# CLIMATE CHANGE IMPACTS, VULNERABILITY AND INSURANCE IN MALAWI'S SMALLHOLDER AGRICULTURE

**DOCTOR OF PHILOSOPHY (ECONOMICS) THESIS**

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**UNIVERSITY OF MALAWI**

**MARCH 2022**

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**By**

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## DECLARATION

I, Assa Mulagha-Maganga, declare that this thesis is a result of my own original effort and work and that, to the best of my knowledge, the findings have never been previously presented to the University of Malawi or elsewhere for the award of any academic qualification. Where other sources of information have been used, it has been accordingly acknowledged.

**Assa Mulagha-Maganga**

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**Signature**

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**(Day/Month/Year)**

## CERTIFICATE OF APPROVAL

The undersigned, certify that this thesis represents the student's onw work and effort. Where he has used other sources of information , it has been dully acknowledged. This thesis has been submitted with our approval.

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**Second Supervisor**

## DEDICATION

Memory, Tobin and Reyan

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## ABSTRACT

The study seeks to understand the dynamics of climate impact on crop agriculture, with each chapter addressing a specific topic related to the theme. Chapter 2 examines the current and simulates future economic impacts of climate change on Malawi's smallholder agriculture using Ricardian analysis based on a three-year panel (2010, 2013, 2016) for World Bank's Living Standards Measurement Survey (LSMS) data from 3,531 farming households. The results reveal that more warming negatively affects agriculture returns on the one hand. In contrast, more precipitation generates gains on the other hand. Simulation reveals that global warming impacts will be more critical than precipitation change. With strategic climate adaptation choices. Chapter 3 assesses the magnitude of climate-induced vulnerability to expected poverty among farming households and how climate change shocks relate to ex-post poverty and poverty transition. Vulnerability is strongly associated with short-run climate stresses and less so with long-run climate-related shocks. The effects of vulnerability on actual poverty lessen with time in the long run. Similarly, climate-related stresses worsen the welfare of farming households. The result underscores the importance of livestock in buffering against poverty. Chapter 4 establishes farmers' willingness to pay for weather index insurance for a staple food crop using a contingent valuation experiment. Using data from 10 districts in Malawi, estimates of willingness-to-pay are in the range of US$5.5 to US$15 per hectare per cropping season. At the infancy stage, government subsidies for insurance premiums and linkage of premium payments to Village Savings Groups will be crucial.

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## LIST OF ABBREVIATIONS AND ACRONYMS

| | |
|---|---|
| BCCR_BCM2_0 | Bjerknes Centre for Climate Research, Norway, BCM2.0 Model |
| CCCMA_CGCM3_1 | Canadian Centre for Climate Modelling and Analysis, CGCM3.1 Model, T47 resolution |
| CDF | Cumulative Density Function |
| CGE | Computable General Equilibrium |
| CMIP3 | Coupled Model Intercomparison Project 3 |
| CNRM_CM3 | Meteo-France, Centre National de Recherches Meteorologiques, CM3 Model |
| CRRA | Constant Rate of Risk Aversion |
| CSA | Climate Smart Agriculture |
| CSIRO_MK3_5 | CSIRO Atmospheric Research, Australia, Mk3.5 Model |
| DT | Drought Tolerance |
| EAs | Enumeration Areas |
| FAO | Food and Agriculture Organization |
| GCMs | Global Circulation Models |
| GDP | Gross Domestic Product |
| GFDL_CM2_0 | NOAA Geophysical Fluid Dynamics Laboratory, CM2.0 Model |
| GFDL_CM2_1 | NOAA Geophysical Fluid Dynamics Laboratory, CM2.1 Model |
| GLS | Generalized Least Squares |
| GTAP | Global Trade Analysis Project |
| IHPS | Integrated Household Panel Survey |
| IHS4 | Integrated Household Survey |

| | |
|---|---|
| INGV_ECHAM4 | INGV, National Institute of Geophysics and Volcanology, Italy, ECHAM 4.6 Model |
| INMCM3_0 | Institute for Numerical Mathematics, Russia, INMCM3.0 Model |
| IPCC | Intergovernmental Panel on Climate Change |
| IPSL_CM4 | IPSL/LMD/LSCE, France, CM4 V1 Model |
| LMSM | Living Standards Measurement Survey |
| MIRAGE | Model for Integrated Research on Atmospheric Global Exchanges |
| MIROC3_2_MEDRES | CCSR/NIES/FRCGC, Japan, MIROC3.2, medium resolution |
| MIUB_ECHO_G | Meteorological Institute of the University of Bonn, ECHO-G Model |
| ML | Maximum Likelihood |
| MLM | Multinomial Logit Model |
| MPI_ECHAM5 | Max Planck Institute for Meteorology, Germany, ECHAM5 / MPI OM |
| MRI_CGCM2_3_2A | Meteorological Research Institute, Japan, CGCM2.3.2a |
| NSO | National Statistical Office |
| PDF | probability density function |
| SRES | Special Report on Emissions Scenarios |
| SSA | Sub-Saharan Africa |
| TE | Technical Efficiency |
| TERM | The Enormous Regional Model |
| TEV | Total Economic Value |
| UKMO_HadCM3 | Hadley Centre for Climate Prediction, Met Office, UK, HadCM3 Model |

| | |
|---|---|
| UKMO_HadGEM1 | Hadley Centre for Climate Prediction, Met Office, UK, HadGEM1 Model |
| UNFCCC | United Nations Framework Convention on Climate Change |
| VEP | Vulnerability as expected poverty |
| VER | Vulnerability as uninsured exposure to risk |
| VEU | Vulnerability as low expected utility |
| VIF | Variance Inflation Factor |
| VSLAs | Village Savings and Loans Associations |
| WTA | Willingness to Accept |
| WTP | Willingness to Pay |

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# CHAPTER 1

# INTRODUCTION

## 1.1 General Overview

In rain-fed agricultural communities, climate change has substantial impacts on agriculture output. Optimal climate conditions for dry-land crop production, including the proper amount of warming and rainfall during the production cycle, are critical factors for agriculture outcomes. The emerging literature on climate change hot spot analysis predicts increases in warming of 2ºC to 3ºC by 2050 and a general decline in rainfall and water availability (UNFCCC 2006). It is projected that these changes will affect food and water resources that are critical for livelihoods (Hassan and Nhemachena 2008). The developing regions like Sub-Saharan Africa (SSA) has been dominated by countries whose economies heavily rely on rain-fed agriculture for employment and food security (Livingston, Schonberger and Delaney 2011). Given the importance of the contribution of the agriculture sector to the national economy and people's incomes and consumption, climate impacts on crop production will have negative livelihood outcomes for smallholder farmers (Chalise, et al. 2017)

There is also a large body of literature providing evidence that southern Africa is vulnerable to climate change. However, few rigorous studies have focused on the economic impacts of climate change on agriculture (Mutsvangwa, 2011; Jain, 2007; Gbetibouo & Hassan, 2005). Methodologies used in most of these studies are restrictive. Thus, one of the objectives of this study is to measure the current and future economic impact of climate change on smallholder agriculture. In this regard, this study makes two key contributions to literature. First, it attempts to quantify the economic impacts of climate change on agriculture by focusing on Malawi in Southern Africa. The second contribution is methodological. It modifies the Ricardian model for the estimation of impacts while taking care of farm-level technical inefficiencies.

It is believed that the effects of climate-related extreme events on the economic lives of farming households have intensified in recent years, most significantly due to global warming (Barnett and Mahul 2007), in turn exposing farmers to poverty-related vulnerabilities. The need arises to understand the nature and extent of vulnerability to the climate impacts on farming households in general to aid documentation and packaging of practical and workable adaptation strategies to mitigate negative climate change impacts. Climate variability will relay greater vulnerability on most of the farmers in developing countries, not because the level of climate variability is high, but because of over-dependence on rain-fed agriculture. Despite this importance, studies on the vulnerability of farming households to climate change are limited in the tropics. For Africa in general, a few studies have assessed the vulnerability of households to climate shocks (Mansour and Hachicha 2014, Dercon 2004, Dercon 2005, Hoddinott and Quisumbing 2003). While these studies are informative, their coverage is limited to a few countries. The second objective of this study is, therefore, to examine farmers vulnerability to poverty under climate-induced stresses in Malawi.

Given the intensity of climate-related shocks, agriculture risk management is becoming a contemporary issue as variability in climate is predicted to worsen in the future, which will pose further increasing uncertainties on agriculture output and performance of the agriculture sector in general (Antón, et al. 2013). In developing countries, weather index crop insurance has emerged as one potential sustainable risk management strategy for farmers that transfers climate triggered risks from farmers to insurance brokers (Barnett and Mahul 2007). It is a better option than traditional crop insurance because it reduces the risk of adverse selection and moral hazard. Therefore, the provision of index-based crop insurance to farmers could be a sustainable risk management strategy that can cushion or offer long-run income growth for farmers in low-income countries (Cole, et al. 2013). As efforts to help farmers to manage climate risks through subscription to weather index insurance are in infancy, an initial understanding of the farmers' willingness to pay a premium for index insurance services is a first step to shape proper packaging of the weather index policy. Thus, the last objective of this study is to elicit farmers' willingness to pay for weather index insurance in Malawi for maize crop.

## 1.2 Organization of the Thesis

This thesis is organized into five chapters. The current chapter presents a general introduction to the chapters that follow and provides an outline of the thesis. While the general theme of this thesis is climate impact on crop agriculture, each chapter is meant to be a stand-alone by addressing a specific topic.

The first study, Chapter 2, enumerates the economic impacts of climate change on smallholder agriculture. The study uses three-wave panel data between 2010 to 2016. First, I estimate the technical efficiency of farmers among smallholder farmers. In turn, the efficiency scores are used to adjust the Ricardian Model in the estimation of climate impacts. Using Global Circulation Models and various emission scenarios, I calibrate future impacts of climate change on agriculture.

Chapter 3 assesses the poverty vulnerability of farmers to climate-related shocks. In this chapter, I quantify the magnitude of climate stress-induced vulnerability to poverty among farming households. Second, I quantify the effects of ex-ante climate stress-induced vulnerability on ex-post poverty and also the relative effects on climate-related stresses on poverty transition between 2010 to 2016.

