part of broad spectrum of agricultural technologies adopted by farmers in both developing and developed countries. In literature, researchers have modeled the adoption of agricultural technologies through a number of theories. This section offers a brief analysis of three such theories common in literature.

The theory of planned behavior (TPB) is a social psychological theory useful in predicting and explaining individual behavior (Wauters *et al.*, 2010). The theory argues that one's behavior can be inferred from their intentions (Daxini *et al.*, 2018; Mutyasira *et al.*, 2018; Shaman Herath, 2010; Wauters *et al.*, 2010). For instance, one can infer the behavior of smallholder farmers in adopting agricultural technologies from their intentions to adopt or not to adopt. Intentions are in turn based on beliefs people have towards a given behavior (Daxini *et al.*, 2018); the beliefs include control, normative and behavioral beliefs (Wauters *et al.*, 2010). The beliefs are based on three considerations, which include perceived behavioral control (PBC), subjective norm (SN) and attitude (Daxini *et al.*, 2018; Mutyasira *et al.*, 2018; Shaman Herath, 2010; Wauters *et al.*, 2010). Attitude refers to a person's negative or positive assessment of engaging in the said behavior while SN describes the perceived social pressure to engage in the given behavior (Shaman Herath, 2010; Wauters *et al.*, 2010). Lastly, PBC is the perceived own capacity and capability to engage in a given behavior by an individual (Wauters *et al.*, 2010). When the intention is strong, one is more likely to engage in a given behavior (Mutyasira *et al.*, 2018).

Tambo and Abdoulaye (2012) argued that the theory of diffusion of innovation (DOI) anchors on the dissemination of information regarding a given innovation as a main factor in the decision of individuals to adopt the innovation. Agricultural technologies are a form of innovations in agriculture, which smallholder farmers can embrace. DOI theory emphasizes that the features of a technology are key in the adoption of a given technology by people, either individually or as a social group (Aubert *et al.*, 2012; Simin & Janković, 2014). The attributes of an innovation can be understood through an innovation's ease of use, trial-ability, compatibility, observability and usefulness (Aubert *et al.*, 2012). Ease of use refers to the extent of understanding an innovation and utilization of it and trial ability refers to the degree of utilizing an innovation for a constrained time horizon (Aubert *et al.*, 2012). Compatibility is the level that an innovation addresses felt needs as well as is in line with the socio-cultural ideals of a people and known ideas and observability is the extent to which the outcome of innovation is visible to potential users (Aubert *et al.*, 2012). Lastly, usefulness is the degree that an innovation is thought to be better than current practice (s) (Aubert *et al.*, 2012).

Utility maximization theory as used in agricultural technology adoption literature describes the difference in utility from adopting or not adopting a given innovation (Awotide *et al.*, 2016). Utility is a formal way of expressing an individual's preferences when that individual is faced with a choice between two or more consumption bundles (Varian, 2010). Utility maximization theory posits that a potential household adopts a given agricultural technology if the utility from adoption exceeds the utility from non-adoption (Ogada *et al.*, 2014). Taking μ_a to depict utility from adoption and μ_{na} to depict utility from not adopting, then a household adopts a given technology if $\mu_a > \mu_{na}$. This study was anchored on the utility maximization theory.

2.5 Empirical studies

2.5.1 Risk attitudes and adoption of agricultural technologies

Ambali *et al.* (2019) analyzed how farmers' risk preferences influenced their decision to adopt high yielding rice varieties in Nigeria. The study employed an instrumental variable probit model. The results of the study showed that the more risk averse a farmer was, the less likely they were to adopt high yielding rice varieties. Crentsil *et al.* (2018) used a hazard model to assess how aversion to risk and ambiguity among smallholder Ghanaian farmers influenced their adoption of three aquaculture technologies; a type of fish feed, floating cages and a fast-growing tilapia breed. They used incentivized experiments to elicit farmers risk preferences and a variation of two-color urn experiment to measure ambiguity aversion. They found that the more risk averse a farmer was the more likely they were to adopt the three-aquaculture technologies in question. On the other hand, ambiguity aversion had no influence on the uptake of the given technologies except that it slowed down the adoption of floating cages.

Cotty *et al.* (2018) used a linear regression model to find out whether farmers' risk aversion and their inter-temporal time preference influenced fertilizer use among Burkinabe maize farmers. They used non-incentivized risk and time experiments to capture risk attitudes and time preferences of farmers respectively. The results of the study showed that farmers with low discount rates, patient farmers, statistically purchased more fertilizer as compared to impatient farmers. The study found farmer risk aversion did not have a significant influence on fertilizer usage among Burkinabe maize farmers.

Shimamoto *et al.* (2018) used a linear probability model to determine whether rice farmers' risk aversion influences their adoption of post-harvest technology, moisture meters, in Cambodia. They went further and accounted for farmers' extent of loss aversion and probability weighting. The results of the study were that risk aversion significantly influences the uptake of moisture meters. The more one was risk-averse, the more likely they were to adopt moisture meters. Farmers' extent of loss aversion and probability weighting did not have significant influence on the adoption of moisture meters. It is evident from literature that farmers' risk aversion may influence technology adoption positively, negatively or not influence at all. Therefore, this current study sought to find out how Nyando basin farmers' risk preferences influenced their likelihood and intensity of adoption of CSA technologies.

2.5.2 Diversification of livelihood sources

Gebru *et al.* (2018) analyzed the factors that determine livelihood choices among rural households in Ethiopia. The study employed a multinomial logit model to determine how various factors influence the choice of non-farm, on-farm and off-farm income generating activities. The results of the study showed that the age of household head, dependency ratio, distance to market, extension services access and agro-ecology had a significant negative influence on households' livelihood choices. Alternatively, education and annual income of household head, membership of house-head to cooperative society, land size, access to credit and farm inputs access had a significant positive effect on households' choice to diversify livelihood strategies.

Kassie *et al.* (2017) analyzed the factors that influence the diversification to non-agricultural income generating activities among Ethiopian farm households. The study employed a binary logit model corresponding to whether a farm household had diversified to non-agricultural income generating activities or not. The results of the study showed distance to market, tenure security of land, membership to a cooperative society and extension service access had significant effect on the likelihood of households diversifying to non-agricultural livelihood activities.

Mackenzie *et al.* (2017) analyzed the factors that influenced the choice of livelihood sources among farmers in Botswana. They employed multinomial logit model to determine the factors that influence choice of crop farming, tourist based activities and livestock farming as livelihood strategies. The results of the study showed that the age of household head, gender, wealth of household (poor, middle, and rich), and distance to market, extension services access, farm size, and land ownership by a household had a significant influence on choice of livelihood strategies among farmers in Botswana. This current study aimed at determining how household demographic factors, socio-economic characteristics and institutional factors influence livelihood diversification among the Nyando basin households for relevant policy recommendations. Analysis of the factors influencing livelihood diversification was conducted against the background that the Nyando basin has been adversely affected by climate change, which makes dependence on on-farm income a risky undertaking.

Dependence on on-farm income sources may predispose the Nyando basin households to periods of inadequate or no income, which can make it hard for them to cater for their daily needs including been food secure.

2.5.3 Livelihood diversification and adoption of agricultural technologies

Teshager Abeje *et al.* (2019) analyzed the influence of livelihood diversification on the level of adoption of sustainable land management practices among rural Ethiopian households by using an ordered probit model. The results of the study showed that livelihood diversification had a significant negative effect on the intensity of adoption of sustainable land management practices. Diiro and Sam (2015) used semiparametric estimator of binary outcomes to determine the influence of non-farm income on technology adoption, improved maize seed, among Ugandan farmers. Non-farm income is a mark of diversification of livelihood sources among farming households. The results of the study showed` that non-farm income had a significant positive effect on the decision of households to adopt improved maize seed.

Hailu *et al.* (2014) analyzed the factors influencing the adoption of agricultural technologies and the effect of the adoption on farm income among Ethiopian farming households. The study considered the adoption of high yielding seed variety and chemical fertilizer. The study employed two regression models; probit and ordinary least squares (OLS) regression models. They analyzed the factors influencing separately the uptake of chemical fertilizer and high yielding seed varieties using binary probit model. They employed the OLS model to determine the impact of adoption on farm income. The results of the study showed that adoption of technology had a significant positive impact on farm income. Alternatively, results from the probit model showed that off-farm income had a significant positive influence in the adoption of chemical fertilizer but had no significant effect on the uptake of high yielding seed variety.

The findings in literature show that livelihood diversification may have a significant influence or no influence on the adoption of agricultural technologies by smallholder farmers. The focus of this current study was to add knowledge to literature by determining the effect of livelihood diversification on the likelihood and intensity of adoption of CSA technologies among the Nyando basin rural households.

2.5.4 Adoption of agricultural technologies

Aryal *et al.* (2018) analyzed the factors that influenced the probability and intensity of adoption of several CSA practices in the Gangetic plains, India. The study employed multivariate probit (MVP) and ordered probit (OP) models in data analysis. The OP model was to analyze factors influencing the intensity of adoption of CSA practices. The results of the MVP model showed that there were significant positive and negative correlations in the adoption of various CSA practices. There was a positive and significant correlation in the adoption of site-specific nutrient management practices and stress tolerant seed varieties, minimum tillage and stress tolerant seed and lastly, site-specific nutrient management and minimum tillage. However, adoptions of minimum tillage and crop diversification had a significant negative correlation.

The results of the OP model showed that household socio-economic characteristics, institutional factors, farmland characteristics and climate risks had significant influence on the intensity of adoption of given CSA practices.

Jerop *et al.* (2018) analyzed the factors that influenced the likelihood and intensity of uptake of varied agricultural innovations in the marketing and production of underutilized cereals in Kenya. The study considered the likelihood and intensity of uptake of group marketing, conservation tillage, improved varieties and integrated pest and weed management. The study used both MVP and OP models for analysis purposes. The results of the MVP model showed that there were significant and positive correlations in the adoptions of group marketing and conservation tillage; conservation tillage and integrated pest, weed management; improved varieties and integrated pest, and weed management. The results of the OP model showed that plot size, off-farm or non-farm income, technical training, and extension contact and credit access had significant influence on the intensity of adoption of varied agricultural innovations in cereal production and marketing.

Kurgat *et al.* (2018) analyzed the factors that influence the adoption of sustainable intensification practices (SIPs) in vegetable production among Kenyan rural and peri-urban households. The study employed the MVP model in analyzing factors influencing the adoption of integrated soil fertility, improved irrigation, crop diversification and organic manure as SIPs. The results of the study showed that there were significant positive and negative correlations in the adoption of the SIPs. There was positive correlation in the adoption of crop diversification and organic manure; improved irrigation systems and integrated soil fertility management. There was negative correlation in the adoption of integrated soil fertility management and organic manure use: crop diversification and integrated soil fertility management.

Teklewold *et al.* (2013) analyzed the factors that hinder and influence the uptake of various sustainable farming technologies in Ethiopia. The study employed both MVP and OP models in data analysis. The results of the MVP model showed that there are significant positive and negative correlations in adoption of various agricultural innovations among farmers in Ethiopia. The results of the OP model showed that household socio-economic characteristics, institutional factors, environmental stresses and plot-related variables had significant influence on the intensity of adoption of sustainable agricultural practices among rural Ethiopian households.

