FARMERS ADAPTATION TECHNOLOGIES TO CLIMATE CHANGE IN PANGANI RIVER BASIN: TECHNICAL EFFICIENCY AND YIELD RISK

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ABSTRACT

The study to investigate farmer's adaptation technologies to climate change in Pangani river basin, Tanzania focused on two central themes mainly yield risks and the efficiency of adopted farm technologies to climate change adaptation. A total of 420 randomly selected smallholder farmers from twelve villages were included in the study. Data were collected by questionnaire survey in a survey, farm observations, and focus group discussions. Three approaches were employed to address the above themes. The first approach was the multinomial endogenous switching regression model of climate change adaptation and crop yield to determmine analyze factors that influence farm technology adoption and the effects of adopted farm technologies on the smallholder farmers productivity. Secondly, the method of Just and Pope's Production function to determine the risk implications of the different technologies and lastly, a stochastic frontier approach was used to analyze farm technical efficiency of adopted farm technologies. Results showed that adoption decisions on related technologies were influenced by farmer characteristics, plot-level factors and weather variables. Adoption of farm technologies increases maize yield and the highest payoff was achieved when farm technologies are adopted in combination rather than in isolation. However adopted farm technologies perform differently along the Pangani river basin underscoring the importance of careful geographical targeting when promoting and scaling up farm technologies. The smallholders were found to be technically inefficient, producing only 59.9 per cent of the potential output. Great inter-household variations in technical efficiency existed, influenced by farmer characteristics, production environment and production risks. The results have the following implications. First, a one-size-fits-all approach is not an advisable approach for developing and promoting technologies. It is important to disseminate farm technologies that are appropriately tailored to a specific area instead of

making blanket recommendations that promote similar technologies to all farmers. Secondly, there is a need for the government, and development partners to provide incentives to accelerate complete adoption of these technologies. Thirdly, there is a need to address the constraints reducing farmer efficiency. Viable alternatives should include improving transport and marketing infrastructure, encouraging the smallholders to supplement inorganic fertilizer with manure, and use of soil and water conservation measure.

DECLARATION

I, ARBOGAST BERNARD MOSHI, do hereby declare to the Senate of Sokoine University of Agriculture, that this thesis is my own original work done within the period of registration and that it has neither been submitted nor being concurrently submitted in any other institution.

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DEDICATION

To my parents, my father Mr Bernard Moshi, mother Kostansia Moshi, my beloved wife Adelaide Matemba, my daughter Giovanna, and my son Ivan.

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LIST OF ABBREVIATIONS

AMCEN	African Ministerial Conference on Environment
CDM	Clean Development Mechanism
CSAG	Climate System Analysis Group
EAC	East African Community
EMA	Environmental Management Act
ENSO	El Niño Southern Oscillation
ESR	Endogenous Switching Regression
FAO	Food and Agricultural Organization of United Nations
GBS	General Budget Support
GCAP	Climate Adaptation Partnership and Partners
GCMs	Global Circulation Models
GDP	Gross Domestic Product
GHGs	Greenhouse Gases
Ha	Hectare
IPCC	Inter-governmental Panel on Climate Change
IUCN	International Union for Conservation of Nature
LDCs	Least Developed Countries
MDGs	Millennium Development Goals
NAPA	National Adaptation Programme of Action
NBS	National Bureau of Statistics
NCCS	National Climate Change Strategy
NEAP	National Environmental Action Plan
NEMC	National Environment Management Council
PCA	Principal Component Analysis

REDD+	Reducing Emissions from Deforestation and Forest Degradation
TMA	Tanzania Meteorological Agency
UNDP	United Nations Development Programme
UNEP	United Nations Environmental Program
UNFCCC	United Nations Framework Convention on Climate Change
URT	United Republic of Tanzania
USD	United States Dollar
VIF	Variance Inflation Factor
VPO	Vice President's Office
WEMA	Water Efficient Maize for Africa

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background Information

Climate change is a topical subject of global importance as it is one of the major environmental changes affecting ecosystems and human lives. Studies indicate that over the past years, mean temperature levels in Africa have increased whereas precipitation levels have declined (AMCEN, 2011; UNEP, 2013). Furthermore, there is an increase in spatial and temporal variability of rainfall leading to more intense and widespread droughts and aggravated flooding in Africa over the past few decades (Thornton *et al.*, 2011). Climate change poses the greatest threats for mankind's survival and for sustainable development. The impacts associated with climate change are already happening in many systems and sectors essential for human livelihood especially in the most vulnerable communities.

It is believed that Africa is highly vulnerable to climate change and climate variability due to the fact that the majority of its people depend on subsistence rain-fed agriculture (Boko *et al.*, 2007). Studies undertaken to analyze the impact of climate change on crop, livestock and mixed crop-livestock production in Africa indicated that the increasing temperature and a decrease in precipitation will significantly reduce income from agriculture (Nhemachena and Hassan, 2008; Deressa *et al.*, 2011).

The wider global climate change trends are clearly reflected in Tanzania. Due to her geographical location and the topographical characteristics, the country offers the best opportunity to study and further understand global climate trends. Recent studies have suggested that, alongside other East African countries, climate change has badly affected

Tanzanian economy especially the agricultural sector. Deteriorating water quality and quantity, loss of biodiversity and declining agricultural productivity due to climate change, are no longer potential threats but rather threats that have already struck and caused Tanzanians repeated misery (URT, 2013a).

Studies show that in Tanzania the mean annual temperatures and average daily temperatures will rise by between 2 to 4°C by the year 2075 as a direct consequence of climate change (URT, 2003; World Bank, 2012). Apart from temperature data, change in rainfall patterns is likely to be more intense and with immediate severe effects. In Tanzania, rainfall models indicate that rainfall will become less predictable and their intensity more volatile (Hamisi, 2012; Mwandosya *et al.*, 1998). Such major changes in rainfall patterns will inevitably have severe consequences to society, some of which (repeated droughts and floods) are already happening and have greatly affected livelihoods of people and various sectors of the economy (GCAP, 2011). These sectors include the agriculture, water, health, forestry and wetlands, energy, coastal and marine sectors, as well as wildlife, tourism and industry (URT, 2007).

1.2 Agricultural Production and Climate Risk in Tanzania

Agriculture plays a key role in Tanzania's economy, employing about 80% of the total population. The majority of agricultural output is by small-scale farmers, and much of it is low input agriculture being carried out at a subsistence level. Agriculture is crucial to the livelihoods of the majority of Tanzania's rural population. Agriculture has been one of the most vulnerable sectors to climate change in Tanzania because it mainly depends on rainfall, which is highly variable in terms of the amounts and distribution (URT, 2012a). The nature and type of vulnerability of agricultural sector to such variability includes: decreased crop production that is influenced by rainfall variability and unpredictable seasonality of rainfall, degradation of the natural resource base as well as environmental degradation (URT, 2007).

The consequences of these impacts have been reductions in employment, lower agricultural export earnings and other losses associated with a decline in rural income, reduced consumption and investment and destocking (URT, 2012a). Further, it has been noted that significant droughts already have additional multiplier effects on the economy as indicated by the rate of inflation, interest rates, credit availability, levels of savings, the government budget deficits and external debt stocks (World Bank, 2010). Similar studies found that if rainfall decreases by 15% by the year 2030, then production of major food crops (maize, rice and legumes) could be expected to decrease by up to 16% (1 million tones/ year), and losses of up to 25% – 35% would be expected by the year 2050 (URT, 2013b). This prediction suggests that, climate change will lead to losses of about 1.5%–2% of annual GDP by 2030 (GCAP, 2011). This implies economic losses of at least US$1.5 billion per year by 2030 based on 2006 prices (Bezabih *et al.*, 2011). The cumulative effect of these losses is likely to reduce Tanzania's chances of achieving key economic and development targets, which would in turn delay national plans to achieve middle income status by the year 2025.

As these effects of climate change are becoming more severe and repeated, they continue to impoverish the population in Tanzania. Different societies have developed diverse strategies to cope with the challenges associated with climate change. Some of the broad livelihood strategies include using improved farm technologies (agricultural intensification), bringing new plots of land under cultivation, changing planting dates, creating a natural resource based portfolio and other livelihood activities (livelihood diversification) as well as migration are broad livelihood strategies (FAO, 2011) that are available for households as adaptive responses. Worth noting, most smallholder farmers due to their mistrust of improved production technologies continue to relying on local coping strategies that leave them vulnerable to both climate change and the associated poverty in the longer term (Thornton *et al.*, 2011).

1.3 Government Initiatives to Enhance Agricultural Productivity

In response to climate change impacts to natural and social systems, several national programmes have been devised which address climate change directly and indirectly. These programmes are in line with international agreements such as the United Nations Framework for Convention on Climate Change (UNFCCC) and the corresponding Kyoto Protocol[1]. Some of the programmes, strategies and plans formed by the Tanzanian government to address climate change challenges include the National Climate Change Strategy (2012), The National REDD+ Strategy (2013), the Agriculture Climate Resilience Plan (2014-2019) and the Tanzania National Adaptation Programme of Action (NAPA) (URT, 2007; URT, 2012b; and FAO, 2015).

The main goal of these programmes is to enable Tanzania to effectively adapt to climate change and participate in global efforts towards mitigation in order to achieve sustainable development (URT, 2013a). In implementing these programmes, the Ministry of Agriculture, Food security and Cooperatives (MAFC), attempted to operationalize NAPA priorities through the Agriculture Sector Development Strategies (ASDP) (URT, 2012a). The ASDP identified several strategies which are meant to increase the resilience of communities in rural areas to cope with the adverse effects of climate change. In particular, promoting Sustainable Agricultural Practices (SAPs) has been given high

[1] The Kyoto Protocol is an international agreement linked to the United Nations Framework Convention on Climate Change, which commits its parties by setting internationally binding emission reduction targets.

priority (Asfaw *et al.*, 2013; FAO, 2013). These practices among others include use of improved technologies for Soil and Water Conservation (SWC), improved seeds varieties and use of inorganic fertilizer, use of organic manure and intercropping with legumes. These efforts have had little achievements, especially in the use of fertilizer and improved maize varieties (Simtowe *et al.*, 2011).

For instance, the national panel survey found that only 12% of farmers had used chemical fertilizers in 2008/09 which increased to 16.5% on a repeat panel survey done in 2010/11 (URT, 2011). The use of improved maize seeds increased from 4% of the total planted area in 1998 (Hassan *et al.*, 2001) to 17% in the year 2007 (Lyimo *et al.*, 2014). This situation hinders achieving the Tanzania Agriculture and Food Security Investment Plan (TAFSIP) 2011-12 to 2020-21 which in turn undermines the targeted annual growth rate of agricultural GDP, set at 6% and food and nutrition security in the country (URT, 2011).

Further, there is great variation in the adoption of these technologies across agro-ecological zones and households within the country (URT, 2013a). Even among the adopters, not all the land under a given crop is planted using improved technologies (IFDC, 2014), which indicates that adoption levels of improved farm technologies is still low despite various efforts being made.

In the same vein the yield of major food staples, in particular maize has been stagnant (Fig. 1), over the past two decades. The main reasons have been: low adoption of improved farm technologies and the impact of climate (Thornton *et al.*, 2009; FAO, 2016). These impacts mainly include increased exposure to extreme climate events such as droughts, dry spells and floods leading to frequent crop failures (URT, 2014b). Another source of low productivity has been the inefficient use of improved farm technologies (WEMA, 2010).

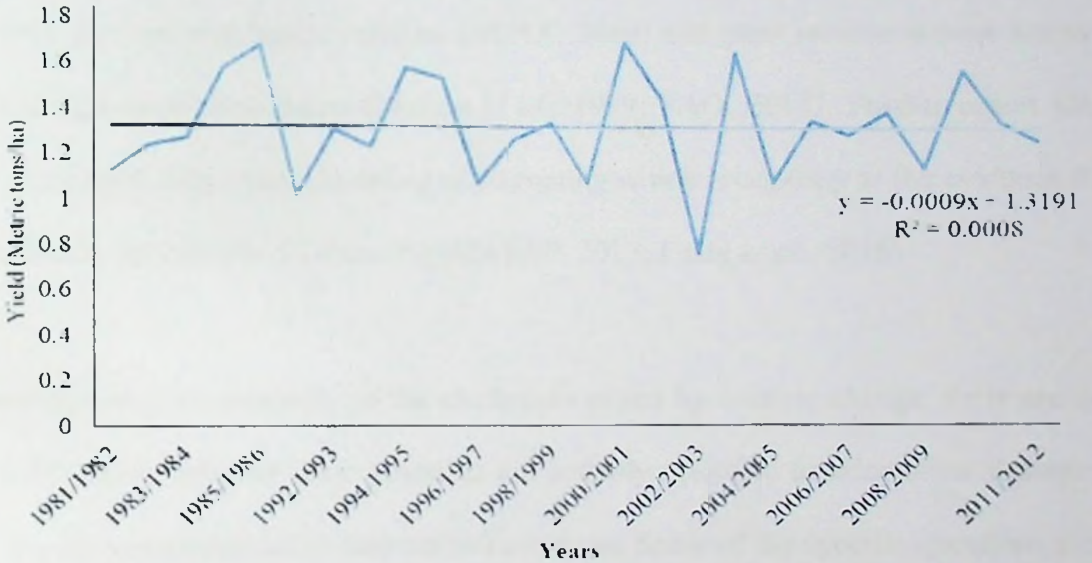

Figure 1: Trends in Maize Productivity in Tanzania, Source: NBS (2014)

Given the fact that agricultural production remains the main source of income for most rural communities, the increased risk of production failure associated with increased frequency of extreme events poses a major threat to food security and poverty reduction. Adaptation of the agricultural sector to the adverse effects of climate change is thus an important priority to protect and improve the people's livelihoods in Tanzania.

1.4 Problem Statement

The governments of Tanzania and other development partners have had various initiatives to enhance agricultural productivity, especially of the smallholders. High yielding crop varieties have been introduced and disseminated, fertilizer prices have been subsidized, and Soil and Water Conservation (SWC) technologies have been promoted. Despite these efforts, adoption rates of most of the improved farm technologies remains low and varying widely across households and regions (Lyimo *et al.*, 2014). Moreover, even for technologies that have been relatively better adopted like inorganic fertilizers and improved maize seeds varieties, adoption rate are still low. The adoption rates are as low as 12% for fertilizer in maize production (Magrini and Vigani, 2014; URT, 2014a) and 30% for improved maize varieties (AGRA, 2010) and great variations exist across regions and agro-ecological zones (Mafuru *et al.*, 1999; FAO, 2015). Further report shows that yields have either been declining or stagnating which is contrary to the evidence that these technologies are yield-enhancing (MAFAP, 2013; Haug *et al.*, 2016).

Considering the enormity of the challenges posed by climate change, there are questions which arise; whether these practices are actually effective as adaptation strategies in the specific circumstances of farmers in Tanzanian. Some of the specific questions are: (i) Are these technologies yield-increasing? (ii) Do farmers who adopt the technologies perform better in terms of net-returns compared to farmers who do not adopt? (iii) Are farmers using the technologies efficiently? (iv) Which practices or combination of technologies can be considered "climate smart" in the Tanzanian context? Answers to the four questions are important to various stakeholders including the Government, Development Partners and farm households. Based on answers to these questions (the government and development partners) will be able to understand the constraints to adoption of improved farm technologies by the smallholders. The answers will also provide information to facilitate farmers to adopt agricultural technologies that are more adapted to specific areas for sustainable development of the agricultural sector in the face of climate change.

This study is therefore set out to provide an important contribution to Tanzania's Adaptation Programme of Action (NAPA) whose overall vision is to identify immediate and urgent climate change adaptation actions that are robust and can lead to long-term sustainable development in a changing climate. This study was conducted in Pangani river basin located in north-eastern Tanzania, which is among nine water basins found in Tanzania[2]. Pangani river basin has been selected purposively because of the observed and projected wide ranging impacts of climate change (IUCN 2009).

1.5 Justification of the Study

Increasing climate risks and uncertainty from climate change is eroding the level of resilience of both socio-economic and ecological systems (Adger *et al.*, 2003). Due to this situation farmers are compelled to make decisions to change from one farming practice to the other in search of options for stabilizing their livelihoods. This study focused on analyzing the determinants of household farming practice selection and productivity impacts of five different potentially risk-reducing climate-smart agricultural practices (maize-legume intercropping, soil and water conservation (SWC), improved maize seed varieties, use of inorganic fertilizer and use of animal manure). These technologies are considered effective in terms of increasing the resilience of agricultural systems and reducing vulnerability among farmers to climate shocks, and in this way contribute to adaptation.

Several studies have been conducted in Tanzania to determine factors that influence adoption of improved farm technologies among farm households (Sarris and Karfakis, 2010; Thornton *et al.*, 2009; Lyimo *et al.*, 2014). These studies have concentrated on the adoption of individual farm technologies, ignoring the influence of climate change effects in shaping farmers input preferences and the interdependence of the farm technologies. Such partial analyses yield biased inconsistent and inefficient estimates if simultaneity in decision making exists (Teklewold *et al.*, 2013). This thesis fills such methodological gaps

[2] Tanzania has nine water basins, namely the Pangani river basin, Rufiji water basin, Lake Victoria basin, Wami / Ruvu basin, Lake Rukwa basin, Lake Tanganyika basin, Ruvuma and the Southern Coast basin and Lake Nyasa basin.

by accounting for the possibility of famers' choosing a mix of farm technologies. In order to model such simultaneous and correlated farming technologies a method that takes into account potential interdependence between different practices has to be used.

Moreover, unlike previous studies that stop at the analysis of factors that influence farm technology adoption, this thesis goes a step further to estimate the causal impact of using such practices on productivity on farmers' fields, the magnitudes of technical inefficiency and yield risk faced by agricultural producers in Tanzania.

By shedding light on these issues, novel insights from the study findings will first, contribute to knowledge on smallholder farmers' adaptation decision-making and key factors motivating their decisions to change their farming practices in response to climate change. Second, the study is intended to contribute to measures for enhancing adaptive capacity and long-term resilience of smallholder farmers in poor local community settings. Third, results from this study will be a catalyst in designing, developing and implementing appropriate, suitable as well as viable adaptation policies to improve farmer's adaptive capacity to climate change. Lastly, as the study delves into new grounds on estimation of impacts of farm technologies on household welfare. This approach is important to the body of knowledge for further research on farmer's adaptation to climate change.

1.6 Objectives

1.6.1 Overall objective

The overall objective of the study is to determine farmers' technical efficiency and yield risks related to technologies adopted for adaptation to climate change in order to generate reliable knowledge to enhance their food security in Pangani river basin. To achieve the above goal, four specific objectives were pursued as follows.

1.6.2 Specific objectives

i. Identify and analyze factors that influence farm technology adoption to climate change effects among the smallholder farmers in Pangani river basin.

ii. To assess the effects of adopted farm technologies on the smallholder farmers productivity.

iii. To determine the yield risks of adopted farm technologies by smallholder farmers' in Pangani river basin.

iv. To determine and compare the technical efficiency of farmers who adopted farm technologies relative to farmers who did not adopt.

Addressing these objectives involved seeking answers for a number of hypotheses and research questions that are listed next.

1.7 Research Question

Specific objective one was addressed by the following research question:

What are the farmer's climate change adaptation strategies that are successful for risk management to current climatic conditions for various areas of Pangani river basin?

1.8 Research Hypotheses

On the basis of specific objective two, three and four, three hypotheses were tested as follows:

i. The first null hypothesis states: The adoption of farm technology practices has no significant impact on farm household maize output levels in Pangani river basin. The alternative hypothesis states that the adoption of farm technology practices has a significant positive impact on farm household maize output levels in Pangani river basin. Using mathematical notation these can be written as:

$$H_0 : ATT = ATU \quad (1)$$
$$H_1 : ATT > ATU \quad (2)$$

Where:

ATT = Average maize yield in kilogramme per hectare for the treated farm plots

ATU =Average maize yield in kilogramme per hectare for the untreated farm plots

ii. The second null hypothesis states that: The adopted farm technologies are yield risk decreasing where risk is measured in terms of the variance of yield. Where the alternative hypothesis states that: The adopted farm technologies are yield risk increasing or risk neutral. Mathematically these notations are written as:

$$H_0 : \frac{\delta \operatorname{var}(y)}{\delta x_i} = \frac{\delta h}{\delta x_i} < 0 \quad (3)$$

$$H_1 : \frac{\delta \operatorname{var}(y)}{\delta x_i} = \frac{\delta h}{\delta x_i} \geq 0 \quad (4)$$

Where

y = Maize yield in kilogram per hectare

h = variance of maize yield

x_i = vectors of inputs

i= number of farm plots

iii. The third null hypothesis states that: The efficiency scores associated with farm adaptation technologies are not significantly different according to the number of adaptation technologies adopted and rainfall in Pangani river basin. Mathematical notation:

$$H_n : \tau_1 = \tau_2 = \dots\dots = \tau_n = 0 \quad (5)$$

$$H_1 : \tau_1 \neq \tau_2 \neq \dots\dots \neq \tau_n \neq 0 \quad (6)$$

Where:

τ_1 = the technical efficiency scores of farmers who adopted the adaptation technologies

τ_2 =technical efficiency for farmers who did not adopt.

1.9 Organization of the Study

This study is organised in five chapters as follows; Chapter one presents the introduction. Chapter two presents the literature review in relation to climate change. Strategies for adaptations are reviewed covering patterns of climate change impact on agriculture, adaptation practices used by farmers, problems encountered by farmers in climate adaptation as well as various analytical methods for assessing farming practice selection decisions, and efficiency of farm technologies. The theoretical and conceptual frameworks are also presented in this chapter. Chapter three describes the methodology, which covers a description of the study area; research design, the analytical and empirical models, sampling technique and data management. Chapter four presents results of the study followed by discussion of the findings. Conclusion and recommendations are made in chapter five.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Climate Change Definition

According to the Inter-governmental Panel on Climate Change (IPCC), climate change refers to a change in the state of the climate that can be identified (e.g. using statistical tests) by changes in the mean and/or the variability of climatic properties that persists for an extended period, typically a decade or longer. Climate change refers to any change in climate over time, whether due to natural variability or as a result of human activity (IPCC, 2007). This usage differs from that in the United Nations Framework Convention on Climate Change (UNFCCC), where climate change refers to a change of climate that is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and that is in addition to natural climate variability observed over comparable time periods (UNFCC, 1992). The UNFCCC thus makes a distinction between "climate change" attributable to human activities that leads to altering the atmospheric composition, and "climate variability" attributable to natural causes.

From the IPCC definition, there are many influences over the earth's climate, which can be distinguished into 'natural' and 'anthropogenic' (human-induced) factors. Since the beginning of the 20th century, scientists have been observing a change in the climate that cannot be attributed exclusively to any of the 'natural' influences of the past (IPCC, 2014). This change in the climate, also known as global warming, has occurred faster than any other climate change recorded by humans before and is therefore of great interest and importance to the community since it is largely caused by human activities.

Since the industrial revolution, human activity has increased the amount of greenhouse gases in the atmosphere. Such gases absorb heat from the atmosphere leading to more heat being retained in the atmosphere and thus an increase in global average surface temperatures and subsequently altered precipitation patterns (UNEP, 2013). Future climate scenarios have been developed based on modelling which attempts to project future climate based on historical behaviour with adjustments made to reflect various greenhouse gas (GHG) emission scenarios.

2.2 Climate Trends and Projections in Tanzania

This section describes the current climate of Tanzania, as well as future projections of climate change.

2.2.1 General climate

The United Republic of Tanzania covers an area of 885 800 square kilometers and extends from the Indian Ocean coastline to more than 1000 kilometers inland (URT, 2011). The topography ranges from sea level to over 1600 meters altitude in the west. Mountain Kilimanjaro, located in Tanzania is at 5895 meters altitude. Much of the country lies above 1000 meters altitude with many areas being above 1500 meters in the centre and north. The coastal areas and southern areas are generally lower altitude. The northern borders lie almost on the equator while the southern border is at around 12°S (URT, 2009). This places Tanzania directly in the tropics climatologically and hence the climate is entirely driven by tropical processes. However, the range in altitude and associated climate impacts result in significant climate gradients across the country. In addition, the presences of Lake Tanganyika to the west and Lake Victoria to the north are potential sources of moisture to surrounding areas.

The ocean coastline is warm and generally wet with Dar es Salaam experiencing a mean of over 1000mm per year of rainfall; daily maximum temperatures ranging between 29°C and 32°C. This is in contrast to Tabora in the centre which experiences a mean annual rainfall of less than 500mm per year and average daily maximum temperatures slightly cooler, ranging from 27°C and 31°C. Mwanza, on the coast of Lake Victoria experiences around 700mm/year which is higher than Tabora, most likely a result of the moisture supplied by Lake Victoria, however mean daily maximum temperatures are lower hovering between 27°C and 28°C (URT, 2011).

Being in a tropical location, seasonality is tied to the movement of the Inter-tropical Convergence Zone (ITCZ), which moves north and south during the year. Additionally the ITCZ often splits into two branches over East Africa (Dodman and Diagana, 2006). The ITCZ in the tropics often results in two rainy seasons, which can be seen at a number of locations in Tanzania. This dual season occurs as the ITCZ moves southwards at the beginning of dry season (June to October) and then northwards at the end of the season. Rainfall is associated with the shift in the ITCZ, hence an early summer and a late summer rainfall season.

The movements of the ITCZ are sensitive to variations in the Indian Ocean sea-surface temperature which varies from year to year; hence the onset, duration and intensity of these rains vary considerably each year (Hamisi, 2012). One of the most well documented ocean influences on rainfall in this region is the El Niño Southern Oscillation (ENSO)[3]. El Niño episodes usually cause greater than average rainfalls in the short rainfall season (OND), whilst cold phases (La Niña)[4] bring a drier than average season.

[3] El Niño and La Niña are complex weather patterns resulting from variations in ocean temperatures in the Equatorial Pacific. El Niño refers to the large-scale ocean-atmosphere climate interaction linked to a periodic warming in sea surface temperatures across the central and east-central Equatorial Pacific.

[4] La Niña represent periods of below-average sea surface temperatures across the east-central Equatorial Pacific

2.2.2 Climate change projections

Several studies have been undertaken to predict the future climate of Tanzania. One of the earliest and most comprehensive study on climate change in Tanzania was done by Mwandosya *et al.* (1998), covering the period 1994 to 1996. The study employed a General Circulation Model (GCM), using data from 1951-1980 as the baseline. The study compared baseline climate projections to the '$2XCO_2$' scenario[5], which assumes a doubling of baseline concentration of greenhouse gases by 2075.

Major findings of the study were: temperature was expected to increase from 3.6°C to 3.8°C in the western and south western parts of the country; and between 2.7°C and 3.1°C in the south eastern, eastern and north eastern zones of the country. In the case of rainfall change, the results predict an increase in rainfall precipitation of 5% to 45% in northern and south eastern areas of the country, with the highest increases occurring close to Mount Kilimanjaro and a decrease of 5% to 15% in central, western, south western, southern and eastern parts of the country (IDS, 2012).

The second study by Hulme *et al.* (2001) looked at rainfall in East Africa over the twentieth century and found 'some evidence of long-term wetting'. The authors used 7 GCMs[6] to project climate change using four scenarios for three periods of this century (2020s, 2050s, and 2080s). The results indicated rainfall will increase by 5% to 30% over

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[5] A plausible and simplified description of how the future climate may develop based on a coherent and internally consistent set of assumptions about driving forces of climate change and key relationships.

[6] The term 'General Circulation Model (GCM)' as it applies to the area of the environment can be defined as 'A global, three-dimensional computer model of the climate system which can be used to simulate human-induced climate change. GCMs are highly complex and they represent the effects of such factors as reflective and absorptive properties of atmospheric water vapor, greenhouse gas concentrations, clouds, annual and daily solar heating, ocean temperatures and ice boundaries. The most recent GCMs include global representations of the atmosphere, oceans, and land surface. See climate modeling'

the December– January season and decrease by 5-10% during the period July – August in East Africa.

A further study of climate change prediction in Tanzania was undertaken by the Climate System Analysis Group (CSAG) at the University of Cape Town in South Africa. This work employed a downscaling methodology (Self Organizing Map based Downscaling) with nine global climate models. For each of these, the first simulation was of the period 1961 to 2000 (Adosi, 2002). Two other projections were done using the development scenarios of B1 and A2. And the second and third simulations were of the period 2046–2065 and 2081–2100 respectively (URT, 2003). The simulations were downscaled regionally within various locations in Tanzania (Dar es Salaam, Dodoma, Kilimanjaro, Mbeya, Mwanza), generating climatological summary statistics.

The main conclusions of the CSAG study were: rainfall was projected to increase during March to May the late part of the wet season with the possibly of some drying in the early summer period, indicating a seasonal shift of weaker rains early in the season and stronger rains later in the season. Further, it did not appear that the later periods (2081-2100) would have significant wetting compared to the earlier period (2046-2065), suggesting that there may be a limit on precipitation. For temperature it was predicted that in general across the 9 GCMs, for the earlier period the predicted temperature change was around 1.5°C for the B1 scenario and 2°C for the A2 scenario. For the later period, increases were around 2°C for the B1 scenario and as high as 4°C for the A2 scenario.

In reviewing the evidence, the projected temperature increases are in the same range for both the Mwandosya *et al.* (1998) and the CSAG studies and they also coincide with the projections of the IPCC Fourth Assessment Report for Africa (Boko *et al.*, 2007). Overall, two important information emerged from the reports, which have important implications for agriculture: the first is that rainfall patterns are increasingly unpredictable and expected to become more variable. This includes shifts in the onset of the rainy season and increasing seasonal variations. Current weather cycles such as El Niño and La Niña will continue to impact climate variability, but it is unknown how climate change will affect the frequency and severity of these events, and predictions about the impacts in Tanzania are unreliable (GCAP, 2011). These extreme events have dramatic impacts on infrastructure and the economy as whole. The impact cut across key sectors including agriculture, industrial processing, manufacturing, tourism, infrastructure, health and others.

2.3 Climate Change Effects on Crop Yield

Agriculture is one of the most vulnerable sectors to climate change. The Declaration of the World Summit on Food during 2009 in Rome Italy stated that: "Climate change poses additional severe risks to food security and the agriculture sector (Kang *et al.,* 2009)". The expected impact is particularly fraught with danger for smallholder farmers in developing countries, notably the Least Developed Countries (LDCs) (Agrawala *et al.*, 2003; IPCC, 2012). The changes in crop production related climatic variables will possibly have major influences on regional as well as global food production (World Bank 2010). In predicting future impacts on crop yields, a number of crop simulation tools, such as CERES-Maize (Kang *et al.*, 2009), CERES-Wheat, (Eitzinger *et al.*, 2003) SWAP (Soil–Water–Atmosphere–Plant) (Gagnon and Agrawala, 2006) and SWAT (Soil And Water Assessment Tool) simulation tools have been used to evaluate the possible impacts of climate variability on crop production, especially to analyze crop yield-climate sensitivity under different climate scenarios.

Agarwala *et al.* (2003; 2006) estimated the effect of climate change on maize yields using Crop Environment Resource Synthesis model (CERES-Maize). In general, simulation results show that maize yields were lower, a result of higher temperatures and decreased rainfall. The average yield decrease over the entire country was 33%, but simulations produced decreases as high as 84% in the central regions of Dodoma and Tabora. Yields in the northeastern highlands decreased by 22% and in the Lake Victoria region by 17%. Yields in the southern highland areas of Mbeya and Songea were estimated to have decreases of 10-15%.

Further, Knox *et al.* (2011) found that in general the trend on African maize production appeared to be decreasing. Specific for Tanzania maize productivity is forecast to decline between 10% and 20% by the year 2050. In addition, GCAP *et al.* (2011) conducted a study on maize production, which is highly vulnerable to the combined effect of rising temperature and decreasing rainfall. If rainfall does not decrease, then impacts would be expected to be minor or even positive. However, if rainfall decreases by 15% as projected by some models for some areas by 2030, then production could be expected to decrease in those areas by up to 16% (1 million tonnes/ year), and losses of up to 25%– 35% (2 – 2.7 million tonnes) would be expected by 2050.

Using CIMMYT data from more than 20 000 historical maize trials in Africa, combined with daily weather data, Lobell *et al.* (2011) estimated that each degree day spent above 30°C reduced the final yield by 1% under optimum rain-fed conditions and by 1.7% under drought conditions. The outputs of temperature simulations for 2050 in Sub-Saharan Africa shows a general trend of warming, with maximum temperatures predicted to increase by 2.6°C and minimum temperatures by 2.1°C. Overlaying temperature simulations with drought susceptibility maps show Southern Africa will likely be most affected. This challenge provides farmers with the means to respond both to the threats and opportunities posed by climate change.

2.4 Adaptation to Climate Change in the Agriculture Sector

As the effects of climate change become more severe and repeated in nature and as such effects continue to impoverish the population, different societies have developed diverse strategies to adapt to the challenges. However the ability to adapt to these changes is characterized by the adaptive capacity of the farmer and is related to the assets that one has access to (financial, natural resource, human and social capital) and levels of risk aversion to different adaptation options (FAO 2009; IPCC, 2014).

Studies have shown that some societies in Tanzania are already coping with the effects of climate change. It is worth noting that, most farmers find it hard to cope with climate change using modern technologies like high input agriculture because of their low adaptive capacity and risk aversion towards improved farm inputs. Such farmers rather rely more on their indigenous skills (Shemsanga *et al.*, 2010). However, most of these local copping strategies could only be applicable in the short term which leaves smallholder farmers vulnerable to both climate change and the associated poverty in the long term (URT, 2013b).

Meanwhile, the government and development partners stress on the use of improved agricultural technologies which are considered better for improving productivity in the face of climate change. In particular, promotion of sustainable agricultural practices is given high priority, due to its expected productivity benefits as well as the potential to mitigate the effects of weather variability and climate change. The adoption and diffusion of specific sustainable agricultural practices (SAPs) have become an important issue in the development policy agenda for Sub-Saharan Africa (Kassie *et al.*, 2010; Teklewold *et al.*, 2013), especially as a way to tackle these impediments. The Food and Agricultural Organization (FAO) argues that sustainable agriculture consists of five major attributes: it conserves resources, is environmentally non-degrading, is technically appropriate, is economically, and socially acceptable (FAO, 2009). Accordingly these practices broadly defined include conservation tillage, legume intercropping, legume crop rotations, improved crop varieties, use of animal manure, complementary use of organic fertilizers, as well as soil and stone bunds for soil and water conservation (Kassie *et al.*, 2008; Wollni *et al.*, 2010).

The potential benefits of SAPs lie not only in conserving the soil but also in enhancing the natural resources (increasing soil fertility and soil organic matter) without sacrificing yield levels. This makes it possible for fields to act as a sink for carbon dioxide, to increase the capacity of the soil to hold water, and reduce soil erosion (FAO, 2010). Furthermore, by retaining fertile and functioning soils, SAPs can also have positive impacts on food security and biodiversity (Wollni *et al.*, 2010). Crop rotation and diversification via intercropping enable farmers to grow products that can be harvested at different times and that have different climate or environmental stress-response characteristics. These varied outputs and degrees of resilience are a hedge against the risk of drought, extreme or unseasonal temperature, and rainfall variations that affect productivity of small holder systems.

Notwithstanding their benefits, as well as national and international efforts to promote these technologies, their adoption rate is still low in various regions of Tanzania (URT, 2013a; Asfaw, 2013). A better understanding of constraints and challenges that condition farmer' adoption behaviors is therefore important for designing policies which could stimulate adoption of SAPs

2.5 Challenges Facing Farmers in Climate Adaptation

In carrying out adaptation measures to reduce the effects of climate variations on agricultural production, farmers encounter challenges and problems. Among them is the lack of adaptive capacity and their risk attitude toward a given adaptation strategy (Dercon and Christiansen, 2007). Adaptive capacity is the ability or potential of a system to respond to climate variability and change in a manner that reduces vulnerability (Saris and Karfakis, 2010). The indicators of adaptive capacity enumerated in the third assessment report of the IPCC (2001) were generally based on assets and resources which reflect the sustainable Livelihood Framework (SLF). These include economic resources, technology, infrastructure, information and skills, institutions and equity (Katungi and Smale, 2007). It means that poor households with limited livelihood assets appeared to be more vulnerable to the impacts of climate change and are more food insecure compared to the well-off group. Kang *et al.* (2009) noted that, lack of adaptive capacity due to constraints on resources such as access to information on weather forecasts or better farm technologies often result in further food insecurity.