Chapter 4 consolidates a particular risk management strategy which is index insurance. The motivation is that climate risk management through subscription to weather index insurance is in its infancy. Thus, an initial understanding of the farmers' willingness to pay a premium for the insurance services is a first step to shaping the proper packaging of the weather index policy. In this chapter, I identify the determinants of the willingness of farmers to pay for Weather Index Insurance. In turn, I estimate the mean Willingness to Pay for weather index insurance and compare estimates from parametric and non-parametric methods.

Finally, in chapter 5, a summary and some general conclusions are presented.

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# CHAPTER 2

# ECONOMIC IMPACT OF CLIMATE CHANGE:

# ECONOMIC IMPACT OF CLIMATE CHANGE ON SMALLHOLDER CROP AGRICULTURE

## 2.1 Introduction

### *2.1.1 Background*

Climate change has threatened economies that heavily depend on agriculture and forest sectors for rural livelihoods, which has, in turn, preconditioned farmers to adopt strategies that can reinforce their individual resilience to climate change impacts (Rosenzweig & Parry, 1993; Gbetibouo & Hassan, 2005; Kurukulasuriya, et al., 2006). With regard to the agricultural sector, climate change will have agrarian impacts on agricultural production, which will, in turn, have trickle-down effects on agriculture commodity prices, demand, trade, regional competitive edge, and welfare effects on both demand and supply. These agro-economic impacts will predominantly depend on the extent of climate change and the region's capacity to assimilate the climate change impacts (Xiang, Takahashi, Suzuki, & Kaiser, 2011).

Sub-Saharan Africa (SSA) has been dominated by countries whose economies heavily rely on agriculture for employment and food security (Livingston, Schonberger, & Delaney, 2011). Although the agriculture sector has a large number of small-scale farmers, they mostly produce under unfavourable climatic (low precipitation and high temperatures) and environmental (low soil fertility) conditions (Mutsvangwa, 2011). With regard to climate conditions, the need arises to understand the nature and extent of the impacts on agriculture in general, and the small-scale agriculture in particular to aid documentation and development of practical and plausible means of enhancing communities' capacity to reduce vulnerability and to mitigate negative climate change impacts.

Malawi, like most countries in southern Africa, has not been spared by climate change and variability and is one of the most vulnerable countries. A survey of historical climate data from the World Bank shows that there has been an increasing trend of mean annual temperature. From the mid-1970s, the increase in warming (°C) intensified while there was a gradual decline in annual rainfall (Figure 2.1).

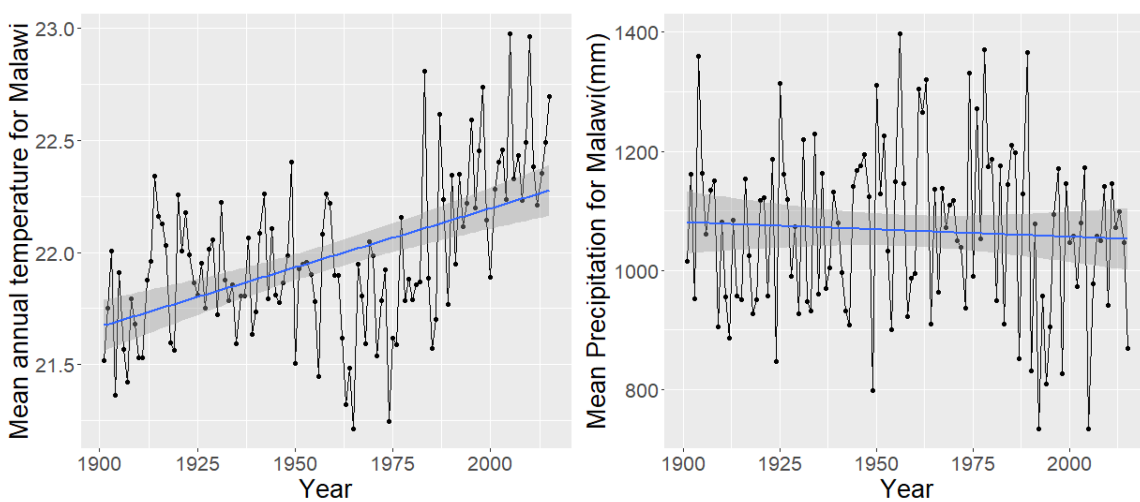


***Figure 2.1: Historical movements of mean annual temperature and rainfall in Malawi***

Recent literature on climate change models and hot spot analysis suggests potential increases in warming of 2°C to 3°C by 2050 and a general decline in rainfall and water availability in the country (UNFCCC, 2006). It is expected that such climatic changes will affect food and water resources that are critical for livelihoods (Hassan & Nhemachena, 2008). According to (Kadji, Verchot, & Markensen, 2006) the increasing temperatures coupled with reductions and high variability in rainfall will consequently lead to a decline in crop (cereal) production in selected areas. Given the importance of the contribution of the agriculture sector to the national economy and people's incomes and consumption, the climate impacts on crop production will have social and economic concerns (Chalise, Naranpanawa, Bandara, & Sarker, 2017). These impacts will trickle down to other non-agriculture sectors and further exacerbate economic stresses and challenges on households that are already poor (IPCC, 2013).

Climate change impacts vary spatially across a diverse range of agro-ecological scales. Unlike the urban sector, climate risks are more acute in the rural because of high poverty levels and heavy reliance on sectors that are very sensitive to changes in climate variables, low education level, inadequate institutional and economic capacities (IPCC, 2007; UNFCCC, 2006; Preston, et al., 2008). It is reasonable, therefore, to expect that any unfavourable impacts will be more prominent among the poor whose social welfare systems are fragile and predominantly sustain their livelihoods from farming, especially rain-fed farming since it is highly susceptible or sensitive to climate variability (Calzadilla, Zhu, Rehdanz, Tol, & Ringler, 2013; Bandara & Cai, 2014). Consequently, they are hooked in a cycle of poverty with limited escape holes. The resilience of agriculture will depend on producers' capacity to systematically adapt their agriculture systems to changing environmental and economic conditions. This will be of particular importance as climate shifts change the nature and magnitude of these environmental shocks. Those that may not adapt will incur economic losses over time, and ultimately this will threaten the economic viability of their future agriculture ventures.

### *2.1.2 Problem Statement*

Although clear evidence exists that southern Africa is vulnerable to climate change, few studies have focused on the economic impacts of climate change on agriculture (Mutsvangwa, 2011; Jain, 2007; Gbetibouo & Hassan, 2005). Most of the related studies have focused on developed countries in Europe, the United States, China, Australia despite that the poor countries, most of those in Southern Africa, whose mainstay is agriculture, will be hardest hit by the effects of climate change (Bandara & Cai, 2014; Kahsay & Hansen, 2016; Parry, Rosenzweig, Iglesias, Livermore, & Fischer, 2004; Schellnhuber, et al., 2013; Wheeler & Von Braun, 2013). Particularly in Malawi, most of the existing information on climate impacts on agriculture is qualitative and limited. No study, to the knowledge of the author, has quantitatively enumerated the economic impacts of climate change on agriculture. It is this backdrop that has stirred this direction of research.

This chapter makes two key contributions to the body of knowledge. First, it attempts to quantify the economic impacts of climate change on agriculture by focusing on Malawi in Southern Africa. Lack of research on assessing the economic impacts of climate change on Malawian agriculture presents an important limitation when it comes to formulating appropriate policy options and response packages to mitigate against climate impacts on smallholder farming. Despite the universal consensus of the impacts of climate change on agriculture, the Malawi case hasn't been studied to date. The study, therefore, takes space to analyze the economic impacts of climate change on agricultural production in Malawi.

The second contribution is methodological. There are different approaches that have previously been used in climate impact assessment, and these are reviewed, in terms of their relative strengths and weaknesses, in the next section of literature reviews. These include agronomic, computable general equilibrium and Ricardian methods. The Ricardian approach uses the profit function (Mendelsohn & Nordhaus, 1996), which, from economic theory, assumes that the farmer's production function is operating on the frontier and any deviations are attributed to effects of climate change. This study relaxes this assumption and allows the data to speak for itself of whether the farmer is operating on the frontier and, if not, eliminate the biases from technical inefficiencies. This study addresses these problems by using a two-stage estimation of a Ricardian Model. In the first stage, a technical efficiency model is estimated from which technical inefficiency scores are derived and used as inputs into the second stage for correcting the technically inefficient output in the Ricardian model. Thus, differential output as a result of farmer specific inefficiencies for farmers facing similar climates are eliminated, and thus, any further differences could be attributed to climate effects.

### *2.1.3 Objective of the Study*

#### 2.1.3.1 Main Objective

The overall objective of this study is to measure the economic impact of climate change on smallholder agriculture.

2.1.3.2 Specific Objectives

i. To assess the impact of climate change on crop agriculture when there is technical efficiency.

ii. To simulate future effects of climate change on returns to crop agricultural enterprises.

## 2.2 Literature Review

### *2.2.1 Introduction*

This section reviews those methodologies and empirical literature related to assessing the economic impact of global and local climate change. Among other things, this literature review further highlights the appropriateness of the Ricardian approach to assess the economic impacts of climate change on the agricultural sector.

It has long been known that climate change has impacts on agriculture. There has been a burgeoning body of research with different methodologies across disciplines to explain the linkages between climate change and agriculture. The field of economics has employed different methods to explain changes in climate variables and associated levels of damage caused on agriculture so that the findings can shape the policy landscape. These methodologies are discussed below.

Assessing the climate change impact on agriculture is the subject of abundant literature divided into experimental simulations and cross-sectional analyses (Mendelsohn & Dinar, 2003; Mendelsohn, 2007). First Agronomic-Simulation studies were kick-started around the 1980s through the 1990s by (Adams, 1989; Kaiser, Riha, Wilks, Rossiter, & Sampath, 1993; Rosenzweig & Parry, 1994; Adams, Fleming, Chang, McCarl, & Rosenzweig, 1995). Ricardian cross-sectional Hedonic models were first championed by (Mendelsohn, Nordhaus, & Shaw, 1994). These have further been regrouped into three; agronomic-simulation models, Computable General Equilibrium models and Ricardian cross-section models. From all the three approaches, the take-home message has been that climate change reduces the global output level and has been more pronounced in developing areas. The following sub-sections review these three approaches in detail.