The studies employed the use of the MVP model in order to analyze the simultaneous adoptions of given technologies in question. A significant positive correlation in the adoption of any two given technologies shows that farmers adopt the technologies as complements while a significant negative correlation shows that farmers adopt the technologies as substitutes. This current study sought to find out whether Nyando basin smallholder farmers adopt CSA technologies as either substitutes or complements and factors influencing the intensity of adoption.

Shikuku *et al.* (2017) analyzed farmers' attitudes to climate adaptation strategies and factors influencing the uptake of the given strategies in East Africa CCAFS sites: Nyando in Kenya, Hoima in Uganda, Borana in Ethiopia and Lushoto in Tanzania. They employed both the OLS and the binary probit regression models. The results of their study showed that farmers have a favorable attitude towards adopting improved crop management technologies. Conversely, smallholder farmers expressed an unfavorable attitude towards adoptions related to water, soil and land management. The results from the OLS regression showed that male-headed households, a household with a member active in crop related groups, large resident household size, and experience of more hunger months increased a household's adaptation index (Shikuku *et al.*, 2017). The probit regression results showed that the more a household has many resident members the more likely it would adopt agroforestry, practice irrigation and plant short-cycle crop varieties. Adult male-headed households have a higher probability of adopting agroforestry as compared to adult female-headed households. Membership of a household member to farming groups and agricultural extension services access increased the probability of adopting terracing. Asset-endowed households have a higher likelihood of adopting mulching and practicing irrigation (Shikuku *et al.*, 2017).

Bernier *et al.*, (2015) analyzed institutional and gender aspects of climate smart agricultural technologies in Nyando and Wote CCAFS sites, both in Kenya. They employed a two-stage Heckman selection model to analyze awareness (first stage) and adoption (second stage) of CSA technologies. They noted that there are differences between genders in awareness of various climate smart farming technologies among farmers in Nyando. Once farmers were aware of various CSA technologies, adoption of the given technologies does not differ significantly between the genders. Other factors discussed by Bernier *et al.* (2015) that influenced farmer adoption of CSA technologies include; production system, plot and household specific factors, weather shocks, access to weather-related information, social capital, access to loans and off-farm income, land ownership and lastly, the innovativeness and traditional orientation of farmers. This current study extended the findings of Bernier *et al.* (2015) and Shikuku *et al.* (2017) by analyzing the factors influencing the likelihood and intensity of adoption of multiple CSA technologies by the Nyando basin smallholder farmers. This current study also analyzed how Nyando basin farmers' risk attitudes influenced their adoption of CSA technologies in the region.

Table 2. 1: Summary of key studies

Author	Focus	Methodology	Findings	Knowledge gap
(Crentsil *et al.*, 2018)	Assessed how risk and ambiguity aversion influence adoption of aquaculture technologies in Ghana	Used hazard models and incentivized experiments	More risk averse farmers are likely to adopt the said agricultural technologies whereas ambiguity aversion does not influence technology adoption	If farmers perceive new agricultural technologies to be risk reducing, they are more likely to adopt the technologies despite their risk aversion.
(Cotty *et al.*, 2018)	Analysed whether Burkinabe farmers' risk and time preferences influence their fertilizer use decisions	Used linear regression model	Farmers' inter-temporal time preference influenced their adoption of fertilizer but risk preferences did not	Farmers' risk aversion may not have a significant effect on agricultural technology adoption
(Shimamoto *et al.*, 2018)	Determined whether farmers' risk preferences influences their adoption of post-harvest technology, moisture meters, in Cambodia	Used linear probability model	Risk averse farmers are likely to adopt moisture meters as an agricultural technology	A hypothetical experiment can be used to elicit farmers' risk preferences

(Gebru *et al.*, 2018)	Analysed determinants of livelihood diversification strategies among rural households in Ethiopia.	Used multinomial logit	Household head characteristics, institutional factors, household demographics and resources influence choice of household livelihood sources	Rural farming households diversify their livelihood sources to supplement the low income they receive from on-farm sources.
(Kassie *et al.*, 2017)	Investigated factors that influence diversification to non-agricultural income generating activities in Ethiopia	Used binary logit model	Institutional factors influence choice to diversify to non-agricultural activities	Diversification of livelihood sources to non-agricultural activities enables households earn more income, which can lead to the adoption of new agricultural technologies
(Mackenzie *et al.*, 2017)	Analysed the factors that influence the choice of livelihood sources among farmers in Botswana	Used multinomial logit	Household head, household and institutional factors have a significant influence on choice of livelihood strategies among farmers in Botswana	Important to analyse the socio-economic and institutional factors influencing livelihood diversification to inform relevant policy recommendations.
(Teshager Abeje *et al.*, 2019)	Analysed the effects of livelihood diversification on the intensity of adoption of sustainable land management practices among rural Ethiopian households	Used ordered probit model	livelihood diversification has a significant negative effect on the intensity of adoption of sustainable land management practices	Explore the relationship between livelihood diversification and level of adoption of sustainable land management practices

(Aryal *et al.*, (2018)	Analysed factors influencing the probability and level of uptake of multiple CSA practices in the Gangetic plains in India	Used MVP and ordered probit models	Farmers adopt varied CSA practices as substitutes and complements. Household socio-economic characteristics, institutional factors, farmland characteristics and climate risks have a significant effect on the intensity of adoption of given CSA practices.	Important to offer insights on whether farmers adopt CSA practices in a piecemeal or in a composite manner
(Teklewold *et al.*, 2013)	Analysed the factors that hinder and facilitate the probability and level of adoption of interrelated sustainable agricultural practices (SAPs) in rural Ethiopia	Used MVP and ordered probit models	Farmers adopt various sustainable farming practices as complements and substitutes Household socio-economic characteristics, institutional factors, environmental stresses and plot-related variables have a significant influence on the level of of adoption of SAPs.	Studies that analyse the univariate adoption of SAPs ignore important cross-technology correlation effects and potentially generate biased estimates. Cross-technology correlation information might have important policy implications.

Shikuku *et al.*, (2017)	Analysed smallholder farmers' attitudes to climate adaptation strategies and factors influencing the uptake of the given strategies in East Africa CCAFS sites	Used binary probit and linear regression models	Institutional factors and farmer socio-economic characteristics influence adoptions of CSA practices. Farmers have varied attitudes to CSA practices.	The study analyzed the factors influencing the univariate adoption of CSA practices in the Nyando basin. This current study analyzed the factors influencing joint adoption of CSA practices.
Bernier *et al.*, (2015)	Analyze gender differences in awareness and adoption of CSA technologies in Nyando and Wote, Kenya.	Heckman two-stage selection model	There are gender differences in awareness of CSA technologies. Gender does not play a role in impeding adoption of CSA technologies. Farm characteristics, household demography and institutional factors influence the decision to adopt CSA technologies	Need to put more attention into the risks involved in the adoption of varied CSA technologies.

CHAPTER THREE: METHODOLOGY

3.1 Conceptual framework

One of the primary goals of CSA is to adapt and build resilience to climate change. Adoption of agricultural innovations offers the avenue to achieving this goal. Institutional innovations require a farm systems approach and are beyond the capacity of individual smallholder farmers. However, individual smallholder farmers can embrace some managerial and technological innovations. Technological innovations include site-specific CSA production technologies that enable farmers become resilient against varied climate change effects in different parts of the globe. Farmers can adopt CSA technologies as a bundle of technologies since there is no CSA technology that can singlehandedly make farmers become resilient to climate change.

Institutional factors, climate risks, household head and farm household socioeconomic characteristics influence the agricultural innovations farmers are exposed to and the adoption of site-specific agricultural technologies. Institutional factors can either encourage or discourage the adoption of CSA technologies among smallholder farmers. Some of the institutional factors expected to influence the adoption of CSA technologies include market access, social capital, credit access and extension service access. Climate related risks dictate on the relevant CSA technologies that farmers need to adopt to become resilient to climate change. Climate risks were expected to influence the adoption of CSA technologies.

Household heads as primary decision makers play a major role in determining whether a household adopts or fails to adopt given CSA technologies. Decision making ability of a household head is a product of his socio-economic characteristics, which includes financial risk attitude, age, education level and gender. Farm household socioeconomic characteristics dictate on the resources available to households for investment in varied activities including adoption of CSA technologies. Land size, non-land household assets, household size and livelihood sources are some of the farm household socio-economic characteristics that influence household behavior. Household head and farm household socioeconomic characteristics were expected to influence the decision of Nyando basin households to adopt CSA technologies.

Figure 3.1 summarizes the conceptual framework used in this current study.