Turning towards risk attitudes, it is common knowledge that agricultural production in low-income countries is generally highly diversified, focusing on rain-fed staple crop (Yesuf and Bluffstone, 2009). These activities are inherently risky due to crop yield risks arising from variance in rainfall timing.

Another source of risk is the level and changing output prices. Furthermore, agricultural production is also affected by crop diseases, flooding, frost, all of which can have major effects on rural livelihoods. Investment and production decisions by farm households in low-income countries are therefore made within environments that are at least affected by, but more likely overshadowed and dominated by, a multitude of risks. Promoting improved farm technologies has been suggested as a key adaptation strategy for countries in the developing world, particularly in sub-Saharan Africa in order to mitigate growing water shortages, worsening soil conditions, drought and desertification (Deressa *et al.*, 2011). These technologies can still be too risky for very low-income, risk-averse households, which are typical in rural Tanzania. Thus, in the adoption of technologies, farmers consider not only the impacts on crop yields but also the associated risk effects (Kassie *et al.*, 2008).

The existence of such risks has been found to alter household behavior in ways that at a first glance seem suboptimal. In the empirical literature, many researchers have found that risks cause farmers to be less willing to undertake activities and investments that have higher expected outcomes, but carry with them more risks of failure (Dercon and Christiansen, 2007). For example, it has been found that farm households use less fertilizer, improved seeds and other production inputs than they would have used had they simply maximized expected profits. It is also not uncommon to observe farm households in developing countries being reluctant to adopt new technologies even when they provide higher returns to land and labor than traditional technologies (Asfaw *et al.*, 2013).

Under such circumstances, farm households opt to stick to low-risk technologies despite the low returns, a decision that perpetuates the vicious circle of poverty. The fact that resource-poor farmers forego welfare-improving opportunities because of perceptions of related risks, has important policy implications under average production conditions, but even more so in the face of growing climate variability and climate change.

2.6 Policy Issues on Climate Change in Tanzania

As the effects of climate change and general environmental degradation became more severe and revealing, and with the widespread consensus that poverty alleviation strategies would not be successful without integrating sustainable environmental management, the government of Tanzania took decisive steps towards developing a comprehensive environmental policy in 1994 (URT, 2003) to address environmental challenges facing agriculture. Several interconnected issues had forced the government to take such steps.

These included, the vulnerability of some areas and especially loss of wildlife habitats and biodiversity, deterioration of marine and freshwater ecosystems, widespread deforestation, land degradation, soil erosion and inadequate land and water management at various levels, pollution, high population growth, persistent poverty to the population and climate change. Thus a National Environmental Action Plan was formulated in 1994, which later laid the foundation for National Environmental Action Policy (URT, 1997) and thus clearly acknowledging linkages between poverty, human health and environmental degradation.

Further, the government of Tanzania had realized that dealing with climate change requires local, regional and international efforts as both the causes and effects of climate change recognize no geographical boundaries. In so doing Tanzania has taken some steps to address climate change in its widest sense. Tanzania ratified the UNFCC and its Kyoto Protocol in (1996) and (2002), respectively to ensure that climate change issues are addressed at the national level, supported by national policies and legislation (URT, 2013a). Starting from here, various adaptation and mitigation initiatives and programmes, strategies and plans have been formulated which demonstrates the national commitment in addressing climate change issues for local benefits but also its contribution to global efforts to adapt and mitigate climate change. Among such effort is the formulation of the National adaptation Action Plan (NAPA) in (2007), which act as a basis for identifying and implementing adaptation actions at both sectoral and local levels (URT, 2007).

Furthermore, several mitigation initiatives have been implemented in the context of Clean Development Mechanism (CDM) and other emerging mitigation opportunities such as Reducing Emissions from Deforestation and Forest Degradation (REDD+) (URT, 2013a), which has been under negotiation within the United Nations Framework Convention on Climate Change (UNFCCC) since 2005, with the objective of mitigating climate change by reducing net emissions of greenhouse gases through enhanced forest management. The ongoing national REDD+ initiatives are expected to enhance the contribution of Tanzania to global mitigation efforts such as the net carbon sink through its forests in various forms. This will be achieved by improving and strengthening sustainable land use policies in both the forest and agricultural sector.

Other national initiatives include the National Agricultural Policy of (2013) which addresses environment and climate change issues pertaining to the agricultural sector (URT, 2013b) and the National Climate Change Strategy of (2012). The main goal of the strategy is to enable Tanzania to efficiently adapt to climate change and participate in global efforts towards mitigation in order to achieve sustainable development (Majule *et al.*, 2014). The above theories and factors governing farmers' adoption climate change effects are summarized in the next section.

2.7 Review of Theories Governing Technology Adoption to Farmers Climate Change Adaptation

This part reviews the literature on theories and analytical issues relevant for this study on farm household technology adoption in the face of climate change effect. The review covers theories explaining farm household production planning and related analytical issues, which include evaluation methods to determine farmer's choice of farm technologies, risk attitudes towards farm technologies and measurement of farm efficiency.

2.7.1 Farm household production theories

Farm production theory begins with the farmers as individual decision makers who in their desire to maximize some objective function are concerned with questions which include what to produce? When to produce? How much to produce? and which technology to use? (Samuelson and Nordhaus, 2005). These questions imply that, farmers can vary the level and kind of farm inputs. Hence methods of farm production attain analytical relevance when placed in the context of farm household goals and the resource constraints they face. In reality household have several goals such as long term income stability, family food security and others which then influence production choices.

Two alternative economic theories of peasant household behavior are presented below. Each approach assumes that peasant households have an objective function to maximize, subject to a set of constraints. Moreover, these theories are based on a set of assumptions about the workings of the wider economy within which peasant production takes place. Not all these assumptions are shared by all theories, but all adopt the same theoretical method to explain farm household behavior. The theories are: (i) the utility maximization theory and (ii) the risk aversion theory.

Pertaining to utility maximization, this theory treats peasant households both as consumers and producers. The two sides are therefore important in analyzing their decision-making processes. Assuming missing labour market and unlimited supply of land, the theory posits that farm household decisions would be more influenced by household size and structure (Chayanov, 1966). The assumption of missing labour market and unlimited supply of land are the main weaknesses of this model in its original form in Chayanov's seminal work during the 1920s.

Chayanovian model was later modified by neoclassical economists during the 1960s to include perfect markets in order to explain the duality of farm household consumption and production decisions. The farm household, therefore, maximizes the utility of consuming home-produced, market-purchased goods, and leisure time, subject to full income constraint (Bliss and Stern, 1982). Production and consumption decisions would be recursive (separable) if markets existed and functioned properly. This is because prices would be exogenous, leisure and labour-time would be independent, household labour allocation would be determined by market wage and the household full income would be the only thread between household consumption and production (Singh *et al.*, 1986).

Where markets are missing or highly imperfect, household decision becomes non-recursive because the household deliberately decides how much time to allocate to production, which affects consumption of leisure (Singh *et al.*, 1986). In such cases, consumption of goods and income affect each other. In developing countries, agricultural households face either missing or highly imperfect markets characterized by high transaction costs and constraints on marketed quantities (Tversky and Kahneman, 1992).

The recursive and non-recursive farm household models fail to recognize the role of risk and uncertainty in peasant household production decision-making. Farm households are not risk-neutral and assuming so leads to over-simplification of the objective function and the constraints (Taylor and Adelman, 2003). This is the gap that risk aversion theory fills, which recognizes that smallholders produce under great risks and uncertainty arising from weather, pests and diseases, price volatility and social uncertainty (Koundouri *et al.*, 2006). As a result, they exercise a lot of caution in their decision-making.

The risk aversion model analyses decision-making by peasant households from two related perspectives: a disaster-avoidance approach and an expected utility approach. The disaster-avoidance model asserts that, when choosing among risky income streams, households first opt for safety and from the safe alternatives they choose based on expected utility and possibly expected income (Sadoulet and De Janvry, 1995). This model is based on a feasible decision process, (or a rule of thumb) known as the safety first model of choice under uncertainty (De Brauwa and Eozenoub, 2014).

In this model the decision maker is assumed to ensure survival for him or herself and therefore wants to avoid the risk of his or her income or return falling below a certain minimum (subsistence) level. Thus, risk is defined as the probability that the stochastic variable in question (such as income) will take on a value not less than some critical or disaster level. This safety-first criterion can lead to the household favoring either risky income streams or low risk alternatives (Mendola, 2007). This is to say that there are no reasons to expect that individuals behave in conformity with the expected utility theory at very low levels of income, often under stressful circumstances. The disaster avoidance perspective is helpful for describing individual choice under such conditions.

Under the expected utility approach, also known as full optimality approach, a farm household chooses among risky alternatives based on its preference of the possible outcome and the probability of its occurrence (LaFave and Thomas, 2014). Farm households are viewed as utility maximizers but constrained by risks. Other things being equal, households choose low-risk high-utility productive activities. This makes the Von Neumann-Morgenstern expected utility model appropriate for such analysis.

Since agricultural markets are highly imperfect or in some cases missing in developing economies, this study is premised on the non-separability of household production and consumption decisions, first introduced by Singh *et al.* (1986) and advanced by others like De Janvry *et al.* (2010) and Taylor and Adelman (2003). Thus smallholder households are viewed as utility maximizers constrained by market conditions, income and stochastic production risks. These assumptions are used as a benchmark in modelling farmer's technology adoption decisions presented in the next section.

2.7.2 Determinants of farmers technology adoption decisions

When it comes to the adoption of a new technology, farmers are faced with choices and tradeoffs. Differences in adoption decisions are often due to the fact that farmers have different cultures, resource endowments, objectives, preferences, and different socio-economic backgrounds (De Janvry, 2010). It follows that, some farmers may adopt new technology while others do not. In such a context, farmers' decisions regarding the adoption of farm technology can be explained using the theory of maximizing expected utility. Based on this theory, a farmer will adopt a given new technology if the expected utility obtained from the technology exceeds that of the old one (Tversky and Kahneman, 1992).

Furthermore, it can be conjectured that within the broad set of farm management technologies available to farmers, certain technologies are more likely to be adopted in combination with other technologies (Kassie *et al.*, 2008). Thus, there are likely to be portfolios of technologies which can be considered part of a wider approach to pest management. However, there are differences in the degree and extent of technology adoption within the farming community in relation to technology adoption (Teklewold *et al.*, 2013; Asfaw *et al.*, 2014). Some farmers may adopt fewer technologies than others while some may adopt almost all technologies available.

For farmers who adopt each technology, higher yields are expected. In knowing the desired impact of each technology, just comparing yield levels between adopters and non-adopters may be misleading, because there may also be differences in the use of other inputs, which may lead to spurious conclusions, because not all of the observed differences can be attributed to adopted technology alone. A regression model of a production function, which contains technology adoption as a treatment variable and controls for the use of other inputs can help in this respect.

However, unless a randomized experiment is carried out, farmers decide themselves whether or not to adopt the technology. Adopters and non-adopters may therefore, differ systematically, which can lead to non-random selection bias (Winters *et al.*, 2011). When panel data exist, fixed-effects estimators can be used to control for farm and household level heterogeneity, but very often only cross section data are available for impact assessment.

Statistical methods to deal with selection bias in cross-section data include Propensity Score Matching (PSM) and Instrumental Variable (IV) approaches (Deaton, 2010). Propensity Score Matching can only control for observed heterogeneity, while technology adoption may also be determined by unobserved factors such as farmers' ability and motivation (Di Falco and Chavas, 2009). Meanwhile, Instrumental Variable (IV) approaches can be controlled for unobserved heterogeneity, but they mostly build on the assumption that the treatment effect can be represented as a simple parallel shift with respect to the outcome variable which is not appropriate to assume for selected farm technologies under the study. The reason is that the farm technologies are hypothesized to not only impact yield but also the output responsiveness of other inputs.

To address this problem, this study models farmers' choices of combinations of farm adaptation strategies and their impacts in a setting of a multinomial endogenous switching regression counterfactual framework. This approach is a relatively new selection-bias correction methodology based on the multinomial logit model estimated using the '*Selmlog*' STATA command (Bourguignon *et al.*, 2007). This approach allows us to get both consistent and efficient estimates of the selection process and a fairly good correction for the outcome equations, even when the independence of irrelevant alternatives (IIA) assumption is not achieved.

This framework also has the advantage of evaluating both individual and combinations of practices, while capturing the interactions between choices of alternative practices (Di Falco *et al.*, 2011). Estimation is done in two steps, simultaneously. In the first stage, farmers' choices of farm technology adoption are estimated using a multinomial logit selection model, while recognizing the inter-relationships among them. In the second stage, the impacts of farm technology adoption on the outcome variables are evaluated using ordinary least squares (OLS) with selectivity correction terms.

From the above, understanding the determinants of the farm technology adoption decision has been of interest to this study, however further interest has been the role of risk attitudes in technology adoption by farmers. This is because risk attitudes towards farm technologies have important implication for the competitiveness of firms as the adoption of new technologies often have the potential to considerably enhance agricultural productivity.

2.7.3 Risk implication of adopted farm technologies

Considerable research has attempted to provide empirical evidence on how risk influences the nature of farmer's decisions in agricultural production. These attempts can be categorized into two groups of studies. The first group aimed at estimating producer's attitude towards risk that influence input allocation and output supply decisions. These studies have employed either the experimental or econometric approaches to elicit risk attitudes of individual producers. The experimental approach is based on hypothetical questionnaires regarding risky alternatives or risky games with or without real payments (Di Falco and Chavas (2009). Among studies which have employed this approach include; Binswanger (1981) that used risky games with real payments to measure Peasant's risk preferences in an experiment in India and in Mozambique (De Brauwa and Eozenoub, 2014).

Meanwhile, the econometric approach is based on individuals' actual behaviour assuming expected utility maximization. Studies that have used this approach to elicit producer's risk attitudes include; Antle (1983), Bozzola (2013) and Di Falco *et al.* (2012). However, the econometric approach has been criticized for confounding risks behaviour with other factors such as resource constraints faced by individual decision makers (Wik *et al.*, 2004). This is particularly important in developing countries where market imperfections are prominent and production and consumption decisions therefore are non-separable (Sadoulet and De Janvry, 1995).

The second groups of studies have attempted to investigate the influence of risk on agriculture production by directly incorporating a measure of risk in the traditional production functions. Such studies include work by Just and Pope (1979) who focused on production risk, measured by the variance of output. The findings suggested use of the production function specifications satisfying some desirable properties. The main focus in their specification is to allow inputs to be either risk increasing or risk decreasing. Some of the studies that have used this approach includes, Fufa and Hassan (2005); Kato *et al.* (2008) and Di Falco and Chavas, 2009). In the current study, the Just and Pope stochastic production function was used to analyze the effect of improved farm technologies on the distribution of maize yields in Pangani river basin, Tanzania.

2.7.4 Efficiency of farmers adaptation technologies

Turning to the literature on efficiency measurement, efficiency is used to assess economic performance of a firm, farm or organization. Efficiency usually refers to the economic or productive efficiency of a firm, farm or organization which means it is thriving in producing as much output as feasible from a known set of inputs (Fried *et al.*, 2008). Efficiency has two components, technical and allocative efficiency. Technical efficiency is the capability of a firm to produce as much output as is achievable with given sets of inputs or the capacity of a firm to use as minimum inputs to achieve a given level of output (Coelli *et al.*, 2005). Allocative efficiency refers only to the adjustment of inputs and outputs to reflect relative prices, having chosen the production technology. Economic efficiency is the situation when technical and allocative efficiencies are combined.

Estimation approaches to productive efficiency are broadly grouped into parametric (stochastic) and non-parametric (deterministic) frontiers. For instance, the data envelopment analysis (DEA) is a non-parametric method that uses linear programming techniques to derive efficiency estimates. Several parametric methods are based on the econometric estimation of the frontier, which involves a variety of estimation strategies, including corrected ordinary least squares, feasible generalized least squares and maximum likelihood. Within each empirical framework, a series of modelling decisions must be made, and there is no widely accepted methodology for guiding such decisions (Kim and Coelli, 2009).

Data envelopment analysis was first introduced in the work of Farrell (1957) and developed further by other authors like Banker *et al.* (1984) and Charnes *et al.* (1985). The DEA is a piecewise-linear convex hull approach to frontier estimation. It envelops all observations in order to identify an empirical frontier that is used to evaluate the performance of production units represented by those observations. It only requires the specification of an objective (e.g., input/cost minimization or output/revenue maximization), not functional form or efficiency distribution, to determine the frontier and efficiency estimates (Coelli *et al.*, 2005).

The DEA approach accommodates both input and output oriented efficiency measures. It also allows the calculation of scale efficiency when the returns-to-scale assumption is appropriate. Also the DEA's non-parametric nature enables it to avoid confounding the effects of misspecification of the functional form (of both technology and inefficiency) with those of inefficiency (Fried *et al.*, 2008). The main weakness of DEA approach is that, it does not distinguish data noise and inefficiency (Charnes *et al.*, 1985). However stochastic DEA models, which eliminate such problems, have been developed in literature (Coelli *et al.*, 2005). However, empirical implications of these models are extremely difficult due to rigorous data requirements. In addition to the inputs and outputs data, it is necessary to have information on expected values of all variables, variance-covariance matrices for all variables, and probability levels at which feasibility constraints are to be satisfied (Lovell, 1996).

The parametric frontiers unlike to non-parametric approach, involves modelling the production frontier using various econometric techniques. Its most popular representative is the stochastic frontier analysis (SFA). The main advantage over its non-parametric counterpart lies in its stochastic nature, which enables it to distinguish between the effects of noise from those of inefficiency, thereby pro-viding the basis for statistical inference (Fried *et al.*, 2008). However, this is achieved at the cost of being more restrictive in parameterization (of both technology and inefficiency), as compared to DEA (Kim and Coelli, 2009).

Being a parametric method, SFA imposes a technology structure through specifying a functional form, of which the Cobb-Douglas and translog functions are most widely used. The translog function provides a second order approximation to an arbitrary functional form. It typically involves estimation of many more parameters than the number of variables in the regressor set because of the squared and cross-product terms. The Cobb-Douglas function imposes more structural restrictions on the production technology but involves fewer parameters to be estimated. The challenge is confronting the inevitable trade-off between parsimonious but inflexible parameterizations, and flexible parameterizations which consume many degrees of freedom. In many cases where the parsimony alternative has been chosen, the use of an overly restrictive functional form results into a confounding inefficiency with specification error (Lovell, 1996). This offsets its advantage of being able to distinguish noise from inefficiency, compared to the non-parametric method.

The SFA model distinguishes itself from other econometric models by partitioning the stochastic error term into two components: the systematic random error accounting for statistical noise and the inefficiency component. The latter term is assumed to follow some particular distributions, of which the most frequently used are half-normal, truncated normal, exponential and gamma distributions. Different distributions could potentially give rise to different efficiency estimates and the extent to which the efficiency scores and their ranking are sensitive to distributions is not well documented in the literature.

However, empirical studies where different distributional assumptions are used for comparison showing that both the rankings and the efficiency score are generally quite similar across distributions ((Kim and Coelli, 2009). Hence, the choice of distribution is a matter of computational convenience, i.e. some software packages facilitate some particular distributions (for example, both FRONTIER 4.1 and STATA supports half and truncated normal distributions, while the latter accommodates also exponential distribution. LIMDEP is capable of these three plus the gamma distribution).

The SFA model has gained increasing popularity since it can accommodate various research questions, such as to compare producers' relative efficiencies, productivity changes over time and especially to examine effects of management and environmental factors on inefficiency, which cannot be done through a one stage analysis using a non-parametric approach. Given such a background, this study used SFA to empirically measure the productivity and technical efficiency of maize farmers and identifies factors that explain the variation in the efficiency of individual maize farmers in the study area.

2.8 Conceptual Framework

To address the objectives of this study, a conceptual framework, illustrated in Fig. 2 was developed that served as a guide. This conceptual framework draws from theories of utility maximization and loss avoidance in agriculture that explain changing farm management systems in terms of changing microeconomic incentives facing farmers as a result of climate variability (Binswanger, 1981).

In this framework, climate stimuli present a risk or an opportunity to a particular farmer depending largely on his/her perception or their subjective view of the situation. Once a stimulus has been perceived, the farmer can choose to manage the situation, depending on his or her levels of adaptive capacity. Given asset endowments, households make decisions regarding adoption of technology to generate positive social and economic outcomes. Some of the climate smart strategies recommended to farmers includes; crop diversification, use of improved seed varieties, changing planting and harvesting period, intercropping and soil and water conservation measures as previously mentioned (IPCC, 2012).

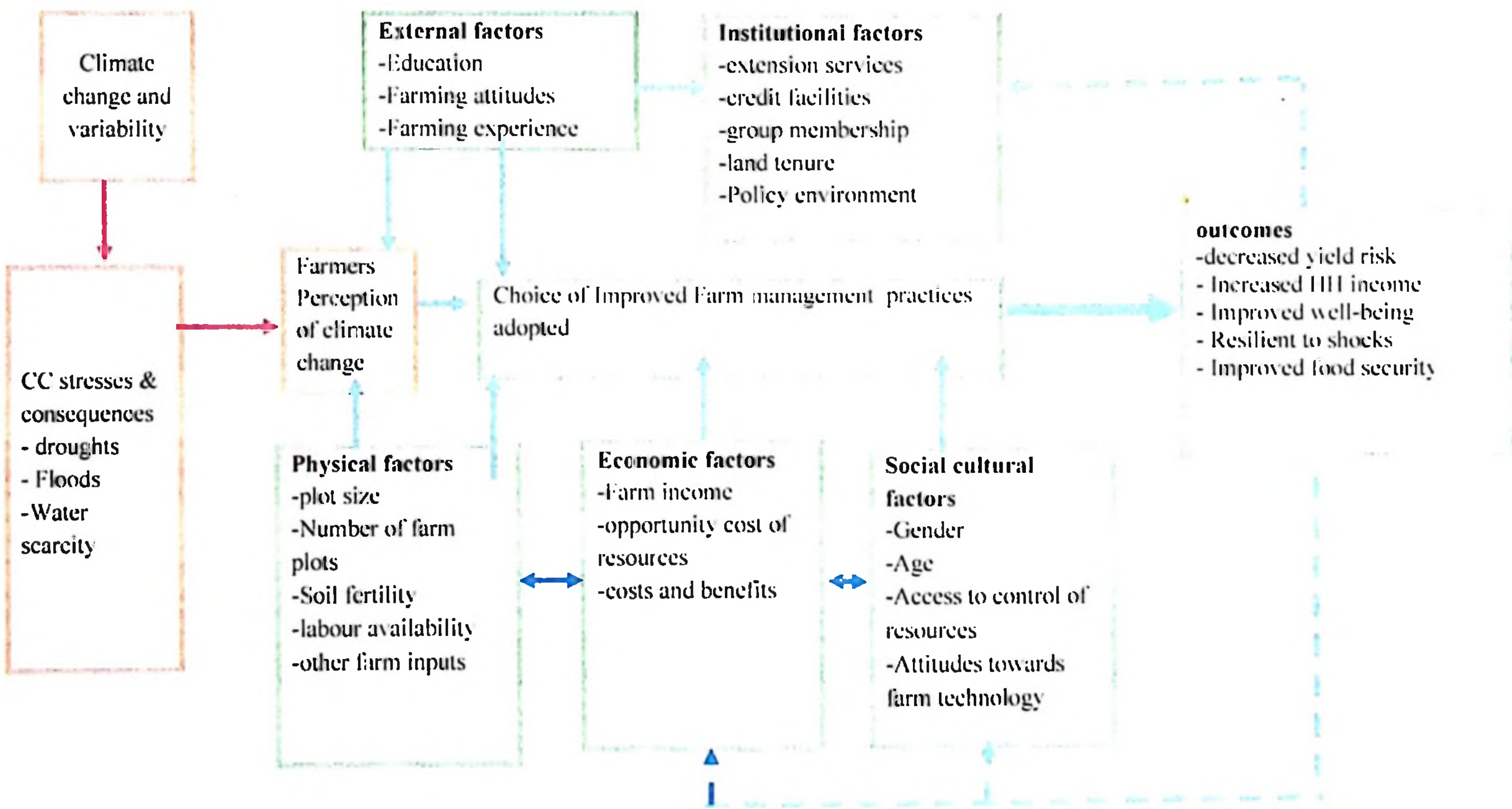

Figure 2: Conceptual Framework of farmers adaptation technologies to climate change

Adapted and Modified from (Carney, 1998)

Farmers' decisions about whether and how to adopt new technology are conditioned by the dynamic interaction between characteristics of the technology itself and the array of conditions and circumstances. A wide range of factors that influence smallholder farmers' decision to adopt better farm management practices are identified in the literature (Kasie *et al.*, 2010; Asfaw *et al.*, 2013). These factors are grouped into those that relate to characteristics specific to; (i) farmers and farms, (ii) economic factors, (iii) institutional and policy factors as well as (iv) biophysical (agro-ecological) factors. Hence, farmers assess their situation and make a decision to adopt none, one, two or more technologies depending on their judgments, risk aversion and economic ability.

Depending on the type of technology adopted, there will be differences in the farm yield and technical efficiency at each farm plots. The key outcomes include outcomes such as agricultural productivity, household income and household welfare indicators, and changes in natural resource conditions, particularly land degradation or improvement. These outcomes are not only important for people at present but also affect households' endowments and opportunities in the future (indicated by the arrows from outcomes to the economic and institutional factors influencing farmers to select better farm management practices. In the next chapter methodological issues are discussed into more details.

CHAPTER THREE

3.0 METHODOLOGY

3.1 Study Location

This study was conducted in Pangani River Basin located in the North Eastern part of Tanzania. The Pangani River Basin is about 43650 Square Kilometers, with about 5% of this area in Kenya, and the remainder distributed across the Arusha, Manyara, Kilimanjaro and Tanga regions of Tanzania. The Pangani River system drains the southern and eastern sides of Africa's highest peak, Mt. Kilimanjaro (5985 meters above sea level) as well as Mt. Meru (4566 meters), then passes through the arid Masai Steppe, draining the Pare and Usambara Mountains before reaching the coastal town of Pangani, marking its estuary with the Indian Ocean (PBWA, 2010).

Pangani Basin is one of Tanzania's most productive areas, with nationally important agricultural outputs and hydropower production (95 Megawatt, 17% of Tanzania's national power grid capacity) as well as globally due to important forest and biodiversity resources within the area (Fig. 3).

The basin is currently home to 6.8 million inhabitants (URT, 2012b). 90% of this population lives in the highlands where the population density is up to 300 people per sq. km, compared to 65 people per sq. km in the lowlands (IUCN, 2009). Such high population density in Pangani river basin coupled with climate change is posing pressure to the basin natural resources.

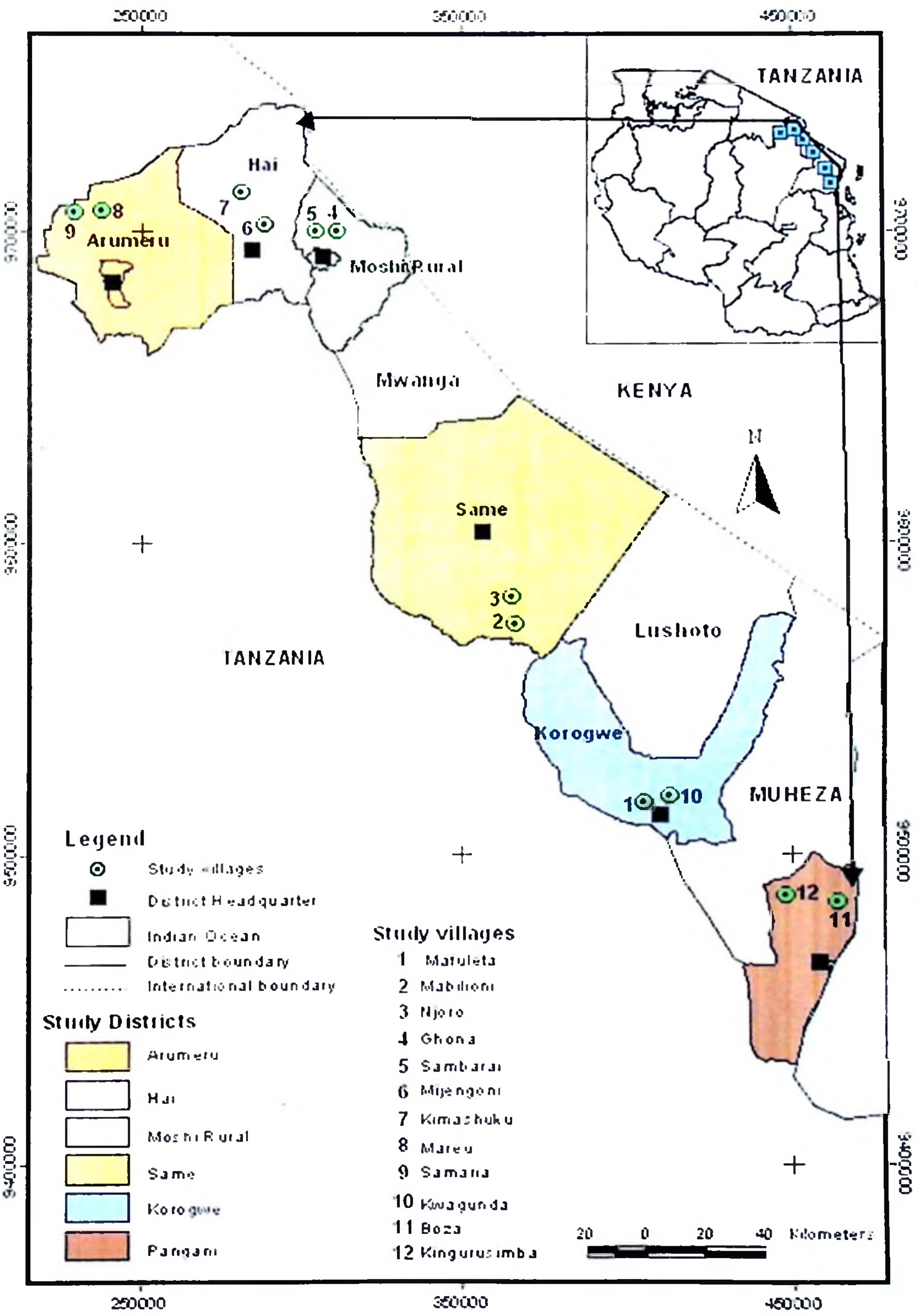

Figure 3: A map showing the study areas

Climate change has had a significant effect on the basin and the situation is expected to worsen. The glacial ice caps of Mt. Kilimanjaro, towering over the basin, are expected to disappear completely by 2020 and increased temperatures are expected to result in a 6-9% annual reduction in surface flows. Climate change and abstractions over the past decades have reduced in-stream flows from several hundred to less than 40 cubic meters per second (IUCN, 2009).

The basin has high spatial variability of rainfall, mainly characterized by the topography. While mountainous parts of Kilimanjaro, Meru, Pare and Usambara receive more rainfall (typically between 800 and 1200 mm per annum) a vast majority of low lying areas receive less than 500 mm per year. The basin has been divided into three distinct rainfall pattern namely high, Moderate and low rainfall areas (Ndomba, 2010). The high rainfall areas receives about 1200 -1500 mm of rainfall per year This zone is located on the slopes of Mt Kilimanjaro, Meru, and Pare and Ngorongoro mountain ranges. Most areas in the in the high rainfall zone rise to an altitude of 1500 meters above sea level. The moderate rainfall area receives rainfall ranging from 700 to 1200 mm per annum with moderately reliable distribution and amount. Moderate rainfall areas are located between 900 and 1500 meters above sea level. The low rainfall area receives rainfall less than 700 mm per year with very erratic distribution. Low rainfall areas are always in the lowland plains below 900 meters above sea level (Ndomba, 2010).

Rain-fed agriculture is a major source of food and most cash crop production (Mtalo *et al.*, 2010). Maize is the most ubiquitous crop, grown by most small holder farmers throughout the Basin (IUCN, 2009) and accounts for 10% of the total national production of the cereal (Nkonya and Mwangi, 2004) and it is one of the nation's maize surplus areas. The total area under maize production in the zone is about 160 700 ha. Incidences of crop failures in the basin and Tanzania occur quite frequently due to erratic rainfall. Erratic and significantly delayed short and long rains have been substantially affecting production of maize in the basin resulting into food shortages (Welling *et al.*, 2011). It has been noted that low laying areas of Pangani river basin are drought prone and different methods for improving food productivity from rain-fed agriculture must be adopted (Mongi *et al.*, 210). For planning purposes it is essential to assess the viability of rain-fed agriculture with a view of advising farmers on the most suitable crops to be grown in different areas to maximize the output of rain-fed agriculture.

3.2 Analytical Methods

Having described the areas for this study, the main focus now is on methodological issues that were used for analysis consistent with the study's specific objectives. This was accomplished by determining the farmers' choice of farm technology adoption, the impacts of farm technologies on farm household output, risk implication of adopted farm technologies and technical efficiency of adopted farm technologies. In the sub-sections that follow, the models to address each of the objectives are presented including the definition of the variables. The measurement and expected sign of the variables are also given.

3.2.1 Choice of farm technology adoption

This section models farmers' choice of farm adaptation technologies to climate change and outcome variables (maize output per hectare) in a multinomial endogenous switching regression (ESR) framework as discussed in section (2.7.2) above. The estimation of endogenous switching regression encompasses two stages. In the first stage, a farmer's choice of farm technologies is modelled using a multinomial logit selection model[5], while recognizing the inter-relationships among the choices. In the second stage of the estimation, the impacts of each farm technology on outcome variables are evaluated using ordinary least squares (OLS) with a selectivity correction term from the first stage.

3.2.1.1 Multinomial selection equation for determinants of farm technology adoption

As reviewed in section 2.7.2 above, an assumption is made that farm households face a choice of 'j' mutually exclusive strategies to changes in mean temperature and rainfall, which can be indexed $j = 1 \ldots M$. We assume that farmers aim to maximize their output, (A_i), by comparing the profit provided by k alternative farm technologies. In the first stage, let A^* be the latent variable that captures the expected output from implementing strategy j $(j = 1 \ldots M)$ rather than implementing any other strategy k. The requirement for farmer i to choose farm technology, j, over any other alternative technologies, k, is that $A_{ij} > A_{ik}$ where $k \neq j$, or equivalently $\Delta A_{ik} = A_{ij} - A_{ik} > 0$ where $k \neq j$. The expected profit, A_{ij}^*, that the farmer derives from the adoption of package j is a latent variable determined by the observed household, plot and location characteristics (x_i) and unobserved characteristics (ε_{ij}) which is given as

$$A_{ij}^* = x_i \alpha_j + \varepsilon_{ij} \qquad \text{.........(7)}$$

Where: x_i is observed exogenous variables (household, plot and location characteristics) and ε_{ij} is unobserved characteristics. Let (Φ) be an index that denotes the farmer's choice of package, such that:

$$\Phi = \begin{cases} 1 \; if \; A_{i1}^* > max_{k \neq 1}(A_{ik}^*) \; or \; \eta_{i1} < 0 \\ \vdots \qquad \vdots \qquad\qquad \vdots \\ M \; if \; A_{iM}^* > max_{k \neq M}(A_{ik}^*) \; or \; \eta_{iM} < 0 \end{cases} \qquad \text{.........(8)}$$

Where: $\eta_{ij} = \max_{k \neq j}\left(A_{ik}^* - A_{ij}^*\right) < 0$ (Bourguignon *et al.*, 2007).