### *2.2.2 Agronomic-Simulation models*

Agronomic studies emphasize the dynamic physiological process of plant growth and seed formation. These models press their focus on state-space plant growth functions. Plant growth potential is linked to temperature (available energy). However, these models do not factor in essential variables for plant growth, such as moisture and plant nutrition. Furthermore, these models do not endogenize farmer behaviour and economic considerations, and sometimes the focus is on a single crop (Adams, 1989; Rosenzweig & Parry, 1994). On the other hand, other studies have made departures from agro-simulation models (Kaiser, Riha, Wilks, Rossiter, & Sampath, 1993; Adams, Fleming, Chang, McCarl, & Rosenzweig, 1995; Schlenker & Roberts, 2006), allowing for crop substitution with a profit maximization analysis for different cropping patterns, to correct for the flaws in agro-simulation models.

Agro-simulation models are powerful in that they factor in all weather conditions experienced over the entire production season. However, agro-simulation models have two weaknesses. The first is high uncertainty levels about the technology (function form) and its parameters. The complex nature of these models makes them non-estimable with statistical tools (Wallach & Thorburnb, 2014). If it were possible, many agronomists would be sceptical about interpreting physiological estimates and possible misspecification and bias (Sinclair & Seligman, 2000). Second is a simplifying assumption of the independence of a production system to farm managers' behaviour (Schlenker & Roberts, 2006). In reality, farmers adapt their production system to climate change to reduce damages from climate change or take advantage of the new opportunities presented by the new climate.

### *2.2.3 Computable General Equilibrium (CGE) models*

CGE models are a commonly used tool for quantifying the costs and gains from environmental policy. The aim is to simulate the interaction between economic activity and the environment. Furthermore, these models deal with how environmental policies influence technological development and production (Van Ierland, 1999). The CGE literature reveals that analysis of climate change impacts and corresponding adaptive strategies has taken two routes. First is based on intra-country CGE models that focus on domestic impacts, which allows for more detailed analysis in terms of mapping out the impacts to the domestic economy (Calzadilla, Zhu, Rehdanz, Tol, & Ringler, 2013; Borgomeo, et al., 2018; Elshennawy, Robinson, & Willenbockel, 2016). Second deals with multi-country CGE models at the highly-aggregated level (e.g. GTAP model). The focus is on assessing regional impacts driven by inter-country trade linkages (Ochuodho, Lantz, & Olale, 2016; Ouraich & Tyner, 2012).

A price change in the CGE model causes simultaneous reactions in all markets considered in a given general equilibrium analysis. This property is essential for the two main advantages: the micro foundation and economic feedback processes. The micro foundation consists of the three conditions, namely market clearance, zero profit of firms and income balance of the households. With the presence of forward and backward feedback for a given price change, the models can be used for long-term planning and analysis (Walz & Schleich, 2009). A significant weakness of CGE is the use of observations from one year to calibrate shift parameters. In addition, the utility and production functions are constrained into a particular function form, i.e. constant elasticity of substitution (Sancho, 2009). These models also use econometric tools to produce parameters that are external to the CGE model calibration. These best guess" values add significant uncertainty to the model. The chosen elasticity can incredibly influence the sensitivity of the results (West, 1995).

The available literature reveals several related studies. Others have used a bottom-up CGE model for Australia to assess drought impacts (Horridge, Madden, & Wittwer, 2005). This model was called The Enormous Regional Model (TERM), which specialized in handling highly disaggregated data for several countries. It can aid the analysis of the impacts of climate stress shocks for a given region. It models the region as one economy. It disaggregates the region into different sectors based on each country's Input-Output tables.

Laborde (2011) analyzed the impacts of climate-induced yield changes on the agriculture in South Asia and investigated the potential for trade policy options to mitigate the latter. An improved version of the CGE model called MIRAGE CGE was used using two steps. In the first stage, the yield was estimated using the IMPACT model for 13 SRES scenarios. These were, in turn, introduced as external shocks in the MIRAGE CGE model. The benchmarked results are compared with the results from eight different trade policy landscapes for the region. Rubin and Hilton (1996) examined the employment impacts of climate change on several sectors of Michigan's Pere Marquette Watershed region. Rosenberg (1993) examined the climate change impacts on several states in the USA.

Several studies have been undertaken in Africa using the CGE approach to model climate impacts. Diao et al. (2008), building on the CGE work of Roe et al. (2005), used a country-based CGE model to assess the impacts of conjunctive natural resource management in Morocco. The objective of the study was to determine the direct and indirect effects of groundwater regulation on agriculture and nonagricultural sectors under different scenarios such as (i) increasing costs of extraction, (ii) regional transfers of surface water, and (iii) the effect of drought due to water supply. More recently, Mideska (2010) has applied a general equilibrium analysis to quantify the impacts of climate change on GDP in Ethiopia.

### *2.2.4 Ricardian models*

Having explored earlier models, each one has its limitations. Agronomic models are weak to capture adaptation and mitigation strategies, and CGE models are highly aggregated.

Mendelson et al. (1994) proposed the Ricardian approach to aid the assessment of agrarian impacts of climate change while overcoming the limitations of earlier agronomic models. The idea behind the proposed model was that there is a correlation between land values and climate variables following the work of David Ricard (1772 – 1823). It first estimates the relationship between climate and agricultural land values. As such, an understanding of land values across different locations with varying states of climate variables would necessitate an understanding of climate impacts on agriculture. The Ricardian approach builds on hedonic pricing models. The model makes a simplifying assumption that the current value of a parcel of farmland equates to the sum of discounted future rents (Schlenker & Roberts, 2006). The difference in farmland values will reflect the difference in the productivity of crops grown on it, given the capital and labour quantity. The net difference will be the difference in yield value between farmlands of different locations facing different climates. With this understanding, David Ricardo puts it that the land value is the value of the product from a given piece of land, which is taken as the rent paid by the producer for using the land (Onyekuru & Marchant, 2016)

The Ricardian model is a regression of farmland values on a number of variables, i.e. climate, economic and other relevant variables (Mendelsohn, Nordhaus, & Shaw, 1994; Mendelsohn & Nordhaus, 1996; Adams, Fleming, Chang, McCarl, & Rosenzweig, 1995). In a well-behaved marketing system, the value of a parcel of land should reflect its profitability. In turn, spatial variation in climate derives spatial variation in land use which affect land values (Polsky, 2004) if other factors of production are controlled. This background shows that it is possible to establish a quantifiable relationship between climate and farmland values using regression-based methods within the framework of cross-section data. The estimated coefficients for the climate variables would reflect the economic value of climate to agriculture, given all other factors held constant.

The Ricardian cross-sectional approach automatically nests farmer adaptation strategies by including adaptation choices farmers would employ to adapt their operations to a changing climate. An important example of farm-level adaptive systems is crop choice, where each state of climate would command a different crop that would best suit it. Therefore, a farmer is expected to switch crops to suit a given state of climate and, in turn, reduce the impact of climate stress on selected crops (Mendelsohn, Nordhaus, & Shaw, 1994; Mendelsohn & Nordhaus, 1996; Mendelsohn & A, 1999). With the Ricardian approach, it is possible to assess the sensitivity of impacts under two scenarios. You can quantify the climate impacts first in the presence of adaptation and second in the absence of adaptation.

The incorporation of adaptation strategies in the Ricardian model reduces the costs of climate impacts on agriculture (Polsky, 2004). Adaptation is driven by the knowledge the farmer has. A farmer as a rational economic agent will use this knowledge to maximize benefits and minimize losses in the presence of climate change. For instance, a standard Ricardian model would imply that if growing a maize crop is more profitable than growing cassava, in turn, the climate becomes more suitable for cassava than maize. In that case, those farmers' crop choice (adaptation) will reflect the changing climate by drawing on the experiences of cassava farmers elsewhere and switching from maize to cassava (Polsky, 2004; Moniruzzaman, 2015; Wineman & Crawford, 2017).

For changes in Ricardian values to exactly capture the value of climatic change, output and input prices must remain constant. This is a strict assumption that may not likely work in real-world situations. First, private adaptations made by farmers in response to climatic change would likely generate supply changes that, in turn, would affect output prices. As the theory of firm notes that when product supply increases, there will be a corresponding downward shift in its prices and vice versa. The increased production (supply) would also mean that the demand for inputs would have also increased. Second, the global climatic change would likely affect agricultural resources across countries, consequently affecting world prices and the demand for local agricultural commodities (Kane, Reilly, & Tobey, 1991; Rosenzweig & Parry, 1993; Darwin, Lewandrowski, McDonald, & and Tsigas, 1994; 1995).

This alone should not in any way make us conclude that a change in Ricardian rents has no value. When biases as a result of price changes are not large enough, the corresponding changes in Ricardian rents could approximate the true value of climate change in agriculture (Darwin, 1999). Mendelsohn and Nordhaus (1996) noted that the bias as a result of 25 percent climate triggered a decline in agricultural commodity supply is likely not going to exceed 5 percent given constant demand. However, they did not extend their analysis to take care of crop demand or supply changes. If large enough, increases in crop supply can drive prices of agricultural products below their marginal costs of production, causing farmers in some regions to cease production. This relates to another limitation of the Ricardian approach; specifically, changes in Ricardian rents do not provide information about the welfare implications of climatic change for specific agents. Schimmelpfennig et al. (1996), for example, noted that Ricardian models could not assess how the effect of climatic change might be distributed among agricultural producers and consumers. Also, international trade can help transfer damages or benefits from one country to another. Such information is important to policymakers. To design workable international treaties, negotiators need to know the total magnitude of any economic benefits or damages that might be incurred under global climatic change and to whom such benefits or damages accrue, that is, who wins and who loses from the treaties and given climate scenarios.

### *2.2.5 Empirical Studies on Climate Change Impacts in Agriculture*

The Ricardian technique for estimating the economic impacts of climate change on agriculture has drawn an unusual amount of attention and criticism (Polsky, 2004). The approach has been applied in a variety of countries, including Zimbabwe, Zambia, South Africa, Cameroon, United States, Canada, England and Wales, India and Brazil, Cameroon, China, and Sri Lanka. This section highlights some of the insights provided by this literature that shape the present study. While these studies are not specific to crops of focus in this study, they still provide insights to shape the landscape of this study.