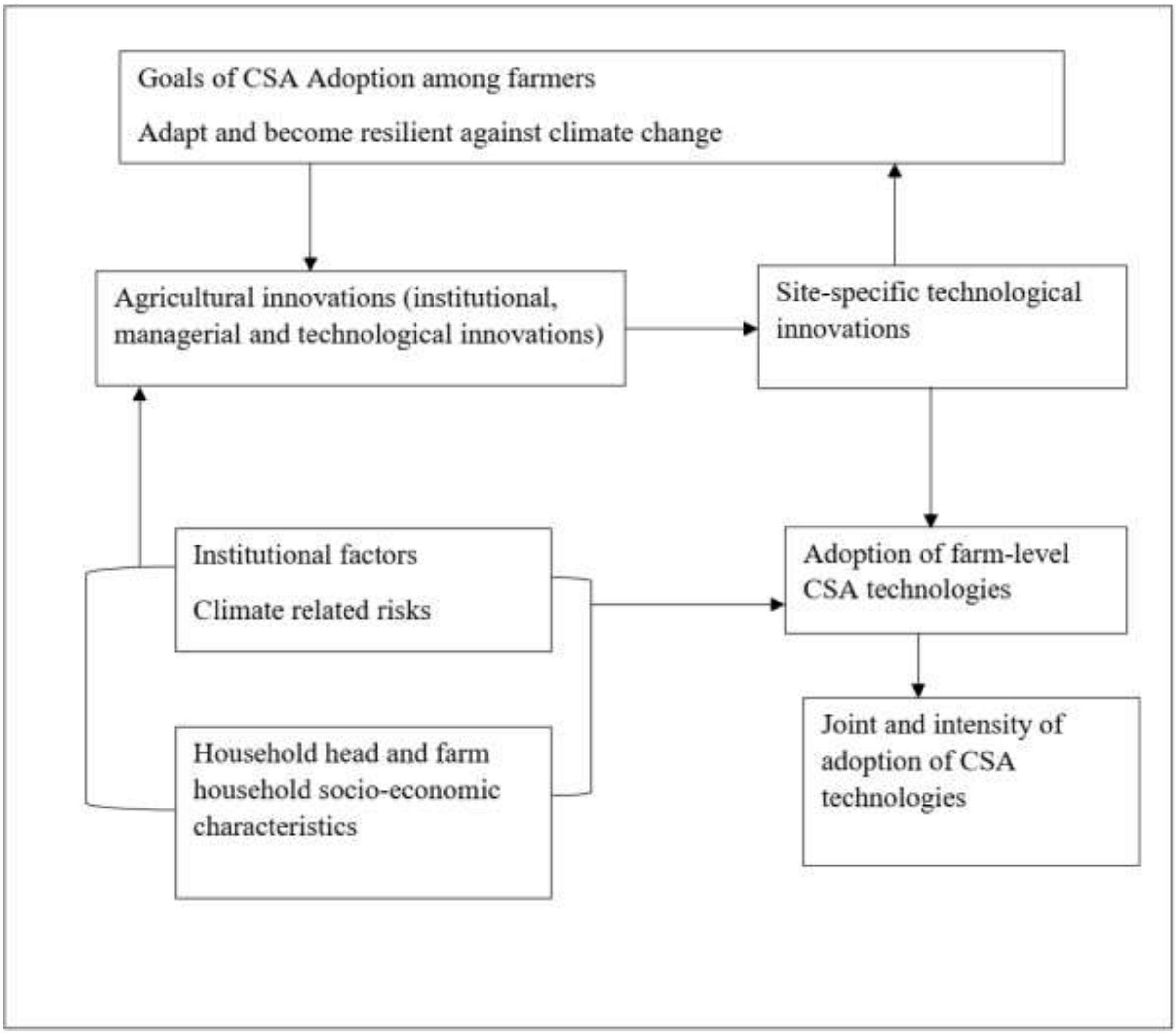


Figure 3. 1: Conceptual framework

Source: Author's own conceptualization

3.2 Theoretical framework

In this study, farmers were assumed to form preferences over the choices they face. Farmers in the Nyando basin have a portfolio of CSA technologies to adopt as they mitigate and become resilient to adverse climate change in the region. As such, farmers were assumed to form preferences over the choices they made on whether to adopt CSA technologies or not. Hardaker *et al.* (2015) noted that farmers as decision makers (DMs) make choices that bear inherent risk, that is, decisions are made under uncertain conditions, which precipitate to risky outcomes. Farmer decisions can result in consequences that can be expressed as a single attribute; increase in maize yield or a multiple outcomes as increased milk yield, increase in net profit or even reduced debt burden (Hardaker *et al.*, 2015). In economics preferences are assumed to satisfy certain axioms; that is preferences are complete, reflexive, transitive (Varian, 2010) continuous and independent (Hardaker *et al.*, 2015; Levin, 2006; Varian, 2010).

Complete: This axiom allows for the comparison of two bundles, say bundle x and bundle y. A DM either prefers bundle x to y or y to x or is indifferent between them.

Reflexive: This is a trivial axiom that states that a given bundle x is as good as it is.

Transitive: This axiom states that if a DM prefers bundle x to bundle y or is indifferent between the bundles ($x \geq y$) and still prefers y to z or is indifferent between the bundles ($y \geq z$) then the DM must prefer x to z or be indifferent between the bundles ($x \geq z$).

Continuous: This axiom states that if a DM prefers x to y and y to z, then there is a subjective probability p(x) that makes the DM indifferent between y and a lottery that results in x with probability p(x) and z with probability 1 – p(x), expressed as follows;

$$p(x) + (1 - p)\, z \approx y \qquad (1)$$

Independence: This axiom states that if a DM prefers x to y and z in a given uncertain situation, the decision maker will prefer a lottery yielding x and z to a lottery yielding y and z when probability of (x) is equal to the probability of (y); p(x) = p(y), expressed as follows;

$$p(x) + (1 - p)z \geq p(y) + (1 - p)z \qquad (2)$$

The above axioms form the basis of the expected utility theory pioneered by Daniel Bernoulli in 1738 and revised by John von Neumann and Morgenstern in the 20th century (Hardaker *et al.*, 2015; Varian, 2010). The theoretical grounding of study is the expected utility theory. This theory holds that if choice x is preferred to choice y then, expected utility of x (U_x) is greater than the expected utility of y (U_y), that is, $U_x > U_y$ and the vice versa holds. Therefore, farmers in the Nyando basin will adopt given CSA practice (m) if the utility of adoption is greater than the utility from not adopting (Teklewold *et al.*, 2013) as shown in equation (3).

$$Y_{im}^{*} = Um - Uo > 0 \qquad (3)$$

Y* is a latent variable that captures the benefits to farmer (i) from adopting given CSA practice (m). Um is the expected utility from adopting while Uo is the expected utility from non-adoption. The CSA technologies considered in this study include; terraces (T), inorganic fertilizer (F), ridges and bunds (R) and stress-tolerant livestock; sheep and goats (S). . These CSA innovations are part of a broader pool of CSA innovations appropriate for the Nyando CCAFS site (Bernier *et al.*, 2015). Consideration of all the CSA innovations was beyond the scope of this current study.

The expected utility theory was also used in this study to characterize risk aversion among the Nyando basin farmers. According to Jin *et al.* (2017) and Cotty *et al.* (2018), the utility function showing farmers risk aversion is as shown in equation (4).

$$U_{(w+x)} = \frac{(w + x)^{1-r}}{1 - r} \qquad (4)$$

Where r stands for the coefficient of relative risk aversion, x is the expected payoff and w is the background endowment of wealth. The study assumed the background endowment of wealth that risk experiment subjects had to be zero. Trained enumerators presented to the risk experiment subjects six ordered options to choose only one option (Appendix 1). The subjects were asked to assume the six options as representing six business ventures, either an on-farm or an off-farm business. The trained enumerators showed the research subjects six decision cards and explained the instructions as indicated in appendix one. The enumerators emphasized that a respondent can only pick one of the six choices. Once, the enumerator was convinced that a respondent understood the risk experiment; the enumerator allowed the respondent to pick one of the gamble choices as shown in appendix one.

3.3 Analytical model

Objective one: To assess risk attitudes of Nyando basin smallholder farmers

In assessing farmers' risk attitudes, this study relied on the expected utility of the farmer when he is faced with a lottery that has two possibilities, A and B with p and (1 – p) as respective probabilities (Appendix 1). Following Cotty *et al.* (2018), farmer's expected utility level is as shown in equation (5).

$$EU = pU(w + y) + (1 - p)U(w + z) \qquad (5)$$

Where EU is the expected utility of a farmer when faced with a lottery with two options; $(w + y)$ and $(w + z)$ and p and $(1 - p)$ as respective probabilities.

Assuming that a farmer has a constant relative risk aversion utility function, the implied CRRA parameter as reflected by farmer's choice from a list of six gamble choices was used as a reflection of farmer risk attitude. It is not possible to identify the precise CRRA parameter since the CRRA parameters were captured as intervals. Therefore, the midpoint of the interval where a farmer's choice lied was used to estimate the idiosyncratic CRRA parameter due to a farmer; Cotty *et al.* (2018) used a similar approach.

Descriptive statistics was used in the analysis of this objective and an independent t-test was used in testing whether the Nyando basin smallholder farmers are risk averse or not.

Objective two: To determine factors influencing diversification of livelihood strategies among Nyando households

Livelihood sources include on-farm, off-farm and non-farm income generating activities. Off-farm and non-farm activities include a wide range of choices including but not limited to off-farm self-employment and salaried employment. On the other hand, on-farm income generating activities are limited to crop and livestock farming on one's farm. The dependent variable captures whether a household depends on either on-farm only or has diversified its livelihood to engage in non-farm or off-farm sources of livelihood. The outcome variable is a binary choice, whether a household has diversified to at least off-farm or non-farm income generating activities or not.

Wooldridge (2016) recommends the use of either binary probit or binary logit regression models when dealing with binary response choices. The binary logit model was used to test this hypothesis; household head socioeconomic characteristics, household resources and institutional factors do not significantly affect diversification of livelihoods among Nyando households Following (Wooldridge, 2016), the following binary logit model was used as shown in equation (6).

$$P(Y_i = 1/X_i) = G(\beta_0 + \beta_1 X_1 .. + \beta_k X_k) = G(\beta_0 + X\beta) \tag{6}$$

Where G is the standard logistic function, which takes the form shown in equation (7)

$$G(z) = \exp(z) / [1 + \exp(z)] = \Lambda(z) \tag{7}$$

Where P = is the probability of the i[th] household diversifying their livelihood sources into off-farm or non-farm activities, X_i= is the vector of explanatory variables; household head and household socio-economic characteristics and institutional factors, β_k are the parameters to be estimated. G is the cumulative distribution for standard logistic function, which takes values between zero and one. This means that the estimated response probabilities are between zero and one (Wooldridge, 2016). Interpretation of the effects of independent variables on the dependent variable relied on their marginal effects because interpretation of the coefficients would not lead to meaning analysis (Byamungu, 2018; Greene, 2011). Therefore, marginal effects for the logit model were also generated.

Objective three: To determine how Nyando farmers' risk attitudes and livelihood diversification influence their adoption of CSA technologies

The net gain (Y^*_{im}) for adopting CSA practice m by farmer i is a latent variable influenced by farmer risk attitude, livelihood sources and other household specific and location characteristics (χ_i) and the unobserved factors captured in the error term (ε_i) (Aryal *et al.*, 2018) as shown in equation (8).

$$Y^*_{im} = \chi_i\beta_m + \varepsilon_i \qquad (8)$$

Where (m = terraces (T), inorganic fertilizer (F), ridges and bunds (R), stress-tolerant livestock (S)) corresponding to the CSA technologies analyzed in this study.

The β is the estimated beta coefficients for each of the explanatory variables and ε is a normally distributed error term with a constant variance and zero mean (Ω, 0). It is the binary outcome for each decision to adopt practice m that is observed since the latent variable is unobserved as shown in equation (9) (Teklewold *et al.*, 2013).

$$Yim = \ 1\ if\ Yim* > 0\ and\ 0\ otherwise \qquad (9)$$

Where (m = terraces (T), inorganic fertilizer (F), ridges and bunds (R), stress-tolerant livestock (S)). Multivariate probit (MVP) and ordered probit (OP) models were used in the analysis of this objective.

In the MVP model where the simultaneous adoption of multiple CSA technologies is possible, the errors terms will together follow a multivariate normal (MVN) distribution with zero conditional mean and variance normalized to unity; MVN(0,Ω), (Teklewold *et al.*, 2013). The covariance matrix is as shown in table 3.1..

ρ is the correlation between error terms. The necessary condition is that the values of the off-diagonal elements be non-zero which leads to equation (9) been a MVP model (Aryal *et al.*, 2018)

Table 3. 1 Covariance matrix of the error terms in the multivariate probit model

1	ρTF	ρTR	ρTS
ρFT	1	ρFR	ρFS
ρRT	ρRF	1	ρRS
ρST	ρSF	ρSR	1

The MVP model has a weakness in that it does not inform on the intensity of adoption of CSA technologies for any given farmer ((Aryal *et al.*, 2018). To overcome the MVP model weakness, the study employed a model that accounted for the different intensity in adoption of the four CSA technologies among farmers. Kpadonou *et al.* (2017) noted that intensity of adoption is count data, which is still ordinal in nature, making the use of Poisson models inappropriate in modelling the intensity of adoption. Poisson models assume equal probability of adopting one or more technologies, which is not the case, because the adoption of the second or more technology is conditional on the adoption of the first technology (Maguza-Tembo *et* *al.*, 2017). In this study, it was assumed that before a farmer adopts a subsequent CSA practice they should have gained experience with previous adoption of CSA practice(s). Therefore, the probability of adopting any subsequent CSA practice will differ from the probability of adopting the previous CSA practice(s). Following Kpadonou *et al.* (2017), an OP model was employed to account for the intensity of adoption of the four CSA technologies and factors influencing the level of adoption of the technologies.