Equation (8) implies that: farm household i will choose strategy j in response to long term changes in mean temperature and rainfall to maximize their expected profit if strategy j provides expected yields greater than any other strategy $k \neq j$, that is, if $\eta_{ij} = \max_{k \neq j}\left(A_{ij}^{*} - A_{ik}^{*}\right) > 0$. Under the assumption that ε_{ij} are independent and identically Gumbel distributed, that is, under the Independence of Irrelevant Alternatives (IIA) hypothesis, the probability that farmer i[th] with characteristics x will choose package j can be specified by a multinomial logit model (McFadden, 1973) where the probability of choosing strategy j (P_{ij}) is presented as:

$$P_{ij} = P\left(P\eta_{ij} < 0 \mid x_i\right) = \frac{\exp\left(x_i\alpha_j\right)}{\sum_{k=1}^{M}\exp\left(x_i\alpha_k\right)} \quad \text{......(9)}$$

The parameters of the latent variable model can be estimated by maximum likelihood (Maddala, 1986). The expansion and linearization of equation (9) gives equation (10), which will be used for parameter estimation, using frontier regression analysis.

$$\begin{aligned} P_{ij} = {} & \alpha_0 + \alpha_1 \ln X_1 + \alpha_2 \ln x_2 + \alpha_3 \ln x_3 + \alpha_4 \ln x_4 + \alpha_5 \ln x_5 + \alpha_6 \ln x_6 + \\ & \alpha_7 D_1 + \varepsilon_8 D_2 + \alpha_9 D_3 + \varepsilon_i \end{aligned} \quad \text{......(10)}$$

Where: P_{ij} = Latent variable the probability of choosing strategy j for j=1,....5,

Where: j_1 = Inorganic fertilizer,

j_2= improved maize seeds,

j_3= manure application,

j_4 = Legumes intercropping and

j_5= soil water conservation.

The independent variables include:

x_1 = Household head experience in maize farming

x_2 = Distance to the input market in Kilometers

x_3 = Farm household access to extension service

x_4 = Household asset index

x_5 = Coefficient of rainfall variation

x_6 = Rainfall satisfaction index

D_1 = dummy variable for observations from the high rainfall areas

D_2 = dummy variable for observations from the Moderate rainfall areas

D_3 = dummy variable for observations from the low rainfall areas

$\alpha_0 - \alpha_9$ = regression coefficients

ε_i = error term

Detailed descriptions of the variables for the multinomial logit model are presented in Appendix 1.

3.2.1.2 Multinomial logit outcome equations: determinants of maize yield

In the second stage of multinomial endogenous switching regression, the relationship between the outcome variables and a set of exogenous variable x (plot, household and location characteristics) is estimated for the chosen farm technology. From the selection equation specified in equation (8) above it implies that farm households face a total of M regimes (one regime per strategy, where j=1 is the reference category "non-adapting"), and that there is a yield equation for each possible regime. The selection equation (8) implies that, to adopt a given farm practices farmers face M regimes defined as follows.

$$Regime\ 1: y_{i1} = x_i\beta_1 + \varepsilon_{i1} \qquad if\ A_i = 1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (11a)$$

$$\vdots \qquad \vdots \qquad \vdots$$

$$Regime\ M: y_{iM} = x_i\beta_M + \varepsilon_{iM} \qquad if\ A_i = M \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (11m)$$

Where: y_{ji}= Continuous variables, representing maize yield in kilogramme per hectare of farm household I in regime j, (j=1...M).

x_i = vector of explanatory variables for i= 1, 2.....420.

β_{ji} = coefficient associated with explanatory variables

ε_{ii} =unobserved stochastic component which verifies $E(\mu_{ii}|X_i, Z_i) = 0$

and $V(\mu_{ii}|X_i, Z_i) = \sigma_i^2$

When estimating an OLS model, the maize yield equations (11a)-(11m). However, if the error terms of the selection model (1) η_{ij} are correlated with the error terms u_{ij} of the maize yield functions (11a)-(11m), the expected values of u_{ij} conditional on the sample selection are nonzero, and the OLS estimates will be inconsistent. To correct for the potential inconsistency, we employ the model by Bourguignon et al. (2007), which takes into account the correlation between the error terms η_{ij} from the multinomial logit model estimated in the first stage and the error terms from each net revenue equation u_{ij}. We refer to this model as a "multinomial endogenous switching regression model" following the terminology of Maddala (1986) extended to the multinomial case.

Bourguignon et *al.*, (2007) show that consistent estimates of βj in the outcome equations (11a) to (11m) can be obtained by estimating the following selection bias-corrected maize yield equations,

$$y_{i1} = x_i\beta_1 + \sigma_1\left[\rho_1 m(P_{i1}) + \Sigma_j \rho_j m(P_{ij})\frac{P_{ij}}{(P_{ij}-1)}\right] + v_{i1} \quad if \;\; A_i = 1 \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots (12a)$$

$$\vdots$$

$$y_{iM} = x_i\beta_M + \sigma_M\left[\rho_M m(P_{iM}) + \Sigma_j \rho_j m(P_{ij})\frac{P_{ij}}{(P_{ij}-1)}\right] + v_{iM} \quad if \;\; A_i = M \;\ldots\ldots\ldots\ldots\ldots (12m)$$

Where: P_{ij}= represents the probability that farm household i chooses strategy j as defined in (8), ρ_j= is the correlation between u_{ij} and η_{ij}, and m (P_{ij}) = $\int J(v - \log P_j)g(v)dv$ with J *(.)* being the inverse transformation for the normal distribution function, g *(.)* the unconditional density for the Gumbel distribution[7], and $v_{ij} = \eta_{ij} + \log P_j$. This implies that the number of bias correction terms in each equation is equal to the number of multinomial logit choices M.

The endogenous switching regression model described above can be used to compare the expected technology's net effect on yield of farm households that adopted relative to farm households that did not adopt. The model also enables to investigate the expected technology's net effect on yield in the counterfactual hypothetical cases that the adopted farm households did not adopt, and that the non-adopted farm household adapted. In particular, this estimation follows Bourguignon et *al.*, (2007) and Di Falco and Veronesi, (2011), and at first the expected maize yield is derived from the farm households that adapted, that is, in this study means $j = 2 \ldots M$ ($j = 1$ is the reference category "non-adapting"), as shown in equation (7a-7m).

$$E(y_{i2}|A_i = 2) = x_i\beta_2 + \sigma_2\left[\rho_2 m(P_{i2}) + \textstyle\sum_{k\neq 2}^{M}\rho_k m(P_k)\frac{P_{ik}}{P_{ik}-1}\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots (13a)$$

$$\vdots$$

$$E(y_{iM}|A_i = M) = x_i\beta_M + \sigma_M\left[\rho_M m(P_{iM}) + \sum_{k=1\ldots M-1}\rho_k m(P_{ik})\frac{P_{ik}}{P_{ik}-1}\right] \ldots\ldots\ldots (13m)$$

Then, the expected maize yield of farm households that adopted strategy j in the counterfactual hypothetical case that did not adapt (j=1) is derived as:

$$E(y_{i1}|A_i = 2) = x_i\beta_1 + \sigma_1\left[\rho_1 m(P_{i2}) + \rho_2 m(P_{i1})\frac{P_{i1}}{P_{i1}-1}\textstyle\sum_{k=3\ldots M}\rho_k m(P_{ik})\frac{P_{ik}}{P_{ik}-1}\right] ..(14a)$$

$$\vdots$$

$$E(y_{i1}|A_i = M) = x_i\beta_{M1} + \sigma_{M1}\left[\rho_{M1} m(P_{i1}) + \sum_{k=2\ldots M}\rho_k m(P_{i,k-1})\frac{P_{i,k-1}}{P_{i,k-1}-1}\right] \ldots (14m)$$

[7] The Gumbel distribution is good for modeling extreme values of a random variable. Specifically, it is useful when looking at the maximum value of a set of random variables.

These expected values were used to derive unbiased estimates of the ATT which is defined as the difference between equations (13a) and (14a) or equations (13b) and (14b). These expected values were derived from the ESR empirical model that is specified next. The specification of the Multinomial ESR outcome equation is based on a review of theoretical work and previous similar empirical adoption and impact studies (Di Falco *et al.*, 2010; 2011; Kassie *et al.*, 2010, 2012; Wollni *et al.*, 2010) as discussed in section 2.7.2 above.

In order to estimate the ESR outcome equations for the *M* adoption regimes. Different functional forms were tested, including linear, quadratic and double-log specifications, which are commonly used in empirical analyses with micro data (Battese *et al.*, 1997; Wollni *et al.*, 2010). Double-log specifications showed the best empirical fit. We used a Wald test to establish whether the Cobb-Douglas specification without input interaction terms, or the translog with input interactions, is more appropriate. The null hypothesis in favor of the Cobb-Douglas specification was not rejected. Natural logarithm of maize yield per acre as dependent variable was used, which is a function of input use, also expressed in natural log-terms, and other relevant household and contextual variables. The specification of the Cobb Douglass model is presented in equation (15).

$$Y_{ij} = \beta_j + \Pi X_{ij}^{\beta_j} e^{\varepsilon_{ij}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (15)$$

Where: Y_{ij} = output for the i[th] respondent associated with j[th] farm technology

Π = a steady multiplicative symbol

e = natural logarithm

ε = error term

β_0 = An intercept for the j[th] farm technologies

β_{ij} = Parameter estimates

The log liner transformation of Equation (15) gives equation (16), which will be used for parameter estimation, using frontier regression analysis.

$$\ln y_{ij} = \beta_{0j} + \sum_{k=1}^{K} \beta_{kj} \ln(x_{kj}) + u_{ij} \quad \text{...} (16)$$

Where: ln = the natural logarithm

The Cobb Douglas frontier equation in equation (16) was expanded to include the independent variables as presented in equation (17)

$$\begin{aligned}\ln y_i &= \beta_0 + \beta_1 \ln X_1 + \beta_2 \ln x_2 + \beta_3 \ln x_3 + \beta_4 \ln x_4 + \beta_5 \ln x_5 + \beta_6 \ln x_6 + \\ &\beta_7 D_1 + \beta_8 D_2 + \beta_9 D_3 + \varepsilon_i\end{aligned} \quad \text{..................} (17)$$

Where $\ln y_i$ = The natural logarithm of maize yield per hectare was used as dependent variable. Other variables are as previously defined in equation (10) above.

The empirical results of this analysis will be useful for a better understanding the adoption process and the impact of selected farm technologies in the face of climate change important. The next section provide estimation of the risk implication of these technologies on maize yield.

3.2.2 Risk implication of adopted farm technologies

In this section the econometric analysis determines how smallholder farmers use inputs to enhance productivity and reduce yield variability. Based on the review made in section (2.8.3) above, the Just and Pope (J-P) (1979) stochastic production framework will be used. The J-P function is represented as:

$$y = g(x, v) \quad \text{...} (18)$$

Where: y = output,

x = vector of controllable inputs (e.g. fertilizer, land, labour),

v = vector of non-controllable inputs (e.g., weather conditions), and

$g(x,v)$= the largest feasible output given x and v.

Of particular interest here are the interactions between the inputs (x, which include maize seeds and inorganic fertilizer) and the random variables (v, which represent production uncertainty).

The focus on production uncertainty as represented by the stochastic production function $y = g(x,v)$, where weather conditions (v) are not known at planting time, but the farmer has a subjective distribution regarding the weather variable. Just and Pope (1978) proposed to specify the production function as follows:

$g(x,v) = f(x) + [h(x)][e(v)]$ .... (19)

Where f (.) = mean production function,

h (.) = variance (or risk) function, and

x and z = vectors of inputs and

e = exogenous stochastic disturbance or production shock (error term)

g (x,v) = as previously defined

$h(x) > 0$ and $e(v)$ = random variable with mean zero and variance 1

The expected value of output is given by equation (20) as:

E (y) = f(x) ....(20)

While the variance of y is a product of the variance of (e) and *(h(x)* which is equal to *(hx)*. It is presented as:

$E(y) = f(x)$ and $Var\ (y) = Var\ (e)h(x) = h(x)$

This makes $\frac{\delta Var(y)}{\delta x} = \frac{\delta h}{\delta x}$ ....(21)

Then it follows that when $\frac{\delta h}{\delta x} > 0$, then the corresponding inputs (x) is risk-increasing implying that, a rise in that variable indicates an increase of the variability of yield. Meanwhile if the derivative of the variance of output is negative ($\frac{\delta h}{\delta x} < 0$) then the input is risk-decreasing that is it indicates a decrease of the variability of production. Note that $e(v)[h(x)]$ behaves like an error term with mean zero and variance equal to $h(x)$. From an econometric viewpoint, this formulation is also useful because the variance function can be interpreted as a heteroskedastic[8] disturbance term. This can be seen by reformulating the J-P form as:

$$y = f(x;\alpha) + u \qquad (22)$$

Where u is the error term with variance $\mathrm{var}(u) = [h(x;\beta)]^2 \sigma_\varepsilon^2$. This formulation is also useful from an econometric viewpoint, because it makes the variance function to be interpreted as a heteroskedastic disturbance term (Asche and Tveteras 1999).

Since production uncertainty appears as heteroskedasticity in an econometric model, the parameters in the mean production function cannot be efficiently estimated if the production risk is not accounted for. Hence the first issue to address when modelling maize farmers yield risk was to investigate whether any significant production risk was present. Since production risk is specified as heteroskedasticity in the J-P framework, any test against heteroskedasticity was used (Asche and Tveteras 1999). If heteroskedasticity is not detected, this can be regarded as evidence against production risk, and the researcher can proceed within a conventional deterministic production model framework.

[8] Heteroskedasticity is a statistical term used to describe the behaviour of a sample's variance and standard deviation. If the quality is present, then the variance and standard deviation of the variable are not constant over the entire graph of the sample data. If these measures are constant, then the data is said to be homoscedastic

Since production risk was detected, then the mean production function and the variance function has to be estimated as specified in the next section.

3.2.2.1 Empirical model for the mean function

We assume that the production technology has the general Just-Pope form given in the following equation (23).

$y_i = f(x_i, D, \alpha, \mu_i) + u_i$ and $var(u_i) = h(x_i; D, \beta, \lambda_i)$..............................(23)

Where: x_i = vector of input used

D = dummy variable for rainfall patterns

α and β are vectors of parameters for the mean and variance function respectively

μ_i = farm plot specific effect on mean output

λ_i = farm plot specific effect on output risk

u=error term

In estimating the above J-P function, three functional forms of production functions namely: Cobb-Douglas, quadratic and translog are used for the Just and Pope Production function (Di Falco and Chavas, 2009). Because of the multiplicative interaction between the mean and variance, a translog functional form would violate the Just and Pope (1979) assumption of an additive interaction between the average and variability functions. The Cobb-Douglas production function, is unsuitable in this analysis because the model cannot handle a large number of inputs, the function is based on restrictive assumptions of perfect competition in the factor and product markets and it assumes constant returns to scale. In addition, a linear quadratic functional form has been the best in different studies (Di Falco *et al.*, 2012; Guttormsen and Roll, 2013). The choice of this functional form over other forms is maintained for two reasons. First, it is consistent with J-P postulates-there is an additive interaction between the mean and variance output function. Second, it is flexible in the sense of a second-order approximation of any unknown mean output function (Kumbhakar and Tsionas, 2008). A Linear Quadratic (LQ) mean production function is specified in equation (24).

$$y_i = \alpha_0 + \sum_k \alpha_k x_{ki} + 0.5 \sum_l \sum_k \alpha_{lk} x_{li} x_{ki} + u_i \quad \text{...(24)}$$

The linear quadratic (LQ) mean production function in equation (24) was expanded to include the independent variables as presented in equation (25).

$$\begin{aligned} y_i = {} & \beta_0 + \beta_1 x_1 + \beta_2 x_1^2 + \beta_3 x_2 + \beta_4 x_2^2 + \beta_5 x_3 + \beta_6 x_3^2 + \beta_7 x_4 + \beta_8 x_4^2 + \beta_9 x_5 \\ & + \beta_{10} x_6 + \beta_{11} x_1 x_2 + \varepsilon_i \end{aligned} \quad \text{.................... (25)}$$

Where: y_i = Maize yields in Kilograms per hectare (kg/ha).

x_1 = Amount of fertilizer used per hectare (Kg/ha).

x_2 =amount of improved maize seeds in kilogramme per hectare.

x_3 = Amount of manure applied in kilograms per hectare (kg/ha).

x_4 = Rainfall precipitation in mm during planting season.

x_5 = Dummy variable for legumes intercropping (=1, if the maize farm plot was intercropped with legumes, 0 otherwise).

x_6 =Dummy variable for soil water conservation, (=1, if the maize farm plot was had soil water conservation technoloy, 0 otherwise).

x_7 = altitude (proxy for temperature).

Other variables are as previously defined. Detailed descriptions of these variables are presented in Appendix 2.

3.2.2.2 Empirical model for the variance function

For the variance function, we employ a special case of Harvey's specification, $\text{var}(u) = \exp[Z\beta]$ where the Z's are input levels. A nice property of the variance function in

Harvey's (1976) formulation is that it also ensures positive output variance in the empirical analysis. Note that in the Just-Pope model, var(y) = var(u). The variance function was expressed as:

$$\operatorname{var}(u_i) = \exp\left(\beta_k x_{k,i} + 0.5\sum_k \sum_l \beta_{kl} x_{k,i} x_{l,i} + \lambda_i \right) \qquad (26)$$

The linear quadratic function in equation (26) was expanded to include the independent variables as presented in equation (27)

$$u_i^2 = \beta_0 + \beta_1 x_1 + \beta_2 x_1^2 + \beta_3 x_2 + \beta_4 x_2^2 + \beta_5 x_3 + \beta_6 x_3^2 + \beta_7 x_4 + \beta_8 x_4^2 + \beta_9 x_5 + \beta_{10} x_6 + \beta_{11} x_1 x_2 + \varepsilon_i \qquad (27)$$

Where: u_i^2= variance of maize yield. All other variables are as previously defined in equation (18) above.

The empirical analysis of risk implication of farm adaptation technologies was meant to generate information that will help to identify appropriate agricultural practices that act as a buffer against climate change. Further, this study argues that the adaptation measures farmers take to reduce the negative impacts of climate change do affect farmers' efficiency of production. To support this argument, one further step was followed to understand how climatic factors especially seasonal rainfall and agro-ecological settings affect production efficiency among small scale farmers. This is achieved in the next subsection.

3.2.3 Technical efficiency of adopted farm technologies

From the review made in section (2.7.2), the study used Stochastic Frontier Production Function (SFPF) to estimate the technical efficiency of maize farms in Pangani basin.

The study followed Battese (1992) and Battese and Coelli (1995) models to specify a stochastic frontier production function which was originally proposed independently by Aigner *et al.*, (1977) and it is specified as follows:

$$y_i = f(x_i\beta)\exp(\varepsilon_i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(28)$$

Where: y_i = Production of the i-th farm (i=l, 2, 3 ... n);

x_i = Vector of functions of input quantities applied by the i-th farm;

β = Vector of unknown parameters to be estimated;

ε_i = The error term that is composed of two independent elements, v_i and u_i such that $\varepsilon_i = v_i - u_i$

The stochastic frontier approach, unlike other parametric frontier measures makes allowance for stochastic errors arising from statistical noise or measurement errors (Sharma and Leung, 1998). As stated earlier, the stochastic frontier model decomposes the error term into a two-sided random error. One of them is v_i that captures the random effects outside the control of the firm - the decision making unit (Battese and Coelli, 1995). These include random factors such as measurement errors and weather. This is a random error having zero mean, $N(0;\delta^2 v)$ and it is assumed to be symmetric independently distributed as $N(0;\delta^2 v)$ random variables and independent of u_i .The other one is the one-sided efficiency component, u_i. The u_i is a non-negative truncated half-normal $N(0;\delta^2 u)$ random variables associated with farm-specific factors, which leads to the i^{th} farm not attaining maximum efficiency of production; u_i is associated with technical inefficiency of the farm and ranges between zero and one (Kim and Coelli 2009). However, u_i can also have other distributions such as gamma and exponential. Following Battese and Coelli (1995), the technical inefficiency effects, u_i in equation (28) can be expressed as:

$$u_i = z_i\delta + w_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(29)$$

Where: w_i are random variables, defined by the truncation of the normal distribution with zero mean and variance $\sigma^2 u$, such that the point of truncation is z_i i.e. $z_i\delta \geq -z_i\delta$. Beside the farm-specific variables, the z_i, variables in Equation (28) may also include input variables in the stochastic production frontier (29), provided that the inefficiency effects are stochastic.

The Technical Efficiency (TE) of an individual farmer is defined as the ratio of the observed output to the corresponding frontier's output, conditional on the level of input used by the farmer. Hence the TE of the farmer is expressed as:

$$TE_i = \frac{y_i}{y*} = \frac{f(x;\beta)\exp(v_i - u_i)}{f(x_i,\beta)\exp(v_i)} = \exp(-u_i) \text{...(30)}$$

Where: y_i is the observed output and y_i * is the frontier's output.

Given the assumptions of the above stochastic frontier model, inference about the parameters of the model can be based on the maximum likelihood estimation because of the standard regularity conditions hold. Aigner *et al.* (1977) suggested that the maximum likelihood estimates of the parameters of the model can be obtained through parameterization $\sigma_u^2 + \sigma_v^2 = \sigma_s^2$ and $\gamma = \frac{\sigma_u}{\sigma_v}$. However Battese (1997) replaced σ_v^2 and σ_u^2 with $\sigma_u^2 + \sigma_v^2 = \sigma^2$ and $\gamma = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}$, so that $0 \leq \gamma \leq 1$. In the case of $\sigma_v^2 = 0$, γ would be equal to 1 and all the differences in error terms of the frontier production function are the results of management factors under the control of the producer. When $\sigma_u^2 = 0$, γ would be equal to zero, which means all the differences in error terms of the frontier production function are the results of factors that the producer has no control over, (random factors).

This also implies the existence of a stochastic frontier. If γ is close to one it indicates that the random component of the inefficiency effects makes a significant contribution to the analysis of the production system. The technical inefficiency (TI) of an individual farm is defined as:

$$TI_i = 1 - (\exp(-u_i)) = 1 - \left(\frac{y_i}{y_i^*}\right) \quad \text{...(31)}$$

γ statistic is used for hypothesis testing through the generalized likelihood ratio tests. These test employ the following calculation (Greene, 2003).

$$LR(\lambda) = -2\left\{\ln \frac{L(H_0)}{L(H_1)}\right\}$$

$$= -2\{\ln[L(H_0)] - \ln[L(H_1)]\} \quad \text{......................................(32)}$$

Where: L (H_0) and L(H_1) denote the values of the likelihood function under the null hypothesis (H_0) and alternative (H_1) hypotheses, respectively. If the given null hypothesis is true, then has approximately a chi-square distribution or mixed chi-square distribution when the null hypothesis involves $\lambda = 0$ (Khan *et al.*, 2010).

3.2.3.1 Empirical model specification

A number of previous studies specified a Cobb-Douglas production function to represent the frontier function; however, the Cobb-Douglas imposes a severe prior restriction on the farm's technology by restricting the production elasticities to be constant and the elasticities of input substitution to unity (Wilson *et al.*, 1998). This study specifies the stochastic frontier production function using the flexible translog specification as follows.

$$\ln y_i = \beta_0 + \sum_{j=1}^{K} \beta_j \ln(x_{ij}) + \frac{1}{2}\sum_{j=1}^{K}\sum_{h=1}^{K} \beta_{jk} \ln(x_{ij})\ln(x_{ik}) + v_i - u_i \quad \text{................................(33)}$$

Where: ln = natural logarithms;

y_i = quantity (or value) of agricultural output of the i-th farmer; x = vector of the input quantities;

β = vector of parameters;

i= number of respondents;

k,j = input variables. Other variables are as previously defined.

The frontier function in equation (33) was expanded to include independent variables specified as:

$$\ln y_i = \beta_0 + \beta_1 \ln x_1 + \beta_2 \ln x_2 + \beta_3 \ln x_3 + \beta_4 \ln x_4 + 0.5\beta_{11} \ln x_1^2 + 0.5\beta_{22} \ln x_2^2 + 0.5\beta_{33} \ln x_3^2 + 0.5\beta_{44} \ln x_4^2 + \beta_{12} + \ln x_1 \ln x_2 + \beta_{13} \ln x_1 x_3 + \beta_{14} \ln x_1 \ln x_4 + \beta_{23} \ln x_2 \ln x_3 + \beta_{24} \ln x_2 \ln x_4 + \beta_{34} \ln x_3 \ln x_4 + \alpha_1\alpha_{11} + \alpha_2 D_2 + \alpha_3 D_3 + v_i - \mu_i \quad (34)$$

Where: y_i = denotes the maize output (in kg) of the ith farmer (i = 1,2,3.....N; N = 682)

x_1 = Labour used for all farm operations (from land preparation to harvesting) (persons days),

x_2 = quantity of inorganic fertilizer used (kg),

x_3 = the quantity of manure/FYM (Kg),

x_4 = Capital (Tsh),

D_1 = Dummy variable for improved maize seeds,

D_2 = Dummy variable for Soil Water Conservation (SWC),

D_3 = Dummy variable for legume intercropping, β and α are parameter to be estimated.

In the above estimation, the measurement of farm specific technical efficiency was based on deviations of realized output from the frontier output. The observed deviations from the frontier model were estimated from the equation given below.

$$u_i = \delta_0 + \delta_1 z_1 + \delta_2 z_2 + \delta_3 z_3 + \delta_4 z_4 + \delta_{44} z_4^2 + \delta_5 z_5 + w_i \qquad (35)$$

Where: z_1 = Farm size (hectare),

z_2 = Number of farm plots,

z_3 = Household wealth index,

z_4 = Rainfall precipitation during planting season (millimeters),

z_5 = Altitude (proxy for temperature) (Meters above sea level),

$\delta's$ = Parameter estimated,

w_i = Unobservable random variables

Detailed descriptions of the parameters for these variables are presented in Appendix 3.

3.2.3.2 Elasticity of input and returns to scale

Determination of elasticities is necessary for the estimation of responsiveness of yield to inputs. In the Cobb Douglas stochastic frontier production function, the estimated as a regression produced coefficients that were directly and easily interpretable as elasticities of output with respect to inputs. On the other hand for a Translog stochastic frontier production function, the estimated coefficients cannot be directly interpreted as elasticities. This is because the output elasticities with respect to the inputs are functions of the first order and second order derivatives, together with the level of inputs used. The factor elasticities were calculated from the OLS estimates of the translog production function with respect to each farm plot as:

$$e_i = \frac{\delta \ln y}{\delta \ln x_i} = \beta_i + \beta_{ii} \ln \bar{x}_i + \sum_{j \neq i} \beta_{ij} \ln \bar{x}_i \qquad (36)$$

Where: e_i = partial elasticity of input x_i

$\overline{x_i}$ = mean values of respective conventional inputs

Using equation (36), output elasticity with respect to input, x_i evaluated at the sample mean were thus computed from the following equations:

$$e_{x_1} = \frac{\delta \ln y}{\delta \ln x_1} = \beta_1 + \beta_{11} \ln \bar{x}_1 + \beta_{12} \ln \bar{x}_2 + \beta_{12} \ln \bar{x}_3 + \beta_{14} \ln \bar{x}_4 \text{ .... (37).}$$

$$e_{x_2} = \frac{\delta \ln y}{\delta \ln x_2} = \beta_2 + \beta_{22} \ln \bar{x}_2 + \beta_{12} \ln \bar{x}_1 + \beta_{23} \ln \bar{x}_3 + \beta_{24} \ln \bar{x}_4 \text{ ....(38)}$$

$$e_{x_3} = \frac{\delta \ln y}{\delta \ln x_3} = \beta_3 + 2\beta_{33} \ln \bar{x}_3 + \beta_{13} \ln \bar{x}_1 + \beta_{23} \ln \bar{x}_2 + \beta_{34} \ln \bar{x}_4 \text{ .... (39)}$$

$$e_{x_4} = \frac{\delta \ln y}{\delta \ln x_4} = \beta_4 + \beta_{44} \ln \bar{x}_4 + \beta_{14} \ln \bar{x}_1 + \beta_{24} \ln \bar{x}_3 + \beta_{34} \ln \bar{x}_4 \text{ .... (40)}$$

The analytical framework presented above determined the type of data and sample size as presented in the next section.

3.3 Sampling and Sample Size

The study adopted a cross-sectional research design and a mixed methods approach was used in data collection. The sampling unit was individual farmers growing maize. The sampling frame for the study included all smallholder farmers in Pangani basin. The entire number of smallholder farmers growing maize in the basin was about 747,641 (URT, 2012b). Using Yamane (1973) the sample size calculated was approximately 420. A multistage sampling with stratification technique was used in the selection of the farmers. The first stage involved dividing the Pangani river basin into three strata based on rainfall pattern namely high rainfall, Moderate rainfall and low rainfall areas. These classifications were meant to obtain the actual range of adaptation measures that have been adopted by farmers in different rainfall pattern.

The second stage involved random selection of the district from each zone (Table 3). The selection of villages constituted the third stage. Two villages were randomly selected from each of the selected district making a total of 12 villages. The last stage was the selection of farmers from the chosen villages. In each village. sampling frame was used to select random samples of 35 households from the village household register giving a total of 420 respondents.

Table 1: Distribution of sample villages

Region	District	No of villages	Name of village	Rainfall category	Number of respondents		
					Male	Female	Total
Arusha	Arumeru	2	Samaria	Low rainfall	29	6	35
			Mareu	High rainfall	27	8	35
Kilimanjaro	Hai	2	Kimashuku	High rainfall	28	7	35
			Mijongweni	Low rainfall	30	5	35
	Moshi	2	Sambarai	High rainfall	28	7	35
	Rural		Ghona	Moderate rainfall	26	9	35
	Same	2	Njoro	Low rainfall	27	8	35
			Mabilioni	Low rainfall	30	5	35
Tanga	Korogwe	2	Mafuleta	Moderate rainfall	31	4	35
			Kwagunda	Moderate rainfall	27	8	35
	Pangani	2	Boza	Moderate rainfall	32	3	35
			Kigurusimba	Moderate rainfall	30	5	35
Total		12			345	75	420

3.4 Data Collection

A structured questionnaire was employed to collect data from the smallholder farmers. The questionnaire contained a wide range of information including: household understanding about climate change, household characteristics, households' production activities, grid point from each village, plot specific characteristics, including adoption of sustainable agricultural practices for each household (Appendix 11). Other information collected at the plot level was crops grown, crop production estimates, labor inputs associated with each type of agricultural activity. Some of key socioeconomic elements collected about the household include; age, gender, education level, family size, asset ownerships, distance a household lies from input and output markets and extension officers. The field survey was conducted from November 2013 to June 2014. The information on crops and livestock production and prices of products sold collected from the respondents was based on crop year July 2013-June 2014.

Secondary data included daily average temperature, daily maximum temperature, daily minimum temperature and daily precipitations from the weather stations of nearby study villages within the Pangani river basin from 1983 to 2013. These information were gathered from Tanzania Meteorological Agency (TMA). Other secondary information includes the type of soil and the main crops produced from each village. These information were obtained from Pangani Basin Water Board Authority, Mlingano Agricultural Research Institute and Regional and Districts offices found in Pangani River Basin.

3.5 Data Analysis

The first step in the analysis of data was to identify selected farm level adaptation technologies for each farmer in the sample. In this respect, descriptive statistics was used to compile and compare the adopted adaptation technologies in different areas of Pangani river basin. Then household characteristics and plot characteristics were identified for each farmer and compared. Descriptive statistics for this purpose included the frequencies, means and standard deviations. The results were then presented in tables and charts from which inferences were drawn. Comparison of means was made using an independent sample t-test, while comparisons of variances were being done using chi-square tests at 5% significance level.

To analyze rainfall and temperature variability in the study areas, trends and variability in total seasonal and annual rainfall derived from monthly rainfall observations were computed. Data were evaluated for discontinuities by inspection of each time series and then tested for homogeneity using the Student's t-test. Trend analysis was done to reveal the general movement of the rainfall pattern, examining evidence of any changes in the trend of rainfall amounts. Such patterns were investigated by use of graphical and statistical methods. Regression analysis was done to determine the magnitude, direction and significance of the trends in annual and seasonal rainfall for each sample village district. Variability of annual and seasonal rainfall was assessed using the Coefficient of Variation (CV) techniques. Rainfall data were analyzed using INSTAT statistical package.

In order to determine communities' perceptions of rainfall trends and variability, the individual subjective rainfall index was constructed to measure the farmer specific perception related to rainfall satisfaction from such questions as whether rainfall came and stopped on time, whether there was enough rain at the beginning and during the growing season, and whether it rained at harvest time. The responses for these questions were dichotomized in such a way that those who responded on time (best) coded into one and others (worst) into zero. The responses were summed and divided by the number of rain related questions (eight in this case). So the most favourable rainfall outcome is one and the least is zero. Then farmers attitude towards selected farm technologies was measured as a pooled score and responses to attitudinal statements were derived on a five point Likert type scale as follows: 1= Strongly Agreed (SA); 1 = Agreed (A); 3 = Undecided (U); 4 = Disagreed (D); 5= Strongly Disagreed (SD). Scores on all items were then totaled to yield a composite attitude score for each farmer. The higher the score the more favorable the attitude towards adopting technologies for climate change adaptation.

Pertaining to objective one and two of this study, the multinomial endogenous switching regression analysis was used to examine farmers' factors that hinder or accelerate adaptation strategies in terms of farming practices selection and to analyze effects of various farm level adaptation technologies adoption on the smallholder farm yield. Prior to running the multinomial endogenous switching regression model, a choice of exclusion restrictions or instrumental variables was made. In order to check the econometric validity of the instrumental variables, the Hausman tests were conducted. Further a check for multicollinearity and heteroskedasticity problems in all regression models using the Variance Inflation Factor (VIF) and White test respectively. In performing the Multinomial switching regression analysis, three steps were followed. The first step, was to model the determinants of farmers adopting the technology, and in the second step, was to model the outcome of maize yield of farmers from adopting a given farm technology. The third step was to determine the treatment effect between adopters and non adopters. This analysis was achieved by using the Selmlog command available in STATA software.

Pertaining to the third specific objective, the estimation procedure proceeded in the following steps. First, the mean production equation was estimated using the econometric specification in equation (25). Under the exogeneity assumption of the independent variables in (25), the parameters were consistently estimated through OLS to give the estimated mean production.

From this first step, it was clearly intuitive that a good estimation of the mean function was particularly crucial since specification errors in its approximation could be reverberated across the whole model, thereby biasing the estimation of the variance function. Hence, different alternative functional specifications of the mean function including quadratic, translog, and log-log specifications were tested. To ascertain the econometric performance of each specification, the Akaike Information Criterion (AIC) was used. In this step, a flexible quadratic stochastic production function was selected. The estimation of equation (25) poses at least three econometric challenges which were taken care by performing various diagnostic tests. Based on the OLS estimates, the first test was for the presence of multicollinearity using the variance inflation factors (VIF) and also by pairwise correlations. Secondly, the presence of endogeneity and unobservable heterogeneity (for instance differences in farmers' abilities) for some of the variables could lead to biased estimates and misleading conclusions (Greene, 2003). To test for endogeneity, the Durbin-Wu-Hausman test (Koundouri *et al.*, 2006) was used.

Third, was the tests for heteroskedasticity or the presence of significant marginal output risk in input levels were performed by using Breusch-Pagan (B-P) and Goldfeld-Quandt (G-Q) tests (Breusch and Pagan, 1979). The tests provide substantial evidence of output heteroskedasticity in input levels, and accordingly indicate that output risk is present in maize farming. Since production risk was found to be present, the mean function was reestimated by using White's heteroskedasticity-consistent covariance estimator to provide valid inference. Next, the variance function was estimated in a separate step, using the predicted residuals from the estimated mean function.

The fourth objective of this study was analysed using equation (34). In this analysis, five conventional inputs for maize production were used as outlined in section (3.2.3). The model was run using FRONTIER Version 4.1 (Coelli, 1996) to obtain farmer specific technical efficiency (TE). In this analysis, generalized likelihood ratio test was used to test the presence of inefficiency effect on the frontier model and distribution functional form of the error term. The first test was on the appropriateness of the functional form tested by estimating both the Cobb Douglas and the Translog production functions. The null hypothesis stated that the coefficients of the second-order variable in the translog model are zero implying that the Cobb-Douglas function is the best fit for the model. The second test statistic was that of selecting the appropriate. The null hypothesis was stated as: the error term has a distribution that is half normal, hence the assumption that the technical efficiency component assumes a half normal distribution. The alternative (LU) hypothesis was that the error term has a distribution that is truncated normal.

The third test was on the effect of the three different rainfall pattern on the inefficiency. The last null hypothesis was stated as: the mean technical efficiency for high rainfall areas is the same as that of moderate and lower rainfall areas. The entire hypothesis with the exception of the third one (i.e. the difference in mean technical efficiency) was investigated using the generalized likelihood-ratio statistic (LR) which was given by equation (32). After obtaining farm level technical efficiency which ranges between 0 and 1, the source of technical inefficiency variation observed among farmers were determined by regressing TE against selected independent variables as presented in equation (35). In order to get valid results, tests for factors that influence the robustness of cross-sectional data analyses were taken in to account as presented in the discussion of findings next.