To begin with, Mendelsohn et al. (1994) novel study sets the base for subsequent studies that empirically apply the Ricardian climate analysis approach. By directly observing farmland values, they quantified the direct impacts of climate change on agricultural yield and farmers' response in terms of input substitution and choice of different adaptive strategies under varying climates. From this, they learnt a quadratic relationship between agricultural land values and temperature and precipitation. Their estimates indicate that impacts of global warming in the United States agriculture were lower than those from the traditional production function approach, but both were negative. Their results were dependent on the type of model and climate scenario used in the analysis.

A couple of years later, Mendelsonh et al. (1996) refined earlier work of the Ricardian model for measuring the agrarian impacts of climate change, focusing on the impact of climate change on land prices. The study was based on cross-sectional data in the US again. The findings revealed that seasonal temperatures, in all seasons except autumn, increased farmland values. Similarly, the estimated impacts of global warning on US agriculture were consistent with earlier findings.

Mendelsohn and Dinar (2003), revisited the U.S. case study by Mendelsohn et al. (1994), to validate whether surface water extraction could explain the differences in farmland values in the United States and whether adding these variables to the Ricardian model could alter the sensitivity of agriculture to climate change. Unfortunately, the value of irrigated farmland was neutral to precipitation but gained from temperature. The reason was that sprinkler systems are used primarily in wet, cool sites, whereas gravity, and especially drip systems, helped compensate for higher temperatures. They did not underplay the role of irrigation in climate impacts management as it could serve as an adaptation strategy for low precipitation related stress.

In African, there has also been a growing number of studies using the Ricardian approach. These studies are country-specific, while some focused on several African countries. The early work in Africa by Gbetibouo and Hassan (2005) analyzed the current and predicted future impacts of climate change on South African agriculture. They regressed farmland value on climate, geo, soil and farmer specific characteristics to characterize the effect of private adaption on land values. The analysis was done for several crops across 300 districts of South Africa, focusing on maize, wheat, sorghum, sugarcane, groundnut, sunflower and soybean. The findings showed that the gains from an increase in temperature were very high compared to an increase in precipitation. They did further analysis to check the dynamics of impacts across seasons.  It was found the impacts were not distributed uniformly across different regions as such private adaptations would require to be different for different locations or regions to minimize the climate impacts. The impacts in some regions would require a major shift in farmers' behaviour and practices, including a change in the farming calendar and total switch to or dis-adoption of certain crops. Deressa et al. (2005) narrowed down the analysis to focus on climate impact on sugarcane production in South Africa. While other studies used cross-section data, this study used time series data for the period 1977 to 1998. The results indicated that predicted changes in climate variables like temperature negatively impacted net revenue from sugarcane production compared to changes in precipitation. Irrigation did not play a big role in reducing damages when compared dryland conditions and irrigated systems corroborate the earlier finding by Mendelsohn and Dinar (2003), in the US.

Within the same southern Africa, a study by Mutsvangwa (2011) used the Ricardian model to analyze climate impacts on agriculture in Zimbabwe. The empirical findings revealed a strong relationship between temperature, moisture and farm profits in Zimbabwean

Agriculture. Rain-fed farming was very sensitive to marginal changes in precipitation, whereas irrigated farming was a little more inelastic. The results affirmed the necessity of irrigation farming as a solid adaptive strategy to climate change impacts due to moisture stress. A scenarios analysis showed that a rise in warming would reduce farm profits for rain-fed farming while it would incur profit gains for irrigated farms. Jain (2007), applying the approach to Zambia, showed that an increase in temperature in November and December and a reduction in mean precipitation in January and February are negatively related to farm profits. In contrast, an increase in mean temperature in January and February and an increase in mean annual runoff would benefit farmers.

In East Africa, Deressa (2007) employed the Ricardian model to assess the impacts of climate change on Ethiopian agriculture and to explain private adaptations to varying environmental factors. The study carried assessment of the sensitivity of farmland values to unit changes in precipitation and temperature under varying seasons. In addition, it analyzed the impact of even climate scenarios on farmers' profits per hectare. Furthermore, it assessed the impact of predicted climate scenarios on-farm profits for 50 years in the future. The findings revealed that Ethiopian agriculture would benefit from increased precipitation and declining temperatures. Similarly, Kabubo-Mariara and Karanja (2007) established the same trend between climate variables and farm profits in Kenya. Relating to the earlier studies by Jain (2007), Mutsvangwa (2011) and Deressa et al. (2005) it shows that the close to the equator, there are negative impacts of warming as the areas already experience high temperatures.

In West Africa, Molua and Lambi (2007) assessed the impact of climate change on Cameroonian agriculture. The study employed the Ricardian model to quantify a relationship between climate and net farm revenue. Their analysis found that farm profits declined proportionately with precipitation decreases and was inversely related to temperatures. The study reaffirmed that agriculture in Cameroon is often limited by seasonality and the availability of water supplies. Although other physical factors, such as soil and relief, had a significant influence on agriculture, climate remained the dominant predictor of the agricultural enterprise choice. Onyekuru and Marchant (2016), in studying impacts on forest resource use in Nigeria, established positive gains from precipitation and marginal losses from warming. However, the study registered mixed impacts of precipitation across varying seasons, although the net outcome was positive gains.

Seo and Mendelsohn (2007) used a cross-section Ricardian model to quantify the impacts of climate change on large and small livestock farms in selected countries in Africa. Their findings showed that the large specialized farms were more vulnerable to changes in warming and precipitation in comparison with a small farm. The larger farms were learned to rely on commercial beef and other species that are not tolerant to high temperatures, compared to small farms that have no traditional livestock species like goats and sheep that can do better in dry and warm environments.

## 2.3 Methodology

### *2.3.1 Theoretical Framework*

There has been a shift in the approach to modelling climate impacts on agriculture. Most recent studies on the impact of climate change on agriculture (Mendelsohn, Nordhaus, & Shaw, 1994; Mendelsohn & Nordhaus, 1996; Mendelsohn & A, 1999; Liu, Li, Fischer, & Sun, 2004; Onyekuru & Marchant, 2016) use the Ricardian analysis following Mendelsohn et al., (1994) while most of the earlier studies employed the production function approach (Rosenzweig & Iglesias, 1994).

The Ricardian model adopts a production function, $f: \mathbb{R}_{+}^{n} \rightarrow \mathbb{R}_{+}$, which is continuous, strictly increasing and strictly quasiconcave on $\mathbb{R}_{+}^{n}$ of the form:

$$y = f(x, e) \tag{2.1}$$

Where $\mathbf{y} \in Y$ is a production plan with a feasible output set: $Y \equiv \{y \in \mathbb{R}_{+}^{n-m}: (y, -x) \in Z$ for some $\in \mathbb{R}_{+}^{m}\}$, $e$ is a vector of climate factors. The elements of $y$ indicate the quantities of outputs for various commodities and are limited by technical and climate constraints. The input requirement set is given by $V(y) \equiv \{x \in \mathbb{R}_{+}^{m}: (y, -x) \in Z\}$ for $y \in Y$ for a feasible output vector $y$. Similarly, a set of climate factors, $e$, such as temperature and precipitation are given by $Q(y) \equiv \{e \in \mathbb{R}_{+}^{k}: (y, -e) \in Z\}$ for $y \in Y$. Given a set of factor prices, $w \gg 0$, $e$ and output levels $y \in f(\mathbb{R}_{+}^{n})$, the farmer's cost function is the minimum value function:

$$\min_{x \in \mathbb{R}_{+}^{n}} w.x = c(y, w, e) \qquad s.t \qquad y = f(x, e) \tag{2.2}$$

The climate vector enters the cost function because it embodies inputs (think of climate variables as inputs into production) that either increase or reduce adaptation costs to climate change. We assume that $x^*\gg 0$ and that $f$ is differentiable at $x^*$ with $\nabla f(x^*) \gg 0$. The profit function assumes that the farmer's production $f$ (.) exists at a maximum, while in reality, the farmer's production is affected by farm-specific technical inefficiencies. This unrealistic assumption will be relaxed later. Using the cost function at given market prices, farm profit a given farmer seeks to maximize is given by;

$$\pi^*(p,w) = \sup\{\pi(x;p,w,e) = pf(x,e) - w^{\perp}x - rL: x \in \mathbb{R}_+^m\} \quad (2.3)$$

Where $r$ is annual cost or rent of land in hectares, $L$, at a given site, $p$ is output price, $x$ is the input vector, $w$ are factor prices. Perfect competition in the land market will drive profit to Zero, although this is an ambitious assumption for developing countries (Dinar, et al., 1998) which will later be clarified. If the farmer is not renting the land from someone else, $r$ assumes a shadow price.

$$p_i y_i^* - c_i^*(y_i^*, w, e) - rL_i^* = 0 \quad (2.4)$$

If the production of a certain commodity maximizes the net revenue from a piece of land, given $e$ (climate variables), the observed market rent on land will be equal to the annual net profits from the production of the commodity. Solving for $r$ in equation 2.4 gives net revenue per hectare, which is a proxy for land value per hectare. We, therefore, get;

$$r = \frac{p_i y_i^* - c_i^*(y_i^*, w, e)}{L_i^*} \quad (2.5)$$

Due to the imperfect land market and lack of data on farm land values in Malawi, annual net revenue provides a good estimate of $r$ (Liu, Li, Fischer, & Sun, 2004; Dinar, et al., 1998). Since this is a problem involving a stream of benefits over a long span of time, we introduce the concept of the time value of the money discounting factor. Consequently, net revenue from the land ($V_L$) will reflect the present value of future net productivity;

$$V_L = \int_0^{\infty} \frac{p_i y_i^* - c_i^*(y_i^*, w, e)}{L_i^*} e^{-rt} dt \quad (2.6)$$