The described MVP and OP models were used in testing this hypothesis; Nyando basin farmers' risk attitudes and household livelihood diversification do not significantly influence the adoption of given CSA technologies.

3.4 Description of variables and their expected signs

Table 3.2 gives a description of the explanatory variables used in this study. Emphasis is put on hypothesized influence on the adoption of CSA technologies where (+) shows that the variable increases the probability of adoption while (-) shows that the variable reduces probability of adoption of given CSA practice.

Risk attitude of a farmer was expected to have either a positive or a negative influence on the adoptions of given technologies among smallholder farmers in the Nyando basin. Previous studies have shown that farmers' risk aversion may influence, discourage or have no influence on the probability of farmers adopting agricultural technologies (Cotty *et al.*, 2018; Crentsil *et al.*, 2018; Vieider *et al.*, 2014). Farmers risk attitude was inferred from the coefficient of relative risk aversion parameter of a farmer corresponding to his choice in the risk experiment (Appendix 1). Age of the farmer was expected to have a negative influence on the likelihood of a farmer adopting CSA innovations. This is because older farmers have a short career horizon, which acts as a disincentive to invest in new farming practices (Rajendran *et al.*, 2016). Similarly, age was expected to have a negative influence on the likelihood of farmers diversifying. Kassie *et al.* (2017) found that with increase in age of the household head, a farm household is less likely to diversify. Age in this study was captured as a continuous variable by taking the years of the household head. Farmers' education was expected to have a positive influence on the probability of a farmer adopting given CSA technologies. Education tends to open one's mind to new ideas that can be of benefit (Rajendran *et al.*, 2016). Education was expected to favor positively diversification of livelihoods among households. Education enables one to acquire the necessary capabilities and skills crucial for diversification. Education in this study was captured as a dummy variable,whether the household head has completed secondary school education or not.

Diversification of livelihoods was expected to have a double effect on the probability of farmers investing in CSA technologies. This is because farmers with off-farm sources of income may have the necessary resources to invest in CSA technologies or off-farm employment may act as distraction from investing in agricultural technologies (Rajendran *et al.*, 2016). In this study, off-farm employment was captured as a dummy variable, whether a household has diversified from farm-only sources of income or not.

Labor availability within a household is expected to favor the adoption of given CSA technologies because the technologies do not require mechanization per se but rely on labor available to the household (Rajendran *et al.*, 2016). Labor availability within a household was expected to influence positively the likelihood of the household diversifying its livelihood sources. A household that has many of its members able to offer labor was expected to diversify some of that labor away from on-farm income generating activities to other income sources. Labor availability in this study was captured as a continuous variable of the number of household members within the age limits of 14 and 64 years.

Gender of the household head was expected to have either a positive or a negative influence on the adoption of given CSA technologies. This is because male and female farmers may have different attitudes to varying agricultural technologies as noted by Bernier *et al.* (2015). Gender of the household head was expected to influence positively diversification if household head is male. Female farmers in rural areas may be time-constrained to engage in a multiple of activities outside the farm environment (Gecho *et al.*, 2014). The gender of the household head was captured as a dummy variable.

Livestock ownership, land size and asset index were used to represent the wealth status of farming households in this study. Wealthy households were assumed to have a higher probability of adopting given CSA technologies. This because wealth acts as a crucial buffer against risks in investing in climate smart innovations that require use of cash outlay and other household resources (Kurgat *et al.*, 2018; Rajendran *et al.*, 2016).Similarly, wealth was expected to encourage households to diversify to off-farm and non-farm income generating activities. Wealth acts as a pull factor in encouraging livelihood diversification among households(Kassie *et al.*, 2017).

Livestock ownership was captured in this study as a continuous variable by taking the total number of each type of livestock in the household from sheep, goats, cattle, donkey and poultry and then converting to equivalent tropical livestock units (TLUs). Land size was captured as a continuous variable as the total size of land in acres owned by a household. Asset index was derived from the results of a principal component analysis (PCA) run in Stata analysis software of the total value of varied households' assets. The assets include all the non-land assets owned by the household excluding livestock ownership. (Teklewold *et al.*, 2013) used a similar approach of getting the total value of non-land assets among Ethiopian farmers in calculating farmer wealth status.

Distance to the market was expected to have a negative influence on the probability of adopting agricultural technologies. This is because distance to the market increases the transaction costs associated with purchase of necessary inputs (Ahmed, 2015). Distance was also expected to influence negatively the probability of households diversifying their livelihoods. Gebru *et al.* (2018) found similar results. In this study, distance to the nearest market is a continuous variable captured as the number of kilometers to the nearest market. Another factor of interest in this study is social capital, which was expected to influence positively the adoption of agricultural technologies considered in this study. Social capital complements and substitutes provision of formal extension service, such that it can encourage the uptake of agricultural technologies among farmers (Rajendran *et al.*, 2016). (Ahmed, 2015) found that cooperative membership of a household head had a positive influence on adoption of varied agricultural technologies.

Social capital was also expected to encourage household livelihood diversification because it promotes the sharing of crucial information that can encourage households to diversify (Gebru *et al.*, 2018).Social capital was captured as a dummy variable, whether a household head is a member of community-based groups including agricultural related groups. Social capital was expected to influence positively livelihood diversification. This is because social capital should act as a source of information and ideas that could potentially promote livelihood diversification among rural households. Kassie *et al.* (2017) found that social capital enhances one's entrepreneurial skill, which eventually favors livelihood diversification.

Farmer training by non-governmental organizations such as research institutes was expected to have a positive influence on the adoption of agricultural technologies by farmers. Rajendran *et al.* (2016) noted that farmers trust training institutions like non-governmental organizations and as such, the farmers take seriously, what they are taught and implement accordingly. Farmer training was expected to have a negative significant influence on the probability of households diversifying. Gecho *et al.* (2014) found that farmer training on agricultural related topics discourages farm households from diversifying their sources of income from farm only sources. Farmer training was captured as a dummy variable, of whether the household head received any training on any agricultural related topic from any research institute or non-governmental organization in the past five years.

Access to credit was assumed to favor the adoption of agricultural technologies among farmers. Credit access allows a household to have enough cash to spend on technologies that require immediate or substantial cash outlay (Kurgat *et al.*, 2018). Credit access is expected to favor household diversification due to the fact that credit provides farmers with the much needed working capital for various income generating activities (Gebru *et al.*, 2018). Access to credit was captured as a dummy variable on whether a household head accessed credit in the last twelve months.

This study analyzed the effects of climate change stresses on livelihood diversification and the adoption of given CSA technologies. Teklewold *et al.* (2013) pointed out that environmental stresses erode the confidence that farmers have in potential agricultural technologies. Aryal *et al.*, (2018) also noted that farmers adopt various agricultural technologies to adapt to risks brought about by undesirable climate variability. Adverse climate risks experienced by farmers were expected to favor livelihood diversification. This because climate change risks threaten the reliability of on-farm income as a livelihood source. This study obtained the subjective response of whether a farmer had experienced floods and droughts within the past five years. The response given by farmers was captured as a dummy variable. Floods and droughts were expected to have a positive influence on the adoptions of agricultural technologies considered in this study. It was expected that farmers view adoption of agricultural technologies as an avenue for building resilience to environmental stresses. Lastly, location corresponding to county of residence of respondents was captured as a dummy variable. Location informs the varied cultural, infrastructural and governance difference between regions. Location was expected to have either a positive or a negative influence on adoption of technology.

Table 3. 2: Description of explanatory variables used in the study

Variable	Description and measurement of variable	Expected sign
Risk attitude	CRRA parameter	+/-
Livelihood choice	Dummy, 1 = if household has diversified its livelihood sources 0 = otherwise	+/-
Land size	Total size of land owned by household in acres	+
Social capital	Dummy 1 = if household head is member of community based groups, including agricultural related groups, 0 = otherwise	+
Distance to market	Number of kilometers to nearest market	-
Credit access	Dummy, 1 = household received credit in past one year, 0 = otherwise	+
Location	Dummy= located in Kisumu county, 0 = otherwise	+/-
Education	Dummy, 1 = household head has secondary education, 0 = otherwise	+
Farmer training	Dummy 1 = household head has received agricultural related training, 0 = otherwise	+
Age	Years of the household head	-
Family size	Number of household members in adult equivalents (between 14 and 64 years)	+
Gender	Dummy, 1 = household head is male, 0 = otherwise	+/-
Livestock ownership	Tropical livestock units	+
Asset ownership	An asset index generated from value of non-land and non-livestock assets owned by a household	+
Climate risks	Dummy, 1 = experienced climates risks, 0 = otherwise	+

3.5 Model Diagnostics

3.5.1 Multicollinearity

Wooldridge (2016) recommends that in estimating regression results, there should be less correlation between explanatory variables and suggests the use of variance inflation factors (VIFs) to test for presence of multicollinearity. A VIF of less than 10 is recommended. VIFs were obtained for all of the explanatory variables. The mean VIF for the explanatory variables used in the logit model is 1.463 (appendix 2). The mean VIF for the explanatory variables used in the MVP and OP models is 1.465 (appendix 3). Since the mean VIF for both models is less than 10, it means there is no presence of multicollinearity.

3.5.2 Heteroscedasticity

Following Wooldridge (2016) a test to determine whether there was constant variance across the error terms was done using Breusch-Pagan test for heteroscedasticity (BP test). The BP test was run for the logit, the MVP the OP models in Stata. The BP test for logit model failed to reject the null hypothesis that there was constant variance across the error terms with a chi-square value of 0.85 and p-value of 0.3577 (appendix 4 (A4.1)). Similarly, the BP test for the MVP and OP models failed to reject the null hypothesis that there was constant variance across the error terms with a chi-square value of 1.10 and p-value of 0.2942 (appendix 4 (A4.2)).

3.6 Data sources

3.6.1 Sampling procedure

Multistage sampling technique was used in obtaining the sample size for the study. In the first stage, Kisumu and Kericho counties were purposively chosen but within the contiguous Nyando basin, Nyakach – Soin administrative regions

In the second stage, households in both CSVs and non-CSVs were purposively selected within the contiguous Nyando basin. The study ensured that sampled households in CSVs and non-CSVs were very similar in observable characteristics; main agricultural activities; climate and soils. In the last stage, stratified random sampling was employed in selecting individual households. The different strata considered in the sampling included first, whether a household owns sheep and goats and if it owns; whether the owned sheep or goats are the improved breeds or the indigenous ones and second whether a household has high or low crop and land management technologies. The key reason for considering these strata is that the study focused on the upscaling of stress-tolerant livestock; sheep and goat breeds, and crop and land management technologies in the Nyando basin.