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

4.1 Social Demographic Characteristics

This section describes the socio-economic and demographic characteristics of respondents from the study area. This information was obtained using the administered questionnaire. The information is helpful in discussing and explaining some variables and issues related to results. In addition, the data shed light on profiles and basic characteristics of the respondents. The discussion mainly focuses on those explanatory variables influencing the adoption of farm technologies, as identified in the previous chapter. Such characteristics includes age, gender, household size, level of education, farming experience, and size of farm plots used for maize production. The values of the variables are presented in three categories of rainfall pattern, namely: lower rainfall, moderate and higher rainfall areas.

Analysis of the data showed that of 92.2% male headed households and 7.8% female headed households. The data indicated that males were highly represented in questionnaire filling compared to females, because respondents were household heads and most of the households are headed by males. Table 4.1 summarizes the percentage distribution of the respondents.

In terms of age group, the analysis of the data showed that, majority of the sampled households, about 55.6%, 65.7% and 61.5% in the lower, moderate and higher rainfall areas, respectively fall within 41-60 years age bracket (Table 2). These results imply that the small holder farmers in the area were within the economically active age range, of 41-60 years. Taking into account objectives of the study, having a high percentage of respondents aged 40 and above was appropriate because the information sought required one to have a historical understanding of the state of climate in the local area at least for the past 30 years. It required one to have an understanding of how the state of the local climate has been behaving (changing or not), the extent to which the farmers have been changing their farming practices in line with changing climate and other factors during the past 30 years.

The respondents' education level was one of the information to capture whereby 3.4% of the smallholder farmers never attended school, that is, they had no formal education, while about 96.6% of the respondents had formal education, out of the 96.6%, about 79.8% had attended basic education, that is seven years of primary school, 11.5% attended secondary school while about 7.6% attended higher institution at various levels (Table 2). This suggests that majority of the farmers in the study area could read and write. With this level of education one can be said to have some literacy and numeracy skills that is important to obtain and apply relevant information concerning the changing climate, which thereby increases farm level adaptation options. Literature indicates that improving education and disseminating knowledge is an important policy measure for stimulating local participation in various development and natural resource management initiatives (Deressa *et al.*, 2011). However, it is notable that reading is not the only way of obtaining knowledge, and for the smallholder farmers, local knowledge may play an important role as well.

From the data, most of the households had between 2 to 5 adult equivalent, representing 65.8% of the total sample. The household size of less than 2 adult equivalent represented 5.4%, while above 5 adult equivalent households represented 29.1% (Table 2). This implies that, the farmers in the area had a large family size, which could reduce the demand for hired labour as members of the farm families could carry out some of the farming and non farming activities. Family size in adult equivalent units is a potential indicator of labour supply for production and labour bottleneck can be also a significant constraint to the use of some farm management practices. For instance, investment in soil water management practices can be particularly labour demanding and may be too expensive to undertake for household with limited labour supply.

Farming experience is also reported and it reveals that a greater proportion (54.7%) of the farmers had about 10- 20 years of farming experience, 21.7% of the farmers had 21 to 30 years of farming experience, 11.2% of the farmers had 31-40 years of farming experience and above, while 8.7% of the farmers constitute those with less than 10 years of farming experience in the study area. This implies that, the respondents are experienced farmers; hence they have acquired enough farming experience needed to perceive the effect of climate change on farming activities. Maddison, (2006) noted that farming experience enhances the probability of uptake of various adaptation technologies as experienced farmers have better knowledge and information on changes in climatic conditions and livestock management practices. Since the experienced farmers have high skills in farming techniques and management, they may be able to spread risk when facing climate variability.

Table 2: Percentage distribution of basic household characteristics of the surveyed farmers

Variable name	High rainfall n=105	Moderate rainfall n=175	Lower rainfall n=140	Full Sample N=420
Age of the household head				
20 -40	19.1	28.3	28.1	25.8
41-60	55.6	65.7	61.5	61.2
> 61	26.5	8.1	12.3	14.6
Gender (% male)	93.2	92.0	91.1	92.2
Household size (adult equivalent)				
<2	4.1	1.8	11.2	5.4
2-5	68.1	63.1	65.3	65.8
>5	28.5	36.6	25.7	29.1
Education				
Illiterate	2.90	4.1	3.2	3.4
Primary	74.3	81.6	82.2	79.8
secondary	13.2	11.7	9.1	11.5
Tertiary	10.2	4.1	7.8	7.6
Experience in maize production (years)				
< 10	8.1	11.3	8.9	9.2
10.-30	75.5	75.7	79.2	76.5
>30	18.2	14.2	13.9	15.8
Membership in social groups	49.4	33.6	29.4	39.9
Average Distance to the nearest input market (km)				
<1	0.0	40.0	40.7	80.8
1-5	12.9	120.2	40.8	280.4
>5	0.0	0.0	40.2	40.3

In addition to the conventional household characteristics and endowment variables, the survey also collected data related to membership in social groups that can influence technology adoption decisions. The results revealed that majority (39.9%) of the respondents participated in or were members of social groups or organizations. Memberships in social groups play three distinct roles in adoption of agricultural technologies (Katungi and Smale, 2007). First, they act as conduits for financial transfers that may relax the farmer's credit constraints. Second, they act as conduits for information about new technology. Third, they can facilitate cooperation to overcome collective action dilemmas, where the adoption of technologies involves externalities. Isham (2000) shows that ethnically based and participatory social affiliations act as forms of social capital in the decision to adopt fertilizer.

Market access is another important factor affecting adoption of agricultural technologies. The scenario was not the same across all districts with respect to farmers that reside over 10 km from the nearest market. Most respondents 80 live less than one kilometer to the nearest market, 280 farmers live in one to five kilometer, and while 40.3% live in over five kilometer away. Input markets allow farmers to acquire the inputs they need such as different seed varieties, fertilizers and irrigation technologies. At the other end, access to output markets provides farmers with positive incentives to produce cash crops that can help improve access to farm inputs and hence their ability to respond to changes in climate (Maddison, 2006). Madison observed that long distances to markets decreased the probability of farm adaptation and that markets provide an important platform for farmers to gather and share information on climate change adaptation.

It was important also to know the wealth status of maize farmers because it can have some implications on other variables. This information was obtained by determining the household asset index, a proxy for household wealth. In doing so, a wealth index based on durable goods ownership and housing condition, an agricultural machinery index, and livestock size was included. Following the method of Córdova (2008), Principal Component Analysis (PCA) was used to assign weights to household assets to generate a proxy for wealth "asset index". Assets with most variation across households were weighted greater than those more commonly found. The asset indices of the interviewed households are presented in Fig. 4. The analysis revealed that, the household asset indices ranged from -0.78 to 7.63. The mean wealth index of the poor class was -0.63 while the average is -0.02, and the well off is 1.88. About 43.2% of the households are poorly endowed, having a wealth index less than zero. Based on this categorization, about 14.4% of the sampled households were very wealthy, 20% were wealthy, and 22.4% were poor.

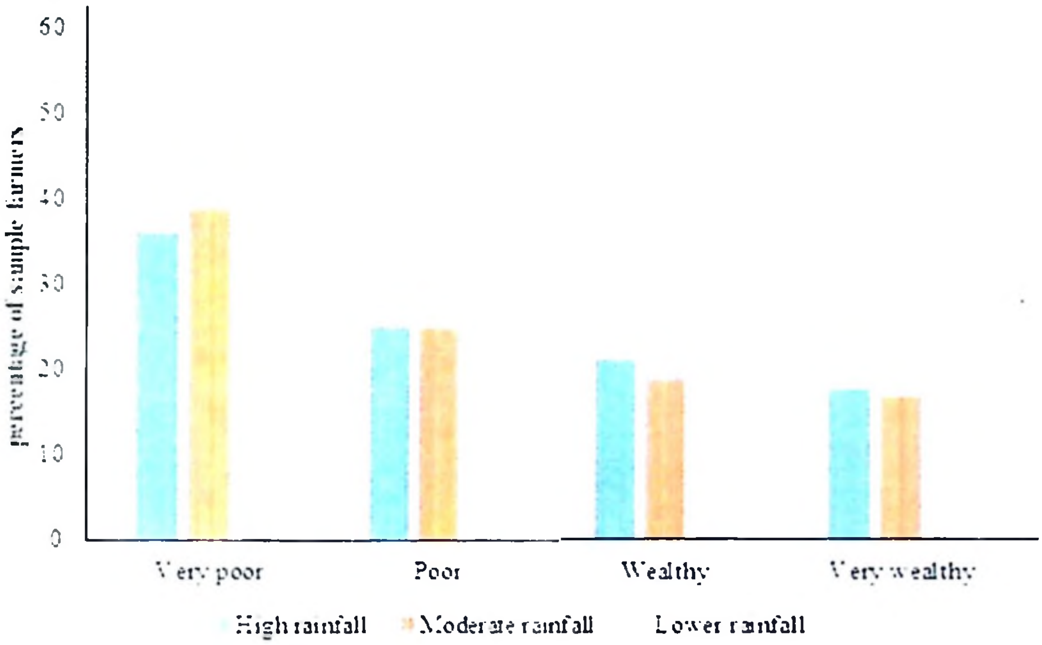

Figure 4: Distribution of household farmers within asset index categories

4.2 Sources and Access to Adaptation Related Information

Access to climate and adaptation related information is one of the important aspects that may serve to explain adaptive capacity of an individual. It is due to this fact that the study had to seek information from farmers. which could indicate their best means and ways to access adaptation related information. From the analysis. about 85.7% of farmers depend on radio and television as their means for accessing information on climate and adaptation. In addition. community meetings. family members and extension agent were also found to be important sources of information to farmers. especially climate change and adaptation related information. Fig. 5 provides a graphical summary of the responses of the farmers on their sources of adaptation related information to illustrate the findings.

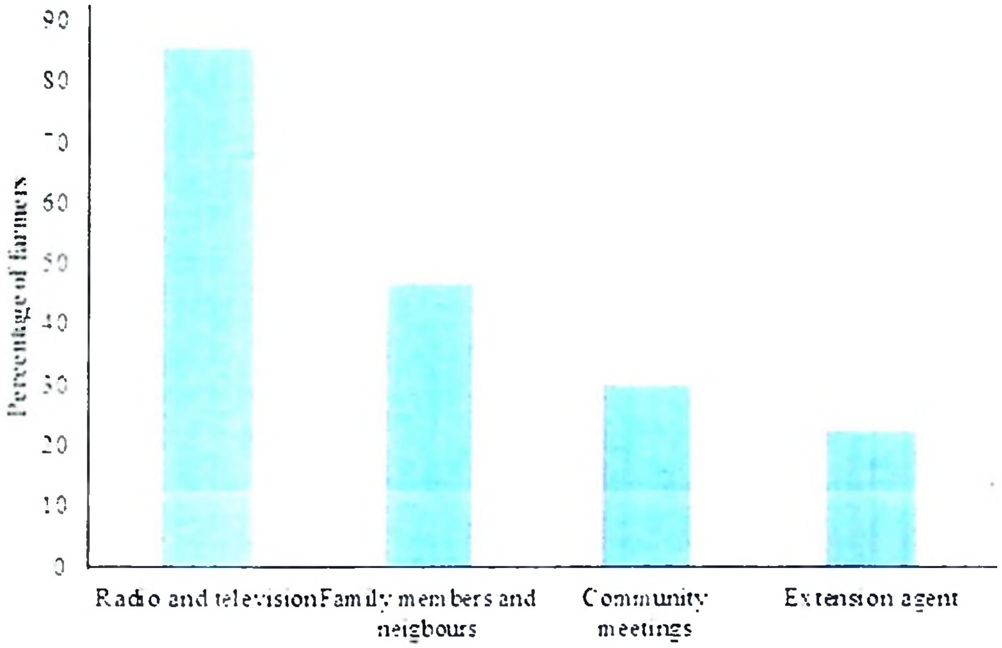

Figure 5: Sources of adaptation information for the smallholder farmers

In terms of overall summary, the data revealed that radio is the most dependable source of information by 85.7% while community meetings rank the second in terms of importance in this case with 47.1%. In addition, the use of family members and neighbors seemed to play a great role in facilitation information access to farmers as the former scored 30.2% while extension agent 22.6%. Much as there has been an improvement in the media as primary sources of information, (in this context, adaptation related information); from observation and various scholarly works, there are various obstacles that hinder full access to information by smallholder farmers in rural areas. They include lack of electricity and poor infrastructures (Mafu, 2004) and poor or lack of road networks.

Results from this study are similar to those from some other studies (Ndaki, 2014; Mwalukasa, 2013; Churi *et al.*, 2012). In his study on agricultural information sources that are used for climate change adaptation conducted in Dodoma, Tanzania, Mwalukasa (2013) found that friends and public extension services were the main sources of adaptation information for farmers. In addition to those, he (ibid.) also found use of radio and cellphones were important sources for farmers to access adaptation information. While many of his findings are in agreement with findings from this study, it is important to argue here that in this study the role of extension workers as a source of agricultural and adaptation related information to farmers was not much appreciated by the smallholder farmers.

Pertaining to the type of information required by farmers, data analysis showed that most of the farmers sought pieces of information on the following aspects: types of crops and crop varieties tolerant to poor conditions such as continued droughts (80.3%); different crops and crop varieties with good markets (57.9%); alternative livelihood options to reduce the severity of climate change impacts (61.5%) (Fig.6). The results clearly reflect farmers' concerns, especially on perception of changes in the local climate. However, farmers also expressed interest in other types of information including; accessibility to credits and incentives (75.6%); crop insurance system (46.2%); weather forecasts, predictions, and timely disseminated information to farmers (78.4%); and adaptation knowledge and technologies (71.6%).

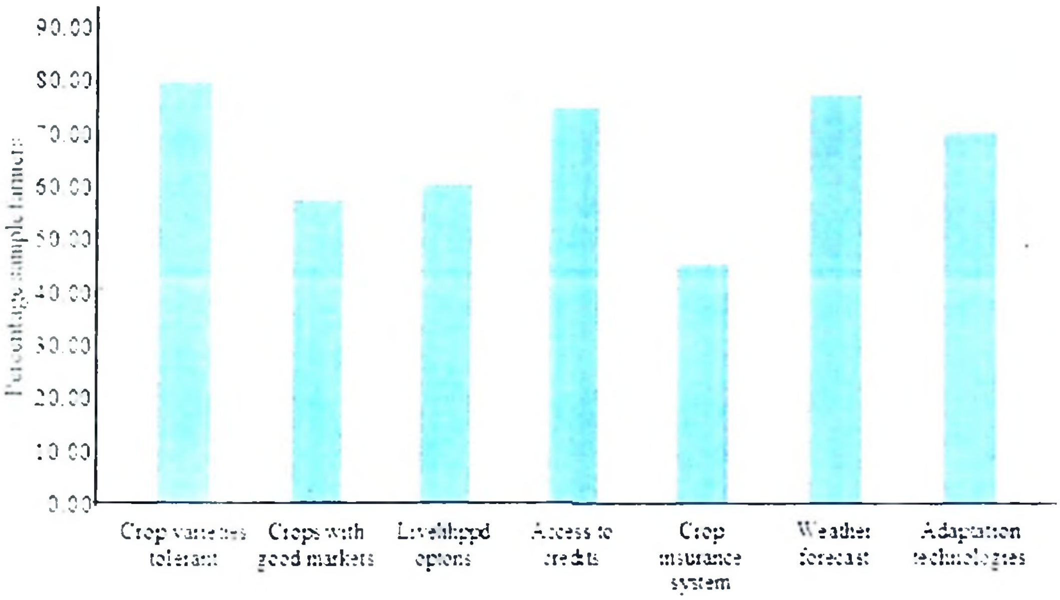

Figure 6: Type of information needed by farmers

The need for alternative livelihood options amidst concerns that perceived changes in the local climate compromise agricultural production, leading to various implications in terms of household incomes and food availability was raised as another type of information farmers needed to support their adaptation efforts. This was expressed by 61.3% of respondents from all villages. In addition, it is interesting also to note that information about crops tolerant to poor climatic conditions was found to be needed by 80.2% of the respondents. The results clearly reflect farmers' concerns, especially on perception of changes in the local climate.

Information about the availability and access to credits as well as incentives is also needed by farmers. Smallholder farmers wish to obtain such incentives to support them for not only adapting to changes in the climate as they perceive but also for increasing production to ensure food security for their families as well as tangible, enough incomes. Support in terms of inputs, markets, transport and irrigation infrastructures, communication is needed by farmers. Therefore, information about availability and access to incentives and credits, both as individuals or collectively is what they need. However, farmers expressed concerns about better management of the incentives already provided especially in inorganic fertilizers, which they claimed did not reach them and when it did, it was normally insufficient and difficult to access.

4.3 Access to Credit and Government Subsidies

Incentives such as subsidies, credits and crop insurance are identified as possible policy and strategic interventions to support enhancing adaptive capacity and resilience of the farmers to the adverse impacts of climate change (IPCC, 2007). In the face of efforts to enhance adaptive capacity of many farmer communities vulnerable to the impacts of the changing climate, the importance of crop insurance cannot be overemphasized (Boko *et al.*, 2007). Many adaptation discussions within the UNFCCC context, for example, emphasize on the need to consider crop insurance as an option to support smallholder farmers in the developing world, especially in Africa, to enhance their adaptive capacity. Panda *et al.* (2013), for example, attempted to define adaptive capacity in agricultural as the tendency towards adopting farming practices intended to maintain higher yields amidst climate change. In that context, the authors identified crop insurance as a stronger variable characterizing high adaptive capacity against low adaptive capacity because with crop insurance, farmers can take the risk of planting higher yielding crop varieties and in the end, they can harvest unlike those with no access to crop insurance. It is this necessity and need for such incentives that led to inclusion of these issues in the list of possible intervention for enhancing adaptive capacity and long-term resilience to farmers.

Table 3: Percentage distribution of farmer's access to government subsidy and credit

Variable	High rainfall n=105	Moderate rainfall n=175	Lower rainfall n=140	Full Sample N=420
Access to formal/informal credit	18.10	14.29	29.29	19.05
Access to government subsidy	0.00	16.57	22.86	19.29

Table 3 provides detailed illustrations reflecting the farmers responses on access to government subsidy and credit. In general, it was well accepted by 19.1% of all respondents who had access to credit while 19.3% had access to government subsidy (improved maize seeds and inorganic fertilizer) as an appropriate policy and strategic intervention to support farmers' adaptation and enhance long term resilience to climate change. As some of the practices analyzed require high up-front costs, which often constitute a severe constraint, access to credit should be guaranteed in order to make climate-smart farming practices affordable for even the poorest of farmers. Having access to financial resources enables farmers to make use of available information and improve their management practices in response to changes in the climate. For instance, with financial resources and access to markets farmers are able to buy new crop varieties, new irrigation technologies and other important inputs they may need to change their practices to suit the forecasted climate changes.

The study also provide information on incentives as an important intervention to support farmers in enhancing their adaptive capacity and long term resilience. Financial and other forms of incentives such as subsidies to farmers are proposed as appropriate interventions, which can enhance farmers' adaptive capacity especially in the developing world where the smallholder farming system mostly depends on rainfall and less sophisticated farming technologies. The incentives have potential to both increase production through intensification and enhance sustainable utilization of little available resources such as water for irrigation. These forms of incentives have been a subject for discussion even within the UNFCCC negotiation process.

They are appropriate potential policy and strategic interventions for long-term resilience to farmers (IPCC, 2007). It is from this viewpoint that many farmers and experts as well as leaders who participated in FGDs had strong arguments that the government has to support farmers to access soft loans, inputs, and improved drought resistant, higher yields and other crop taking into account the state of the changing climate. Many farmers complain that poor access to inputs is exacerbating effects of the perceived changes in the local climate hence poor harvests. While the government provides little inputs to farmers, they are not enough, its management is very poor, leading to corruption practices. These will improve their farming activities in a sustainable way and increase production.

4.4 Farm Plots Characteristics

Smallholder farmers were also asked to indicate the size of their arable land holding. Results in Table (4) indicate about 52.0% of farmers had one plot of land operation in the study area. 24.7% had two plots and 18.5 had three plots which is generally very small.

Table 4: Percentage distribution of farm plots characteristics

Plot characteristics	High rainfall n=105	Moderate rainfall n=175	Lower rainfall n=140	Full Sample N=420
Total number of plots				
1 plot	51.33	38.33	62.50	52.00
2 plots	25.33	27.50	23.75	24.70
3 plots	15.83	27.50	13.75	18.50
4 plots	7.50	6.67		4.75
Total farm size in hectares				
<1	0.83	0.83	0.63	0.75
1-2	57.50	31.67	46.88	50.50
3-5	32.50	51.67	38.75	40.75
>5	9.17	15.83	13.75	8.00
Average Distance to the plot in walking minutes				
<10 min	38.33	20.00	25.00	27.50
10-20min	61.67	80.00	74.38	72.25
>20min	0.00	0.00	0.63	0.25

The results suggest that land is a limiting factor in northern Tanzania. This is especially true for the Kilimanjaro and Meru mountain slopes. The land shortage results in small plots and a large number of holdings. When farmers start farming, most have small holdings. They normally increase their farm size through buying, renting from other farmers. In case of distance to the farm plots, the majority of the farmers have the maize fields within a distance of 1 km from the household. However, comparing the total average distances, farmers in lower rainfall areas, in general, have a slightly longer trip to their maize fields than the farmers in moderate and higher rainfall areas. The increasing distance from home to the farm plot have been found to have a negative influence on decision to use improved farm inputs. The distance between the dwelling and the plot is also a common element negatively influencing the input choice; the longer the distance, the higher are transportation costs, the lower the incentive to adopt a technology, which is consistent with other findings (Teklewold *et al.*, 2013).

In the next section, data on changes in the local climate are presented by comparing smallholder farmers and other stakeholders' perceptions against rainfall and temperature records from various meteorological stations.

4.5 Perception and Awareness of Climate Change

Before exploring factors that motivated farmers to change farming practices, it was necessary to get a clear picture of their perceptions and those of other stakeholders on how they explain the state of the local climate including their forecast according to their experience and knowledge. It was much more important as well, to understand the state of the local climate by analyzing actual rainfall and temperature records for the area. The focus on rainfall and temperature are due to these being necessary elements of climate for crop production (Lobell and Burke, 2008) and thus for smallholder farmers' survival since their main economic activity is rain-fed crop production. Data presentation on the state of climate will not only reveal what exactly smallholder farmers perceive against the actual rainfall and temperature records but also is going to serve as an important entry point and a baseline for the next chapters' discussions and conclusions of this study.

4.5.1 Smallholder farmers' perceptions of climate change

The first research question in this study was intended to help to identify what are the farmer's climate change adaptations that are successful risk management strategies to current climatic situations for various areas of Pangani river basin. To achieve answers to this question, it was first important to identify how smallholder farmers perceive and explain their local climate; that is, to identify the perceptions on the state of the local climate for the past 30 years or more, and how they conceived those perceptions in relation to their livelihoods. In addition, it was envisioned to appreciate their prediction on how the state of the local climate would be in the future, taking into account their current perceptions, information access, and local experiences as well knowledge. Perception in the context of adaptation is considered an important aspect for those who are stressed to awaken and take initiatives as well as measures to adapt (Maddison, 2006). For smallholder farmers, perception on changes in the local climate may help to make decisions to change their farming practices to accommodate themselves to the climatic changes. It is in this line of argument that it was necessary to identify perception as a first step.

During the survey, the sampled farm households were asked questions about their observations regarding the patterns of temperature and rainfall over the past 3 decades. Then those who have perceived the change in rainfall and temperature were further asked to identify the direction of the change. Results from the study showed that smallholder farmers had various, mostly negative, perceptions on the state of their local climate within that time frame and they seemed to perceive many changes to have taken place in their local climate when they compared the current state of the local climate against the past 30 years. The most notable and commonly cited changes included the following: the amount of rainfall was on the decreasing side; the temperature was on the increasing side; rains have become shorter than normal; and farmers feel that the onset of rainfall is now abnormally late. Table 5 and depict results from the questionnaire.

Table 5: Percentage distribution of farmers' perceptions of rainfall trend

Perception	High rainfall (n=105)	Medium rainfall (n=175)	Low rainfall (n=140)	Overall (N=420)
Decrease in precipitation	89.40	90.90	91.90	90.70
Precipitation stayed the same	10.60	9.10	8.10	9.30
Increased in frequency of droughts and floods	34.10	25.60	26.60	28.60
Increase in rainfall variability	24.31	13.42	10.33	15.95

The data indicated that 90.7% of the respondents perceived rainfall to have been decreasing over the past 30 years. However, 28.6% perceived to have experienced increased in frequency of droughts and floods while 9.3% perceived that rainfall remained the same. At the disaggregated level of rainfall pattern, most of the results reflected the general overview from all three rainfall patterns. The results showed no major variations from the general summary on the changes in the climate. Almost all the perceptions from the questionnaire indicated a similar trend even at the village level.

Additionally, many respondents claimed to have observed changes that have been characterized by a decrease in the amount of rainfall during the main season. Moreover the onset of rainfall has shifted. The data showed that 24.3% for higher rainfall areas, 13.4% for moderate rainfall areas, and 10.3% for lower rainfall areas felt the variability of rainfall has increased.

In addition to their perceptions of changes in rainfall and temperature, farmers were asked to give their views on statements about changes in their environment. A subjective index was obtained from asking farmers a series of questions related to rainfall adequacy in the previous growing season, in order to understand their perceptions of rainfall variability and how it relates to actual variation computed from weather stations. The subjective rainfall satisfaction index was calculated to represent households' perceived rainfall adequacy in the preceding agricultural season.

Table 6: Distribution of farmer's rainfall satisfaction index

	High rainfall (n=105)		Moderate rainfall (n=175)		Low rainfall (n=140)		Overall (N=420)	
Indicator Variables	Mean	St.d	Mean	St.d	Mean	St.d	Mean	St.d
Annual Rainfall trend Decreasing	0.11	0.31	0.09	0.29	0.08	0.27	0.09	0.29
During growing season Rainfall come on time	0.21	0.41	0.27	0.44	0.36	0.48	0.28	0.45
During growing season Rainfall stopped on time	0.30	-0.46	0.26	0.44	0.30	0.46	0.29	0.45
Enough rain at the beginning of the growing season?	0.18	0.38	0.18	0.39	0.16	0.37	0.25	0.43
Enough rain during the growing season	0.26	0.44	0.23	0.42	0.25	0.43	0.17	0.38
Frequency of heavy rainfall increase	0.24	0.43	0.20	0.40	0.25	0.43	0.23	0.42
Number of Rainfall days decrease	0.14	0.35	0.14	0.35	0.16	0.37	0.15	0.35
frequency of dry spells/ droughts increased	0.18	0.38	0.32	0.46	0.43	0.49	0.30	0.46
Average rainfall satisfaction index	0.20	0.28	0.21	0.40	0.25	0.41	0.22	0.40

Table 6 shows questions with their average score in the right side. The respondents were asked whether rain came and stopped on time, whether there was enough rain at the beginning and during the growing season and whether it rained at harvest time. The responses were dichotomized in such a way that those who respond "on time" coded into one and others (early /late) into zero. The responses were added and divided by the number of rain related questions (5). So the most favorable rainfall outcome was one and the least was zero.

In general, it was found that farmers in both regions had a strong perception of changes in their local environment. The subjective rainfall satisfaction index was 0.22, which indicates that during the growing season of February to July the rainfall situation was undesirable. Farmers' generally reported late on set of rain, poor distribution within the season, and sometimes early cessation. Also farmers highlighted specific problems of variability in the duration, timings and intensity of the rains, including winds and heavy rains at the start of the seasons. In the moderate and lower rainfall areas of the basin respondents highlighted drought as an increasing problem as well as more frequent flash floods as a result of increased rainfall intensity. In the highland areas increased rainfall intensity leading to increased run off was reported.

4.5.2 Rain patterns and characteristics

To verify the farmers' perception regarding long-term change in temperature and precipitation, the historical regional annual rainfall and temperature data for the period 1983–2013 were analyzed. The results indicated that there has been a decreasing trend of rainfall for Lyamungo, Pangani and Same rainfall stations. If one observes closely the graphic representation of the results (Fig. 7-9), a difference is depicted through a negative gradient. In these graphs there is observed a decreasing trend of total annual rainfall for Pangani, Same and Lyamungo weather stations.

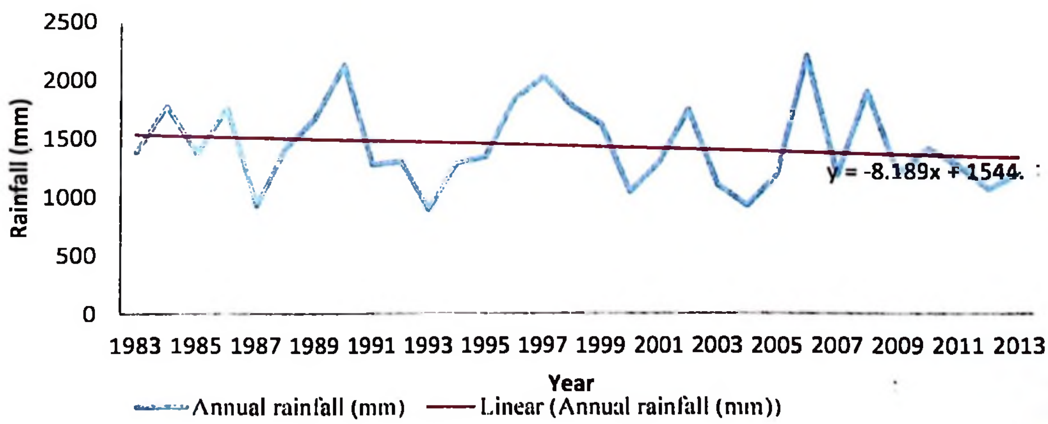

Figure 7: Trend of annual rainfall for Lyamungo rainfall station in Moshi district from 1983-2013

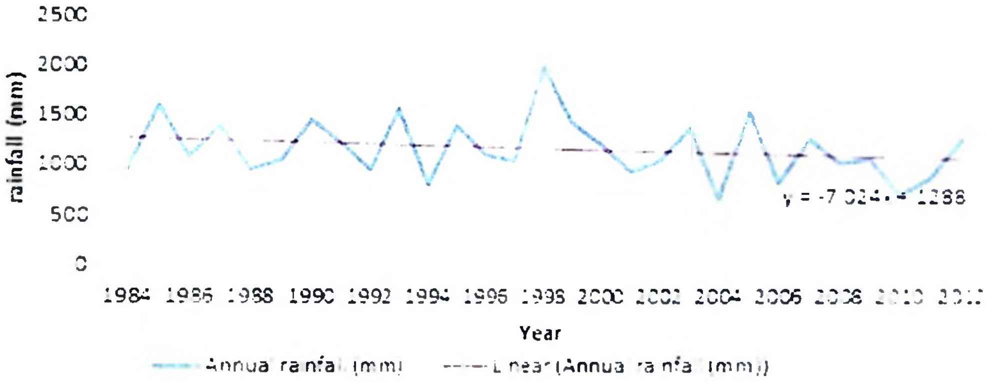

Figure 8: Trend of annual rainfall for (mm) in Pangani district from 1983-2013

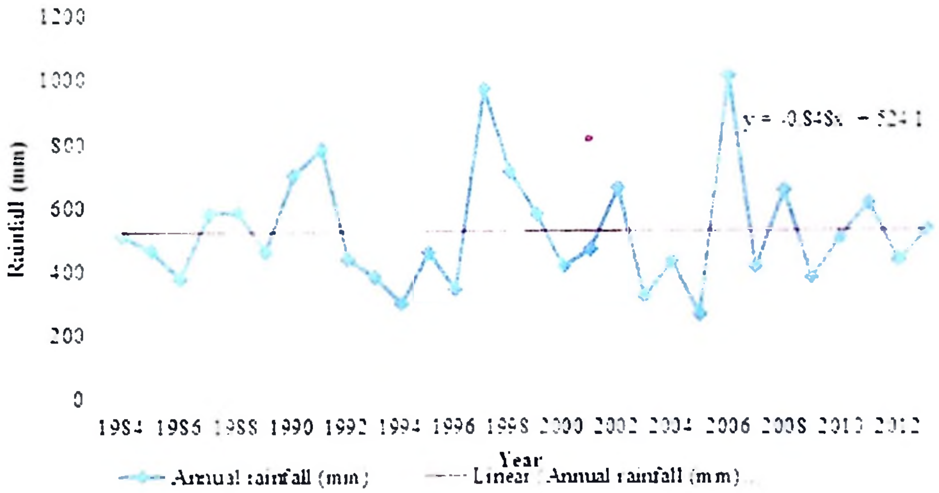

Figure 9: Trend of annual rainfall for Same district from 1983-2013

These results show that farmers' perceptions of climate variability are in line with actual climatic data, noting variability in the duration, timing and distribution within seasons, including in winds and heavy rains at the start of the seasons. This is a common finding also reported by other studies regarding perceptions of resource users of climate change such as in the Sahel (Mertz *et al.*, 2009), Nile basin of Ethiopia (Nhemachena and Hassan, 2008) and Zambia (Nyanga *et al.*, 2011), where farmers perceived increased variability of rainfall and shifts in the growing seasons.

These changes confirm the report by Maddison (2006) that the rainfall in Africa is less predictable and shorter in duration. It has also become erratic with extremes that normally lead to flooding and drought. These results conform to the perceptions of the smallholder farmers that rainfall for the past thirty years showed a decreasing trend.

4.5.3 Farmers' perceptions towards temperature

Regarding the state of temperature, many farmers expressed views that it has been increasing for the past 30 years with the following percentages: 18.2% in higher rainfall areas, 31.10% in moderate rainfall areas and, 42.7% in lower rainfall areas. In some of the instances, increased occurrence of malaria was used as justification for the increase of temperature in the area. For example, in the focus group discussion at Sambarai and Ghona villages, some of the interviewees argued that thirty years ago, they rarely had malaria and they were being told that the other villages in lower parts of the mountains had malaria. But now they experience incidences of malaria and mosquitoes, much as they are located in the highlands.

Table 7: Percentage distribution of farmer's perceptions of rainfall trend

Perception	High rainfall (n=105)	Medium rainfall (n=140)	Low rainfall (n=175)	Overall (N=420)
An increase in Temperature	18.20	31.10	42.70	30.50
Temperature stayed the same	81.80	68.90	57.30	69.50

To try to cross-check the perception of farmers and stakeholders that temperature has likely been increasing within the past thirty years, mean maximum and minimum temperatures for Same meteorological station for 30 years (1983-2013) were collected and analyzed using Instat software to get the general trend of temperature. The results indicated an increasing trend for both maximum and minimum temperatures (Appendix 4).

In general, the results from the preceding section on the state of the local climate indicate that long-term trends in both temperature are increasing and for rainfall they are decreasing. Some other studies conducted in the country and across the African continent have documented this fact (Mongi *et al.*, 2010; Gbetibouo *et al.*, 2009; Agrawala *et al.*, 2003). What needs to be noted is that in this study, all three sources of data confirmed this fact. Results from the questionnaire interviews and from focus group discussion indicate the perceptions that there are changes in the local climate in the area involving decreasing rainfall and increasing temperature trends. These results were crosschecked through the use of actual rainfall and temperature data from stations within the study area and nearby main meteorological stations. All these sources yielded similar results on the aspect of changes in the local climate, specifically rainfall and temperature trends. Even though much needs to be done to quantify the magnitude of changes in both, temperature and rainfall, the fact that the long-term records in rainfall showed a decreasing trend is an issue that requires policy and strategic focus.

Similar results have been documented in other studies in the past. While some differences in terms of focus, methodologies and findings are evident, the results from this study are similar to findings from some of the related studies (Acquah and Frempong, 2011; Gbetibouo *et al.*, 2009; Maddison, 2006). For example, in their study on farmers' perception of the impact of climate change on food crop production and the adaptation strategies to cope with climate change in Volta Region-Ghana, Acquah (2011) found that most of the farmers perceived an increase in temperature and a decrease in precipitation.

It was argued with evidence in previous chapters that a majority of Tanzanians particularly the rural poor depend heavily on rain-fed farming. The decreasing rainfall and increasing temperature trends raise concerns and worries on the future and livelihoods of the rural poor smallholder farmers if this kind of situation continues. While it is true that these farmers have accumulated enough knowledge and experiences to cope with similar changes however, if the magnitude of change increases it may overwhelm them and their level of local knowledge and experiences may have a limit in supporting their local adaptation.