In equation 2.6, the interest is to measure the sensitivity of land value ($V_L$) to marginal changes in climate variables (temperature and precipitation) or their spatial variation. A shock on a climate variable will be transmitted into a change in land values. Consider an environmental change from state 1 to 2, which, in turn, causes a change in climate inputs from $e_1$ to $e_2$. A change in profit ($\Delta W$) from this climate change is given by:

$$\Delta W = W(e_2) - W(e_1) = \int_0^{Y2} [(p_i y_i - c_i(y_i, w, e_2)/L_i] e^{-rt} dY - \int_0^{Y1} [p_i y_i - c_i(y_i, w, e_1)/L_i] e^{-rt} dY \quad (2.7)$$

Having unchanged output prices, say $p_0$, the consumer welfare (for consumers purchasing the commodity in question) is not affected but producer welfare (or the profit per hectare). Therefore, the economic welfare change here is measured by the change in the value of the land that is caused by the change in environmental factors. In the original work of Ricardian analysis of climate change impacts, Mendelsohn et al. (1994) make an assumption that market prices do not change in response to change in environmental variables; therefore, considering a constant price vector $p = [p_1, p_2, p_3, ..., p_m]$ the above equation reduces to:

$$\Delta W = W(e_1) - W(e_2) = [py_2 - \sum_{i=1}^{n} c_i(y_i, w, e_2) - [py_1 - \sum_{i=1}^{n} c_i(y_i, w, e_1) \qquad (2.8)$$

Manipulating and substituting equation 2.4 into equation 2.8 yields;

$$\Delta W = W(e_2) - W(e_1) = \sum_{i=1}^{n} (r_2 L_{2i} - r_1 L_{1i}) \qquad (2.9)$$

Where $r_1$ denotes the value per hectare of land area $L_1$ in state 1 (baseline), and $r_2$ denotes the value per hectare of land area $L_2$ in state 2. Thus, the present value of the welfare change is:

$$\int_0^Y \Delta W e^{-rt}\, dt = \sum_{i=1}^{n} (V_2 - V_1) \tag{2.10}$$

The integral over a closed set [0, $y$] is the value of the climate change as defined by the Ricardian analysis. Empirically, after estimating the base model with baseline climate condition, one can examine the value of future climate change by plugging any climate change scenario two into the base model (e.g. cooling or warming weather, change in precipitation trends).

Given the profit function in (2.3), an assumption that the farmer is operating on production frontier (maximum) is lifted because of inherent farmer specific technical inefficiencies. Ignoring these inefficiencies could result in biasing the impacts of climate variables on net farm revenue. For example, farmers facing the same climate change would still have different outputs. As such, a generalized attribution of output differential to climate impacts could result in idiosyncratic estimates of climate impacts which embodies both true climate impacts and farmer technical inefficiency effects. Thus, in this study, we modify the profit function (2.3) by adjusting production plan *f*(.) for farm-specific technical inefficiencies for farmers facing similar climates. This is further explained in section 2.3.2.1, in which I include climate-related variables in the model.

Following the recent work on technical efficiency in production (Kumbhakar & Tsionas, 2006), the production technology can be represented by:

$$y_{it} = f(x_{itj}, \Theta), i = 1, \dots, n \tag{2.11}$$

Where $y_{it}$ and $x_{itj}$ are defined as scaler output and vector of inputs, respectively, used in the production plan, subscript *i* indexes farmers, *t* is time, *j* indexes input type, and $\Theta = x_{itj}^{e}/x_{itj} \leq 1$ for input $j$ = 1, …, *J* is the input-oriented efficiency score vector. The input-oriented technical inefficiency for a given farm is given by $1 - \Theta = (x_{itj} - x_{itj}^{e})/x_{itj}$ for farmer *i* and $\forall j$, which is defined by how much inputs could be reduced without altering level of output. Since our interest is output, output-oriented technical efficiency, given climate state $\bar{e}$ and frontier output $f(x_{itj}, \bar{e})$, is represented by:

$$y_{it} = f(x_{itj}, \bar{e}). \mathit{\Lambda} \tag{2.12}$$

Where $\mathit{\Lambda}$ is output-oriented technical efficiency scalar which is defined as the ratio of observed output to frontier output. Thus, technical inefficiency at a given farm is given by $1 - \mathit{\Lambda} = (f(x_{itj}, \bar{e}) - y_{it})/f(x_{itj}, \bar{e})$ which shows how much output could be increased without altering inputs or climate-related variables. The inefficiency scores are in turn used to scale output in (2.3) and end with a profit function whose production function lies on the frontier.

### *2.3.2 Econometric strategy*

This section sets out to present the empirical strategy used to estimate the impacts of climate change on agriculture. Building on the theoretical framework above, this is rolled in two sections; First, it starts with laying out a procedure of estimating the production function and derivation of the technical efficiency scores from the production plan. The second subsection presents the methods for estimating the Ricardian model while using the estimated efficiency scores as inputs to correct for interior output of a given production set.

2.3.2.1 Estimation of technical efficiency scores

Following Fousekis and Klonaris (2003), the empirical application of the frontier is specified in the translog form, which: (i) is locally flexible (offers a second-order differential approximation of an arbitrary function); (ii) permits the performance of statistical tests on the structure of the underlying production technology; and (iii) accommodates the inclusion of the one-sided error to estimate Technical Efficiency (TE) for every observation. In general terms, we consider the following production technology for output-oriented efficiency measurement or the best practice frontier (Aigner et al. 1977; Meeusen and Van der Broeck 1977):

$$y_{it} = \{f(x_{it,}, \Theta_{it})\}^{Ii}\{f(x_{it}) \cdot \Lambda_{it}\}^{1-Ii}\exp(v_{it}) \qquad (2.13)$$

Where $v_{it}$ is the random error term, $I_i$ is a transformation indicator between input or output oriented technical efficiency. It takes a value of 1 if we are using input-oriented technical efficiency and 0 if it is output-oriented technical efficiency. The index *i* is a cross-section farm unit, and *t* is the time period for indexing the wave in panel data. Adopting a flexible function form, equation (2.13) can be presented in the following form:

$$y_{it} = I_{it}\left\{\beta_0 + (x_{it} - \theta_i 1_J)'\beta + \frac{1}{2}(x_{it} - \theta_i 1_J)'\Gamma(x_i - \theta_i 1_J)\right\} + (1 - I_{it})\left\{\beta_0 + x'_{it}\beta + \frac{1}{2}x'_{it}\Gamma x_{it} - \lambda_{it}\right\} + v_{it} \qquad (2.14)$$

From (2.14), the output-oriented model introduced by Aigner et al. (1977) and now widely used in literature, is presented as:

$$\mathbf{y}_{it} = \beta_0 + \boldsymbol{x'_{itj}\beta} + \frac{1}{2}x'_{itj}\Gamma\boldsymbol{x_{itj}} + x'_{itj}\gamma\boldsymbol{x_{itk}} - \lambda_{it} + v_{it} \qquad (2.15)$$

Where, $\lambda_{it}$ is the non-negative inefficiency component. $v_{it}$ is assumed to be independently and identically distributed, symmetric and independent of $v_{jt}$. Thus, the composite error term $\varepsilon_{it} = v_{it} - \lambda_{it}$ is asymmetric. The term $\beta$ represents the parameter vector of linear terms, $\Gamma$ represents the parameter vector of quadratic terms, and $\gamma$ represents the parameter vector of interaction terms. The Technical Efficiency scores are given by:

$$TE = \frac{\boldsymbol{y}_{it}}{\boldsymbol{y}_{it}^{*}} = \frac{E[\boldsymbol{y}_{it}|\lambda, \boldsymbol{x}]}{E(\boldsymbol{y}_{it}|\lambda_{it} = 0, \boldsymbol{x})} = E[\exp(-\lambda)|\, v] \tag{2.16}$$

The production function in (2.15) is assumed to be twice differentiable, and symmetry condition is therefore imposed, prior to estimation, according to $\gamma_{jk} = \gamma_{kj}$. Homotheticity and homogeneity of degree 1 is constrained according to $\sum \beta_k = 1, \sum\sum \gamma_{jk} = 0$.

Consistency of the production frontier with economic theory requires that production function be monotonically increasing and quasi-concave in inputs. If a production frontier is not monotonically increasing, the efficiency estimates of the individual firms cannot be reasonably interpreted. Monotonicity means that the output quantity must be non-decreasing. If any input quantity is increased, quasi-concavity guarantees that the marginal rates of technical substitution are decreasing. In the case of our empirical translog production frontier, monotonicity was held by the following condition:

$$\frac{dy_{it}}{dx_{itj}} = \frac{y_{it}}{x_{itj}} \frac{d\,(\ln y_{it})}{\ln(\,x_{itj})} = \frac{y_{it}}{x_{itj}} \left(\beta \quad + \sum_{i=1}^{n} \gamma_{jk} \ln(x_{it})\right) \in \mathbb{R}_{++}\ \forall\ it \in \{1, \dots, NT\} \tag{2.17}$$

A sufficient condition for the monotonicity is checked by second-order test to verify if the production frontier is non-decreasing in inputs implying the fulfilment of the following expression:

$$f_{jk} = \frac{y}{\mathbf{x_j x_k}} \times \left[(\beta_i + \ln\boldsymbol{x}_k'\beta)\big(\beta_j + \mathbf{ln}\boldsymbol{x}_k'\Gamma - \Delta_{ij}\big) - \Gamma\right] < 0\ \ \forall\ it \in \{1, \dots, NT\} \tag{2.18}$$

Where $\Delta_{ij}$ is the Kronecker delta with $\Delta_{ij} = 1$ if $k = j$ and $\Delta_{ij} = 0$ if $k \neq j$. The necessary and sufficient condition for a specific curvature rests in the semi-definiteness of the bordered Hessian matrix. The Hessian matrix is negative semi-definite at every unconstrained local maximum. The conditions of quasi-concavity are related to the fact that this property implies a convex input requirement set (Chambers, 1988). Given our twice continuously differentiable production function, quasi-concavity is checked using its bordered Hessian matrix:

$$B = \begin{bmatrix} 0 & MP_1 & \cdots & MP_j \\ MP_1 & f_{11} & \cdots & f_{1j} \\ \vdots & \vdots & \ddots & \vdots \\ MP_j & f_{j1} & f_{j2} & f_{jj} \end{bmatrix} \tag{2.19}$$

Where, $f_{jk} = \partial^2 f / (\partial x_j x_k)$ is the second derivative of the production function with respect to the $j^{th}$ and $k^{th}$ input quantity, $MP_j$ is the marginal product of input j. Since all input quantities are generally non-negative ($x_j \in \mathbb{R}_{++} \ \forall \ j$), a necessary condition for quasi-concavity is (Chiang, 1984; Takayama, 1997):

$$|B_1| \leq 0, |B_2| \geq 0, |B_3| \leq 0, \dots , \ |B_n| \times (-1)^n \in\leq \mathbb{R}_+$$

If these theoretical underpinnings are jointly fulfilled, the obtained efficiency estimates are consistent consequently can be relied upon and used to adjust output in the profit function in (2.3). Policy prescriptions based on the Ricardian models adjusted for technical inefficiencies is more accurate than when adjustments are ignored.