The sample size was determined using the following Cochran (1963) formula

$$n = \frac{Z^2 p(1-p)}{e^2}$$

n is the sample size, p is the assumed proportion of residents with desired characteristics, in this study about 70 percent of the residents in the strata considered have the desired characteristics, Z abscissa of the normal curve at 1.96, and e is the allowed measurement error at 0.08.

$$n = \frac{1.96^2 0.7(1-0.7)}{0.08^2} = 126.0525 \approx 127$$

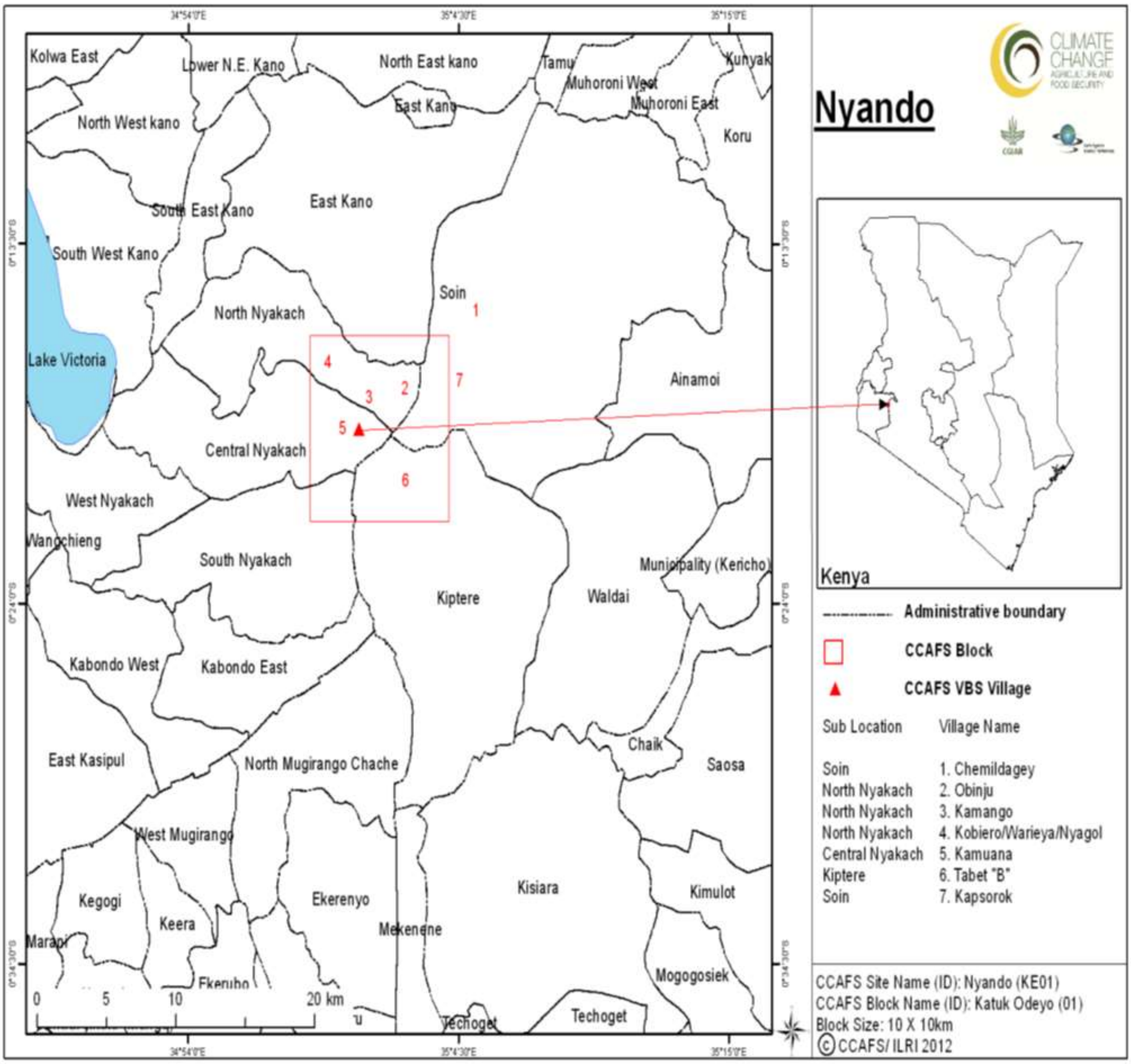
The actual number of duly completed questionnaires was 122; therefore, data from 122 households was used for data analysis.

3.6.2 Data collection Methods

The data used in this study comes from a baseline survey of smallholder farmers within the Nyando basin conducted in the month of February 2019. The data was collected as a collaboration between University of Nairobi, VU University and ILRI. The data consists of household socioeconomic characteristics, a hypothetical risk experiment and type of CSA technologies adopted by Nyando basin households. The particular data needed for this study included; results of the hypothetical risk experiment, type of CSA technologies adopted by farmers and household specific socio-economic characteristics. The data was collected through a face-to-face interview by use of semi-structured questionnaires with responses captured using an open data kit (ODK) software.

3.7 Study area

The study area traverses two counties in Kenya: Kisumu and Kericho counties. The particular site is in Nyando basin. Nyando experiences a humid to semi-humid climate with mean annual rainfall ranging between 900-2000 mm (Bernier *et al.*, 2015). Mixed farming system is the main source of livelihood for most of the households in the Nyando basin (Bernier *et al.*, 2015; Kinyangi *et al.*, 2015). Farmers in the region plant maize, sorghum and rear local cattle and shoat breeds (Aggarwal *et al.*, 2018). Due to adverse climate change, Kericho County has started experiencing flashfloods around lower lying areas of Kipkelion and Soin and erratic rainfall throughout the year(MoALF, 2017a). In a similar manner, because of adverse climate change, Kisumu County has recorded increased cases of floods within the Nyando basin and areas of lower Nyakach (MoALF, 2017b). Additionally, heat stress, vulnerability to droughts and unreliable rainfall has been experienced across the two counties within the contiguous Nyando basin region(MoALF, 2017a, 2017b). These undesired effects of climate change have made it hard for farmers within the region to depend on agriculture as a livelihood source.



Source: (Recha, 2017)

Figure 3. 2 Map of the study area in the Nyando basin

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1 Socio-economic characteristics of Nyando basin smallholder farmers

Table 4.1 shows summary statistics of explanatory variables used in the study differentiated between Kisumu and Kericho counties.

There is a significant difference in the average age of the household head between Kisumu and Kericho smallholder famers. The mean age of the household heads of Kericho smallholder farmers is significantly lower than that of the mean age of household heads of Kisumu smallholder farmers at five percent level of significance. Kericho households have significantly larger plot sizes in acres than Kisumu households at 10 percent level of significance. This is a reflection of the high population density in Kisumu as compared to Kericho county(KNBS, 2019). High population density favors the subdivision of land, which leads to small plot sizes per capita. Kisumu households have a significantly higher asset index as compared to their Kericho counterparts at one percent level of significance. This difference could be explained by difference in value of non-land and non-livestock assets owned by households across the two counties. Kericho residents walk a significantly longer distance to reach their local market centers than Kisumu residents do at five percent level of significance. This difference in distance to market centers could be because of larger farm sizes in Kericho and low population density, which favors a slow development of market centers. There is no significant difference in family size (adult equivalent) and tropical livestock units between Kericho and Kisumu households.

A significantly larger percentage of Kisumu households reported flooding as a major climate risk as compared to Kericho households at one percent level of significance. Nyando area on the side of Kisumu is a lowland area where water from the neighboring hilly Kericho county drains (Owuor *et al.*, 2012).

A significantly larger percentage of Kisumu households receive farmer training as compared to Kericho households. The reason could be that Kisumu households may be exposed to many farmer-training opportunities than Kericho households. There is no significant difference in the percentage of male-headed households between Kisumu and Kericho households. This reflects the fact that many rural households in sub-Saharan Africa are male-headed. There is no significant difference in access to loans, social capital, and literacy, access to off-farm or non-farm income as well as exposure to droughts between Kisumu and Kericho households.

Table 4. 1Socio-economic variables of households by county

Variables	Kericho (51) Mean	Kisumu (71) Mean	Pooled sample mean (122)	t_value	P_value
Age of household head	49.9215	56.986	54.0327	-2.4	.0175**
Family size (adult size)	3.039	3.352	3.2213	-.85	0.260
Tropical livestock units (TLU)	4.6765	3.3355	3.8961	1.5	.137
Total land in acres	6.0835	3.207	4.4094	1.9	.057*
Household asset index	2.294	3.479	2.9836	-4.95	0.0000***
Distance to local market	3.7365	2.55	3.0458	2.4	.0175 **
Gender (1 = male)	0.843	0.788	0.811	0.75	0.453
Literacy (yes completed secondary education)	0.196	0.254	0.2295	-0.75	0.461
Group membership(Yes if household head is member)	0.529	0. 493	0.508	0.4	0.696
Loan access (Yes if household head accessed loans)	0.431	0.451	0.443	-.2	0.834
Diversified (Yes household has off-farm or non-farm income	0.569	0.549	0.557	0.2	0.834
Floods (Yes if experienced floods)	0.138	0.352	0.262	-2.7	0.007***
Drought (Yes experienced droughts	0.51	0.648	0.59	-1.55	0.128
Trained (Yes if household head received agricultural training)	0.451	0.648	0.566	-2.2	0.03**

Source: Survey data (2019)

4.2 **Nyando farmers' risk attitudes**

Table 4.2 shows the summary of the responses from the risk experiment. The risk experiment was designed so that respondents with risk-neutral and risk loving attitudes would choose gamble choices two (2) and one (1) respectively. Otherwise, individuals choosing gamble choices three to six are the ones with a risk-averse attitude to risk. Dave *et al.* (2010) and Holzmeister & Stefan (2020) point out that gamble choice one (1) is chosen by someone with either a risk neutral attitude or a risk seeking attitude and gamble choice two (2) is chosen by someone with either risk neutral attitude or a weak risk aversion attitude. Gamble choices three (3) to six (6) represent varying degrees of a risk averse attitude (Dave *et al.*, 2010)

An independent t-test was used in testing the hypothesis that Nyando smallholder farmers do not have a risk averse risk attitude. The Arrow-Pratt measure was utilized in categorizing households as either risk averse or not. According to the Arrow-Pratt measure of risk aversion, the cut-off point is zero, which depicts risk neutral attitude. A risk parameter above zero ($r > 0$) shows risk aversion attitude while a risk parameter below zero ($r < 0$) shows risk-loving attitude(Binici *et al.*, 2003; Jin *et al.*, 2017).

The midpoints of the coefficient of relative risk aversion intervals corresponding to captured responses were used to find the mean risk aversion level among Nyando basin households. Although it is possible to capture the midpoints of risk parameter intervals of gamble choices two to five, it is not possible to obtain the midpoints of gamble choices one and six. Therefore, the study used the lower bound of gamble choice six and upper bound of gamble choice one for analysis purposes. Cotty *et al.* (2018) used a similar approach in calculating the mean risk aversion level among Burkinabe maize farmers.

Table 4. 2Summary of the Risk Profiles of Nyando rural households

Gamble choice	Coefficient of relative risk aversion interval	Frequency	Percent	Cumulative percentage
1	$r < 0$	39	31.97	31.97
2	$0 < r < 0.5$	7	5.74	37.70
3	$0.5 < r < 0.71$	9	7.38	45.08
4	$0.71 < r < 1.16$	15	12.30	57.38
5	$1.16 < r < 3.46$	38	31.15	88.52
6	$3.46 < r$	14	11.48	100.00

Source: Survey data (2019)

Table 4.3 shows the results of the independent t-test of whether the mean risk aversion level among Nyando smallholder farmers is equal to zero or not. The results of the t-test reject the null hypothesis that mean risk aversion level among Nyando basin smallholder farmers is equal to zero at one percent level of significance. The study found that Nyando basin farmers have a mean CRRA parameter of 1.291, which means that they are moderately risk averse. This result is similar to what Jin *et al.* (2016) found about the average risk aversion level of rural Chinese farmers who were found to be moderately risk averse.