In their study on vulnerability and adaptation of rain fed agriculture to climate change and variability in semi-arid Tanzania, Mongi *et al.* (2010) found that rainfall in the study villages showed a decreasing trend while temperatures showed an increasing trend. Their study concluded that there was strong evidence to demonstrate the vulnerability of rain fed agriculture to adverse impacts of climate change and variability in the study area. Thus, changes in the local climate and its variability have a bearing on increasing vulnerability of the smallholder farmers.

In the next section data on farmers' farm technology adoption in response to climate change are presented. Identification of changes in the farming practices by smallholder farmers not only provided the basis for revealing factors motivating them to happen but also would help in identifying their implications to the smallholder farmers.

4.6 Adoption of Recommended Farm Technologies

The results showed that, farmers have adopted a variety of adaptation strategies such as changing planting, harvesting dates, using different crop varieties and irrigation where possible. Results from the analysis showed that smallholder farmers had continuously been making various changes in their farming practices in the area. The identified changes included shifting to higher yielding crop varieties instead of traditional breeds; introducing new crops and new varieties, which were not commonly cultivated in the area before;

shifting to shorter cycle crop varieties, which can take about three months from planting to harvesting; concentrating on crops that command good market prices; shifting to drought tolerant crops and varieties; and concentrating on and intensifying small-scale irrigation in the river valley instead of depending on rain-fed cultivation alone.

Apart from identifying changes in the farming practices that smallholder farmers have been making overtime, the main focus of the study was to identify the widely promoted agricultural farm technologies which are considered sustainable and productivity-improving practices. The specific farm technologies considered in this study are: maize-legume intercropping, soil and water conservation (SWC) practices, organic fertilizer, inorganic fertilizer and high yielding maize varieties. The distribution of using of these farm technologies are presented in Table 8. This section explores the details of each of the selected adopted farm technologies farming.

Table 8: Distribution of farm practice selection by rainfall pattern

Farm Technologies	High rainfall (n=214)	Moderate rainfall (n=261)	Low rainfall (n=207)	Overall Sample (N=682)	F-Test (F_2,679)
Inorganic fertilizer	64.01	34.10	38.64	44.86	11.04**
Improved seeds	74.29	44.06	56.52	57.33	6.145*
Intercropping	30.91	23.37	43.92	32.11	23.732*
Soil water conservation	30.84	37.54	44.92	37.68	3.001
Animal manure	18.69	28.35	29.95	25.80	2.643

Note: one-way ANOVA (F-test) testing whether at least one of the means in a zone is significantly different from other zones.
*= Significant at least 10 %
**=Significant at least 5 %

4.6.1 Improved maize seeds

As shown in Table 8, about 57.3% of the sampled households used improved maize variety during the 2013/14 cropping season. The adoption and application rate of improved maize variety were found to be significantly different between the rainfall zones at less than 1% level of significance. This reflects differences in the rainfall patterns, the diffusion of improved maize seed varieties had strong regional biases across the three rainfall zones. Hence, promoting the use of improved maize varieties is important in some of the rainfall patterns more than in others. The result further attest that very often farmers cultivate more than one kind of maize variety as the distribution of maize varieties to hedge against rainfall shortfall. Results from focused group discussion revealed that farmers switch from one maize variety to the other variety between years depending on the expectation of rainfall. One of the reasons for switching was availability of government subsidy and income, training from extension agents and weather information.

The farmers mentioned that the advantages of improved maize varieties are that they are also early maturing and higher yielding. Additionally, some farmers mentioned that they are still testing the varieties, indicating that they did not know the full scale of advantages yet. While explaining their reason for not using improved maize variety for the 2013/14 cropping season, 67.5% of the respondents main argument was lack of income to purchase improved seed varieties. The second most important factor was the susceptibility of the improved varieties to pests and diseases, mentioned by 16.2% of the respondents. Other important reasons were lack of information or knowledge about the varieties, and their availability (Fig. 10).

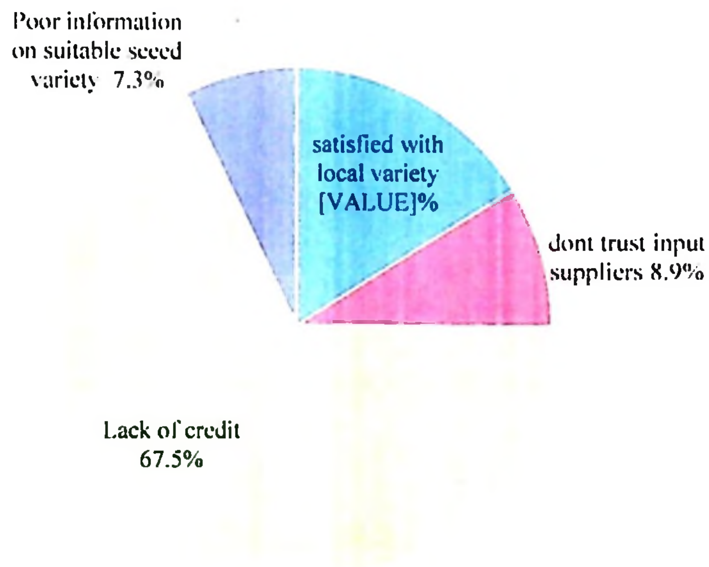

Figure 10: Reasons for not using improved seeds

About 8.9% of the respondents reported reasons such as "I do not trust input dealers". It is also believed that some unscrupulous retailers engage in unethical advertising practices or selling dyed grains under the name of known and trusted genuine varieties at cheap prices. By doing so, they not only cheat farmers but also permanently damage the loyalty farmers have built for the variety over the years. Such practices go against the seed act 2007, which clearly ban import, export, produce, process, distribute or sell seeds unless such person/company is registered (as stipulated in section 14 of the act) (URT, 2007). The implication is characterized by weak measures to protect genuine seed producers and farmers. Hence national seed laws should be enforced by governments to impose several rules on the seed industry, such as on variety registration, seed certification.

About 7.3% of respondents reported they did not have good information on which type of improved seed varieties to use, which means they lacked information regarding the benefits of new varieties and fresh seed. Lack of awareness stems from the fact that numerous varieties are released into the market without adequate farmer education. Giving farmers options by putting on the market different varieties is a good idea but not when they bear unfamiliar names and their characteristics' details/information are scanty. Further it was revealed that some of the seed retailers are not sufficiently knowledgeable about the characteristics of the seed they carry in their stores to be able to educate farmers who buy the seed. This situation discourages adoption of improved maize seeds.

4.6.2 Inorganic fertilizer use

The maize plant uses different nutrients from the soil among which nitrogen, phosphorus and potassium are required in large quantities. In Table 8 above, a significant proportion of sampled farmers (44.8%) used chemical fertilizers for their maize field during the cropping season. These results are somehow contrary to De Groote *et al.* (2002), a study in Northeastern of Tanzania where it was found that, 64.0% of farmers from moderate rainfall zone and 44.4% of low rainfall zone were using inorganic fertilizer. The increasing fertilizer prices force farmers to apply low doses of fertilizer (Nkonya *et al.*, 1998). The most used forms of in-organic fertilizers in both districts were Urea NPK, Di-Ammonium Phosphate (DAP) and MRP, mentioned in order of importance. In some instances combinations of DAP and Urea were used. However, among the chemical fertilizer adopters, the fertilizer rates used were far below the recommended levels, implying that their farms experience fertility depletion. The low application of inorganic fertilizer is one of the major constraints to achieving a Green Revolution in the regions.

Fertilizer use varies widely across the surveyed villages (Appendix 5). The highest proportions were in Kimashuku (67.1) and Sambarai (62.5%) while limited use of fertilizer was found in villages from Same and Korogwe districts. The majority of farmers who didn't use fertilizer reported that their plot was fertile and did not need fertilizer

(52.2%), while 41.1% reported that they lacked funds or that the fertilizer was very costly (Fig. 11). However it was found areas that farmers apply inorganic fertilizer in rice fields and in vegetable production. Further, the focus group discussion found that for some farmers who had access to government subsidy package (improved maize seed and inorganic fertilizer), they resold the inorganic fertilizer to others for use it in rice fields (Kwagunda village) and vegetable production (Mabilioni village).

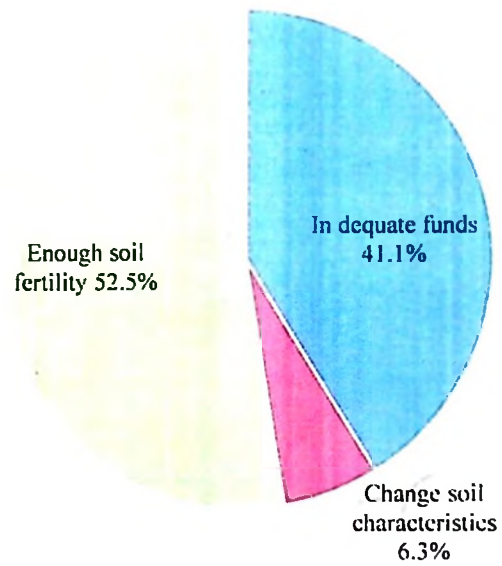

Figure 11: Reasons for not using inorganic fertilizer

The implication from the observations is that most farmers still do not use inorganic fertilizer due to high price of fertilizer and notions of soil having enough fertility. Considering the present low purchasing power of most Tanzanians, agricultural production and productivity can be greatly improved by stimulating a strong increase in fertilizer demand through extension services on the importance of inorganic fertilizer in maize production and lowering inorganic fertilizer prices to make it affordable to many farmers.

4.6.3 Animal manure

Manure is also used by households in adapting to the effects of climate change and variability. Use of livestock manure was related to ownership of livestock. Due to limited availability of livestock manure, farmers prefer to integrate the use of livestock manure with other technologies such as inorganic fertilizer. Livestock manure was used by 25.8% of the farmers. Livestock manure was also applied at each planting pocket as a basal dressing in maize field and later top dressed by inorganic fertilizers. Villages with large livestock keepers (Samaria and Mabilioni showed some usage of animal manure by 24.5% and 36.0% respectively.

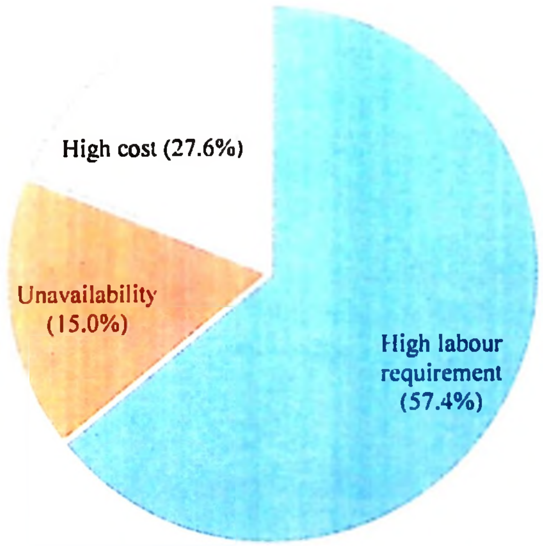

Figure 12: Reasons for not using manure

The reasons for not using manure were its unavailability for some farmers who do not keep cattle and being laborious in applying it in plots far from their home due to its bulkiness. For manure adoption, the higher rainfall areas had the lowest adoption rates although this was appropriately compensated for by the high adoption of inorganic fertilizer. According to adopters of manure, the main constraints on using manure were its high labor requirement for application (57.4%), unavailability (15.0%), and high cost (27.6%) (Fig. 12). Other studies have similarly shown that farmers have rejected manure because of its high labor demands and the variable quality of the product (Kassie *et al.*, 2010).

4.6.4 Intercropping with legumes

While smallholder farming has been and continues to be a major economic mainstay for many in Tanzania, intercropping cereals with legume is necessary in addressing climate change impacts and enhancing their resilience. From this study, the data indicated that intercropping was adopted by 23.7% of the respondents. Details of the results at the villages level are illustrated in Fig. 13. The results differ among the villages. The study revealed that Sambarai, Ghona and Mijongweni villages located in Moshi rural and Hai district respectively showed high levels of multiple cropping compared to other villages while Mafuleta and Kwagunda from Korogwe and pangani districts respectively were the least in. Farmers were asked to explain the reason for preferring intercrop maize with another crop.

The main reasons given by respondents for adopting this practice are shown in Fig. 13. From this figure the most important reason advanced by the farmers include the need to guide and guard against the unpredictability of weather and/or the fear of crops failure and also to enhance the production of other crops household so as to ensure the supply of different crops for the households. The same results were reported by Westengen and Brysting (2014) in their study of crop adaptation to climate change in the semi-arid zone in Tanzania. Farmers were also asked why they were growing maize under monoculture and their answer was clear, to improve production.

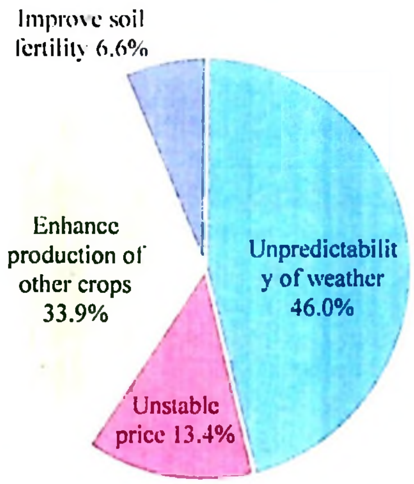

Figure 13: Reason for intercropping legume with maize

4.6.5 Soil and water conservation

In an attempt to tackle the problem of land degradation. several traditional soil fertility maintenance techniques have been identified in the area. Most of the soil and water conservation efforts were directed at controlling soil loss from cultivated fields. Many of soil and water conservation measures introduced to the area are mechanical conservation technologies.

Table 9: Percentage distribution of soil water conservation practices

Variables	High rainfall (n=214)	Moderate rainfall (n=261)	Low rainfall (n=207)	Total (N=682)
Stone and soil bund	16.02	9.15	13.79	12.32
Leaving crop residue in fields after harvest	2.21	7.12	5.42	5.28
Cut – off drains	10.50	7.46	14.29	10.26
Others	4.97	5.42	5.42	1.76

4.6.5.1 Stone and soil bund

A soil bund is an embankment constructed from the soil along the contour with water collection channel or basin at its upper side. It is constructed by throwing soil dug from the basin down slope. It is used to control runoff and erosion from cultivation fields by reducing the slope length of the field, which ultimately reduces and lowers the velocity of runoff. Table 9 shows that 37.6% adopted the structure on their farm plot. According to FAO (2009), it is an effective way of controlling soil loss, retaining moisture and ultimately enhancing productivity of land. Farmers are well aware of erosion problem in the area. Moreover, they agreed that this measure is effective for protecting the soil. The main types of soil water conservation techniques in the study area are explained next.

4.6.5.2 Leaving crop residue in fields after harvest

Leaving crop residues on the field after harvest is another traditional practice used by farmers in the area. Farmers considered it an effective means of moisture conservation in farmlands, which are vulnerable to a lot of moisture loss during the hot seasons. To prevent this, farmers cover the plowed land with crop residues, leaves and twigs. Leaving crop Residue was also practiced to prevent seedbeds from getting exposed to the sun and the direct impact of rain and to protect seedlings from being washed away during rainfall. The survey results show that only 5.3% of the farm plots were implementing this type of measure to improve soil fertility. Crop residues that were left in the field were observed during the transect walks. However in higher rainfall areas Focus Groups noted that, most of the farmers use crop residue as animal feed.

4.6.5.3 Cut – off drains

Cut off drains are channels used to collect run-off from the land above and divert it safely to water way thus protecting the land below from excessive erosion. This structure was adopted by 10.3% of the farm plots (Table 9). The adoption rate was relatively low probably because the fact that the structure is laborious to construct compared to other farm management practices. The drains are constructed along the slope, often covered with grass to prevent destruction, and primarily installed in areas with high rainfall

Farmers construct these drains to prevent loss of seeds, fertilizers, manure and soil due to water flowing onto the plot from uphill. The excess water is disposed away from the field. However, according to farmers, overtime, some of the traditional drain structures enhance soil erosion through time.

4.7 Determinants of Climate Change Adaptation Technologies

This section begins with a discussion of the selection equation, which models the determinants of farmers' technology adoption. For Endogenous Switching Regression analysis, the selection equation is estimated jointly with the outcome equations for the adopter and non-adopter regimes, but for analytical purposes it is useful to discuss the results sequentially. As the chapter progresses, parametric estimation of the impact of farm technologies on maize yield and a detailed discussion of the conditional expectations of these farm technologies is presented in detail.

4.7.1 Factors influencing the choice of climate change adaptation technologies

Prior to the estimating the multinomial logit selection model, the Variance inflation Factor (VIF) test for multicollinearity gave a mean VIF of 1.06 and none of the VIF values were above 2 indicating that multicollinearity was not a concern for this data(Wooldridge, 2002). The collinearity diagnostics using correlation coefficients shows all of the relationships were well within the 0.8 rule of thumb. The collinearity matrix and VIF results are presented in Appendix 6 and 7 respectively. Further the Breusch- Pagan test gave a value of 2.65 and a P-value of 0.0034, indicating presence of heteroskedasticity in the data at 5% level of significance. Hence, the null hypothesis of constant variance of error term was rejected. The Robust command in STATA was used to correct for heteroskedasticity, robust standard errors were used during the regression analysis.

Moreover the Hausman tests was conducted to determine the econometric validity of the variables access to extension services and accessing information on climate change prior to the production period to be used as instrumental variable. The Hausman test in favour of the null hypothesis that the independent variables were exogenously determined was not rejected (F= 1.46, P<0.01), implying that the validity of these instrumental variables is confirmed. Further the admissibility of these instruments was validated by performing a simple falsification test such that: if a variable is a valid selection instrument, it will affect the decision of choosing an adaptation strategy but it will not affect the maize yield per hectare among farm households that did not adapt (Di Falco, Veronesi and Yesuf, 2011).

Table 10 and Table 11 show that access to extension services and accessing information on climate change prior to production period can be considered as valid selection instruments: they are jointly statistically significant drivers of the decision to adapt strategy *(j)* but not of the yield per hectare. In addition, standard errors were bootstrapped[9] to account for the heteroskedasticity arising from the two-stage estimation procedure.

The results of the multinomial logit selection equation are presented in Table 10 shows that the model is well fitted to the data as shown by the low log pseudo likelihood -118.37 and Wald Chi Square (P<0.01). This indicates that the explanatory variables together influence the probability of adoption of farm technologies in the study area. The results show further that adoption decisions of different farm technologies are quite distinct and to a large extent the factors governing the adoption decision of each of them are also different suggesting heterogeneity in the adoption of farm technologies.

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[9] The bootstrap is used in statistics as a resampling method to approximate standard errors, confidence intervals, and p-values for test statistics, based on the sample data. This method is significantly helpful when the theoretical distribution of the test statistic is unknown

The results also show the importance of climatic variables in explaining the probability of farm households' decision to adopt different agricultural practices. It was revealed that greater variability in rainfall increases adoption of risk-reducing practices but they reduce the use of inputs with uncertain benefits in terms reducing risk to current climate stresses. From Table 10 the results show that, greater variability in rainfall increases the probability of adopting soil water conservation measures and using improved maize seed varieties, whereas it reduce the probability of adopting inorganic fertilizer and manure.

Further, in communities where the average delay in the onset of rainy season is high, farmers are more likely to adopt improved seed varieties and soil water conservation practices whereas, the probability of adopting inorganic fertilizer is negatively correlated with delay in the onset of the rainy season. It is also found that higher mean rainfall and higher altitude increase the use of inorganic fertilizer. These results are consistent with findings reported by Kassie *et al.* (2010) and Teklewold *et al.* (2013), who found that yield enhancing technologies like improved seeds and inorganic fertilizer provide a higher crop return in wetter areas than in drier areas. Overall, the findings suggest that farmers are responding to climate patterns based on their adaptation strategies. Hence information on changes in climatic variability should be an integral part of extension activities.

Biophysical plot characteristics are also found to be important determinants of adoption for most of the practices. The plot size had a negative effect on adoption of legume intercropping as well as adoption of improved maize varieties, however, it is positively correlated with the adoption of soil and water conservation measures and inorganic fertilizer. This imply that increase of household landholding by 1 acre, on average, raises the probability of adopting inorganic fertilizer by 5 per cent and decrease adoption of improved maize varieties by 8 per cent. As Tanzania's population growth rate continues to climb with a current growth rate of 3.0% annually (NBS, 2012), it supports the Neo-Malthusian hypothesis that land redistribution and fragmentation arising from population pressure does not lead to more intensification of farming (Asfaw *et al.*, 2014).

At the system level, results show that the greater the distance of the farm plot to the nearest input market, the higher the incentive to use practices requiring less initial capital and less skills (such as manure), the opposite holds true for the use of improved seeds and/or inorganic fertilizers. Most probably this is due to easier access to these technologies by farm households closer to the markets. Households located far from markets essentially incur higher costs of adoption due to transport charges. Moreover, closeness to markets implies that the output can easily be sold more profitably and therefore farmers are motivated to produce larger quantities, which is possible with adoption of inorganic fertilizer and improved maize varieties. The probability of adoption of inorganic fertilizer increased by a larger magnitude because fertilizer required for a unit of cropped land is much heavier than maize seed for the same unit. Basically proximity to market is a proxy for better marketing infrastructure and availability of complementary technologies whose roles in technology adoption are well documented in the literature. In this case the assistance provided by the village extension officer in terms of training and information dissemination is crucial for the use of improved seeds and/or inorganic fertilizers.

Moreover, the results show the key role of rural institutions, social capital and supply-side constraints in governing adoption decisions of farm households. Access to government extension services also plays a significant role though the effect is heterogeneous – positive for inorganic fertilizer but negative for legume intercropping. The greater the access to extension officer services the higher the incentive to use practices requiring less initial capital and less skills (legume intercropping and manure); the opposite holds true for the use of modern inputs. In this case the assistance provided by the extension officers in terms of training and information dissemination is crucial for the use of improved seeds and/or inorganic fertilizers. The distance between dwellings and the farm plot was also negatively influenced the adoption of soil water conservation and manure. The longer the distance, the higher the transportation costs, the lower the incentive to adopt a technology, which is consistent with other findings such as Teklewold *et al.* (2013a).

Further analysis indicates that, the household wealth index was also in line with priori expectations and consistent with the existing literature. The level of household wealth measured by the asset index is negatively associated with the use of manure and legume intercropping, confirming the idea that this practice which require minimal initial investment, is carried out mostly by less wealthy households. In contrast the level of household wealth measured by the wealth index was positively correlated with the use of organic fertilizer and improved maize seed varieties implying that wealthier households use practices that require more initial capital both in terms of general and specific agricultural assets.

Similar to the household asset index, households with credit constraints, (those who need credit but are unable to find it) are less likely to adopt inorganic fertilizer and soil water conservation practices. A similar effect is observed for the adoption of a combination of chemical fertilizer and improved maize seeds. This implies that inorganic fertilizer, which requires cash outlay, is less likely to be adopted by liquidity-constrained households.

Table 10: Parameter estimates of determinants of farm technologies adoption

Variables	Improved seeds only	Improved seeds and Inorganic fertilizer	Improved seeds and Legumes intercropping	Improved seed and SWC	Improved seeds and Manure	Improved seeds with Inorganic fertilizer and SWC	Adoption=0
Ln Plot size (in	-0.082	0.051	-0.442**	0.320	-0.440	-0.155	-0.027
hectares)	(0.487)*	(-0.7)*	(0.484)	(0.417)*	(0.464)	(0.041)	(0.03)
Ln Distance to the farm	0.23	-0.163	-0.110	-0.327*	-1.392**	-0.035	0.035
plot in walking minutes	(0.178)	(-0.246)	(0.174)	(0.168)	(0.187)	(0.165)	(0.37)
Ln Household head	0.020*	0.004	0.020	0.120**	0.231	0.827	0.610
education (years)	(0.034)	(0.517)	(0.036)	(0.031)	(0.039)	(0.246)	(0.20)
Ln Distance to the input	-0.032	-0.039	0.021	0.163	0.133*	-0.036	0.079
market (km)	(0.036)	(0.23)*	(0.037)	(0.034)	(0.036)	(0.044)	(0.03)
Access to extension	0.380	0.741*	-0.093	0.462**	0.321	0.588	0.262
services (=1 if yes)	(0.238)	(3.42)	(0.241)*	(0.223)	(0.251)	(0.258)	(0.19)
Information on climate	1.458*	0.015	-0.145	-0.173	0.198	0.026**	-0.271
change (=1 if yes)	(0.125)	(0.041)	(0.121)	(0.114)	(0.118)	(0.272)	(0.23)
Household asset index	0.492	0.194*	0.144	+0.063	-0.030*	0.386***	0.381
	(0.143)*	(0.473)	(0.135)	(0.129)	(0.135)	(0.129)	(0.125)
Access to credit (=1 if	0.435	0.744**	0.756	-2.027**	0.003	0.396	-0.047
yes)	(0.17)	(0.043)	(0.165)	(0.152)	(0.156)	(0.146)	(0.143)
Ln Altitude	0.006	-0.298	0.093	0.075*	0.274	0.226	-0.238**
	(0.18)	(0.044)	(0.08)	(0.071)	(0.08)	(0.517)	(0.168)
Coefficient of variation	1.925*	-2.171	-0.782	2.234	-1.274	.-0.226	0.274
of rainfall (1983-2013)	(1.25)	(0.272)*	(1.33)	(1.203)**	(1.31)	(0.001)	(0.001)
Rainfall satisfaction	-0.112	-0.042	-0.260	-0.320*	-0.375	0.062*	0.099
index	(0.324)*	(0.129)*	(0.329)	(0.254)	(1.421)	(0.167)	(0.17)
High rainfall (=1 if high	-0.052	0.301*	0.097	-0.058	0.033	0.084*	0.127
rainfall area)	(0.17)	(0.146)	(0.17)	(0.156)	(0.180)	(0.131)	(0.124)
Moderate rainfall (=1 if	-0.112	0.080	-0.852***	0.026	0.012	1.560	.-1.596
Moderate rainfall area)	(0.141)	(0.167)	(0.23)	(0.223)	(0.242)	(0.700)	(0.487)
Low rainfall (=1 if low	0.01	.-0.413*	-0.183	0.051	0.147	0.493	0.442
rainfall area)	(0.17)	(0.092)	(0.18)	(0.1603)	(0.211)	(0.142)	(0.128)
Constant	-6.13**	-0.593	-5.350	2.474**	-1.219	-3.908	-4.109**
	(1.548)	(1.481)	**(1.632)	(1.376)	(1.503)	(2.07)	(1.548)

Log likelihood=-118.37, Wald (χ^2) =286.97, P>(χ^2) =0.0033, Number of observations (plots) 682, Pseudo R^2= 0.3578

(   )=Robust standard errors in parenthesis

***, **, * =significant at 1%, 5%, and 10% level, respectively

Taking productivity impacts as a key indicator of adaptive capacity, the next section discuss the second part of the multinomial endogenous switching regression which is about the implications of adopting a particular strategy on farm households' maize yield.

4.7.2 Effect of adopted farm technologies on maize production

The second stage of the Multinomial Endogenous Switching Regression was to establish the determinant of maize yield. Empirical results of the differential impact of the explanatory variables on maize yield per hectare are presented in Table 11. The coefficient estimates for for various adoption regimes differ notably with respect to some of the variables, indicating that the switching regression approach is preferred over a simple treatment effects model.

Particularly noteworthy is the difference in the coefficient estimate for household asset index, which is much higher for the combination of inorganic fertilizers with improved maize seeds (1.225) and that of inorganic fertilizers with improved maize seed plus soil water conservation (2.057) while the estimate for non-adopters is insignificant (0.381). Households with more assets are able to invest if the technologies are capital-intensive. Maurice *et al.* (2010), found that differences in soil and water conservation investments among farmers in Kenya where investment was greater among households that had more asset than other.

Many variables had a negative relationship between maize yields and manure adoption though not significant. One possible explanation for the negative effect of manure is that the yield benefit of using such practices was not applied in sufficient quantity and also manure content often accrues slowly to the soil compared to other agricultural practices, such as inorganic fertilizer, which tend to have short term returns.

Differences in yield responsiveness are also observed for the high and moderate rainfall area dummy, whose coefficient is positive and large for maize yield produced under a combination of improved maize seeds with inorganic fertilizer (1.012) and the same technologies in combination with soil water conservation measures (2.046), but the impact was small and insignificant for traditional or local maize seeds. However, in low rainfall areas results are reversed where by the coefficient estimate for the dummy variable is much higher for none adaptation (local maize seeds) (0.642) while the estimate for adopters of improved maize seeds only is insignificant (0.01). The estimated results imply that improved maize seeds were probably more negatively affected by less rainfall than local maize seeds.

Table 11: Parameter estimates of the determinants of maize yield

	Improved seeds and Inorganic fertilizer	Improved seeds only	Improved seeds with Inorganic fertilizer and SWC	Improved seeds and Legumes intercropping	Improved seed and SWC	Improved seeds and Manure	Adoption=0
Ln Plot size (hectares)	0.161	0.116	0.019	0.181	0.145	0.063	0.061*
	(0.05)	(0.232)	(0.011)	(0.498)	(0.026)	(0.071)	(0.186)
Ln Distance to the farm plot in walking minutes	0.071	0.172*	0.304	0.411	0.231	-0.027	0.349
	(0.052)	(0.238)	(0.046)	(0.513)	(0.034)	(0.043)	(0.186)
Ln Household head education (years)	-0.045	-0.045	0.008	0.071	0.124	0.049	-0.022
	(0.042)	(0.019)	(0.093)	(0.201)	(0.011)	(0.045)	(0.074)
Ln Distance to the nearest input market (km)	-0.038	0.093	-0.008	0.101	0.104	0.002	0.147*
	(0.045)	(0.021)	(0.016)	(0.781)	(0.221)	(0.003)	(0.015)
Access to extension services (= 1 if yes)	-0.186	0.319	0.188	0.132	-1.032	0.011	0.364
	(0.079)	(0.362)	(0.017)	(1.171)	(0.062)	(0.012)	(0.439)
If received Information on climate (=1 if yes)	-1.307	0.84	1.718	0.303	0.728	-0.001	0.284
	(0.118)	(0.542)	(0.026)	(0.768)	(0.041)	(0.003)	(0.288)
Household asset index	1.225	0.135*	2.057	-2.704	1.731	0.04	0.036
	(0.077)*	(0.356)	(0.017)**	(0.113)	(0.006)*	(0.048)	(0.034)
Access to credit (=1 if yes)	0.105*	0.149	0.04	0.048	0.185*	0.057	0.141
	(0.011)	(0.051)	(0.025)	(0.032)	(0.083)	(0.072)	(0.292)
Ln Altitude (meters)	-0.206	0.005	-3.208	0.125	2.866	0.011	-0.480
	(0.202)	(0.007)	(0.26)	(1.139)	(0.061)	(0.049)	(0.431)
Coefficient of rainfall variation	-0.157*	-0.044	-0.007	0.233*	0.167	0.086	0.035
	(0.115)	(0.531)	(0.026)	(0.701)	(0.038)	(0.076)	(0.263)
Rainfall satisfaction index	0.084	0.036*	0.021	0.211	0.043	0.072	0.061
	(0.071)	(0.327)	(0.016)	(0.749)	(0.04)	(0.059)	(0.282)
High rainfall (=1 if high rainfall area)	0.192***	0.056	0.162*	0.047	0.016	0.157	0.292
	(0.076)	(0.351)	(0.017)	(0.736)	(0.039)	(0.072)	(0.277)
Moderate rainfall (=1 if Moderate rainfall area)	1.012	0.03	2.046	0.179	0.211	-1.529	0.104
	(0.074)*	(0.341)	(0.016)**	(0.862)	(0.046)	(0.104)	(0.31)
Low rainfall (=1 if low rainfall area)	-0.271	-0.059	0.021	-0.182*	0.015	1.625	0.612
	(0.087)	(0.401)*	(0.019)	(2.487)	(0.037)*	(0.052)	(0.86)**
Constant	-0.505**	-0.085	-0.38***	0.059	0.021	0.059	-0.287**
	(0.283)	(1.301)	(0.063)	(0.132)	(0.148)	(0.081**)	(1.203)
LR test of equation independence (Wald	13.11***	27.66****	43.66**		43.66**		1.573

***=significant at 1%, **=significant at 5% and * =significant at 10% level, ( )=Bootstrapped standard errors

4.7.3 Farm technologies treatment effects on maize yield

In this section the implications of adopting a particular strategy on maize yield was investigated. The coefficient estimates from equation (1) in combination with equations (7) and (8) (section 3.6) were used to predict mean yield levels resulting from the adoption of a particular farm technology.

As discussed in section (3.6). there are two simple approaches which could be applied to identify the "best" adaptation farm technology. First, one could compare actual mean yield per hectare from farm plots of adopters against farm plots without improved farm technology. This approach can be misleading since it was assumed that adaptation to climate change is exogenously determined even through it is a potentially endogenous variable.

Hence the difference in yield may be caused by unobservable characteristics of the farm households such as their knowledge. For instance, the apparently most successful farm households could also be the most skilled ones, and so, those that would have done better than the others even without a adapting. Hence this issue can be addressed by estimating counterfactual yields, which generate what farm households would have earned if they had not adapted, by applying equations (8a-8m).

Table 12 presents maize yield per hectare under actual and counterfactual conditions. The expected maize yield is compared under the actual case that the farm household adopted a particular strategy to adapt to climate change and the counterfactual case that did not. (We compare columns (1) and (2) of Table 12). The last column of the table presents the impact of each adaptation strategy on maize yield, which is the treatment effect, calculated as the difference between columns (1) and (2).

Results reveal that adaptation to climate change based upon a portfolio of strategies significantly increases farm households' maize yield. Counterfactual analysis allowed the identification the portfolio of farm technologies that can deliver the highest yields. It was found that the effect of inorganic fertilizer was significant when used along with improved maize seeds varieties. Likewise the combination of soil water and conservation with improved maize seeds and inorganic fertilizer was positive and statistically significant. As a result of these, the null hypothesis that the adoption of farm technology has no significant impact on farm household incomes was strongly rejected at P<0.01 for the combination of inorganic fertilizer and improved seed and at P<0.05 for the combination of soil and water conservation with improved maize seeds and inorganic fertilizer (P<0.05). The key policy inference from these findings is that complementary agricultural technologies yield the best results when they are taken up as a package rather than as individual elements.

Table 12: Average farm technologies treatment effects on maize yield

Farm technologies	(1) Actual maize yield (kg/Ha) (a)	(2) Counterfactual maize yield (if farm households did not adopt) (kg/Ha) (b)	(3) Impact (treatment effect (kg/Ha) (c)
improved seed varieties only	596.639	262.265	334.375*
Improved maize seed + inorganic fertilizer	826.639	368.265	458.375**
Improved maize seed + manure	707.397	361.909	345.488
improved seeds+ SWC	593.054	308.700	284.354
improved seeds+ legumes	458.069	189.422	268.646
Improved maize seed + inorganic fertilizer+ legumes	697.587	259.023	438.563*
improved seed +Inorganic fertilizer + SWC	968.881	393.945	574.936***

Values in columns (2) have been calculated following equations (8a)-(8m). Values in column (3) have been calculated as the difference between columns (1) and (2). ***, **, and * = Significant at the 1%, 5% and 10%.

In general, the above analysis revealed that on average adoption of each of the five farm management practices has a positive impact on the quantity of maize produced per hectare and the impact is higher when the farm technologies were used in combinations, thus suggesting the positive synergies between adaptation technologies. However, increasing yields is just one of the reasons for adopting these technologies. Reducing downside loss can be the other reason. Farmer's attitudes towards adopting these farm technologies and their impact on reducing or increasing yield variability in the face of variable climate conditions are discussed in the next section.

4.8 Attitude of Farmers towards Selected Farm Technologies

Farmers Attitude towards selected farm technologies was measured as a pooled score from responses to attitudinal statements that were made on a five point Likert scale. Scores were assigned on a five point Likert type scale of as follows: 1= Strongly Agreed (SA); 1 = Agreed (A); 3 = Undecided (U); 4 = Disagreed (D); 5= Strongly Disagreed (SD). Scores on all items were then added up to yield a composite attitude score for each farmer. The higher the score the more favorable the attitude towards that variable.