***2.3.2.2 Estimation of panel Ricardian model***

The panel Ricardian model with time-invariant distinctiveness can be estimated under either the fixed effects or random effects framework (Wooldridge, 2002). The choice between the two depends on the assumptions imposed on the relationship between the unobservable individual-specific effect and the covariates. The fixed effects assume the existence of correlation while the random-effects lifts up the assumption.

As this study considers three time periods and the farms are distributed across different districts of Malawi, the analysis must nest both spatial and temporal scale variation. These spatial and time-period specific effects may be treated as fixed effects or as random effects. In the fixed-effects model, a dummy variable is introduced for each spatial unit and for each time period, except one to avoid perfect multicollinearity (Elhorst, 2014). Following Mendelsohn et al. (1994), the Ricardian model of these spatial and temporal effects in a two-way fixed effects approach can be presented as:

$$V_{it} = \psi_i + \lambda_t + \boldsymbol{x}'_{it}\boldsymbol{\beta} + \boldsymbol{e}'_{it}\theta + \boldsymbol{\pi}'_{it}\phi + u_{it} \qquad (2.20)$$

Where the dependent variable, $V_{it}$, is net crop income, $\psi_i = (\psi_{i1,\cdots,}\psi_{iN})^T$ is the full district effects, $\lambda_t$ is time effects, $x_{it}$ is a (*K* x 1) vector of observed determinants of net crop income that are time-varying these are listed in Table 2.1 below, $\boldsymbol{\beta}$ is a (1 x *K*) vector of coefficients, $\boldsymbol{e}'_{it}$ is a vector of linear climate variables that vary by season and space, $\pi'_{it} = e'_{it}e_{it}$ is the quadratic component of climate variables whose parameter vectors is $\phi$, and $u_{it}$ is the random error term. The reasons for including the spatial and time fixed effects are two-fold. First, the spatial fixed effects, $\lambda_t$, can absorb the time-invariant determinants of net crop income. Second, the inclusion of spatial indicators, $\psi_i$, controls for all spatial-invariant variables whose omission could bias the estimates in a typical time-series study (Baltagi, 2005; Hsiao & Tahmiscioglu, 1997; Arellano, 2003).

Treating unbalanced panel data as though it were balanced yields estimates that are inconsistent. However, using deviations from within time from each variable, the fixed effects OLS estimator on an unbalanced panel is consistent (Wooldridge, 2002). If the assumption that there is no correlation between the covariates and unobserved heterogeneity is true, then the estimation of coefficients under random effects framework provides more efficient estimates compared to fixed effects (Cameron & Trivedi, 2005; Nerlove, 2005). Another advantage of random effects is that the time-invariant variables can be included as part of covariates without introducing multicollinearity with the constant. When spatial and time-period specific effects are treated as random effects, $\psi_i$ and $\lambda_t$ are treated as random variables that are independently and identically distributed with zero mean and variance and $\sigma_{\psi}^2$ and $\sigma_{\lambda}^2$, respectively. Both the fixed effects and random effects models were run, and their coefficients were tested using Durbin-Wu-Hausman's test. The test evaluates the consistency of a random-effects estimator when compared to a fixed-effects estimator, which is a less efficient estimator although already known to be consistent. Verbeek (2004) notes that $I_T - (1\ /\ T)\iota_T\iota_T'$ transforms the data in deviations from individual means and $-(1\ /\ T)\iota_T\iota_T'$ takes the individual means, in turn, GLS estimator for $\boldsymbol{\beta}$ can be used. It follows that the fixed and random effects estimators are equivalent for large T as $\Psi \rightarrow 0$ and $T \rightarrow \infty$.

### *2.3.3 Data*

This study used the Integrated Household Panel Survey (IHPS) data that was collected by Malawi's National Statistical Office. The panel comprises three waves (time periods). The first wave was a subset of the third integrated household survey (IHS3) that was conducted from March 2010 to March 2011 under the umbrella of the World Bank Living Standards

Measurement Study. The first wave had 204 enumeration areas (EAs) which were tracked back in 2013 as a second wave in accordance with the IHS3 fieldwork timeline and as part of the Integrated Household Panel Survey. In 2013, a total of 3,246 households in these EAs were visited for data collection. At baseline, the IHPS sample was selected to be represented at the national. Once a split-off individual was located, the new household that he/she formed/joined since 2010 was also brought into the IHPS sample. In view of the tracking rules, the final IHPS sample, therefore, included a total of 4,000 households that could be traced back to 3,104 baseline households. In parallel with the fourth integrated household survey (IHS4) operations, also implemented the Integrated Household Panel Survey 2016 as a third wave or followed up to the IHPS 2013. The IHPS 2016 subsample covered a national sample of 102 EAs (out of the 204 baselines IHS3 panel EAs) and was conducted during the first half of IHS4 fieldwork.

The IHPS consisted of four questionnaire instruments; the household questionnaire, the agriculture questionnaire, the fishery questionnaire, and the community questionnaire. Of interest for this study was the agriculture and household questionnaires. The agriculture questionnaire allows, among other things, for extensive agricultural productivity analysis through the diligent estimation of land areas, both owned and cultivated, labour and non-labour input use and expenditures, and production figures for main crops and livestock. The household questionnaire encompassed economic activities, demographics, welfare and other sectoral information of households. It covered a wide range of topics, dealing with the dynamics of poverty (consumption, cash and non-cash income, savings, assets, food security, health and education, vulnerability and social protection).

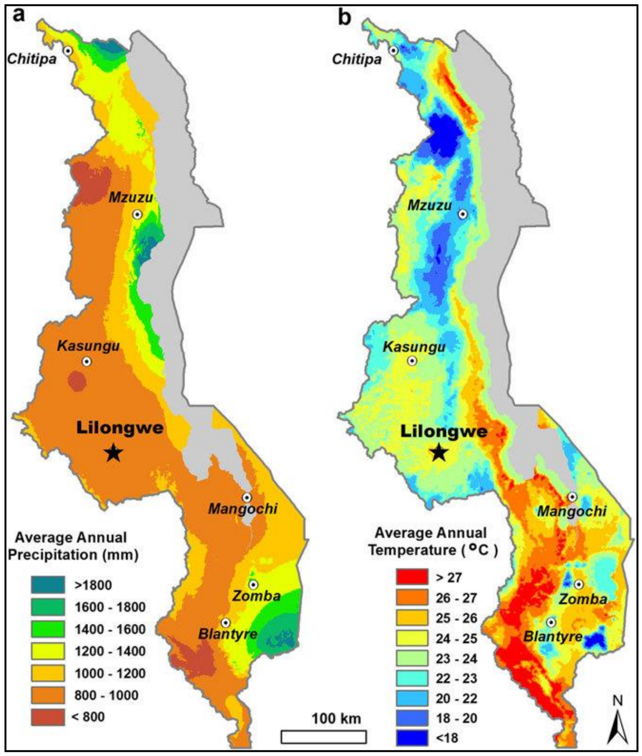


***Figure 2.2: Distribution of the precipitation and temperature across (2015)***

Geospatial data on climate variables (rainfall and temperature) geographical variables (altitude) were also compiled for all waves of the panel. Figure 2.2 shows the distribution of rainfall (Panel a) and temperature (Panel b). Plot level data were generated from the agriculture survey data. There is more precipitation along with the central region lake show, Karonga district and around Mulanje mountain. In contrast, some areas of Rumphi districts and a stretching connecting Neno and Mwanza districts receive low rainfall. There is a low temperature in some areas of Mulanje mountain, some parts of Rumphi and forested stretch in the Mzimba district. High temperatures are in southern districts, including Nsanje, Chikwawa and Neno districts.

## 2.4. Results and Discussion

### *2.4.1 Description of variables*

The descriptive statistics of the variables included for modelling are presented in Table 2.1. The Table comprises variables that are agro-climatic, socio-demographic and climate adaptation. The variables are presented for each wave of the three panels used in this study. The last column presents the summary statistics for the full sample. The mean age of the farming household head for the three panels was 46 years, lying within the economically active age group. The sample was dominated by male-headed farming households. The female-headed households constituted 23 percent of the whole sample. The education level of the farmers was defined as the years of schooling accomplished than the qualifications attached. The use of qualifications attained hides a lot of information as one may attend a particular level of education without attaining qualifications required while still having benefited from the useful knowledge from that level which can shape their thinking and decisions around their farming practices. The level of education varied across years but the mean years of education level attained were 6.6 years which translates into the level of senior primary level of education.

Temperature and precipitation are included as climate variables. These variables exhibit both spatial and temporal variation. The mean annual temperature was 21.4 degrees Celsius and the mean precipitation was 1075.2 mm. The temperature data available was for the annual and wettest quarter (December to February) of the production season. Whereas precipitation data available was for annual, wettest quarter and wettest month (January). The study has been tailored to these levels of data available for the three waves. The initial design was to have different temperature and precipitation variables by seasons of the year. However, as the case with secondary data, the study is constrained to use climate variables presented in Table 2.1, for which data was available for all three panels.