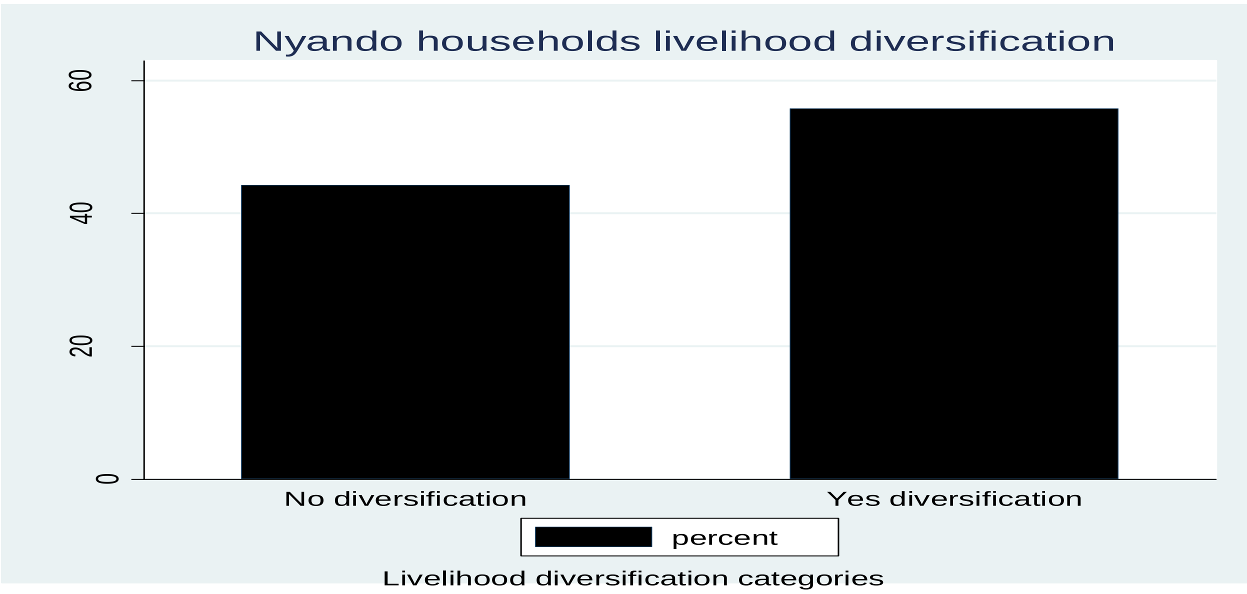
Table 4. 3Independent t-test for Mean Risk aversion level of Nyando basin smallholder farmers

	Respondents	Mean	Standard _Error	t-value	p-value
Mean risk aversion level	122	1.291	.112	11.55	0.0000

Source: Survey data (2019)

4.3 Factors influencing diversification of livelihood strategies among Nyando households

A majority of the sampled households have diversified at 55.74 percent while the rest at 44.26 percent have not diversified as shown in figure 4.1.



Source: Survey data (2019)

Figure 4. 1 Diversification of livelihoods

Table 4.4 shows the results of the binary logit run in Stata version 14 to determine the factors influencing the choice to diversify livelihood sources from on-farm income sources to off-farm or non-farm income sources among the Nyando households. Marginal effects are the ones useful in interpretation of results since coefficients are hard to interpret in a meaningful manner (Greene, 2011). The binary logit model fitted well with a pseudo R-squared of 0.173 and Prob > chi-square (χ^2) of 0.01.

Age has a negative influence on household diversification at five percent level of significance. A unit increase in the age of the household head reduces the probability of a household diversifying its livelihood sources by 0.7 percent. Gebru *et al.* (2018) had similar results where age of the household head negatively influenced livelihood diversification. The probable reason could be that as age of the household head increases, farmers are not motivated to diversify because of short career horizon and rigidity to change as opposed to young farmers who are more flexible to change and have a long career horizon.

As expected, education of the household head positively influenced household livelihood diversification at five percent level of significance. Gecho *et al.* (2014) found similar results where farmers with higher education level are more likely to diversify into off-farm and non-farm livelihood sources. If a household head had completed secondary school education, it increases the probability of a household diversifying livelihood sources by 24.2 percent. The probable reason is that education enables one to obtain the necessary skills and capabilities useful in pursuing diverse livelihood sources. Social capital negatively influenced livelihood diversification at five percent level of significance. This is contrary to what was expected. If a household head belongs to any agricultural related group or other community associations, it reduced the likelihood of a household diversifying by 21.4 percent. This could be because community based organizations emphasize and encourage their members to concentrate more on on-farm income sources than other income sources.

Floods positively increased the probability of livelihood diversification at 10 percent level of significance. Households who had experienced floods were more likely to diversify livelihood sources at 19.9 percent. The reason could be that floods make it hard for farmers to depend on on-farm income sources. Thorlakson (2011) noted that Nyando basin farmers lamented that floods affected negatively overall farm productivity. Lastly, farmer training negatively influenced livelihood diversification at five percent level of significance. Gecho *et al.* (2014) found similar results where agricultural training reduces the likelihood of households diversifying into off-farm and non-farm income sources. If a household head has received any agricultural related training, the household is less likely to diversify by 23.2 percent. The probable reason is that agricultural training equips farmers with the appropriate knowledge and skills required to maximize on farming as a livelihood source.

Results from the binary logit model reject the null hypothesis that household head socioeconomic characteristics and institutional factors do not significantly affect diversification of livelihoods among Nyando basin households. However, results of the logit model failed to reject the null hypothesis that household resources do not significantly affect diversification of livelihoods among Nyando basin households.

Table 4. 4Marginal effects of the factors influencing diversification of livelihood strategies among Nyando basin households

Explanatory variable	Coefficient	dy/dx
Family size	-0.101(0.114)	-0.025(0.028)
Gender of household head*	-0.502(0.580)	-0.118(0.131)
Age of household head	-0.031(0.014)	-0.007(0.003) **
Literacy of household head*	1.079(0.588)	0.242(0.116) **
Land size in acres	-0.036(0.041)	-0.009(0.010)
Asset index	-0.084(0.190)	-0.021(0.046)
Tropical livestock units	0.075(0.070)	0.018(0.017)
Access to loans*	0.273(0.445)	0.066(0.108)
Distance to market	-0.114(0.083)	-0.028(0.020)
Social capital*	-0.893(0.457)	-0.214(0.106) **
Floods*	0.859(0.519)	0.199(0.111) *
Drought*	-0.102(0.456)	-0.025(0.111)
Training*	-0.978(0.460)	-0.232(0.104) **
Kisumu*	0.040(0.501)	0.010(0.122)
Constant	3.621(1.222)	

Note: Standard errors in parenthesis,
Statistical significance at *** *p<0.01,* ** *p<0.05,* * *p<0.1*
N = 122 **Log likelihood = -69.257861, Chi-square** (χ^2)**= 29.002,** $\boldsymbol{Prob > \chi^2 = 0.01}$
Pseudo $\boldsymbol{\mathcal{R}^2 = 17.3}$ %

Source: Survey data (2019). TLU conversion factor: 1 head of cattle = 0.7 TLU, 1 sheep or goat (small stock) = 0.1 TLU, 1 donkey = 0.5 TLU , poultry = 0.01 TLU (Source Hailemichael *et al.* (2016) & Mkonyi *et al.* (2017)).

4.4 Influence of Nyando farmers' risk attitudes and livelihood diversification on their adoption of CSA technologies

MVP Results

The likelihood ratio test of the chi-square (χ^2) (6) = 24.4289 of the independence of error terms is rejected at one percent level of significance, which means that the adoptions of CSA innovations is not mutually independent. Therefore, the adoptions of the four technologies are interdependent, which supports the use of MVP model. Table 4.5 shows that Nyando households adopt given CSA technologies as complements and substitutes. The adoption of terraces and inorganic fertilizer, ridges and inorganic fertilizer have a significant positive correlation, which means that farmers adopted the technologies as complements. The adoption of ridges and stress tolerant livestock have a significant negative correlation, which means that farmers adopted the two technologies as substitutes.

Table 4. 5 Covariance Matrix of the Error terms: Substitutability and Complementarities of CSA technologies

CSA technologies	Terraces	Inorganic fertilizer	Ridges and bunds	Stress-tolerant livestock
Terraces	1			
Inorganic fertilizer	0.518(0.139)***	1		
Ridges and bunds	0.187(0.162)	0.299(0.136)**	1	
Stress-tolerant livestock	-0.037(0.185)	0.322(0.202)	-0.470(0.208)**	1
Likelihood ratio test of] interdependence of the regression: Chi-square(χ^2)(6) = 24.4289 $Prob > \chi^2 = 0.0004$ Statistical significance at *** *p<0.01*, ** *p<0.05*, * *p<0.1*				

Source: Survey data (2019)

Table 4.6 shows the results of the MVP model on household technology adoption decisions. The Wald test ((χ^2 (64) = 286.47 Prob > χ^2 = 0.0000) of the hypothesis that regression coefficients in all the equations are jointly equal to zero is rejected, which means the independent variables have explanatory power.

Family size had a significant positive influence on the decision of a household to adopt ridges and bunds. Erecting of ridges and bunds is a labor-intensive exercise, which necessitates households to take advantage of available family labor. Gender of the household head had a significant positive influence on the decision of household to adopt stress tolerant livestock. Male-headed households (MHHs) have a higher likelihood of adopting stress tolerant livestock as compared to female-headed households (FHHs). Obisesan (2014) found similar results where MHHs are more likely to adopt agricultural technologies than FHHs, the study attributed the difference to gendered access to resources and appropriate information.

Land size had a significant positive influence on the decision of a household to adopt stress tolerant livestock, terraces and fertilizer use. In addition, asset index has a significant positive influence on the decision of a household to adopt stress tolerant livestock. Asset index and land size are measures of the wealth of a household. A wealthier household is more likely to adopt stress tolerant livestock, fertilizer and terraces. Wealthy households are able to deal with any risks that come with the adoption of various agricultural technologies (Teklewold *et al.*, 2013). Access to off-farm or non-farm income negatively influenced the probability of a household adopting stress tolerant livestock. Ahmed (2015) found similar results where access to off-farm or non-farm income had a significant negative influence on technology adoption. Ahmed (2015) attributed the negative influence to some technologies been labor intensive and households may not have labor allocated for the same. Similarly, the adoption of stress tolerant livestock may require allocation of labor for its safe caring and thus households that have diversified may not allocate the labor needed.

Risk attitude had a significant negative influence on whether a household adopts terraces and ridges and bunds. Ambali *et al.* (2019) found similar results, whereby farmers who avoided taking risks were less likely to adopt agricultural technology. Erecting of terraces, ridges and bunds may require cash outlay in paying for required labor and purchase of appropriate tools. Risk averse farmers may be unwilling to spend their limited cash reserves on the same. Access to loans had a positive significant influence on the decision of a household to adopt stress tolerant livestock. Adoption of stress tolerant livestock requires cash outlays and loans provide the needed cash. Loans provide farmers with access to cash if they are not able to self-finance (Jerop *et al.*, 2018; Teklewold *et al.*, 2013).