The mean scores for each of the five point Likert scales as well as the overall sample mean are reported in Table 13. The table also displays the results for the analysis of variance (ANOVA), conducted to check the statistical significance of differences between the three rainfall regimes. The results show that the proportion of the means for farmers attitudinal preference were above the cut-off point of 2.5 they were however, varied along the rainfall patterns. The most preferred farm technology was the use of improved seed varieties, which recorded an average rating of 4.43. For those farmers who still rely on local maize varieties. Their main argument was that an improved seed requires more inorganic fertilizer and they distrust input dealers regarding the quality of seeds.

However farmers' attitude towards inorganic fertilizer was significantly different along the three rainfall pattern with a decreasing trend from high, medium to the lower rainfall pattern. The main argument of farmers who dislike using inorganic fertilizer was the belief that their plots were fertile. They believe inorganic fertilizer will damage the natural fertility of their plots. The low rate of application of inorganic fertilizer has been pointed out as one of the main constraints to achieving a Green Revolution in sub Saharan Africa (IFDC, 2006).

Table 13: Distribution of farmer's attitude towards selected agricultural technologies

Farm technologies	high rainfall (n=105)	Moderate rainfall (n=175)	Low rainfall (n=140)	Overall (N=420)
Inorganic fertilizer	4.19	3.03	2.57	3.73
Improved seeds	4.48	4.40	4.49	4.43
Legumes intercropping	3.55	3.28	2.91	3.26
Soil water conservation	3.25	3.25	3.51	3.33
Organic manure	2.90	2.91	2.90	2.91

Further, the results showed that, in low rainfall areas farmers perceived higher importance of soil water conservation measures compared with farmers from other areas. Use of inorganic fertilizers was ranked highest in higher rainfall areas while soil conservation was ranked the first in low rainfall areas. Applications of organic manure were ranked least in all the three rainfall regimes.

4.9 Yield Risk of Adopted Farm Technologies

Prior to estimating the mean and variance functions, necessary steps explained in section 3.6 were taken to ensure valid results including test for multicollinearity, endogeneity and heteroscedasticity. The test for multicollinearity problems reveals that, the VIFs were less than 2.0 and the pairwise correlations were also less than 0.5, indicating that the standard errors were not affected by collinearity problems and therefore multicollinearity was not a problem (Results are presented in Appendix 9). Concerning presence of endogeneity, Wu-Hausman test was performed to determine whether variables were endogenous to the model. The null hypothesis that the variables were exogenous was not rejected since the

P-value was very high (0.61) indicating absence of endogeneity within the variables to be estimated.

Results from the econometric analysis for the mean output function are presented in Table 15. At first results from the linear quadratic mean production function was estimated using ordinary least squares (OLS). The model fit is relatively good with an adjusted R^2 of 0.75.63%. Based on the OLS estimates, two heteroskedasticity tests namely the White's test, and the Breusch-Pagan test were performed to test for the presence of significant marginal output risk in input levels. The results in Table 14 showed that all of the tests rejected the hypothesis of homoskedasticity at the 0.001 level, indicating the presence of output risk in our small-scale agricultural production sample.

Table 14: Heteroskedasticity tests

Test	χ^2 test statistic	df.	P-Value
White's test (imtest.white)	264.13	93.00	0.000
Breusch-Pagan test (hettest)	65.58	1.00	0.000

As the heteroskedasticity tests provide evidence that production risk is present, the production function was re-estimated together with the variance function using the maximum likelihood estimator and correcting for heteroscedasticity as explained in section 3.6.

Table 15: Parameter estimates for the mean yield function

	Coefficient for the Mean production function							
	High rainfall		Moderate rainfall		Low rainfall		Overall sample	
Independent variables	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Inorganic fertilizer	1.01***	0.064	2.46**	0.045	4.03**	0.049	1.39***	0.064
Inorganic fertilizer squared	-0.01*	0.028	-0.03**	0.029	-0.01	0.032	0.01*	0.028
Improved seeds	0.57*	0.263	0.31	0.223	0.09	0.225	0.56	0.263
Improved seeds squared	0.039	0.068	0.430	0.026	0.433	0.110	0.043	0.063
Inorganic fertilizer ×Improved seeds	0.06***	0.205	0.01	0.105	0.02	0.122	0.05***	0.205
Manure	-0.050	0.043	-0.18	0.042	-0.3	0.064	-0.2	0.043
Manure squared	0.001	1.166	0.002	1.635	0.003	0.603	0.002	1.166
Precipitation	0.130	0.072	0.21*	0.072	0.11	0.081	0.2	0.072
Precipitation squared	0.321	0.198	-0.01	0.219	-0.1	0.247	0.03	0.198
Legumes intercropping	0.23*	0.075	0.69**	0.087	0.33	0.081	0.74**	0.075
Soil water conservation	0.43*	0.078	1.63	0.066	0.15**	0.082	0.88***	0.078
Altitude	0.08	0.079	-0.06	0.074	0.01	0.081	-0.07*	0.079
Constant	3.256***	0.078	6.147***	0.079	5.614	0.094	4.574***	0.078
Adj R-squared	0.773		0.698		0.792		0.756	
Joint significance: F (10, 482)	71.10***							

Significance levels are denoted by one asterisk (*) at the 10% level, two asterisks (**) at the 5% level, three asterisks (***) at the 1% level. SE= Robust standard errors.

Results from the mean function are reported in Table 15 showing that the coefficient of the linear term for inorganic fertilizer is positive, but the interaction effect of inorganic fertilizer and improved maize seeds is negative in both high and moderate rainfall areas. To provide a meaningful interpretation of the estimated parameters, empirical results were consequently presented in terms of elasticities as shown in Appendix (10). It can be seen that the output elasticity for the mean function was positive for most of the inputs. This confirms the priory expectation that all the inputs will increase the mean output. The results reveals that fertilizer was found to be the most important output in terms of output elasticity, with a sample average value of 0.45 which imply that fertilizer application increase maize output by 45%. This could be attributed to the low nutrient composition of the soil that cannot meet crop nutrient demand in the Pangani basin (Kaihura *et al.*, 2001).

Furthermore the estimated coefficient for improved seed varieties is positive but only statistically significant in high rainfall areas. However the joint effects of inorganic fertilizer and improved maize seeds represented by the coefficient of the interaction term was statistically significant in all the three rainfall patterns with evidence of increasing marginal returns. This implies that there is complementarity between the two inputs towards increasing maize productivity.

The results also revealed that, rainfall had a significant positive effect on maize yield in moderate rainfall areas only. When evaluated at the sample means, the elasticity of maize yields with respect rainfall is positive (0.215) implying that a 1% change in rainfall precipitation will change maize yield by 0.215%. Adopting soil and water conservation practices showed significant positive impact in high and low rainfall areas.

For the variance function, parameter estimates are presented in Table 16. Both the linear and quadratic coefficients of inorganic fertilizer are statistically significant in high and moderate rainfall areas. The positive linear term and the negative quadratic term imply that inorganic fertilizer reduces the variance of yields. Evaluated at the sample means for the other variables, it was found that inorganic fertilizer decreases the yield variance by 0.011. The coefficient of the interaction effect between inorganic fertilizer and improved maize seeds is negative and statistically significant at $P<0.05$. This implies the range of values where improved maize seeds reduces risk exposure tends to increase with use of inorganic fertilizer, reflecting the synergy effects of inorganic fertilizer on improved seeds towards reducing crop failure under the harsh environmental conditions. However in low rainfall areas fertilizer use was associated with a positive and significant effect on the variability of maize yield, implying that inorganic fertilizer increase yield variability in this area.

The phenomena of increasing yield variability in low rainfall areas that is associated with fertilizer use, could be attributed to variation in application levels (rate) and management (timing and application methods) among farmers and also due to lower water potential in some areas, which limits fertilizer uptake by plants (Thierfelder and Wall, 2012). This is also consistent with Fufa and Hassan (2005) who argued that the yield response of crops to different levels of fertilizer under farmer's management conditions depend on a number of interacting factors that include bio-physical factors such as soil type, the time and the amount of rainfall, date of planting and management practices such as the rate and method of fertilizer application.

Table 16: Parameter Estimates for variance function

Independent variables	Coefficient for Variance function							
	High rainfall		Moderate rainfall		Low rainfall		Overall sample	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Inorganic fertilizer	-0.058*	0.006	-0.012	1.1	0.0132*	0.007	-0.004*	0.64
Inorganic fertilizer squared	-0.002*	0.02	0.002	0.01	-0.001*	0.03	0.002	0.04
Improved seeds	-0.004	0.007	-0.005	1.21	0.003	0.008	-0.003	0.92
Improved seeds squared	0.045	0.001	0.046	0.15	0.049	0.002	0.003*	0.14
Inorganic fertilizer× Improved seeds	0.001*	0.045	0.002*	0.23	0.242	0.001	0.030	0.02
Manure	0.003	0.456	0.001	77.59	0.007	0.024	0.009	0.56
Manure squared	0.159	0.001	0.013	0.12	-0.003	0.01	-0.004	0.04
Precipitation	-0.024	0.199	0.011	3.93	-0.919*	0.246	-0.003*	3.58
Precipitation squared	0.003	0.263	0.002	4.77	0.004*	0.228	0.002	9.95
Legumes intercropping	0.188	0.02	0.384*	0.02	0.015	0.03	0.116	0.01
Soil water conservation	0.211	0.01	0.2	0.06	-0.666*	0.01	-0.182	0.09
Altitude	0.007	4.874	0.002	0.32	0.002	5.135	0.001	0.29
Constant	0.584	0.32	-1.466	0.21	0.284	0.326	0.593	0.49
Adj R-squared	0.093		0.11		0.103		0.091	
Log-likelihood function =-204.96								

Significance levels are denoted by one asterisk (*) at the 10% level, two asterisks (**) at the 5% level, three asterisks (***) at the 1% level.
SE= Robust standard errors.

In low rainfall areas, the coefficient for soil water and conservation measures was significantly different from zero, which means it had a risk reducing effect. This explains why soil water conservation practices were rated high in low rainfall areas implying that these measures would be appropriate strategies to adapt for climate change in low-rainfall areas.

4.10 Technical Efficiency of Maize Farmers in Pangani River Basin

Based on the model discussed in the previous section (3.3.4), the next discussion presents the farmers technical efficiency and its determinants. In this analysis, various test were carried out to determine the appropriate functional form; the presence of inefficiency in the production input-output data and appropriate distribution formal of the error term.

4.10.1 Results of the tests of hypothesis for parameters of the stochastic frontier and inefficiency model

The results of these tests of hypothesis for parameters of the stochastic frontier and inefficiency effects model are presented in Table 17. From the table, the first column represents the restriction imposed or the null hypotheses. The second column represents the calculated test statistic. The third column represents degrees of freedom, the fourth column represents the critical values for the test statistic and the fifth column represents the decision; whether restriction is valid or not which determine whether the null hypothesis is accepted or rejected.

The first test involved selecting the functional form of the model, a Cobb-Douglas or translog function was suitable for the data. The null hypothesis was the Cobb Douglas functional form best fits the data while the alternative hypothesis was the translog functional form fits best he data. From Table 17, results showed that, the value of likelihood ratio statistics was 171.15 which is greater than the critical tabulated Chi square value of 20.41 with 12 degrees of freedom at 5% level of significance. So the null hypothesis was rejected and thus, the translog functional form was preferred over the Cobb Douglass functional form.

Table 17: Log likelihood tests for underlying hypothesis

Null hypothesis	λ	Degree of freedom	Critical values	Decision
H_0:Frontier is Cobb Douglas ($\beta_{ij} = 0$)	171.15	12	20.41	Reject H_0
H_0:Half normal distribution (μ=0)	5.64	1	3.841	Reject H_0
$H_0: \gamma = \delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = \delta_7$	12.22	5	10.371	Reject H_0

The second test statistic was that of selecting the appropriate distribution formal of the error term. Given a Translog stochastic frontier production function best fits the data, the null hypothesis stated that the distribution was half- normal (μ=0); the alternative hypothesis stated that the general truncated normal distribution (μ>0). By imposing this restriction, the likelihood ratio value (LR) was 5.64 while the critical likelihood ratio at one degree of freedom ($\chi^2_{0.95}(1)$) was equals to 3.841. Since the calculated LR value was greater than the critical value. The null hypothesis was rejected which implies that truncated-normal distributional assumption of one sided error term was more appropriate for the data in the study area than half-normal.

The third test involved evaluating the presence of inefficiency. In other words, assessing farm specific factors and their effect on the overall technical efficiency of farmers. The null hypothesis stated that the functional form had no inefficiency factors and the alternative stated that the inefficiency factors existed.

Using Kodde and Palm table (because γ_m has mixed chi-square distributions) and 5 as degree of freedom (diff in parameter in restricted and unrestricted model i.e. number of the difference in parameters in OLS and final MLE model). The value of the likelihood ratio was found to be 12.22 which is greater than the critical Chi square value of 10.371 at 5 degree of freedom. The null hypothesis of no technical inefficiency effect is therefore rejected at 5% level of significance, which implies that, the traditional response function (OLS) production function is not an appropriate representation of the sample data. This result is supported by the γ_m parameter associated with the variance of the technical inefficiency effects in the stochastic frontiers are estimated to be 96.3% confidence level which indicates a high level of technical inefficiency exists among the sampled farmers.

The wide variation in technical efficiency is an indication that most of the farmers were still using their resources inefficiently in the production process and there still exists opportunities for increasing their crop production by improving their current level of technical efficiency.

4.10.2 Technical efficiency estimates

The maximum likelihood estimates of the parameters from the translog model are given in Table 18. The results show that the value of gamma (γ) was 0.96 and was significantly difference from zero at 5% ($p<0.05$). This implies that 96% of random variation in maize production is explained by inefficiency suggesting that only 4% of the variation in maize output is due to random shocks outside the farmer's control. The value of Sigma squared of 0.87 was high and significant at 5% indicating the goodness of fit of the data.

The ratio of the estimated coefficients to their corresponding standard errors (t-ratios) were used to calculate the P- values to test the statistical significance of the parameters. It is evident from Table 18 that seven of the estimates of the coefficients associated with the production function using conventional inputs are statistically significance.

Table 18: Maximum likelihood estimates of the stochastic frontier model

Variables	Parameter	Coefficient	Standard- error	t-ratio	P-value[10]
Constant	β_0	13.279	6.029	2.203	0.028**
Ln Labour	β_1	-5.735	4.163	-1.378	0.169
Ln Fertilizer (kg)	β_2	0.528	0.207	2.545	0.011**
Ln manure (kg)	β_3	-0.707	0.391	-1.809	0.071
Ln Capital (Tsh)	β_4	0.008	0.003	3.232	0.001**
Ln Labor2	β_{11}	1.007	0.719	1.401	0.162
Ln Fertilizer2	β_{22}	0.034	0.014	2.441	0.015**
Ln Manure2	β_{33}	0.011	0.013	0.852	0.394
Ln Capital 2	β_{44}	-0.002	0.006	-0.362	0.718
Ln Labour*ln fertilizer	β_{12}	-0.099	0.216	-0.458	0.647
Ln labor*Ln manure	β_{13}	0.197	0.113	1.747	0.081
Ln labour*Ln capital	β_{14}	-0.002	0.001	-2.603	0.009***
Ln fertilizer*Ln manure	β_{23}	-0.017	0.009	-1.803	0.072
Ln Fertilizer *Ln Capital	β_{24}	0.000	0.000	0.312	0.755
Ln Manure*Ln capital	β_{34}	0.000	0.000	0.412	0.680
Improved maize seeds	α_1	0.073	0.033	2.224	0.027**
Soil Water Conservation	α_2	0.044	0.022	2.020	0.044**
Legume intercropping	α_3	-0.003	0.035	-0.083	0.934
Sigma-squared	σ^2	0.873	0.274	3.186	0.002***
Gamma	γ	0.963	1.150	0.837	0.403
log likelihood		-383.331			

Significance levels are denoted by two asterisks (**) at the 5% level, three asterisks (***) at the 1% level.

Further, for dummy variables, the results shows that the coefficient of the dummy variable representing adoption of improved maize seeds and Soil Water Conservation technologies are both positive and significant, indicating that adoption of these technologies increased frontier maize output. This implies that as these use of improved maize varieties and Soil water conservation technologies were applied by 53.81 and 37.98 respectively, more efforts to enhance their application should be made. These results suggest that the model is fairly fit for the data sets of selected farmers.

[10]Calculated using excel programme (=TDIST(x.DF.tails) where x is the t value, DF degrees of freedom and tails, the hypothesis tails.

However it should be kept in mind that the t-ratios could be misleading on account that multicollinearity, resulting from inclusion of the second order terms in the model may be contributing to the high standard errors observed. If this is the case, consideration of these individual 't' rations may lead to the omission of some important coefficient resulting in misspecification of the model (Coelli, 1996). To avoid this problem, output elasticities of the four conventional inputs were derived at the sample means as presented in Table 19.

4.10.3 Production elasticities and returns to scale

Estimates of output elasticities evaluated at the mean of relevant data points and defined by equation (31 to 34) are represented in Table 19. The results indicate that maize output increases with labour, fertilizer, manure and capital. The size of the elasticities of frontier output with respect to the inputs show the relative importance of the various factors for maize production. In this regard, maize output is most responsive to inorganic fertilizer and least responsive to manure. The low production elasticity of manure confirms the observation in Table 8 above that only 25.81% of the sample farmers used animal manure compared to 44.87% using inorganic fertilizer. Various reasons would explain this phenomenon despite the many potential advantages from organic fertilizer. In areas where livestock rearing is low, manure is not easily accessible to all farmers and therefore the adoption rate is very low. In addition, most farmers would like to get immediate result from adopted technology which contrary to animal manure which takes relatively more time compared to inorganic fertilizer to realize its effect on plant growth.

Table 19: Derived Production Elasticities of maize inputs

Variable	Elasticity
Labour	0.445
Fertilizer	0.563
Manure	0.041
Capital	0.132
Returns to scale	1.181

The model's returns to scale was computed as the sum of partial output elasticities for all inputs. The estimated value was 1.18, which is greater than one. This value is greater than one and hence production in the study area is characterized as increasing returns to scale. If farmers in the study area increase all factor inputs by 1% in the long run, output will rise by 18.1%.

4.10.4 Determinants of technical inefficiency of maize

Using equation (29), the study investigated the determinants of technical inefficiency. The coefficient of the explanatory variables in the technical inefficiency model was of particular interest in terms of making policy options. Parameter estimates in Table 20 show that, the variable related to access to meteorological information (seasonal and daily weather forecasting) has a negative sign that is significant by difference from zero ($P<0.05$). This is an indication that access to weather information reduces technical inefficiency (or increases technical efficiency). These results indicate the importance of information for decisions making in farm management.

In relation to rainfall precipitation, the results showed a negative sign of rainfall precipitation meaning that if the rainfall decreases, then the technical inefficiency increase and thus the technical efficiency would decrease. Hence, maize farms in term of agricultural yields become more inefficient when the rainfall diminishes. The results indicate that an increase in precipitation during planting period by 1% increase maize production by 14.4% in Pangani river basin.

Table 20: Results of the determinants of technical inefficiency of maize farmers

Variable	Parameter	Coefficients	Std error	T-ratio	P value
Constant	δ_0	-13.059	30.259	-0.432	0.666
Information on weather forecasting	δ_1	-0.061	0.027	-2.261	0.024**
Household Asset index	δ_5	0.269	0.214	1.253	0.211
Altitude	δ_2	0.609	0.336	1.815	0.070
Rainfall precipitation	δ_3	-1.446	0.558	-2.592	0.010**
Rainfall precipitation^2	δ_4	0.185	0.754	0.245	0.807
Distance to input markets (Km)	δ_6	-0.349	0.144	-2.416	0.016
Access to credit	δ_7	-0.090	0.035	-2.587	0.010**

**=Significance level at 5%

The dummy variable for access to credit has a negative sign, an indication that access to credit reduces technical inefficiency (or increases technical efficiency). This relationship is significant at the 5% level of confidence. Therefore, alleviating credit constraints enables producers to buy hybrid seeds, and thus decrease technical inefficiency. This finding is consistent with a study by Fufa and Hassan (2005) for the peasant farmers in Ethiopia, where he found evidence that credit had a positive impact on technical efficiency.

Proximity to input markets was negatively and significantly correlated with technical inefficiency, indicating that a household that was closer to an input market had 3.49 per cent higher TE score than its equivalent which was one km further. This relationship is straight forward. Access to markets was directly associated with transaction costs and can negatively influence the smallholder's adoption of improved technologies, through increasing travel time and transport costs. Accesses to markets allow farmers to acquire inputs required for adaptation choices and has been found to be an important factor in determining technology adoption choices among farmers (Asfaw *et al.*, 2010).

4.10.5 Technical efficiency scores distribution across farmers

The technical efficiency (TE) of the ith farm was calculated from the expression given in equation (31) under section 3.3.4. Then the values of TE were multiplied by 100 to convert them to percentage. The TE was computed for each farm plot within the households and was later reorganized under three rainfall patterns: the high rainfall, moderate rainfall and low rainfall areas. Table 20 shows the distribution of predicted technical efficiencies. The minimum estimated technical efficiency score was 4.21%, where as the maximum was 93% and the mean was 59.82%. This is interpreted as follows: in the short run, there is a scope for increasing maize production by 41.9% by adopting technologies and techniques used by the best practice maize farms. This suggests that, on average about 41.9% of maize yield is lost because of inefficiency.

Results further showed that 17.3%, 26.4% and 13.1% of farmers from high, moderate and low rainfall patterns respectively, operate at over 80% mean technical efficiency, which are considered to be within the technical efficient range. This shows that most technically efficient farmers are in the moderate rainfall pattern. On the other hand, 4.21%, 4.23% and 4.36% of producers in the high, moderate and low rainfall patterns respectively have a mean TE below 20%, and thus, are considered technically inefficient. However, analysis of TE of the whole sample indicates that only 20.25% of the farmers are technically efficient, i.e. above 80%. Further analysis reveals that the moderate rainfall zone has the highest number of farms with the highest technical efficiency; where 61.06% of the producers in the moderate rainfall zone has mean technical efficiency above 60%. For the High rainfall zone, only 47.9% have a mean technical efficiency above 60%. Finally, the low potential region has the lowest number of farmers with TE above 60%. Most maize producers are operating below their estimated level of technical efficiency.

Further ANOVA test was conducted to test the equality of the sample mean between the three groups of maize farmers. Results shows that there are significant differences in the farmers' technical efficiencies between the three rainfall patterns at P<5%. The differences in the technical efficiencies among the rainfall patterns reflect the variations which exist in the use of productivity enhancing inputs which are at the disposal of the sampled farmers in the study area.

Table 21: Percentage distribution of technical efficiency by rainfall patterns

Range of TE in Percent	High rainfall n=214	Moderate rainfall n=261	Low rainfall n=207	Total N=682	F-test
<20	4.211	4.211	4.790	4.361	9.153**
20-39	18.421	12.982	17.964	15.888	3.254*
40-59	29.474	21.754	33.533	27.103	1.276*
60-79	30.526	34.737	30.539	32.399	1.89
>80	17.368	26.316	13.174	20.249	3.713
Average TE	58.145	63.101	56.126	59.819	6.75**

*=Significance level at 10%. **=Significance level at 5%

From the analysis of technical efficiency, the study has shown that smallholder maize farmers in Pangani river basin are technically inefficient. This implies that there is room to improve smallholder crop production by enhancing efficiency of the farmers. Thus, improving farmer's efficiency should be accorded priority in pursuit of smallholder agricultural development. Among the drivers of inter-household variations in TE among the smallholders were found to be socio-economic and environmental factors. The above findings underscore the need to invest in improving TE of the smallholders. The findings also highlight what should be targeted with policy interventions to enhance the TE.

One of the key areas of intervention is improving access to credit. The results showed that access to credit reduces technical inefficiency. Thus when farmers use credit to access agricultural inputs the production frontier will shift closer to the potential frontier. Credit is necessary to encourage technical innovation, such as use of yield-enhancing inputs, which cost more but they shifts the production frontier transforming the entire input-output relationship.

Small producers in developing countries appear to be unresponsive to apparently economical technical innovations probably because due to risk aversion in case the technology fails and due to liquidity constraints. At the subsistence level where sheer survival is at stake, risk-averse producers are likely to prefer traditional technologies which may promise a lower average yield with lower variance compared to new technologies that may promise a higher average yield but also present the risk of greater variance. The government should improve operation of rural microfinance institutions such as Village Community Banks (VICOBA) which facilitate farmer's access to credit facilities.

4.11 Summary of the Findings

This study set out to determine the farmer's technical efficiency and yield risk of selected farm technologies in Pangani river basin. In addressing the first objective, the study established that, farmers were able to recognize that temperature have increased while there has been a reduction in the volume of rainfall. Using different statistical techniques including descriptive statistics and the linear trend model, an examination of the annual temperature and rainfall provided an indication that climate has been changing over the past thirty years and hence farmers' perceptions of climatic variability are in line with records climatic data. Results show that farmers in areas of higher mean rainfall tend to use more inorganic fertilizer, while those in areas of delayed onset of rainfall and higher maximum temperatures were more likely to have practice soil and water management practices.

Results from the multinomial logit selection model revealed that the likelihood of adopting selected farm technologies is influenced by observable plot, household and village characteristics. These characteristics include distance of the plot from home, market access, household wealth, education and extension services. These results can be used to inform and target policies aimed at increasing adoption rates of multiple and interdependent improved farm technologies. For example, the correlation of education with increased adoption of Soil water conservation and improved seeds suggests that education can be an important driver for the adoption of sustainable agricultural practices in Tanzania.

Similarly, the significant coefficient of extension services suggests the need for establishing and strengthening service providers to accelerate and support adoption of farm technologies. The effects of weather-related risks are also important for enhancing technology adoption and underscore the need to provide climatic information, not only in terms of rainfall amount but also its timing and distribution. Furthermore, the use of farm technologies is positively associated with the household asset index suggesting that investment in public safety-net programs and risk-protection mechanisms to cushion farmers in time of crop failure.

Regarding the results of adoption effects, adoption of multiple farm technologies significantly increases maize income. The package that contains improved seed varieties, inorganic fertilizer and soil water conservation provides the highest income. Thus the first null hypothesis was rejected, implying that adoption of farm technologies does have a significant impact on smallholder farmers yield at $p<0.01$. This has important policy implications. Efforts to improve productivity and food security should combine improved seed varieties with appropriate agronomic practices that increase the profitability of investments in seed-based technologies while enhancing the ecosystem's resilience and sustainability.

The third objective was meant to provide information on the risk properties of inputs and examine how maize yield risk may influence the way a risk-averse producer chooses the optimum level of inputs for maize production. As expected, all inputs contributed to an increased mean production. The results have demonstrated that although most of the selected farm technologies have significant, positive mean impacts on yields. However, they do not all show a correspondingly similar risk reducing effect for the different rainfall patterns, which might explain their varied adoption rates in these areas.

According to the output variance elasticities, for all the three rainfall patterns inorganic fertilizer and improved maize seeds varieties appear to be the most common measure to increase the mean maize yield and risk reducing effect in production in higher and moderate rainfall areas while in lower rainfall areas inorganic fertilizer shows risk increasing effect. This may explain why risk-averse farmers decline to use fertilizer even when it is free: even though use of fertilizer can be very profitable when applied correctly, it may also increase the variance of yield, which may offset the positive utility of increased production, thereby reducing the utility for a subsistence farmer.

Moreover, soil and water conservation appear to be a good investments in high and low-rainfall areas with a risk-reducing effect on production; intercropping with legume does not seem to have any significant effects on reducing production risk in the lower rainfall areas. On the basis of these results the study concludes that although most of the selected farm technologies have significant, positive mean impacts on yields in low-rainfall areas, they do not all show a correspondingly similar risk reducing effect, which might explain their low adoption rates in these areas. Therefore, promotion of adaptation strategies should be location specific and mindful of spatial and risk-related differences of Tanzania. The results are summarized in Table 22 below.

Table 22: Summary of mean and yield risk on selected farm technologies

Farm technology	Yield Rainfall patterns			Risk Rainfall patterns		
	Higher rainfall	Moderate rainfall	Lower rainfall	Higher rainfall	Moderate rainfall	Lower rainfall
Improved seed varieties	Increase	Increase	Increase	Decrease	Decrease	Decrease
Inorganic fertilizer	Increase	Increase	Increase	Decrease	Decrease	Increase
Legumes intercropping	Increase	Increase	Decrease	Decrease	Decrease	Increase
Animal manure	Increase	Increase	Decrease	Decrease	Decrease	Increase
Soil Water Conservation	increase	Increase	Increase	Decrease	Decrease	Decrease

Objective four of the study set out to provide estimates of technical efficiency in maize production and to explain variations in technical efficiency among farms through managerial and socio-economic characteristics. The overall mean technical efficiency is estimated at 59.9%, implying that there is a 40.1% scope for increasing maize production by using the present technology. However, TE ranges between 4.21 to 93% among the maize producers. A significant variation is observed in the mean level of technical efficiency in the three regions. The moderate rainfall pattern achieved the highest TE of 63.1%, for the higher rainfall areas 58.1% TE is achieved, while the low rainfall areas maize producers achieve only a 56.2%.

The results further show that there are significant differences in the farmers' technical efficiency between the three rainfall patterns at P <5%. The differences in the technical efficiency among the rainfall patterns reflect variations, which exist in the use of productivity enhancing inputs at the disposal of the sampled farmers. In addition to interregional differences in TE, there exists intra-farm efficiency within a region. This is an indication that the efficient and inefficient maize producers coexist in the same environment in a given region. 17.3% of maize producers in the higher rainfall areas, and 26.4% of the farmers in the moderate rainfal' areas regions exhibit the highest TE of over 80%. While in low rainfall areas 13.1% of farm plots have TE of 80%.

The elasticity of inputs was also computed. A 1% increase in fertilizer is estimated to increase yield by 0.56%. In addition, a 1% increases in seed rate increases yield by 0.331%, while an increase in labor by one person-day will probably increase yield by 0.45%. However, results from the translog production function show that the second derivative of the variable seed is negative, (i.e. seed squared) is an indication that an increase in use of seed will increase yield but at a decreasing rate.

CHAPTER FIVE

5.0 CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

This study sought to examine and determine farmers' technical efficiency and production risk of improved farm technologies adaptation technologies to climate change among smallholder maize farmers in Pangani basin, Tanzania. In particular the study pursued four objectives as follows; (i) to identify and analyze factors that influence farm technology adoption to climate change effects among smallholder farmers in pangani river basin, (ii) to determine the effects of adopted farm technologies on the smallholder farmers productivity, (iii) to determine the yield risk of adopted farm technologies by smallholder farmers' in pangani river basin, and (iv) to estimate the frontier production function, and compare the technical efficiency of farmers who adopted farm technologies relative to farmers who did not adopt. The following conclusions were therefore drawn:

Results from the study have indicated that the state of climate has been changing compared to that of over 30 years ago, based on smallholder farmers', perceptions; and over 30 years rainfall and temperature data. Further, smallholder farmers are already using various strategies to cope and adapt to the changes and variability of the local climate. Farmers have been compelled to make decisions to change their farming practices by adopting improved farm technologies. The changes made in the farming practices are not uniform across all villages; variations are observed from one village to the other.

The results also show that when strategies are adopted in combination with others they tend to be more effective compared to a technology adopted in isolation. Adaptation is, therefore, more effective when it is a portfolio of actions rather than one single action.

More specifically, we find that the positive impact of improved seed varieties was highly significant when it is coupled with inorganic fertilizer and soil conservation practices.

For all the three rainfall patterns inorganic fertilizer and improved maize seeds varieties appear to be the most common effective measures to increase the mean maize yield and risk reducing effects on production except in lower rainfall areas. This evidence out passes the reasons given by some respondents that they don't use inorganic fertilizer because their farm plots have enough soil fertility. Moreover soil and water conservation appear to be investments in high and low-rainfall areas with a risk-reducing effect on production. These results have demonstrated that although most of the farm technologies have significant, positive mean, impacts on yields in low-rainfall areas, they do not all show a correspondingly similar risk reducing effect, which might explain their low adoption rates in these areas. Hence, promoting adaptation strategies should be location specific and mindful of spatial and risk-related differences across the country.

The estimated frontier yield function revealed that there was a difference in maize yield between the three rainfall patterns, but the mean TE of moderate rainfall (63.01%) was higher compared to the mean TE from lower rainfall areas. Moreover, results from the inefficiency model show that seasonal climatic conditions and agro-ecological settings affect technical efficiency. These imply that agro-ecology based technologies which can easily be adaptable to climate change and increase production efficiency should be given priority to increase productivity and adaptability to climate change. To make rain fed maize cultivation viable, sustainable and revolutionary, it is no doubt necessary to improve farmers' TE through designing and promoting effective technology extension services, backed up by systematic and persistent research on maize cultivation, including the studies to strengthen drought tolerance through improvements in varieties and farming practices.

5.2 Recommendations

Based on the findings as presented in the main text and summarized under conclusion, a number of recommendations are suggested as follows:

(i) It is important to consider the complementarity of different agricultural technologies in promoting of their adoption. For instance, smallholders may be hesitant to adopt improved maize varieties if they are unable to obtain fertilizer to go with it. Thus, to promote the adoption of complementary technologies, it is important to ensure that they are available and affordable to the smallholders. For example, it may not be useful to subsidize one of the technologies without due consideration of the famers 'capability to afford the complementary package of inputs.

(ii) To deal with the influence of yield and yield variability on farm technology adoption, it is important to ensure that the yield-enhancing technologies are capable of increasing yields substantially and maintain the high yields. Thus, when a technology is associated with high risks that may lead to extreme yield fluctuations, it is useful for the government to insure the farmers against such risks in order to encourage adoption. Index-based crop insurance is an option that could be explored.

(iii) To deal with farmer's inability to afford improved farm technologies, setting up smallholder credit scheme, especially for purchase of farm technologies, is an important step towards accelerating adoption of farm technologies. Since the smallholders may not be able to access credit from the mainstream financial sector because of the risky nature of their business, the government could step in either as a guarantor or as a direct provider of the funds through microfinance institutions. An alternative approach could be to mobilize the smallholders to form organizations through which to pool resources and obtain additional funding from either the government or other micro financial institutions such as SACCOs and VIKOBA.

(iv) To make maize farming viable and sustainable, it is recommended that the government and development partners should improve farmers' TE by designing and promoting effective technologies through extension services, backed up by systematic and persistent research on maize production, including research that is designed to strengthen drought tolerance through improvement in varieties and farming practices.

(v) In the long-run, solutions lie in correcting market imperfections. This is only possible with broad-based national economic development strategies.

5.3 Limitations of the Study

(i) This study faced to some limitations. First, being a cross-sectional survey study. Farm-level panel data was not available. Analysis of the cross-sectional data has some limitations, such as lack of capability to track the dynamics of producer performance over time.

(ii) Since the majority of farmers did not keep any written records, they had to furnish information from their memory. Further, many of the questions on the questionnaires dealt with perceptions of farmers, and so they had the possibility generating bias results. The study attempted to minimize this shortcoming by using trained research assistants to conduct field interviews. Also, triangulation was adopted through research design and data sources, such as interviewing various extension players, individual farmers, and focus group discussion. Moreover the use of verifiable secondary data from the project reports compiled by the PBWA, MAFC, TMA and district agricultural department was very helpful.

(iii) The scope of this study focused on maize. In the absence of additional information (e.g., regarding the behaviour of other crops) it is difficult to generalize the implications of these findings to other crops. The same procedures should be replicated in other districts with different competing crops and agro-climatic environment.

5.4 Areas for Further Research

This study has contributed to understanding how related agricultural technologies influence household adoption decisions. The analysis included production risks as one of the predictor of the decision to adopt improved farm technologies. This was important given that smallholders are risk averse and strive to minimize the risks which may reduce production below the subsistence level. However, farmers are not always driven by consumption alone. Indeed some of their produce is meant for sale, to acquire what may not be produced on-farm. Thus, their adoption of improved farm technologies may also be influenced by risks associated with product marketing. Due to data paucity, the study could not include marketing risks in the analysis. This, therefore, remains a potential area for further research subject to availability of appropriate data.