**Table 2.1: Description of variables used in estimating the Ricardian model**

| Variable | Description | Year 2010 | | Year 2013 | | Year 2016 | | Full data | |
|---|---|---|---|---|---|---|---|---|---|
| | | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| TempAnnual | Annual Temperature, °C | 21.5 | 1.7 | 21.4 | 1.7 | 21.4 | 1.7 | 21.42 | 1.71 |
| TempWettestQ | Temperature of wettest quarter, °C | 23.1 | 1.7 | 23.1 | 1.7 | 23.0 | 1.7 | 23.07 | 1.72 |
| PrAnnual | Annual precipitation, mm | 1065.6 | 223.9 | 1071.3 | 231.4 | 1083.9 | 239.5 | 1075.15 | 233.13 |
| PrWettestQ | Wettest quarter precipitation, mm | 675.1 | 81.6 | 679.4 | 82.6 | 683.0 | 82.8 | 679.86 | 82.46 |
| PrWetstM | Wettest months precipitation, mm | 245.1 | 29.4 | 246.6 | 29.2 | 247.6 | 29.4 | 246.63 | 29.36 |
| gender | Gender (male = 1, female = 0) | 0.78 | 0.40 | 0.78 | 0.41 | 0.75 | 0.43 | 0.77 | 0.419 |
| Age | Age in years | 43.3 | 15.6 | 46.0 | 14.9 | 47.3 | 15.0 | 45.9 | 15.21 |
| Education | Level Education (yrs) | 6.8 | 3.8 | 6.6 | 3.8 | 6.5 | 3.7 | 6.62 | 3.759 |
| intercrop | Intercropping (Yes = 1, No = 0) | 0.4 | 0.5 | 0.6 | 0.5 | 0.6 | 0.5 | 0.53 | 0.499 |
| waterconser | Water conservation (Yes = 1, No = 0) | 0.4 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.47 | 0.499 |
| irrigation | Irrigation (Yes = 1, No = 0) | 0.11 | 0.181 | 0.11 | 0.114 | 0.11 | 0.120 | 0.11 | 0.08 |
| Improvedvar | Improved variety ((Yes = 1, No = 0) | 0.66 | 0.47 | 0.68 | 0.46 | 0.64 | 0.48 | 0.66 | 0.47 |
| dist_road | Distance to nearest road (Km) | 9.59 | 9.570 | 9.83 | 10.193 | 9.45 | 9.906 | 9.61 | 9.920 |
| dist_agmrkt | Distance to market (KM) | | | | | | | 24.98 | 14.044 |
| NR | Net revenue (US$/ Ha) | 247.9 | 105.9 | 281.0 | 74.7 | 250.16 | 76.6 | 259 | 57.3 |
| N | Observations | 2268 | | 2790 | | 3,531 | | 8,589 | |

Also considered in the analysis was a package of farmer adaptation strategies to climate change. These include intercropping, water conservation practices, irrigation and the use of improved crop varieties. Around 66 percent intercropped their fields to spread the risk of total crop failure, about 47 percent engaged of package of soil water conservation practices to detour the crop stress as a result of extreme weather conditions, 66 percent used improved crop varieties which are more tolerant to drought impacts, and 11 percent supplemented their rainfed agriculture with irrigated farming.

### *2.4.2 Economic impacts of climate change on agriculture*

To calibrate the impacts on climate change on agriculture, several models are implemented. The first Ricardian model regresses climate variables and other farmer specific characteristics on Net Farmland revenue per hectare. This acts as a base model before adjusting for the technical efficiency of the farms. The model is re-run with the net farmland revenue per hectare corrected for individual technical inefficiencies of production for farmers facing the same climate in each given climate zone. The output loss per hectare due to farmer specific inefficiency is multiplied by derived output price (derived from the ratio of realized revenue to quantity sold). The imputed value of output loss per hectare is added to the net farm revenue per hectare, which becomes the dependent variable for the TE corrected Ricardian model.

The output loss is determined by the level of inefficiency of each farm derived from the output-oriented production frontier. Frontier models were run for four crops; Maize, Tobacco, Groundnut and Pigeon peas. These were the crops mostly grown in all three waves of the data and allowed for enough degrees of freedom during analysis. While other crops were not commonly grown, those commonly grown reflects farmers' adjustment to engage in crop production that suits their current climates. As such, the exclusion of non-common crops did not affect the representation of the data. Using spatial analysis, the enumeration areas were classified according to their similarities in climates based on climate variables (Figure 2.3).

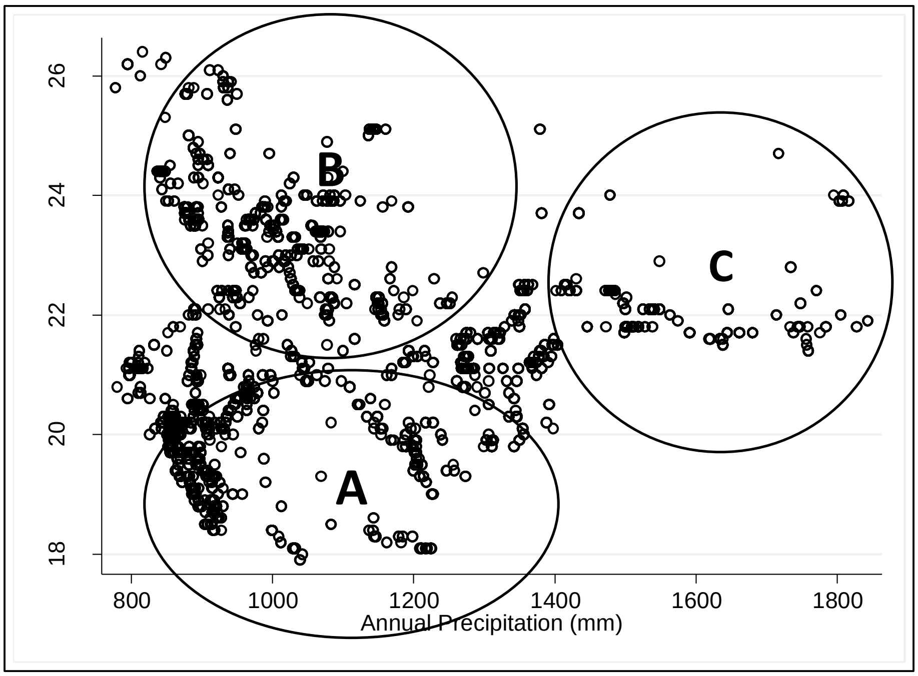


***Figure 2.3: Distribution of climate variables***

These were disaggregated into Low temperature - Low rainfall (Panel A in Figure 2.3), high temperature – low rainfall (Panel B) and moderate temperature – high rainfall (Panel C). High rainfall was associated was moderate temperature. In turn, the stochastic production frontier models were run for the crops and for each of the climates.

Estimation of the production frontiers was done in steps in the search for the appropriate estimator and parsimonious model. In the first step, the Translog production frontier specification was used to discriminate against either fixed or random-effects approaches. For consistency of the estimated production function, monotonicity and homotheticity regularity constraints were imposed on the linear and interactive coefficients of the Translog production frontiers in the estimation procedure. In the ex-post estimation of the Translog production frontier after choosing between the fixed or random-effects model, two issues were evaluated. First, the Translog production function was tested against the restricted Cobb-Douglass counterpart to determine the one that adequately represented the data generation process. The results of testing fixed versus random effects and Translog versus Cobb-Douglass are presented in Table 2.2. Due to inadequate data for certain climatic zones and crops, two models were not implemented. First, the pigeon pea model for low temperature – low precipitation, and second, the groundnut model for high temperature - high precipitation, as can be seen with gaps in Table 2.2.

A total of 10 Translog production frontier models were estimated for the crops under various climates, first with fixed effects and then with random effects. The results for comparing the fixed and random effects coefficients using the Durbin-Wu-Hausman test for each of the models are presented in Table 2.2. The Hausman test results show no systematic differences ($p > 0.05$) in fixed and random models coefficients for maize models. As such, all maize models used the random effects approach. All other models' estimations rejected the random-effects models favouring fixed-effects models ($p < 0.05$). Thus, all other models were implemented using the fixed effects approach.

**Table 2.2: Test results of specification of various Technical Efficiency models**

| | Maize | Tobacco | Groundnut | Pigeon pea |
|---|---|---|---|---|
| **Low temperature low precipitation** | | | | |
| Durbin–Wu–Hausman | 6.89 (0.649) | 118 | 289.51 | - |
| | | (0.000) | (0.000) | |
| LR test for CD vs Translog | 101.44 | 1167.01 | 4.85 | - |
| | (0.000) | (0.000) | (0.542) | |
| **High temperature low precipitation** | | | | |
| Durbin–Wu–Hausman | 4.72 (0.858) | 102.05 | 49.49 (0.000) | 142.42 |
| | | (0.000) | | (0.000) |
| LR test for CD vs Translog | 114.6 | 16.93 | 834.26 | 374 |
| | (0.000) | (0.000) | (0.000) | (0.00) |
| **High temperature High precipitation** | | | | |
| Durbin–Wu–Hausman | 5.60 (0.779) | - | 781.41 | 111.94 |
| | | | (0.000) | (0.000) |
| LR test for CD vs Translog | 25.76 | - | 970.08 | -22.89 |
| | (0.000) | | (0.000) | (0.000) |

Note: In parenthesis are the p-values

In the second step, in trying to develop a parsimonious model, the generalized Likelihood Ratio test was used. A high p-value of the Likelihood ratio test indicates that the data is consistent with the claim that the extra variables together (not just individually) in the Translog specification do not substantially improve model fit. For each Translog model, a corresponding Cobb-Douglass model was estimated for comparison. The results for each model (in Table 2.2) show that the flexible Translog production function fit better than the Cobb-Douglass except for the groundnut model under a low temperature-low precipitation climate. The ten final models chosen after the generalized Likelihood Ratio test were then used for estimating technical efficiency scores.

The technical efficiency results of the four crops are presented in Table 2.3. The results are disaggregated by the panel, climate and crop. The notations for climate A, B and C are as presented previously in Figure 2.2. The scores can take on values between 0 and 1.