Distance to the market had a significant negative influence on the probability of a household adopting stress tolerant livestock. The reason could be transaction costs that increase as distance to the market increases (Teklewold *et al.*, 2013). Alternatively, distance to the market had a significant positive influence on the decision of a household to adopt fertilizer. The probable reason is that households in the Nyando basin collaborate with a local non-governmental organization that brings them farm inputs at their doorstep without requiring them to go the market. Teklewold *et al.* (2013) had similar results where distance to the market had a significant positive effect on the adoption of agricultural technology.

Floods had a significant positive influence on the decision of a household to adopt stress tolerant livestock and fertilizer. Floods are climate risks brought about by adverse climate change. Households have faith that stress tolerant livestock are able to cope well during flooding episodes. At the same time, farmers hope to improve farmland productivity by applying fertilizer since floods reduce the farmland productivity of their farms as noted by Thorlakson (2011). Droughts had a significant positive influence on the decision of a household to erect ridges and bunds. Ridges reduce the speed of surface run-off (Bernier *et al.*, 2015). It is from this reduced surface run-off that ridges and bunds aid in soil moisture retention, which farmers can utilize in periods of dry-spells to plant early maturing crops like vegetables (Wolka *et al.*, 2018).

Farmer training had a significant positive influence on the decision of a household to adopt stress tolerant livestock and terraces. Training offers farmers with the appropriate knowledge and equips them with skills to successfully adopt terraces and stress tolerant livestock for their benefit. Previous studies have found that farmer training favors the adoption of agricultural technologies (Aryal *et al.*, 2018; Jerop *et al.*, 2018; Maguza-Tembo* *et al.*, 2017; Yirga *et al.*, 2015). Lastly, households in Kisumu are less likely to adopt fertilizer, ridges and bunds as climate smart technologies useful in farming. The probable reason could be due to differences in resources used to erect ridges and bunds. Kericho residents are able to use surface rocks, which are plenty, to erect ridges and bunds in their farms, which Kisumu residents' lack. The difference in adoption of fertilizer between Kisumu and Kericho farmers may be due to varied access to farm inputs including fertilizer.

Table 4. 6MVP results of households' technology adoption decisions

Dependent variables/explanatory variables	Terraces	Fertilizer	Ridges and bunds	Stress tolerant livestock
Family size	-0.039(0.069)	-0.062(0.077)	**0.108(0.065)***	-0.050(0.088)
Gender of household head	0.261(0.330)	0.492(0.349)	-0.148(0.361)	**1.420(0.589)****
Age of household head	0.008(0.009)	-0.003(0.009)	0.008(0.009)	-0.012(0.015)
Literacy of household head	0.070(0.331)	-0.192(0.344)	0.314(0.347)	0.835(0.525)
Land size in acres	**0.167(0.069)****	**0.182(0.074)****	-0.028(0.020)	**0.224(0.060)*****
Asset index	0.114(0.112)	0.127(0.123)	0.073(0.109)	**0.267(0.145)***
Off-farm or non-farm income	0.137(0.291)	0.066(0.290)	-0.153(0.277)	**-0.561(0.339)***
Tropical livestock units	0.044(0.055)	-0.073(0.049)	0.031(0.036)	-0.031(0.061)
Risk attitude	**-0.191(0.111)***	0.024(0.109)	**-0.343(0.114)*****	-0.134(0.136)
Access to loans	0.068(0.260)	0.384(0.281)	0.057(0.264)	**0.824(0.335)****
Distance to market	0.046(0.055)	**0.179(0.054)*****	0.076(0.049)	**-0.193(0.068)*****
Social capital	0.188(0.292)	0.281(0.285)	0.208(0.280)	0.445(0.336)
Floods	0.019(0.286)	**0.672(0.320)****	-0.103(0.297)	**0.962(0.347)****
Drought	-0.070(0.280)	0.091(0.274)	**0.745(0.281)*****	0.337(0.347)
Training	**0.464(0.280)***	-0.237(0.267)	-0.151(0.273)	**1.707(0.413)*****
Kisumu	-0.365(0.285)	**-0.600(0.308)***	**-0.625(0.290)****	-0.574(0.369)
_cons	**-1.326(0.757)***	**-1.399(0.777)***	-1.005(0.778)	**-3.691(0.985)*****
Note: Standard errors in parenthesis, statistical significance * *p<0.01*, ** *p<0.05*, * *p<0.1***				
N = 122 (Number of draws = 10) Log likelihood = -230.96552 Wald (χ^2)(64) = 286.47***				

Source: Survey data (2019). TLU conversion factor: 1 head of cattle = 0.7 TLU, 1 sheep or goat (small stock) = 0.1 TLU, 1 donkey = 0.5 TLU, poultry = 0.01 TLU (Source (Hailemichael *et al.* (2016) & Mkonyi *et al.* (2017)).

Ordered probit estimation results

The MVP model tells nothing of the level of adoption of CSA technologies by a farming household and the factors that influence the level of adoption of CSA technologies. The OP model was run to overcome this MVP model weakness. Table 4.7 shows the number of CSA technologies adopted by Nyando smallholder farmers. Barely 15 percent of the farmers have adopted zero CSA technologies addressed in this study while about seven percent representing eight farmers have adopted all the four technologies. About 50 percent of the households have adopted two or three technologies and more than three quarters of the sampled households have adopted one to three technologies.

Table 4. 7 Level of adoption of CSA technologies by Nyando households

CSA technologies adopted	Number of farmers	Percent	Cumulative percent
0	18	14.75	14.75
1	29	23.77	38.52
2	34	27.87	66.39
3	33	27.05	93.44
4	8	6.56	100.00

Source: Survey data (2019)

The ordered probit model fits well with a *Prob > chi-square* (χ^2) = 0.000 and pseudo r-squared of 0.12 . The ordered probit results without marginal effects showing the coefficients are shown in appendix six (6).

Table 4.8 shows the factors influencing the level of adoption of the given CSA technologies by the Nyando basin smallholder farmers. Gender of the household head had a significant negative likelihood on a household adopting one CSA technology but has a significant positive influence on the probability of a household adopting three and four technologies. MHHs are more likely to adopt three and four technologies and less likely to adopt one practice at 13.1, 2.7 and 8.5 percent respectively. This could be because MHHs have more resources as compared to their FHHs counterparts. Appendix five (5) shows the mean value of total CSA technologies adopted by FHHs is significantly lower than that of MHHs at 10 percent level of significance. Household asset index had a significant negative influence on the probability of a household adopting only one CSA technology and not adopting any practice at 3.6 and 3.1 percent respectively. However, asset index had a significant positive influence on the probability of a household adopting three CSA technologies at 5.1 percent. This shows that wealthier households were more likely to adopt more than one site-specific CSA technologies and less likely to adopt one or not adopt at all any CSA technology.

Risk attitude had a significant effect on the probability of a household adopting none, one, three and four CSA technologies. Risk attitude positively influenced the probability of a household adopting none and one CSA practice at 3.1 and 3.6 percent respectively. This means that the Nyando basin farmers are able to deal with the risk of adopting one CSA technology. Alternatively, risk attitude negatively influences the probability of a household adopting three and four CSA technologies at 5.1 and 1.3 percent respectively. This means that Nyando basin farmers perceive risk in the adoption of more than one CSA technology and thus are less likely to adopt many agricultural technologies.

Distance to the market significantly influenced the probability of Nyando farmers adopting none, one or three CSA technologies. Distance to the market negatively influenced the probability of adopting one practice by 1.5 percent and not adopting by 1.4 percent. At the same time, distance to the market positively influenced the probability of adopting of three technologies by 2.2 percent. The probable reason is that farmers may face inhibitive transaction costs in adopting one practice but not so with adopting more than one CSA technology. Floods had a significant negative effect on the probability of a household not adopting any CSA technology. Farmers who had experienced floods were less likely to not adopt any CSA practice at 5.9 percent, which means that floods encourage the adoption of site-specific climate smart technologies by Nyando farmers.

Kisumu farmers are significantly more likely to adopt one or fail to adopt any CSA technology at 12.6 and 10.6 percent respectively. Alternatively, Kisumu farmers are significantly less likely to adopt three and four technologies at 17.8 and 5.3 percent respectively. This could be a reflection of disparity in access to information, resources and skills required for adoption of more than one site-specific CSA technologies between Kisumu and Kericho farmers.

Results of the MVP and OP models led the study to not accept the null hypothesis that Nyando farmers' risk attitudes do not significantly influence the adoption of given CSA technologies. Risk attitudes had a significant influence on the likelihood of adopting terraces and ridges and bunds. The results of the OP model led the study to fail to reject the null hypothesis that household livelihood diversification does not significantly influence the intensity of adoption of given CSA technologies. However, the results of the MVP model rejected the null hypothesis that household livelihood diversification does not significantly influence the adoption of stress tolerant livestock as a CSA technology.

Table 4. 8 Marginal effects of ordered probit estimation results

Variable	Prob (Y = 0/X)	Prob (Y = 1/X)	Prob (Y = 2/X)	Prob (Y = 3/X)	Prob (Y = 4/X)
Family size	-0.004(0.010)	-0.005(0.011)	0.000(0.001)	0.007(0.016)	0.002(0.004)
Gender of household head*	-0.102(0.072)	**-0.085(0.045)***	0.030(0.033)	**0.131(0.073)***	**0.027(0.016)***
Age of household head	-0.001(0.001)	-0.001(0.001)	0.000(0.000)	0.001(0.002)	0.000(0.001)
Literacy of household head*	-0.002(0.047)	-0.002(0.054)	0.000(0.005)	0.003(0.077)	0.001(0.020)
Land size in acres	-0.005(0.004)	-0.006(0.004)	0.001(0.001)	0.008(0.006)	0.002(0.002)
Asset index	**-0.031(0.017)***	**-0.036(0.020)***	0.003(0.006)	**0.051(0.027)***	0.013(0.008)
Off-farm or non-farm income*	0.038(0.039)	0.044(0.045)	-0.003(0.008)	-0.062(0.064)	-0.016(0.018)
Tropical livestock units	-0.002(0.007)	-0.003(0.008)	0.000(0.001)	0.004(0.011)	0.001(0.003)
Risk attitude	**0.031(0.016)***	**0.036(0.018)***	-0.003(0.006)	**-0.051(0.026)****	**-0.013(0.0076)***
Access to loans*	-0.052(0.037)	-0.061(0.043)	0.004(0.010)	0.086(0.060)	0.023(0.018)
Distance to market	**-0.014(0.007)***	**-0.015(0.009)***	0.001(0.003)	**0.022(0.012)***	0.006(0.004)
Social capital*	-0.042(0.039)	-0.047(0.044)	0.005(0.009)	0.067(0.062)	0.017(0.017)
Floods*	**-0.059(0.036)***	-0.077(0.052)	-0.003(0.015)	0.108(0.071)	0.033(0.027)
Drought*	-0.060(0.043)	-0.064(0.044)	0.009(0.013)	0.092(0.061)	0.022(0.017)
Training*	-0.045(0.041)	-0.050(0.043)	0.006(0.010)	0.072(0.062)	0.018(0.016)
Kisumu*	**0.106(0.041)*****	**0.126(0.051)****	-0.002(0.020)	**-0.178(0.067)*****	**-0.053(0.029)***
Note: Standard errors in parenthesis, statistical significance **** p<0.01, ** p<0.05, * p<0.1* N = 122 **Log likelihood = -162.35133 LR (χ^2)(16) = 44.29*** Pseudo $\mathcal{R}^2 = 12.0$** %					

Source: Survey data (2019)

CHAPTER FIVE: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary

This study analyzed risk attitudes among the Nyando basin household heads using a hypothetical risk experiment and found out that they were moderately risk averse with a CRRA parameter of 1.291. This is consistent with previous studies, which have reported that farmers in the developing world are usually risk averse. The procedure used to elicit the risk preferences was the rank procedure where respondent's risk attitude was implied from the CRRA parameters corresponding to their single choice from a list of possible gamble choices. At the same time, the study analyzed the factors that influence diversification of livelihood sources among Nyando basin households. In this study, diversification of a household was defined in terms of whether a household has non-farm or off-farm income sources. Out of the possible explanatory variables hypothesized to influence diversification, five were found to have a significant influence. These include age of household head, education level of the household head, social capital, floods and access to training on agricultural topics by a household.