This study has evaluated the effectiveness of inorganic fertilizers and improved maize varieties in enhancing yields in the face of climate change. The analysis provides confidence to developers and promoters of these technologies, and identifies the circumstances under which the best outcomes would be realized. However, the study was not able to analyze whether the yield increase would be sufficient to compensate smallholders for the costs incurred. Lack of data on input and output prices, and indirect costs were limiting factors. Future research could explore this area as it is important for policy, especially with respect to promotion of adoption of such improved technologies.

REFERENCES

Acquah, H. (2011). Farmers Perception and Adaptation to Climate Change: A Willingness to pay analysis. *Journal of Sustainable Development in Africa* 13(5): 150-161.

Adosi, J. (2002). Trends and Variabiity of Surface Temperature over Tanzania. Metereological Agency, Dar Es Salaam, Tanzania. In: Climate and Land Degradation (Edited by Mannva, V., Sivakumar, and Ndengwa, N.) [http://catalogue.nla.gov.au/Record/4276879] site visited 23/4/2016.

AGRA (2011). East Africa Synthesis Report: Country Case Studies on the Pass Value Chain Strategy/Approach and Its Impact/ Effect on Smallholder Farmer Yields. [www-cif.climateinvestmentfunds.org/sites/aasr -agriculture-in-ssa.pdf] site visited on 22/4/2016.

Agrawala, S., Moehner, A., Hemp, A., Van Aalst, M., Hits, S., Smith, J., Meena, H., Mwakifwamba, S., Hyera, T. and Mwaipopo, O. (2003). *Development and Climate Change in Tanzania: Focus on Mount Kilimanjaro.* Organization for Economic Cooperation and Development (OECD) Paris. 72pp.

Aigner, J., Lovell, C. and Schmidt, P. (1977). Formulation and Estimation of Stochastic Frontier Production Function Models. *Journal of Economics* 6 (1): 21-31.

AMCEN (2011). Addressing Climate Change Challenges in Africa: A Practical Guide towards Sustainable Development. [www.Unep.Org/Roa/Amcen/Docs/ Publications/] site visited on 24/6/2016.

Antle, J. (1983). Testing the Stochastic Structure of Production: A Flexible Moment-Based Approach. *Journal of Business and Economic Statistics* 1:192-201.

Asche, F. and R. Tveteras. (1999). Modelling Production Risk with a Two-Step Procedure. *Journal of Agricultural and Resource Economics* 24: 424-439.

Asfaw, S., Kassie, M., Simtowe, F. and Lipper, L. (2013). Poverty reduction effects of agricultural technology adoption: A Micro-evidence from Rural Tanzania. *Journal of Development Studies* 47(8): 1-18.

Asfaw, S., Shiferaw, B., Simtowe, F. and Lipper, L. (2014). Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. *Food Policy* 37: 283-295.

Banker, D., Charnes, A. and Cooper, W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis, *Management Science* 30(9): 1078 – 1092.

Banker, R. (1984). 'Some models for estimating technical and scale inefficiencies in Data Envelopment Analysis. *Management Science* 30:1078-1092.

Battese, E., Rambaldi, N. and Wan, H. (1997). Frontier Production Function with Risk Properties. *Journal of Productivity Analysis* 8: 269-280.

Battese, G. E. (1997). A Note on the Estimation of Cobb-Douglas Production Functions When Some Explanatory Variables Have Zero Values. *Journal of Agricultural Economics* 48(2): 250-52.

Bezabih, M., Chambwera, M. and Stage, J. (2011). Climate Change, Total Factor Productivity and the Tanzanian Economy: A computable General Equilibrium Analysis. Environment for Development. Discussion paper Series. June 2010, EFD, DP 10-14pp.

Binswanger, H. (1981). Attitudes toward Risk: Theoretical Implications of an Experiment in Rural India. *Economic Journal* 91(364): 867-890.

Bliss, J. and Stern, H. (1982). *The Economy of an Indian Village*. Delhi and New York: Oxford University Press, UK. 240pp.

Boko, M., Niang, I., Nyong, A., Vogel, C., Githeko, A., Medany, M, Osman-Elasha, B., Tabo, R. and Yanda, P. (2007). Africa Climate Change (2007). Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Edited by Parry, M., Canziani, O., Palutikof, J., Van der Linden, P. and Hanson, C.) Cambridge University Press, Cambridge UK. pp 433-467.

Bourguignon, F., Fournier, M. and Gurgand, M. (2007). Selection Bias Corrections Based on the Multinomial Logit Model: Monte-Carlo comparisons. *Journal of Economic Surveys* 21: 174–205.

Bozzola, M. (2014). Adaptation to Climate Change: Farmers' Risk Preferences and the Role of Irrigation. European Association of Agricultural Economists Conference on 'Agri-Food and Rural Innovations for Healthier Societies. Ljubljana, Slovenia. 13pp.

Breusch, T. and Pagan, A. (1979). A simple test for heteroskedasticity and random coefficient variation. *Econometrica* 47: 1287-1294.

Carney, D. (1998). Sustainable Rural Livelihoods: What contribution can we make? London: Department for International Development. [www.eldis.org/vfile/upload/1/document/0812/SLA_Progress.pdf] site visited on 14/5/2015.

Charnes, A., Cooper, W., Golany, B., Seiford, L. and Stutz, J. (1985). Foundations of Data Envelopment Analysis for Pareto-Koopmans Efficient Empirical Production Frontiers. *Journal of Econometrics* 30(1-2): 91-107.

Chavas, J. and Di Falco, S. (2012). On the Role of Risk versus Economies of Scope in Farm Diversification with an Application to Ethiopian Farms. *Journal of Agricultural Economics* 92: 356-375.

Chayanov, A. (1966). *The Theory of Peasant Economy*. The University of Wisconsin Press, New York. 300pp.

Churi, A. J., Mlozi, M. R. S., Tumbo, S. D. and Casmir, R. (2012). Understanding Farmers Information Communication Strategies for Managing Climate Risks in Rural Semi-arid Areas, Tanzania. *International Journal of Information and Communication Technology Research* 2 (11): 2223-4985.

Coelli, T. (1995). Estimators and Hypothesis Tests for a Stochastic Frontier Function. A Monte Carlo Analysis. *Journal of Productivity Analysis* 6: 247-268.

Coelli, T. (1996). A Guide to FRONTIER Version 4.1: A Computer Program for Frontier Production Function Estimation, CEPA Working Paper 96/07, Department of Econometrics, University of New England, Armidale, Australia.

Coelli, T., Rao, C. and Battese, E. (2005). *An Introduction to Efficiency and Productivity Analysis*, 2nd Edition, Springer, New York. 349 pp.

De Brauwa, A. and Eozenoub, P. (2014). Measuring risk attitudes among Mozambican farmers. *Journal of Development Economics* 111: 61–74.

De Groote, H., Doss, C., Lyimo, S. and Mwangi, W. (2002). Adoption of Maize Technologies in East Africa–What Happened to Africa's Emerging Maize Revolution? Paper presented at the FASID Forum V, "Green Revolution in Asia and its Transferability to Africa, Tokyo, and December 8-10, 2002. 22pp.

De Janvry, A. (2010). Agriculture for development: New paradigm and options for success. *Agricultural Economics* 41(1): 17-36.

Deaton, A. (2010). Instruments, Randomization, and Learning about Development. *Journal of Economic Literature* 48: 424-455.

Dercon, S. and Christiansen, L. (2007). Consumption Risk, Technology Adoption and Poverty Traps: Evidence from Ethiopia. World Bank Policy Research Working Paper 4257. 49pp.

Deressa, T., Hassan, R. and Ringler, C. (2011). How Can African Agriculture Adapt to Climate Change: Assessing Household Vulnerability to Climate Change: The Case of Farmers in the Nile Basin of Ethiopia. Research Briefs 15(4), International Food Policy Research Institute (IFPRI).

Di Falco and Veronesi, (2012). How Can African Agriculture Adapt to Climate Change? A Counterfactual Analysis from Ethiopia. *American Journal of Agricultural Economics* 82(2): 321–349.

Di Falco, S., Yesuf. M., Kohlin, G. and Ringler, C. (2012). Estimating the Impact of Climate Change on Agriculture in Low-Income Countries: Household Level Evidence from the Nile Basin, Ethiopia. *Environmental and Resource Economics* 52(4).

Di Falco, S. and. Chavas, J. (2009). On Crop Biodiversity, Risk Exposure, and Food Security in the Highlands of Ethiopia. *American Journal of Agricultural Economics* 91: 599-611.

Di Falco, S., Veronesi, M. and Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro perspective from Ethiopia. *American Journal of Agricultural Economics* 93(3): 829–846.

Dodman, T. and Diagana, C. (2006). *Conservation Dilemmas for Intra-African Migratory Waterbirds.* Waterbirds around the world. Eds. G.C. Boere, C.A. Galbraith and D.A. Stroud. The Stationery Office. Edinburgh, UK. pp. 218-223.

Eitzinger, J., Trnka, M., Hösch, J., Žalud, Z. and Dubrovský, M. (2004). Comparison of CERES, WOFOST and SWAP models in simulating soil water content during growing season under different soil conditions. *Ecological Modelling* 171: 223–246.

FAO (2009). *Coping with Changing Climate: Considerations for Adaptation and Mitigation in Agriculture.* Food and Agriculture Organization, Rome, Italy. 33pp.

FAO (2010). Global survey of agricultural mitigation projects. Mitigation of Climate Change in Agriculture (MICCA) Project. Food and Agriculture Organization of the United Nations (FAO), Rome, Italy. 42pp.

FAO (2011). Save and grow: A policymaker's guide to the sustainable intensification of smallholder crop production. Food and Agriculture Organization of the United Nations, Rome, Italy. 52pp.

FAO (2015). Smallholder productivity under climatic variability: Adoption and impact of widely promoted agricultural practices in Tanzania. Policy brief no.2 June 2015.[ww.fao.org/climatechange/epic] site visited site visited on 14/4/2016.

FAO (2015). The Maize Value Chai n in Tanzania. A report from the Southern Highlands Food Systems Programme, Rome, Italy. 60pp.

FAO (2016). Smallholder productivity under climatic variability: Adoption and impact of widely promoted agricultural practices in Tanzania, by Aslihan Arslan, Federico Belotti and Leslie Lipper. ESA Working Paper No. 16- 03. Rome, Italy.

Farrell, M. (1957). The Measurement of Productivity Efficiency. *Journal of the Royal Statistics Society* 3: 253–90.

Fried, H., Lovell, K. and. Schmidt. S. (2008). *Efficiency and Productivity*. In: H. Fried, C. A. K. Lovell, S. Schmidt (Eds) The Measurement of Productive Efficiency and Productivity Change, New York, Oxford University Press. 63-91pp.

Fufa, B. and Hassan, R. (2003). Stochastic Maize Production Technology and Production Risk Analysis in Dadar District, East Ethiopia. *Agrekon* 42 (2): 116-128.

Gagnon-Lebrun, F. and Agrawala, S. (2006). *Progress on Adaptation to Climate Change in Developed Countries: An Analysis of Broad Trends.* Env/Epoc/Gsp(2006)1/Final, OECD, Paris. 63pp.

Gbetibouo, A., Bryan, E., Deressa, T. and Ringler, C. (2009). Adaptation to climate change in Ethiopia and South Africa: options and constraints. *Environmental Science and Policy* 12(4): 413-426.

GCAP (2011). The economics of climate change in the United Republic of Tanzania. [www.economics-of-cc-in-tanzania.org/images/Final] site visited on 13/3/2016.

Guttormsen, A., Roll, K. and Asche, F. (2013). Modelling production risk in small scale subsistence agriculture. *The Journal of Agricultural Education and Extension* 6: 43-86.

Hamisi, J. (2012). Study of Rainfall Trends and Variability over Tanzania. A Research Project Submitted in Partial Fulfilment of the Requirements for the Postgraduate Diploma in Meteorology University of Nairobi, Nairobi, Kenya. 67pp.

Hulme, M., Doherty, M., Ngara, T., New, G. and Lister, D. (2001). African climate change: 1900-2100. *Climate Research* 17(2): 145-168.

Haug, R., Joseph, P. H., Nchimbi-Msolla, S., Mwaseba, D. L. and Synnevag, G. (2016). If technology is the answer, what does it take? *Development in Practice* Vol. 26(3).

IDS (2012). Towards a Climate Smart Scoping Study on Mainstreaming Climate Change into Tanzania Social Action Fund Productive Safety Net (TASAF III). Final Draft, 2 March 2012. Institute of Development Studies (IDS) Brighton BN1 9RE, UK. 49pp.

IFDC (2014). Consumption of Fertilizers and Fertilizer Use by Crop in Tanzania. [www.ifdcorg.files.wordpress.com/2015/04/Tanzania] site visited on 23/2/2016.

IPCC (2007). Climate Change 2007: *The Physical Science Basis*. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Solomon. S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K. B., Tignor, M. and Miller, H. L. (Eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. 996pp.

IPCC (2012). Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change [Field, C. B., Barros, V., Stocker, T. F., Qin, D., Dokken, D. J., Ebi, K. L., Mastrandrea, M. D., Mach, K. J., Plattner, G. K., Allen, S. K., Tignor, M. and Midgley, P. M. (Eds.)]. Cambridge University Press. Cambridge, UK, and New York, USA. 582pp.

IPCC (2014). Summary for Policymakers. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. 32pp.

Isham, J. (2000). The effect of social capital on technology adoption: evidence from rural Tanzania. Conference on Opportunities in Africa: Micro-evidence on Firms and Households, Middlebury, Vermont. April 9-10, 2000. 41pp.

IUCN (2009). *The Pangani River Basin: A Situation Analysis*. 2nd Edition. 82pp.

IUCN (2010). Climate change modelling for the Pangani Basin to support the IWRM planning process. Pangani River Basin Flow Assessment. Pangani Basin Water Board, Moshi and IUCN Eastern and Southern Africa Regional Programme. 36pp.

Just, R. and Pope, R. (1979). Production Function Estimation and Related Risk Considerations. *American Journal of Agricultural Economics* 61(2): 276–84.

Kaihura, F. B. S., Stocking, M. and Kahembe, E. (2001). Soil Management and Agrodiversity: A case study from Arumeru, Arusha, Tanzania. Paper presented to the symposium on Managing Biodiversity in Agricultural Systems, Montreal, Canada, November 8 - 12, 2001.

Kang, Y., Shahbaz, K. and Xiaoyi, M. (2009). Climate change impacts on crop yield, crop water productivity and food security. A review. *Elsevier* 19: 1665–1674.

Kassie, M., Yesuf, M. and Köhlin, G. (2008). The Role of Production Risk in Sustainable Land–Management Technology Adoption in the Ethiopian Highlands. RFF Discussion Paper EFD 09-13. Washington, DC. 35pp.

Kassie, M., Zikhali, P., Pender, J. and Köhlin, G. (2010). The Economics of Sustainable Land Management Practices in the Ethiopian Highlands. *Journal of Agricultural Economics* 61: 605-627.

Kassiea, M., Moti, J., Bekele, S., Frank, M. and Mulugetta, M. (2012). Interdependence in Farmer Technology Adoption Decisions in Smallholder Systems: Joint Estimation of Investments in Sustainable Agricultural Practices in Rural Tanzania, Selected Paper prepared for presentation at the International Association of Agricultural Economists (IAAE) Triennial Conference, Foz do Iguaçu, Brazil, 18-24 August, 2012. 54pp.

Katungi, E., Machethe, C. and Smale, M. (2007). Determinants of social capital formation in rural Uganda: Implications for group-based agricultural extension approaches. *African Journal of Agricultural Research* 1: 2.

Kim, N. and Coelli, T. (2009). Quantifying the effects of modelling choices on hospital efficiency measures: A meta-regression analysis CEPA Working Paper Series No. WP07/2009. School of Economics University of Queensland St. Lucia, Australia.

Koundouri, P., Nauges, C. and Tzouvelekas, V. (2006). Technology Adoption under Production Uncertainty: Theory and Application to Irrigation Technology. *American Journal of Agricultural Economics* 8(3): 657–70.

Kumbhakar, S. and Tsionas, E. (2008). Estimation of production risk and risk preference function: A nonparametric approach. *Annals of Operations Research* 5: 472-479.

LaFave, D. and Thomas, D. (2014). Farms, Families, and Markets: New Evidence on Agricultural Labor Markets. *Journal of Sustainable Development* 14 (3): 425–431.

Lobell, D. and Burke, M. (2008). Why are agricultural impacts of climate change so uncertain? The importance of temperature relative to precipitation, Environ. *Res. Lett* 3:1-8.

Lyimo, S., Mduruma, Z., and De Groote, H., (2014). The use of improved maize varieties in Tanzania. *African Journal of Agricultural Research* 9(7): 643-657.

Maddala, G. (1986). Disequilibrium, Self-Selection, and Switching Models. *Handbook of Econometrics* 3: 1633-1688.

Maddison, D. (2006). The Perception of and Adaptation to Climate Change in Africa. CEEPA Discussion Paper No. 10, July 2006.

MAFAP (2013). Review of food and agricultural policies in the United Republic of Tanzania. MAFAP Country Report Series, FAO, Rome, Italy.

Mafu, S. (2004). From the Oral Tradition to the Information Era: The Case of Tanzania. *International Journal on Multicultural Societies* 6(1): 53-78.

Mafuru, J., Kileo, H., Verkuijl, W., Mwangi, P., Ananda, J. and Moshi, A. (1999). *Adoption of Maize Production Technologies in the Lake Zone of Tanzania.* International Maize and Wheat Improvement Center (CIMMYT), the United Republic of Tanzania, and the Southern Africa Center for Cooperation in Agricultural Research (SACCAR). 49pp.

Magrini, E. and Vigani, M. (2014). Technology adoption and the multiple dimensions of food security: the case of maize in Tanzania. *Journal of Economic Literature* 18: 217-234.

Majule, E., Janie, R., Mathew, M. and Kaisa, K. (2014). Review of Climate Change Mitigation in Agriculture in Tanzania [www.pics.uvic.ca/sites/default/files/Literature%20Review%20%20Climate] site visited on 22/12/2015.

Mano, R. and Nhemachena, C. (2006). Assessment of the Economic Impacts of Climate Change on Agriculture in Zimbabwe: A Ricardian Approach. CEEPA DP11, University of Pretoria, South Africa. 43pp.

Maurice, O., Nyangena, W. and Yesuf, M. (2010). Production risk and farm technology adoption in the rain-fed semi-arid lands of Kenya. *African Journal of Agricultural Research* 4: 2-28.

Mendola, M. (2007). Farm Household Production Theories: A Review of Institutional and Behavioral Responses. *Asian Development Review* 24(1): 49-68.

Mertz, O., Mbow, C., Reenberg, A. and Diouf, A. (2008). Farmers' Perceptions of Climate Change and Agricultural Adaptation Strategies in Rural Sahel. *Environmental Management* DOI 10.1007/s00267-008-9197-0.

Mongi, H., Majule, A. and Lyimo, J. (2010). Vulnerability and adaptation of rain fed agriculture to climate change and variability in semi-arid Tanzania. *African Journal of Environmental Science and Technology* 4(6): 371-381.

Mwalukasa, N. (2013) Agricultural information sources used for climate change adaptation in Tanzania. *Library Review* 62(5): 266-292.

Mwandosya, M., Nyenzi, B. and Luhanga, M. (1998). *The Assessment of Vulnerability and Adaptation to Climate Change Impacts in Tanzania.* Dar es Salaam, Tanzania: Centre for Energy, Environment, Science and Technology (CEEST). 69pp.

NBS (2012). National Sample Census of Small Holder Agriculture Volume Ii: Crop Sector – National Report. Government Printers. Dar es salaam, Tanzania. 199pp.

Ndomba, P. (2010). Development of rainfall curve for crops planting date in Pangani Basin. *Nile Basin water and Science engineering Journal* 3(1): 13-27.

Nhemachena, C. and Hassan, R. (2007). Micro-level Analysis of Farmers' Adaptation to Climate Change in Southern Africa. International Food Policy Research Institute (IFPRI) Discussion Paper No. 00714. Environment and Production Technology Division. Washington, D.C. 40pp.

Nkonya, E. and Mwangi, W. (2004). The economic rationale of recycling hybrid seeds in Northern Tanzania. *Eastern Africa Journal of Rural Development* 20(1):113-124.

Nyanga, P., Johnsen, F., Aune, J. and Kahinda, T. (2011). Smallholder Farmers' Perceptions of Climate Change and Conservation Agriculture: Evidence from Zambia. *Journal of Sustainable Development* 4(4): 73-85.

Panda, A., Sharma, U., Ninan, K. and Patt, A. (2013). Adaptive capacity contributing to improved agricultural productivity at the household level: Empirical findings highlighting the Aggarwala, P., Kalra, N. and Chander, S. (2006). A dynamic simulation model for the assessment of crop yields, losses due to pests, and environmental impact of agro-ecosystems in tropical environments. *Agric. Syst.* 89: 1–25.

Sadoulet, E., De Janvry, A. (1995). *Quantitative Development Policy Analysis*. Baltimore, Johns Hopkins University Press, Washington. 397pp.

Samuelson, P. and Nordhaus, W. (2005). *Economics*. Tata Mc-Graw-Hill: New Delhi. 344pp.

Sarris, A. and Karfakis, P. (2010). Vulnerability to Climate Change of Rural Households in Tanzania. World Bank, Policy Research Working Paper 2887.

Schultz, T. (1998). Transforming Traditional Agriculture. *American Journal of Agricultural Economics* 70(1): 198-200.

Shemsanga, C. (2010). The Cost of Climate Change in Tanzania: Impacts and Adaptations. *Journal of American Science* 6(3): 182-196.

Simtowe, F., Kassie, M., Afaw, S., Shiferaw, B. and Muange, S. (2011). Determinants of Agricultural Technology Adoption: The Case of Improved Pigeonpea Varieties in Tanzania. *Quarterly Journal of International Agriculture* 50(4): 325-345.

Singh, I., Lyn, S. and John, S. (Eds). (1986). Agricultural Household Models: Extensions, Applications, and Policy, Baltimore, MD: Johns Hopkins University Press, Baltimore. 212pp.

Stephen Lyimo1, Zubeda Mduruma and Hugo De Groot (2014). The use of improved maize varieties in Tanzania. *African Journal of Agricultural Research* 9(7): 643-657.

Taylor, J. and Adelman, I. (2003). Agricultural Household Models: Genesis, Evolution, and Extensions. *Review of Economics of the Household* 1(1): 33-58.

Teklewold, H., Kassie, M. and Shiferaw, B. (2013). Adoption of multiple sustainable agricultural practices in rural Ethiopia. *Journal of Agricultural Economics* 64(3): 597-623.

Thierfelder, C. and Wall, P. (2012). Effects of conservation agriculture on soil quality and productivity in contrasting agro-ecological environments of Zimbabwe. *Soil Use and Management* 28(2): 209–220.

Thornton, P., Jones, P., Alagarswamy, G. and Andresen, J. (2009). Spatial variation of crop yield response to climate change in East Africa. *Global Environmental Change* 19(1): 54-65.

Thornton, P., Jones, K., Ericksen, P. and Challinor, A. (2011). Agriculture and food systems in sub-Saharan Africa in a 4°C+ world. Philosophical transactions. *Series A, Mathematical, Physical, and Engineering Sciences* 369(1934): 117–136.

Tversky, A. and. Kahneman, D. (1992). Advances in Prospect-Theory - Cumulative Representation of Uncertainty. *Journal of Risk and Uncertainty* 5(4): 297-323.

UNEP (2013). Africa Environment Outlook 3. Summary for Policy Makers, United Nations Environment Programme (UNEP), Nairobi, Kenya. 40pp.

UNFCCC (1992). United Nations Framework Convention on Climate Change. United Nations, FCCC/INFORMAL/84 GE.05-62220 (E) 200705, Secretariat of the United Nations Framework Convention on Climate Change, Bonn, Germany. [unfccc.int/resource/docs/convkp/conveng.pdf] site visited on 25/4/2016.

URT (1997). *National Environment Policy*. Division of Environment, Vice President's Office, Dar es Salaam. 44pp.

URT (2003). Initial Communication under the United Nations Framework Convention on Climate Change (UNFCCC), Dar es Salaam, Tanzania. [http://unfccc.int/resource/docs/natc/tannc1.pdf.] site visited on 28/1/2016.

URT (2007). *National Adaptation Programme of Action*. United Republic of Tanzania Vice President's Office, Dar es Salaam. 52pp.

URT (2009). *The United Republic of Tanzania Ministry of Agriculture Food Security and Cooperatives*. Investment Potential and Opportunities in Agriculture (Crop Sub-Sector). Government printers, Dar es Salaam. 32pp.

URT (2011). *Tanzania Agriculture and Food Security Investment Plan (TAFSIP).* Main Document 18 October, 2011. Government Printers, Dar es Salaam. 75pp.

URT (2012a). National Climate Change Strategy. Government Printers, Dar es Salaam, Tanzania. 116pp.

URT (2012b). National Sample Census of Small Holder Agriculture Volume II: Crop Sector – National Report. Government Printers Dar es salaam. 539pp.

URT (2013a). Climate Change Adaptation Information Toolkit for Farming Communities in Tanzania. Vice President's Office, Dar es Salaam, Tanzania. 32pp.

URT (2013b). National Strategy for Reduced Emission from Deforestation and Forest Degradation. Vice President's Office, Dar es Salaam, Tanzania. 66pp.

URT (2014a). Tanzania Public Expenditure Review National Agricultural Input Voucher Scheme (NAIVS). Dar es Salaam, Tanzania. 79pp.

URT (2014b). Tanzania Agriculture Climate Resilience Plan, 2014–2019. [http://www.kilimo.go.tz/publications/english%20docs/ACRP_TANZANIA_ENDORSED.pdf] site visited 22/5/2016.

WEMA (2010). Mitigating the impact of drought in Tanzania: The WEMA Intervention Policy Brief, November 2010.[www.aatf-africa.org/userfiles/WEMA-TZ-policy-brief1.pdf] site visited 20/5/2016.

Westengen, O. and Brysting, K. (2014). Crop adaptation to climate change in the semi-arid zone in Tanzania: the role of genetic resources and seed systems. *Agriculture and Food Security* 3(3).

Wik, M., Kebede, T. A., Bergland, O. and Holden, S. T. (2004). On the measurement of risk aversion from experimental data. *Applied Economics* 2: 44 – 45.

Wilson, P., Hadley, D., Ramsden, S. and Kaltsas, I. (1998). "Measuring and Explaining Efficiency in UK Potato Production. *Journal of Agricultural Economics* 49(3): 294-305.

Winters, P., Maffioli, A. and Salazar, L. (2011). Introduction to the Special Feature: Evaluating the Impact of Agricultural Projects in Developing Countries. *Journal of Agricultural Economics* 62: 393-402.

Wollni, M., Lee, D. and Janice, T. (2010). Conservation agriculture, organic marketing, and collective action in the Honduran hillsides. *Agricultural Economics* 41: 373–384.

World Bank (2010). Economics of Adaptation to Climate Change: Synthesis Report. Washington DC. 164pp.

World Bank (2012). The World Bank Development Research Group Agriculture and Rural Development Team September 2012 Climate Change, Agriculture And Food Security in Tanzania. World Bank, New York. Policy Research Working Paper 6188. 2999.

Yamane, T. (1973). *Statistics: An Introductory Analysis* (3rd Ed.). New York: Harper and Row. 607-610pp.

Yesuf, M. and Bluffstone, R. (2009). Poverty, Risk Aversion, and Path Dependence in Low-Income Countries: Experimental Evidence from Ethiopia. *American Journal of Agricultural Economics* 4(9): 35-52.

APPENDICES

Appendix 1: Definition of explanatory variables used in the multinomial endogenous switching regression model

Variable	Definition	Measurement /value	Expected sign and explanation
X_1	Farm plot size	Hectares (ha), expressed in natural logarithm (Ln)	(+) Farmers who cultivate more area are expected to use more improved inputs.
X_2	Average walking distance from the homestead to the plots in minutes	Time (minutes)	(-) Farm plots further away from homestead are less likely to use improved inputs
X_3	education of household head	Years	(+) More educated persons are less poor, hence more likely to buy and use improved inputs
X_4	Experience in maize farming	Years	(+) experienced farmers are more likely to use improved inputs.
X_5	Walking distance to the nearest input market in km	Kilometers	(-) household farm away from input markets are less likely to use improved inputs. Access to market are directly associated with the transaction costs are barriers to market participation by resource-poor smallholders (Sadoulet and De Janvry, 1995).
X_6	Extension service.	1 = yes, 0 = no	(+) Farmers who receive extension visits and/or training are more likely to purchase and use improved inputs.
X_7	Household asset index.	value	(+) wealthier household are expected to use farm improved inputs.
X_8	Coefficient of rainfall variation	value	(-) greater climate variability as represented by the coefficient of variation of rainfall increases adoption of risk-reducing inputs.
X_9	Rainfall satisfaction index	value	(+) A higher value of the rainfall index is a positive occurrence, and thus the probability of adoption of improved farm technologies
D_1	High rainfall areas	1 = if maize farmer from high rainfall areas, 0 otherwise	(+) Farmers in higher rainfall areas are expected to use more improved inputs
D_2	Moderate rainfall areas	1 = if maize farmer from moderate rainfall areas, 0 otherwise	(+) Farmers in moderate rainfall areas are expected to use more improved inputs
D_3	Low rainfall areas	1 = if maize farmer from low rainfall areas, 0 otherwise	(-) Farmers in low rainfall areas are less likely to use improved inputs

Appendix 2: A Prior Expectation of Variables in the mean and variance function model

Variable	Description	Measurement	Expected Sign	
			Mean yield function	Variance of yield function
In organic fertilizer	Refers to the quantity of chemical fertilizer used by ith farmer for the production year, measured in kilograms.	kg	+	+-
Manure	Refers to the quantity of animal manure used by ith farmer for the production year, measured in kilograms.	kg	+	-
Soil water conservation	Land investment including cut-off grasses, terracing, stone and soil bunds and leaving crop residues after harvest	1=Yes; 0= No	+	-
Improved maize seeds	Refers to the quantity of improved maize seed varieties used by ith farmer for the production year, measured in kilograms.	kg	+	-
Local maize seeds	Refers to the quantity of local/traditional maize seeds used by ith farmer for the production year, measured in kilograms.	kg	-	+
Legume intercropping with maize	Intercrop maize with a legumes	1=Yes; 0= No	+	+-
Precipitation	Precipitation of during production period	Millimeter	+	-
Altitude	Meters above sea level of the farm plot	Meters	-	+

Appendix 3: A Prior Expectation of Variables in the estimation of

Technical efficiency model

Variable	Description	Measurement	Expected Sign
Seed	Is a measure of the quantity of maize seed in kilograms used by the i[th] farmer for the production year	kg	+
Fertilizer	Refers to the quantity of chemical fertilizer used by i[th] farmer for the production year, measured in kilograms.	kg	+
Labour	Measured as the total man-days employed by the i[th] farm during the production year. Hired and family labours were assumed to be equally productive and were aggregated. Man days for labour was calculated as: one adult male working for one day (8 hours) equals one man day; one female and one child (< 18years) working for one day (8 hours) equals 0.75 and 0.5 man days respectively. Classifications are based on similar works done by Coelli and Battese (2005).	Man days	+
Capital	Mechanization cost, cost, cost of agrochemicals, the cost of other services incurred in the production year	Tsh	+
Manure	Refers to the quantity of animal manure used by i[th] farmer for the production year, measured in kilograms.	kg	+
Technical Inefficiency Model			
Credit Access	is a binary variable used to capture the effect of credit on the efficiency of farmers, this variable is measured as a dummy, 1 if farmer had access to credit, 0 if they didn't during the 2012/2013 production year.	1=Yes, 0= No	-
Information on weather forecasting	Variable was measured as a dummy, 1 was assigned to farmers who had information on weather prior to production period.	1=Yes, 0= No	+
Distance	Proximity to the nearest input market	Kilometer	-
Precipitation	Precipitation of during production period	Millimeter	+
Altitude	Height in meters above sea level	Meters	-
Asset index	Wealth indicators based on durable goods ownership and housing condition.	Value	-

Appendix 4: Trends in temperature in Pangani river basin

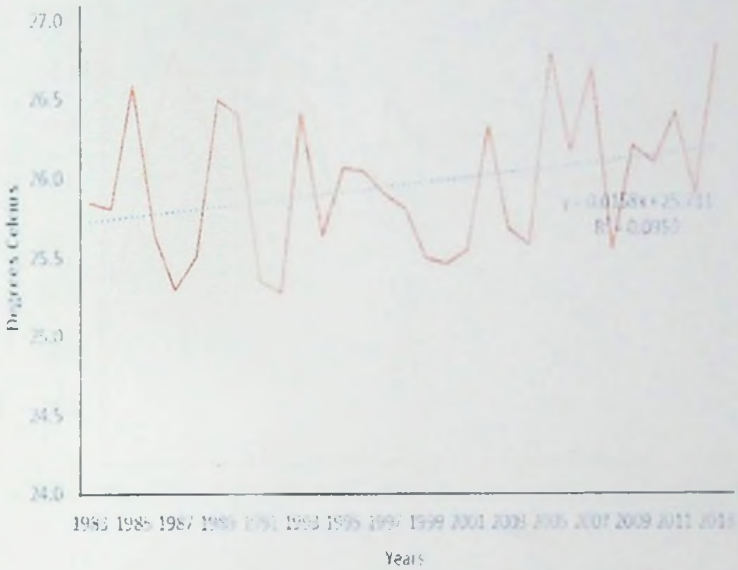

Figure 14: Maximum Temperature trend for Arusha (1983-2013)

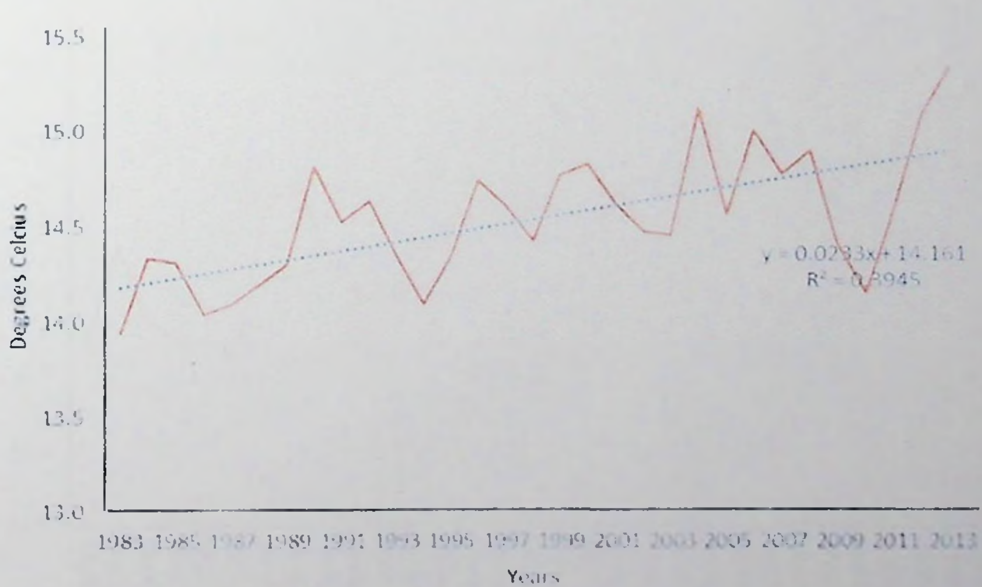

Figure 15: Minimum Temperature trend for Arusha (1983-2013)