The focus of this study was on the factors that influence households to adopt simultaneously several climate smart agricultural innovations and the intensity of adoption. Particular emphasis was on whether farmers' risk attitudes and household livelihood diversification have significant influence on the decision of households to adopt given climate smart innovations. The CSA technologies under study were adoption of stress tolerant sheep and goat breeds and soil improvement technologies that involve use of inorganic fertilizer, terraces and ridges and bunds. Household livelihood diversification and farmers' risk attitude had a significant influence on the decision of households to adopt given CSA technologies. Other explanatory variables that had a significant influence on the adoption of given agricultural innovations include; household family size, gender of household head, land size, household asset index, loan access, distance to nearest market, farmer training, location and climate risks that included floods and droughts. The explanatory variables did not have a significant influence in all the adoption equations and some differed on the direction of the influence. Gender of household head, household asset index, risk attitude, distance to market, floods and location are the variables that had significant influence on the intensity of adoption of given CSA technologies.

5.2 Conclusions

Age of household head, social capital and farmer training had a significant negative impact on the decision of a household to diversify livelihoods. This highlights the need to offer targeted training to farmers, especially old farmers on the need to diversify. Floods and education of the household head had a significant positive influence on household livelihood diversification. This finding stresses the need and importance of formal education, in that it builds the capacity of an individual to be able to engage in varied livelihood sources other than on-farm income sources. It also highlights the role that climate risks play by pushing rural households from on-farm to off-farm or non-farm income sources as livelihood sources.

The use of the ranking procedure in estimating risk attitude among the sampled households proved useful because risk attitude had a significant influence in two out of the four adoption equations. Risk attitude had a significant negative influence on the decision of households to adopt terraces and ridges and bunds. This highlights the behavior of Nyando basin households to shun from risk taking activities, which can be counter-intuitive for them. Climate smart technologies are risk-reducing innovations, which farmers can benefit from adopting them. Land size had a significant positive influence on the decision of households to adopt stress tolerant livestock, terraces and inorganic fertilizer. At the same time, household asset index had a significant positive influence on the decision of households to adopt stress tolerant livestock. Land size and asset index as measures of household wealth emphasize the positive influence that household wealth has on household adoption of agricultural technologies.

Loan access had a significant positive influence on the adoption of stress tolerant livestock, which highlights the cash needs of households in adopting cash-dependent innovations. Off-farm or nonfarm income had a significant negative influence on the decision of households adopting stress tolerant livestock. This could be due to inadequacy of labor available to cater for the labor needs of caring for stress tolerant livestock.

Distance to the market had a significant negative influence on the adoption of stress tolerant livestock. This shows that increases in transactions costs impede households from adopting certain agricultural technologies. Alternatively, distance to the market had a significant positive influence on the decision of a household to adopt inorganic fertilizer. This begs the question of whether there are other avenues, which households far from the market use to access farm inputs.

Family size had a significant positive influence on the decision of a household to adopt ridges and bunds. Floods had a significant positive influence on the decision of household to adopt stress tolerant livestock and inorganic fertilizer while droughts had significant positive influence on the adoption of ridges and bunds. It shows climate risks may prompt households to adopt varied climate smart innovations. Farmer training had a significant positive influence on the decision of households to adopt stress tolerant livestock and terraces. This highlights the key role of farmer training in encouraging farmers to adopt appropriate agricultural technologies. Kisumu households are less likely to adopt inorganic fertilizer, ridges and bunds. This can be explained by differences in resources and differential access and application of appropriate farming knowledge by farming households in the two counties.

5.3 Recommendations

The local county governments of Kericho and Kisumu should strengthen available farmer training initiatives within their respective counties. Farmer training will potentially expose smallholder farmers in the region to available CSA technologies that can be of benefit to them. Farmer training should incorporate options on livelihood diversification since on-farm income sources are susceptible to adverse climate change in the region.

Kenya's national government and local governments of Kisumu and Kericho should spearhead an initiative whereby smallholder farmers engage with agricultural insurance providers. Results of the study showed that Nyando basin farmers are on average risk averse; this makes them potential clients of insurance products. Particularly, farmers should benefit from agricultural weather index based insurance products. This is because adverse climate change exposes smallholder farmers to productions risks. Agricultural weather index based insurance is an appropriate insurance cover against the production risks in both livestock and crop farming.

The national and local governments should provide a conducive economic environment and support financial institutions willing to lend loans to farmers. Farmers will be able to take advantage of access to loans to finance their farm operations including adoption of appropriate CSA technologies.

5.4 Areas of Further Research

This study employed a hypothetical risk experiment to measure farmers' risk attitude using a rank approach. Future studies could consider conducting a real experiment with other methods of eliciting risk preferences other than rank approach. Further, future research can incorporate plot analysis in analyzing the factors that influence the adoption of climate smart agricultural technologies in the Nyando basin region. Lastly, this study only considered the factors that influence the simultaneous adoption and intensity of adoption of four CSA technologies. Further research can incorporate more than four technologies and different technologies than those considered in this study.

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Appendices

Appendix 1

Hypothetical risk experiment question used in the survey

I have six decision cards; each card has two options; Event A and Event B. The probability of either event occurring is 50 percent. Imagine the six decision cards as representing SIX different business ventures (either on-farm or off-farm business) with event A representing high payoff and event B representing a low payoff. Given the opportunity, which of the six options would you pick? I expect you to choose ONLY ONE option among the six decision cards.. **Note: You can only choose one choice.**

[Read out and show the six decision cards, each event has a 50 % chance of occurring]

Table A1: Gamble choices and expected payoff in event A and event B

Gamble choice	Event A (high payoff) with probability, p	Event B (low pay off) with probability, (1-p)	Intervals for the coefficient of relative risk aversion parameter (r) (Not visible to respondents)
1	10000	10000	3.46 < r
2	12000	9000	1.16 < r < 3.46
3	14000	8000	0.71 < r < 1.16
4	16000	7000	0.5 < r < 0.71
5	18000	6000	0 < r < 0.5
6	20000	4000	r < 0

Appendix 2

Table A2: Mean VIF for explanatory variables used in the binary logit model

Explanatory variables	VIF	1/VIF
Tropical livestock units	2.692	.371
Land size in acres	2.499	.4
Asset index	1.737	.576
Kisumu	1.458	.686
Literacy of household head	1.319	.758
Gender of household head	1.264	.791
Social capital	1.227	.815
Age of household head	1.21	.826
Family size	1.207	.828
Distance to market	1.197	.836
Training	1.193	.838
Access to loans	1.169	.856
Floods	1.168	.856
Drought	1.14	.877
Mean VIF	1.463	.

Source Survey data (2019)

Appendix 3

Table A3: Mean VIF for explanatory variables used in the MVP and OP models

Explanatory variables	VIF	1/VIF
Tropical livestock units	2.725	.367
Land size in acres	2.521	.397
Asset index	1.74	.575
Kisumu	1.459	.685
Literacy of education head	1.377	.726
Age of household head	1.283	.779
Gender of household head	1.282	.78
Off-farm or non-farm income	1.271	.787
Social capital	1.268	.788
Family size	1.265	.791
Training	1.237	.808
Drought	1.225	.817
Distance to market	1.22	.82
Floods	1.204	.83
Risk attitude	1.189	.841
Access to loans	1.172	.853
Mean VIF	1.465	.

Source Survey data (2019).

Appendix 4

Table A4.1: Heteroscedasticity Binary Logit Model

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity	
	Ho: Constant variance
	Variables: fitted values of Livelihood diversification
	chi2(1) = 0.85
	Prob > chi2 = 0.3577

Source: Survey data (2019)

Table A4.2: Heteroscedasticity for the Ordered Probit Model

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity	
	Ho: Constant variance
	Variables: fitted values of TOTAL_ADOPTIONS
	chi2(1) = 1.10
	Prob > chi2 = 0.2942

Source: Survey data (2019)

Appendix 5

Table A5: Gender difference in number of CSA technologies adopted

	FHHs (23) Mean	MHHs (99) Mean	Difference in mean	Pooled sample mean	t-vale	P-value
Total CSA technologies adopted	1.478	1.960	-.481	1.869	-1.8	.074

Source: Survey data (2019)

Appendix 6

Table A6: Ordered probit results showing coefficients

TOTAL_ADOPTION	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Family size	0.024	0.056	0.43	0.668	-0.085	0.133	
Gender of household head	0.484	0.285	1.70	0.090	-0.075	1.044	*
Age of household head	0.004	0.007	0.66	0.507	-0.009	0.018	
Literacy of household head	0.009	0.270	0.03	0.973	-0.520	0.538	
Land size in acres	0.028	0.020	1.40	0.160	-0.011	0.067	
Asset index	0.179	0.092	1.95	0.051	-0.001	0.359	*
Off-farm or non-farm	-0.220	0.224	-0.98	0.327	-0.659	0.219	
Tropical livestock units	0.014	0.038	0.36	0.719	-0.060	0.087	
Risk attitude	-0.178	0.086	-2.07	0.038	-0.347	-0.009	**
Access to loans	0.304	0.211	1.44	0.149	-0.110	0.718	
Distance to market	0.077	0.040	1.94	0.052	-0.001	0.155	*
Social capital	0.237	0.218	1.08	0.278	-0.191	0.665	
Floods	0.380	0.247	1.54	0.123	-0.103	0.864	
Drought	0.326	0.220	1.48	0.139	-0.106	0.759	
Training	0.253	0.218	1.16	0.246	-0.175	0.681	
KISUMU	-0.641	0.239	-2.68	0.007	-1.110	-0.172	***
Constant	0.342	0.623	.b	.b	-0.879	1.562	
Constant	1.272	0.629	.b	.b	0.039	2.505	
Constant	2.100	0.635	.b	.b	0.855	3.344	
Constant	3.475	0.679	.b	.b	2.145	4.806	

Source survey data (2019)