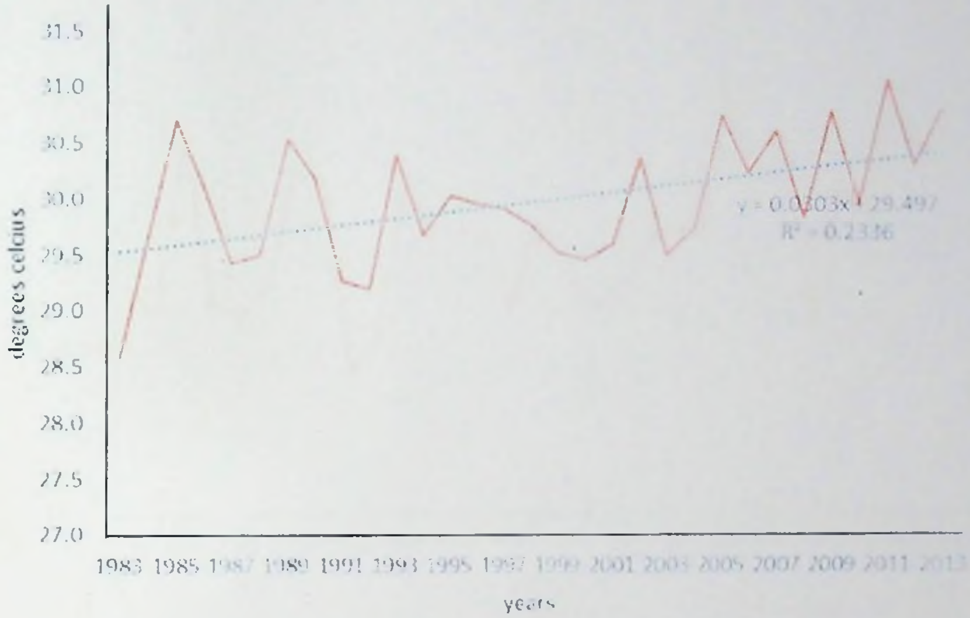

Figure 16: Maximum Temperature trend for KIA (1983-2013)

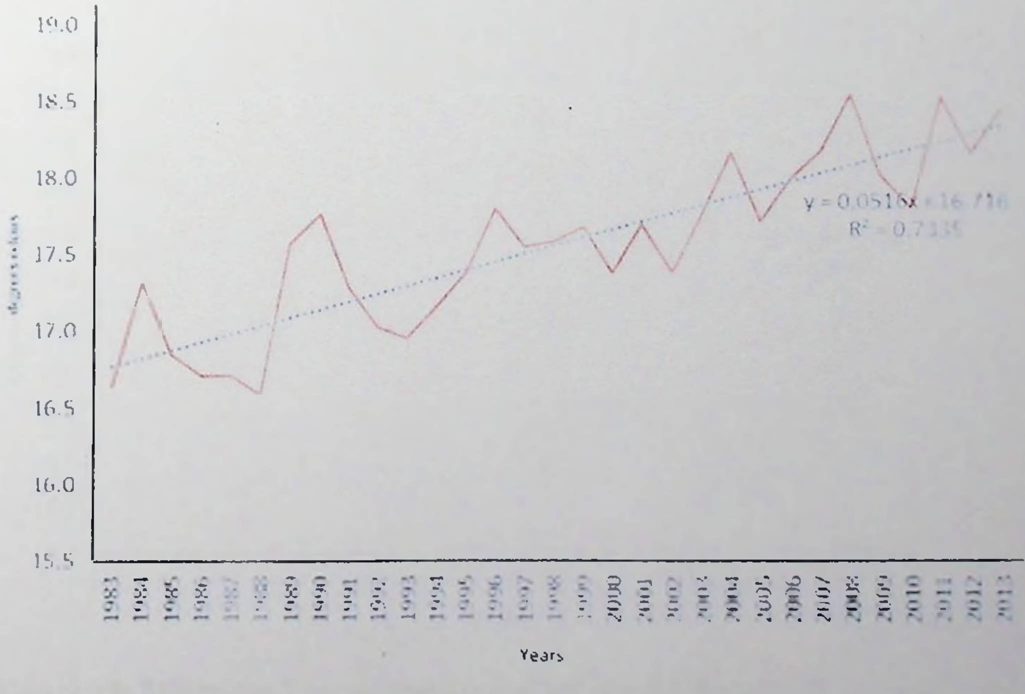

Figure 17: Minimum Temperature trend for KIA (1983-2013)

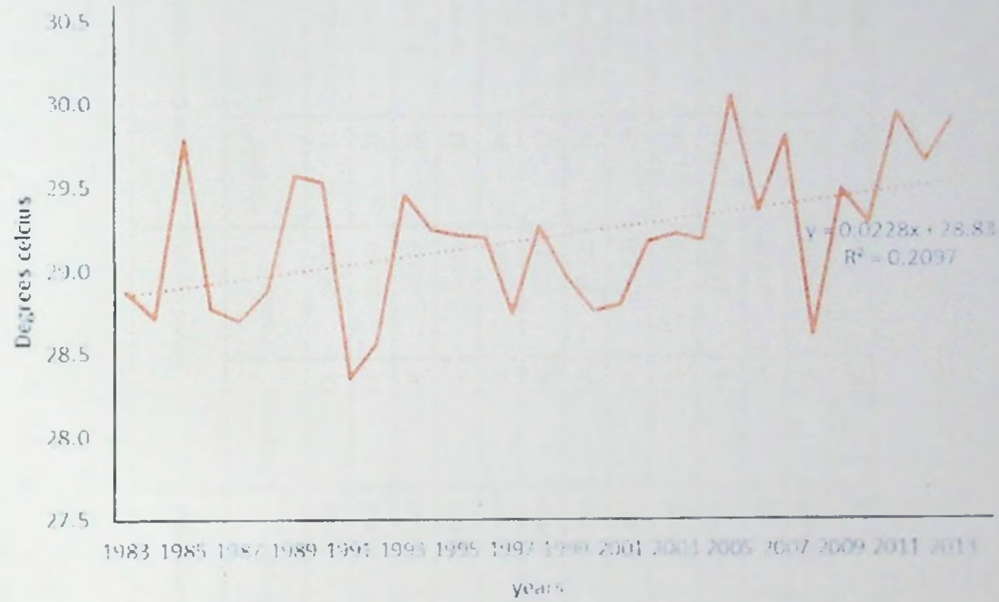

Figure 18: Maximum Temperature trend for Same (1983-2013)

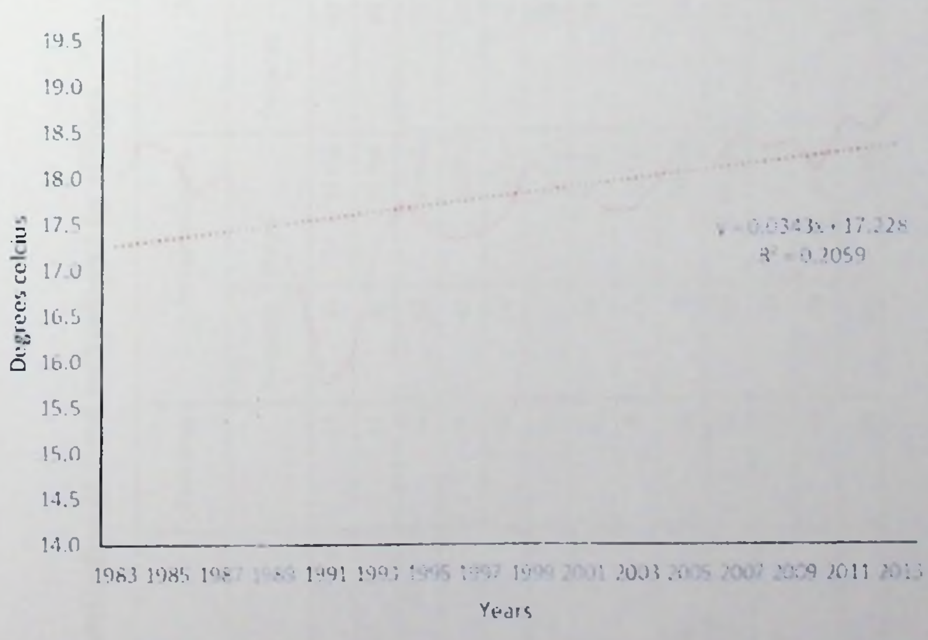

Figure 19: Minimum Temperature trend for Same (1983-2013)

Appendix 5: Distribution of farm technologies by villages

sn	villages	Farm plots	Inorganic fertilizer		Improved seeds		Intercropping		Animal manure		Soil Water Conservation	
			Frequency	Precent	Frequency	Precent	Frequency	Precent	Frequency	Precent	Frequency	Precent
1	Samaria	53	20	37.736	30	56.604	13	24.528	13	24.528	21	39.623
2	Mijongweni	55	31	56.364	40	72.727	23	41.818	11	20.000	21	38.182
3	Njoro	49	15	30.612	24	48.980	15	30.612	20	40.816	28	57.143
4	Mabilioni	50	14	28.000	23	46.000	13	26.000	18	36.000	23	46.000
5	Ghona	73	40	54.795	42	57.534	20	27.397	18	24.658	26	35.616
6	Mafuleta	48	15	31.250	21	43.750	11	22.917	16	33.333	17	35.417
7	Kwagunda	51	14	27.451	19	37.255	12	23.529	15	29.412	18	35.294
8	Boza	47	12	25.532	17	36.170	10	21.277	17	36.170	19	40.426
9	Kigurusimba	42	8	19.048	16	38.095	8	19.048	8	19.048	18	42.857
10	Mareu	64	40	62.300	42	65.625	28	43.750	15	23.438	14	21.875
11	Kimashuku	73	49	67.123	62	84.932	31	42.466	12	16.438	24	32.877
12	Sambarai	77	48	62.538	55	71.429	35	45.455	13	16.883	28	36.364
	Total	682	306	44.868	391	57.331	219	32	176	25.81	257	37.683

Appendix 6: Collinearity statistics for variables in the multinomial endogenous switching regression model

	Plot size (in hectares)	Distance to the farm plot in walking minutes	Household head education (years)	Distance to the input market (km)	Distance to the input market (km)	Access to extension services (=1 if yes)	Information on climate change (=1 if yes)	Household asset index	Access to credit (=1 if yes)	Coefficient of variation of rainfall (1983-2013)	Rainfall satisfaction index	raifall patterns
Plot size (in hectares)	1											
Distance to the farm plot in walking minutes	-0.0835	1										
Household head education (years)	-0.0926	0.0509	1									
Distance to the input market (km)	0.1493	-0.024	-0.1922	1								
Distance to the input market (km)	-0.043	0.0833	-0.0544	-0.0419	1							
Access to extension services (=1 if yes)	0.0092	-0.0153	-0.0078	0.032	0.0069	1						
Information on climate change (=1 if yes)	0.0276	0.0423	-0.0148	-0.0182	-0.0835	-0.0786	1					
Household asset index	-0.1206	-0.0278	-0.0847	0.239	0.1222	-0.0087	-0.0319	1				
Access to credit (=1 if yes)	-0.0239	0.0319	0.0514	0.0679	0.0551	0.0008	-0.0782	0.1677	1			
Coefficient of variation of rainfall (1983-2013)	-0.0051	0.0636	-0.0175	-0.0136	0.0737	-0.1183	0.0111	0.103	0.0732	1		
Rainfall satisfaction index	-0.0848	0.0224	-0.0109	0.039	-0.0189	-0.0555	-0.0058	0.1854	0.0784	0.1632	1	
raifall patterns	-0.0225	0.0198	-0.0242	0.0996	0.006	-0.0056	0.0362	0.1826	0.0313	0.0836	0.1958	1

Appendix 7: Variance inflation factors for the variables in the Multinomial Endogenous switching regression model

Variables	VIF	1/VIF
Plot size (in hectares)	1.16	0.861
Distance to the farm plot in walking minutes	1.16	0.864
Household head education (years)	1.07	0.934
Distance to the input market (km)	1.06	0.942
Distance to the input market (km)	1.05	0.953
Access to extension services (=1 if yes)	1.05	0.955
Information on climate change (=1 if yes)	1.04	0.963
Household asset index	1.03	0.970
Access to credit (=1 if yes)	1.03	0.975
Coefficient of variation of rainfall (1983-2013)	1.02	0.977
Rainfall satisfaction index	1.02	0.979
rainfall patterns	1.02	0.980
Mean VIF	1.06	

Appendix 8: Multinomial endogenous switching regression estimates of the selection bias correction terms

Selection bias correction terms	Inorganic fertilizer	Improved seeds	Inorganic fertilizer +	intercroppin g	SWC	Manure	Adoptioj=0
m(pi1)	0.022 (0.028)	-0.094 (0.068)	-0.033 (0.056)	-0.057 (0.014)	0.005 (0.023)	-0.301 (0.007)**	0.005 (0.015)
m(pi2)	0.259 (0.05)*	0.522 (0.368)	-0.074 (0.133)	0.183 (0.039)	0.123 (0.072)	-0.033 (0.021)	0.086 (0.035)
m(pi3)	0.342 (0.003)	-0.009 (0.017)	-0.008 (0.008)	0.005 (0.001)	0.024 (0.004)	0.712 (0.001)	0.021 (0.002)
m(pi4)	0.023 (0.015)	0.197 (0.141)	-0.017 (0.042)	0.073 (0.010)***	0.121 (0.017)	-0.003 (0.004)	-0.011 (0.011)
m(pi5)	-0.104 (0.136)	0.576 (0.337)	-0.106 (0.321)	0.202 (0.105)	0.195 (0.172)	0.011 (0.06)	-0.045 (0.095)**
m(pi6)	0.039 (0.029)	-0.156 (0.086)*	0.065 (0.073)	-0.014 (0.024)	-0.015 (0.035)	0.764 (0.012)	0.038 (0.021)
m(pi7)	0.008 (0.003)*	0.019 (0.028)	0.005 (0.008)	0.002 (0.002)	-0.018 (0.005)	0.096 (0.001)	-0.007 (0.002)
constant	11.064 (0.189)	5.365 (0.55)	.3.842 (0.554)	-0.125 (0.119)	0.367 (0.286)	2.236 (0.068)	6.016 (0.134)
Wald test on instrumental variables ($\chi 2$)	0.0393**	0.319*	0.0192**	0.0265*	0.145	0.021*	0.132

Note: m(Pij) refers to the correction term described in equation (6a). Bootstrapped standard errors in parentheses. Sample size: 682 plots. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level.

Appendix 9: Collinearity statistics and Variance inflation factor for variables in the Just and Pope production function

Collinearity statistics for variables in the Just and Pope production function

	Inorganic fertilizer	Improved seeds	Manure	Precipitation	Legumes intercropping	Soil water conservation	Altitude
Inorganic fertilizer	1						
Improved seeds	0.1926	1					
Manure	0.1014	0.0039	1				
Precipitation	0.0929	0.131	0.0589	1			
Legumes intercropping	0.1244	0.0433	0.0393	0.0253	1		
Soil water conservation	-0.0704	-0.0279	-0.0132	-0.0152	0.0365	1	
Altitude	0.0311	0.0033	0.0477	0.0643	0.0329	-0.0569	1

Results of the Variance inflation factor for the Just and Pope Regression model

Variable	VIF	1/VIF
Inorganic fertilizer	1.07	0.931
Improved seeds	1.07	0.936
Manure	1.07	0.938
Precipitation	1.04	0.961
Legumes intercropping	1.03	0.968
Soil water conservation	1.03	0.974
Altitude	1.03	0.974
Mean VIF	1.05	

Appendix 10: Elasticity estimates for the mean and variance in function

Elasticity Estimates from the mean function[11]

Independent variables	Higher rainfall	Moderate rainfall	Lower rainfall	Overall sample
Inorganic fertilizer	0.41	0.635	0.138	0.452
Improved seeds	0.164	0.384	0.578	0.409
Manure	0.11	0.126	0.297	0.278
Legumes intercropping	0.129	0.046	-0.01	0.022
Soil water conservation	0.183	0.302	0.313	0.26
Precipitation	0.201	0.447	0.296	0.215
Altitude	0.031	0.087	0.023	0.047

Elasticity Estimates from the variance function[12]

Independent variables	Higher rainfall	Moderate rainfall	Lower rainfall	Overall sample
Inorganic fertilizer	-0.030	-0.005	0.028	-0.011
Improved seeds	-0.091	0.334	-0.439	0.228
Manure	-0.005	-0.072	0.055	-0.007
Legumes intercropping	-0.033	-0.007	0.117	0.047
Soil water conservation	-0.019	-0.129	-0.054	-0.019
Precipitation	-0.064	-0.477	-0.599	-0.337
Altitude	0.025	0.013	-0.036	0.001

[11] Ej = $\frac{(\delta y)}{\delta x_j}\frac{(x_j)}{y}$ is the output elasticity with respect to input j

[12] VEj = $\frac{(\delta \operatorname{var} y)}{(\delta x_j)}\frac{(x_j)}{(\operatorname{var} y)}$ is the output variance elasticity with respect to input j

Appendix 11: Questionnaire

Identification Particulars

Date of interview: ....Time: Start............... Finish.........................

Respondent's number: ....Enumerator's name: ....

Name of Village..Name of Ward ....

Name of Division................................Name of District.......................................

Name of Region.................................

Section 1: Household Characteristics and Occupation:

1.1.1. Please State your relationship to the head of Household of the farm: (*Put a tick(√) in the space provided*)

(1) Head of Household [ ]; (2) Husband [ ]; (3) Wife [ ]; (4) Child [ ];

(5) Grandchild [ ]; (6) Manager/order proxy for owner [ ].

1.1.2. How many are you in your household? .... Members.

1.1.3. Household characteristics(*Put a number of the respondent response in the space provided*)

Household member	Gender: 1. Male 2. Female	Age (years)	Marital Status	Education (years)
Key: 1. Household head 2. Wife 3. Husband 4. Child, Uncle 5. Cousin 6. Others specify			**Key:** 1.Married 2.Never married 3.Separated/divorce 4.widowed	

1.2 Household occupation:

1.2.1 What is the primary occupation of your household?

(1) Agriculture-crop farming only [ ]; (2) Agriculture-livestock farming
(2) only [ ]; (3) Mixed farming-crop and livestock farming [ ]; (4)
(3) Non agriculture (non-farm activities) only [ ]; (5) Both
(4) Agriculture and non-farm [ ], (6) Other specify ....

Section 2: Household Understanding about Climate Change

2.1. How many years have you lived in this area?(*Put a tick(√) in the space provided*)

(1) Less than one year [ ]; (2) 1-10 years [ ]; (3) 11-20 years [ ]; (4) 21-30 years [ ]; (5) 31-40 years [ ]; (6) over 40 years [ ].

2.2. Before this interview, had you heard about climate change?(*Put a tick(√) in the space provided*) *(Enumerator: explain in case the terms are unfamiliar to interviewee)*

(1) Yes [ ]; (2) No [ ]; (3) Don't know [ ].

2.3. If the answers in Yes in 2.2 can you explain what have you heard about the physical effects of climate change?

1. ....
2. ....
3. ....
4. ....
5. ....

2.4. What is the frequency of physical effects of climate change extremes you mentioned in 2.3 above over past 10 years in this area?

S/N	Climate change effect	Frequency
1		
2		
3		
4		
5		

If the answer is yes in 2.2, ask the respondent more about the trends of climate change in the area as follows.

2.5. What has been the trend of rainfall (or precipitation) in the area over the past 10 years? (*Put a tick (√) in the space provided*)

1. Decreases [ ]; 2. Increases [ ]; 3. Fluctuate (increase and decrease) [ ] 4. Don't see any change [ ].

2.6.1 What has been the trend of temperature in the area over the past 10 years? (*Put a tick (√) in the space provided*)

1. Decreases [ ]; 2. Increases [ ]; 3. Fluctuate (increase and decrease) [ ] 4. Don't see any change [ ].

2.6.2 What has been the intensity of rainfall?

(1) High rain for a very short time [ ] (2) low rain for a long time [ ] (3) low rain for a very short time [ ] (4) I don't see any change [ ]

2.7 Have you noticed any change of type, planting period and yield of the crops used to be cultivated in this area ten years ago because of change in the trend of rainfall (or precipitation) and temperature?

(*Put a tick (√) in the space provided*)

1. Yes [ ]; 2. No [ ].

2.8 With reference to the past three years indicate the availability of rainfall during growing season

S/N	During the growing season preceding the last main harvest	Codes	Recorded into	
	Did the rainfall come on time?	1=on time; 2=too early; 3=too late	On time Others (2 and 3)	1 0
	Was there enough rain on your fields at the beginning of the rainy season?	1=enough; 2=too little; 3=too much	Enough Others (2 and 3)	1 0
	Was there enough rain on your fields during the growing season?	1=enough; 2=too little; 3=too much	Enough Others (2 and 3)	1 0
	Did the rains stop on time on your fields?	1=on time; 2=too late; 3=too early	On time Others (2 and 3)	1 0
	Did it rain near the harvest time?	1 = no; 2 = yes No Others (2)		1 0
	Number of rainfall days	1=No change; 2=Reduced; 3= Increased	No change Others (2 and 3)	1 0
	Frequency of heavy rains	1=No change; 2=Reduced; 3=Increased	No change Others (2 and 3)	1 0
	Frequency of dry spells	1=No change; 2=Reduced; 3=Increased	No change Others (2 and 3)	1 0
	Duration of the growing season	1=No change; 2=Reduced; 3=Increased	No change Others (2 and 3)	1 0

Section 3: Household adaptation/copping strategy climate change to risk of climate change

3.1 Below is a series of statements pertaining to sources of farm risks. Indicate which most accurately reflects how important the risks are to your farming operation

	How important are the following risks to your farming operation?	Extremely important	Important	Somewhat important	Not important
1	Risk from deficiency in rainfall causing drought				
2	Risk from excess rainfall				
3	Risk from natural disasters such as heat, fire, flood, storm				

4	Risk from diseases and pests that affect plants and animals				
5	Risk from unexpected variability of yields				
6	Risk from unexpected variability of product prices				
7	Risk from unexpected variability of input prices				
8	Others				

3.2 Below is a series of statements pertaining to farm risk management options. Please tick which most accurately reflects the importance of risk management options in managing your farm operational risks. Please also circle YES if you use the risk management option and NO if you do not use it.

	How important are the following risk management option in your farm operation	Extremely important	Important	Somewhat important	Not important	(1)Yes (2) No
(i)	Having diversified crop farm					
(ii)	Planting several varieties of crops					
(iii)	Apply pests /herbicides					
(iv)	Selection of crop varieties which mature faster					
(v)	Aplication of inoeganic fertilizer					
(vi)	Irrigation					
(vii)	Selection of crop varieties with low price variability					
(viii)	Spreading sale over several time period					
(ix)	Land management practices					
(x)	Othes (specify)					

3.3 How do you get to know that the options you select and adopt (as listed in the table in question (3.2) are good to support you to adapt with the changes? (Please tick as appropriate)

S/N	Source of information	
(i)	Television	
(ii)	Community Meetings	
(iii)	Family embers	
(iv)	The radio	
(v)	Agriculture Extension Officers	
(vi)	Neighbours	
(vii)	Newspapers	
(viii)	Traditional and cultural knowledge	

3.4 What type of information do you think you need most to increase your ability to adapt to climate change impacts?

(i) ....

(ii) ....
(iii) ....
(iv) ....
(v) ....

3.5 In everything you have been doing to cope with short term climatic (temperature and rainfall or precipitation) variations, what has been the main constrains for making necessary adjustments within and between seasons?

(i)..
(ii)..
(iii)..
(iv)..
(v)..

3.6 Has this household, at any time since 2010, due to local food shortages, received support in form of Public food relief? (1) Yes (2) No

3.7 When was the last time the household received food relief? .... (Year)

Section 5: KNOWLEDGE ON AGRICULTURAL TECHNIQUES

5.1 Which of the following agricultural techniques do you have enough knowledge about to be able to practice? (Whether you do practice them or not is not relevant in this question, we will return to that below)

S/N	Agricultural techniques	(1)Yes (2) No	S/N	Agricultural techniques	(1)Yes (2) No
(i)	Crop rotation		(ix)	Chemical fertilizer	
(ii)			(x)	Soil and water conservation (level bunds, grass strips, terracing etc.)	
(iii)	Intercropping with nitrogen fixing crops (beans etc.)		(xi)	Rain water harvesting	
(iv)	Animal manure		(xii)	Irrigation	
(v)	Manure		(xiii)	Others (specify	
(vi)	Pesticides/herbicides				
(vii)	Agroforestry				
(viii)	Others				

Below is a series of statements pertaining to farm technologies. Indicate their importance to your farming operation

S/N	Statements	Inorganic fertilizer	Improved maize seed varieties	Legumes intercropping with maize	Soil water conservation	Animal manure
(i)	Have high labour requirement					
(ii)	They damage the environment					

(iii)	They do not conform to land tenure system					
(iv)	No much difference between using/not using this tech on yield (Does not increases productivity)					
(v)	They are usually more time consuming					
(vi)	It requires more capital outlay					
(vii)	is not efficient in mitigating climate change effects					
(viii)	Is not compatible with other practices in place					
(ix)	If my neighbor seeks my opinion on increasing his farm income. I will definitely advise him to this technology					
(x)	This technology fist need to be proved at other farms in my village					
(xi)	They require regular contact with extension workers					

2.12 Have you used legume intercropping maize in maize farming? 1. Yes [ ]
2. No [ ].

2.11 What are the main reasons for intercropping maize with legumes?
(i) ....
(ii)..
(iii)..
(iv)..
(v)Others, specify

2.12 Have you ever used inorganic fertilizer in maize farming? 1.Yes [ ];
2. No [ ].

2.11 What are the main reasons for inorganic fertilizer maize with other food crops?

(i) ....
(ii)..
(iii)..
(iv) Others, specify

2.13 Have you ever used improved seed in your maize farming activities? Yes [ ]; 2. No 2.11 What the main reasons are for improve maize seed varieties with other food crops?

(i) ....
(ii)..
(iii)..
(iv)Others, specify

2.15 What is the main reason for not using inorganic fertilizer in your plot?
(i) ....
(ii)..
(iii)..
(iv) Others, specify

2.16 What is the main reason for not using improved maize seed varieties in your plot?
(i) ....
(ii)..
(iii)..
(iv) Others, specify

Section 4: Household Land Utilisation

4.1 Does your household own land?

(1) Own [ ]; (2) Rent only [ ]; (3) Own and rent some [ ].

4.2 If your answer is (2) or (3) in 4.1 above, how much have you paid for renting land during the last season (cropping season). ....TSh

4.3 How long have you been growing maize? ....years

4.4 Maize crop production

4.4.1: Question on land/plot used to plant maize

M1:Parcel/plot number	M2:Size (acres)	M3:Soil quality 1=good 2=medium 3=poor	M4: What kind of improvements does this plot have 1=rock bunds 2=soil bunds 3=mulching 4=terraces 5=others 6=none	M5: How was the land prepared last year? 1=by hand 2=by animal traction 3=by tractor 4=others	M6:How was the land cultivate this year? 1=by hand 2=by animal traction 3=by tractor 4=others	M7:Which crop did you grow in the past 3 years	M8: What is the walking distance from your home to the plot	M9: Which variety of maize planted	M10:Which month did you planted maize	M11: Did you intercrop maize with other crop? 1=yes 2=no	M12:In case of intercropping, specify crop and moment of planting
P1											
P2											
P3											
P4											

4.4.2: Question on maize crop produced

Parcel/plot number	M13:Rainfall received in plot this year compared to normal in the past 1=below normal 2=Normal 3=Above normal	M14:Crop damage due to pest/insect/crop disease 1=none 2=little 3=a lot	M15:What is the general slope of the parcel 1=very steep 2=gentle 3=flat	M16:Irrigated 1=yes 2=No	M17:If yes state the type of irrigation 1=gravitational 2=river by pump 3=ground water by pump 4=other	M18:Which month did you harvested maize	M19:How much produce? (kg)	M20:Price/kg(Tsh)	M21:GPS Coordinates
P1									
P2									
P3									
P4									

4.4.3: Household Labour input used in maize production

Parcel/plot	Labour	Where any members of your household involved in						Did you hire in labour outside the household to work on					
		M22:How many household members			M23:How many days in total were member of your household worked			M24:Total number of days worked			M25:Total payment in kind and in cash		
		(1)Planting and land preparation	(2)weeding	(3)Harvesting(including basic processing and storage)	(4)Planting and land preparation	(5)weeding	(6)Harvesting(including basic processing and storage)	(7)Planting and land preparation	(8)weeding	(9)Harvesting(including basic processing and storage)	(10)Planting and land preparation	(11)weeding	(12)Harvesting(including basic processing and storage)
P1	Male												
	Female												
	Children<18												
P2	Male												
	Female												
	Children<18												
P3	Male												
	Female												
	Children<18												
P4	Male												
	Female												
	Children<18												

M24: (8): How many times did you do weeding?
When did you do the weeding?

4.4.4 Non labour inputs

How many of the following labour inputs did your household used in the last cropping season *(please fill the table as per corresponding question)*

Parcel/plot	M26:Type/variety of seeds used	M27:amount of seed in Kg	M28:Price of seed/kg	M29:Organic fertilizer/manure used 1=yes, 2=no	M30:Type of chemical fertilizer used						M31:Pesticide used		M32:Irrigation 1=Yes 2=No	M33:Irrigation cost (Tsh)
					UREA (kg)	price/kg	NPK	price/kg	MRP(minjingu)	price/kg	amount	Price		
P1														
P2														
P3														
P4														

4.4.5 Did you receive input subsidy distributed by the government during planting season? 1=Yes, 2=No

4.4.6 If yes specify the type of subsidy and amount received...

4.4.7 Maize marketing conditions

4.4.7.1 Did you sell any Maize during the last season? (1) Yes (2) No

4.4.7.2 What was the total amount of Maize sold .... Kg

4.4.7.3During the last season cropping season (2013), did you experience any post-harvest loss in maize seeds? (1) Yes (2) No

4.4.7.4 If experience post-harvest loss in maize seeds what was the main cause? ....

4.4.7.5 What is your main market outlet/crop depot for Maize? (1)*At farm gate, (2)In the village market,(3)In market outside the village*

4.4.8 How many parcels of land did you operate for other main food crop production?

C1:Parcel/plot number	C2:Size (acres)	C3:Soil quality 1=good 2=medium 3=poor	C4:What is the general slope of the parcel 1=very steep 2=gentle 3=mostly flat	C5:What kind of improvements does this plot have 1=rock bunds 2=soil bunds 3=mulching 4=terraces 5=ridges 6=others 7=none	C6:How was the land prepared last year? 1=by hand 2=by animal traction 3=by tractor 4=others	C7:How was the land prepared this year? 1=by hand 2=by animal traction 3=by tractor 4=others	C8:Irrigated 1=yes 2=No	C9:If yes state the type of irrigation 1=gravitational 2=river by pump 3=ground water by pump 4=other	C10:What is the walking distance from your home to the plot	C11:Type of cultivation 1=monocro 2=mixed crop
P1										
P2										
P3										
P4										

4.4.9 For each parcel answer the following questions regarding other crops cultivated

Parcel/plot number	C12:Crop code (if mixed. repeat parcel number and list different crop)	C13:Plot Size (acres)	C14:Rainfall received in plot this year compared to normal in the past 1=above normal 2=around normal 3=below normal	C15:Onset of rainfall compared to normal 1=too early 2=normal 3=too late	C16:End of rainfall compared to normal 1=too early 2=normal Too late	C17:Pest cide used/ 1=yes 2=no	C18:Crop damage due to pest/insect/crop disease 1=none 2=little 3=a lot	C19:Organic fertilizer used/manure 1=yes 2=No	C20:Chemical fertilizer used (kg)	C21:Seeds used 1=traditional 2=Improved	C22:How much did you produce?(kg)
P1											
P2											
P3											
P4											

Section 6: Other assets (Household physical assets ownership i.e. Household house, farm machinery and inputs)

6.1.1 Does your household own a house?

(1) Yes [ ]; (2) No [ ].

6.1.2 If the answer is Yes in 5.2.1, would you explain the type of the house your household is owning (*refer to the wall of the house*)

(1) Mud house [ ]; (2) Stick and Mud [ ]; (3) Burnt bricks [ ]; (4) Cement blocks [ ]; (5) Wood [ ]; (6) others specify [ ].

6.1.3 Would you also explain the type of roofing material used in the house your household is owning

(1) Tiles, concrete, or cement [ ]; (2) Galvanized ion or asbestos [ ]; (3) Bamboo or wood [ ]; (4) Mud [ ]; (5) grass [ ]; (6) others specify [ ].

6.1.4 If the answer is No in 5.2.1 above would you explain the type of the house your household is renting (*refer to the wall of the house*)

(2) Mud house [ ]; (2) Stick and Mud [ ]; (3) Burnt bricks [ ]; (4) Cement blocks [ ]; (5) Wood [ ]; (6) others specify [ ].

6.1.5 Household tools, farm tools, machinery, and implements ownership (*fill in the table below*).

	Type	**(1) YYes (2) No**
1	Wired electricity/power	
2	Mobile or fixed telephone	
3	Diesel power generator or similar	
4	Water pipe to house	
5	TV-set	
6	Radio	
7	Bicycle	
8	Sewing machine	
9	Kerosene stove or other modern stove	
10	Motor vehicle	
11	Motor cycle	
12	Solar energy	
13	Biogas	
15	Structures for rain water harvesting	
16	Ox-plough	
17	Diesel pump for irrigation/domestic water use	
18	9.Trator	
19	10.Plough	
20	12.Thresher	

6.2 Livestock ownership

6.2.1 Does your household own livestock, poultry or other farm animal?

(1). Yes [ ]; (2). No [ ].

6.2.2 If the answer is Yes in 5.3.1 above, please fill the table below and if is no proceed to section 6

Type of livestock	Number		Price/animal	Total value (Tsh)
	Local	Improved		
Cattle				
Goat				
Sheep				
Pig				
Poultry				
Others (specify)				

6.2.3 Does your household produce and sell livestock, poultry or other animal products?

(1). Yes [ ]; (2). No [ ].

6.2.4 If the answer is Yes in 5.3.3 above, please specify the products which your household produce from livestock, poultry or other farm animal, sell and their value in the table below:

Own livestock products	Quantity for own use(kg/year)	Quantity sold(kg/year)	Price per unit	Total value (Tsh)
1.Milk product				
2.Meat(slaughtering)				
3.Sheep				
4.Goat				
5.Chicken				
6.Eggs				
7.Leather				
8.Others(please specify)				

Section 7: Household non-farming activities

7.1.1 Does your household engage in non-farming activities?
(1).Yes [ ]; (2).No [ ].

7.1.2 If yes, can you explain why your household is engaging in non-farming activities?
1. ....
2. ....

7.1.3 Please mention the activity or activities you or your household is engaged, the time spent (in hours/day) and how much do you get?

S/N	Activity	Time spend (hrs/day)	Number of days spent in a week	Number of hours spent in 12 months	Wage/day	Wage/hour	Total income in 12 months
1							
2							
3							
4							
5							
6							

7.1.2 Household other sources of income

7.2.1 Did your household borrowed from any of the following sources for financing farming or any other activity over the last 12 months?

Source	Borrowed from (1. Yes 2. No)	Amount received (Tsh)	Interest rate/year	Repayment over how many months/ years
1.Relatives/ friends				
2. Farmer associations/ cooperatives				
3. commercial banks				
4 Other (specify)				

Section 8: Household access to extension services

Please fill the table below the information about extension services your household received over the past 12 months:

	1. Yes; 2. No
8.1. Do you get advice and information from extension workers?	
8.2. How many times do they visit you per year?	
8.3. Do you pay for receiving extension advice?	
8.4. If yes in 8.3, how much does your household pay per visit? (TSh)	
8.5. The extension officials who visit/contact you are from which organization?	
KEY 1. Government agency;2. Agriculture research station;3. NGO 4. Other (please specify)	

Appendix 12: Check list for focus group discussion

1. Name of the village..
2. Total number of farmers in the village...
3. Have you heard about climate change?

....
....
....
....

4. Physical effects of climate change in the village

....
....
....
....

5. Trend in rainfall for the past 30 years in the village? (Increasing/decreasing)

....
....
....
....

6. If there is there any change in planting period of various crops in the village

....
....
....
....

8. Any occurrence of food shortage in the village for the last ten 10 years

....
....
....
....

9. Is drought common in the village?

....
....
....
....

10. Planting seasons for maize crops in the village (Mention the seasons and date)

....
....
....
....

11. Planting dates of maize in the village (approx) for the main season

....
....
....
....

12. Common maize seed varieties/types used in the village
....
....
....
....
13. Intercropping maize with other food crops
....
....
....
....
14. Farm management practices done in response to unreliable weather
....
....
....
....
15 Irrigation activities in maize farms
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....
....
....
16. Types of chemical fertilizer frequently applied in maize farms (and how many times chemical fertilizer is applied e.g during planting, after weeding)
....
....
....
....
17. Use of animal manure in maize farms
....
....
....
18. Availability of subsidy (Ruzuku e.g fertilizes, seeds etc and their types) in the village
....
....
....
19. Availability of extension officers in the village
....
....
....
20. What should be done to improve maize production in the village
....
....
....