**Table 2.3: Mean Technical Efficiency Scores**

| **Panel** | **Climate** | **Maize** | **Tobacco** | **Groundnut** | **Pigeon pea** | **Total** |
|---|---|---|---|---|---|---|
| | A | 0.63 | 0.62 | 0.53 | - | 0.61 |
| | B | 0.66 | 0.58 | 0.51 | 0.74 | 0.65 |
| | C | 0.65 | - | 0.52 | 0.73 | 0.67 |
| 2010 | Total | 0.65 | 0.61 | 0.52 | 0.73 | 0.64 |
| | A | 0.66 | 0.67 | 0.58 | - | 0.64 |
| | B | 0.70 | 0.70 | 0.56 | 0.67 | 0.67 |
| | C | 0.71 | - | 0.52 | 0.67 | 0.68 |
| 2013 | Total | 0.69 | 0.68 | 0.57 | 0.67 | 0.66 |
| | A | 0.67 | 0.66 | 0.53 | - | 0.65 |
| | B | 0.69 | 0.70 | 0.52 | 0.67 | 0.66 |
| | C | 0.68 | - | 0.52 | 0.67 | 0.67 |
| 2016 | Total | 0.68 | 0.66 | 0.53 | 0.67 | 0.66 |
| | A | 0.66 | 0.65 | 0.55 | - | 0.64 |
| | B | 0.68 | 0.64 | 0.53 | 0.68 | 0.66 |
| | C | 0.68 | - | 0.52 | 0.68 | 0.67 |
| Total | **Total** | **0.67** | **0.65** | **0.54** | **0.68** | **0.65** |

The latter is the most efficient farmer operating on frontiers, and any scores less than one means that they are operating below the frontier. The results show that, on average, the farms facing similar climatic conditions are not technically efficient and could increase their output level and net farmland revenue under the same climatic conditions. The within climate variation in output was netted out when estimating the Ricardian Model in the preceding section.

The results of the Ricardian Models are presented in Table 2.4, the middle column for the base model and the last column for the TE corrected model. Both ex-ante and posterior checks were part of the model implementation procedure to validate its robustness. Each model was tested for appropriateness of either fixed effects or random effects using Durbin-Wu-Hausman's test. The base model had $p > 0.05$ for Hausman's Chi-square statistic (2.13), and the TE corrected model reported an insignificant Chi-square statistic of 3.32 ($p > 0.05$). Thus, both models needed to use the random effects approach since, in this case, the random-effects model is more efficient than the fixed effects model, although both are consistent.

There are three types of variables; linear and quadratic climatic terms, farmer characteristics and adaptation strategies. One additional variable that most similar studies (Molua, 2009; Jain, 2007; Nnadi, Liwenga, Lyimo, & Madukweb, 2019) omitted is the interaction (cross-product) of the temperature and precipitation. While the linear terms reflect the uni-directional relationship of the climate variable and the net farm revenue, the quadratic terms reflect the function form or the shape of the curve of net farm revenue with respect to changes in climate variables. The shape of the curve depends on the sign of the coefficient on the quadratic term. The negative sign implies that the curve is concave, while when the sign is positive, it implies a convex shape to climate variable. The linear and quadratic terms of climate variables were highly significant, showing a non-linear

**Table 2.4: Random-effects GLS Ricardian regression model**

| Variable | Base model | | | TE corrected model | | |
|---|---|---|---|---|---|---|
| | **Parameter estimate** | **t-value** | **P-value** | **Parameter estimate** | **t-value** | **P-value** |
| TempAnnual | 293.4 | 5.31*** | 0.000 | 212.78 | 4.08 *** | 0.000 |
| TempWettestQ | 401.1 | 4.65*** | 0.000 | 273.05 | 2.53*** | 0.011 |
| PrAnnual | 2.944 | 2.92*** | 0.000 | 0.50 | 4.88*** | 0.000 |
| PrWettestQ | 4.278 | 1.94* | 0.052 | 5.78 | 2.65 *** | 0.008 |
| PrWetstM | 8.208 | 1.33 | 0.184 | 4.32 | 0.24*** | 0.807 |
| Temp*Precip | -0.009 | -0.58 | 0.562 | 0.05 | 3.87*** | 0.000 |
| sq_TempAnnual | -7.437 | -5.06*** | 0.000 | -6.62 | -3.61 *** | 0.000 |
| sq_TempWettestQ | -9.091 | -4.52*** | 0.000 | -6.14 | -2.73*** | 0.006 |
| sq_PrAnnual | 0.00021 | 2.70*** | 0.007 | 0.00288 | 2.28*** | 0.023 |
| sq_PrWettestQ | -0.001 | -1.78 | 0.074 | -0.00289 | -2.98 | 0.003 |
| sq_PrWetstM | -0.015 | -0.88 | 0.381 | -0.01 | -3.21*** | 0.000 |
| Sex | 30.67 | 1.73* | 0.084 | 21.77 | 1.09 | 0.276 |
| Age | 2.380 | 2.00** | 0.027 | 1.63 | 0.15 | 0.883 |
| Education | 9.45 | 5.82** | 0.000 | 72.46 | 3.91*** | 0.000 |
| Intercrop | 60.03 | 1.42 | 0.155 | 105.06 | 3.20*** | 0.001 |
| Irrigation | 128.59 | 3.92*** | 0.000 | 163.00 | 4.06*** | 0.000 |
| Improved variety | 150.73 | 4.22*** | 0.000 | 226.94 | 3.56*** | 0.000 |
| Water Conservation | 88.65 | 2.47** | 0.015 | 132.82 | 2.07** | 0.039 |
| Distance to road | 0.09 | 0.29 | 0.772 | -0.56 | -2.01** | 0.045 |
| Distance to market | -1.08 | -4.58 ** | 0.000 | -0.71 | -3.48** | 0.001 |
| Constant | -59.403 | -0.47 | 0.640 | 47.12 | 1.26 | 0.208 |
| Wald chi2 | 418.43 | | 0.000 | 293.39 | | 0.000 |
| Hausman Test | 17.25 | | 0.369 | 20.89 | | 0.183 |
| Observations | 5,442 | | | 5,442 | | |

*****Significant at $p$ <0.1, ****** significance at $p$ < 0.05, ***significant at $p$ <0.01

relationship between climate variables and net farmland revenue. Overall, coefficients of the two models were jointly significant, as shown by individual Wald chi-square statistics ($p$ <0.01). The estimation used robust standard errors to control for heteroskedasticity. The variance of the coefficient estimates was stably denoting that there was no serious multicollinearity in the variables.

To get a deeper meaning of the coefficients, a further analysis was done to derive the marginal effects at the mean of each climate variable on net farmland revenue by taking the derivative of the Ricardian Model with respect to the climate variable in question course holding all other variables constant.  The marginal effects at the mean of each climate variable are presented in Table 2.5.

**Table 2.5: Marginal impacts of climate on net farm revenue per ha (US$/Ha)**

| **Climate** | **Marginal net farm revenue per Ha (US$/Ha)** | | | |
|---|---|---|---|---|
| | **Base model** | **TE corrected model** | **Difference** | **P-value** |
| Annual Temperature | -34.53 | -15.35 | 19.17 (190.2) | 0.000 |
| Temperature of wettest quarter | -18.33 | -10.05 | 8.28 (244.4) | 0.000 |
| Annual precipitation | 3.21 | 2.22 | -0.99 (-250.0) | 0.000 |
| Precipitation of the wettest quarter | 3.17 | 1.85 | -1.31 (-250.0) | 0.000 |
| Precipitation of wettest month | 0.92 | 0.66 | -0.26 (-134.3) | 0.000 |

(.) In parenthesis are the t-values for the difference

The marginal effects of the temperature variables show that there are unidirectional impacts on net farm revenue. The findings from the base model show that agriculture will lose out from the general annual increase in warming both for efficient and non-efficient farmers. The marginal impacts from increases in precipitation are positive, of course, with the inefficient farmers benefiting most from increases in annual precipitation and in the wettest quarter of the year. In absolute terms, the greatest impacts (in this case, negative impacts) come from rising warming. This is line with (Molua, 2009).

A further analysis was done to test the significance of the differences in impacts of climate variables on net farm revenue between the two models. The study established that the magnitude of impacts is significantly different ($p < 0.01$) between the base model and corrected for technical efficiency. The base model registered different negative impacts for warming and different positive impacts for increases in precipitation, with varying degrees. This could ascertain the fact that the presence of technical inefficiency in farm-level climate impacts calibration could lead to biasing the impacts of climate variables.

The climate impacts are moderated by adaptation strategies for those farmers that have preconditioned their agriculture through the adaptation of relevant strategies. Several adaptation choices were explored, including intercrops, improved drought-tolerant crop varieties, and irrigation and water conservation practices (i.e., conservation agriculture). Intercropping was positively related to net farm revenue. Certain cover crops included in the intercrop package may have helped reduce crop stress that might come from high temperatures and moisture loss. In other instances, it may help to spread the risk of total crop failure and, in turn, minimize losses in net farm revenue. Irrigation was an important adaptation strategy in the studied farming systems. The fields that were under irrigation realized more net farm revenue than those that did not, in two ways, first through multiple cultivation rounds in a year and reduced crop stress during the rainfed agriculture season. The use of improved varieties also increased the resilience of the agriculture system to climate stresses. It had the potential to increase the yield marginally by US$208 per hectare for technically efficient farmers and US$143 for non-efficient farms, probably because of its high tolerance to drought stresses.

### *2.4.3 Future Uniform Climate scenarios and agricultural impacts*

Using the coefficients of the Ricardian model, I can examine the impacts of the various climates on a country's agriculture while holding all other factors constant. These coefficients are used to experiment with artificial uniform warming scenarios: an increase in temperature by 2.5°C and 5°C (Same artificial scenarios have been used by Molua (2009) in West Africa). I further simulate artificial uniform precipitation scenarios: a decrease in precipitation by 7% and by 14%. Table 6 provides a summary of the outcomes of these artificial uniform scenarios.

**Table 2. 6: Forecasted impacts on net farm revenue from uniform climate scenarios**

| **Climate** | **Annual Warming** | | **Annual Precipitation** | |
|---|---|---|---|---|
| | **+2.5°C** | **+5°C** | **-7%** | **-14%** |
| Base: ΔNet revenue (US$/ha) | -71.71<br>(-27.6%) | -108.9<br>(-41.9%) | 3.18<br>(-1.3%) | 3.14<br>(-1.4%) |
| Base: ΔTotal net revenue (Million US$) | -400.13 | -607.61 | 17.71 | 17.5 |
| TE: ΔNet revenue (US$/ha) | -48.4<br>(-12.0%) | -81.5<br>(-20.2%) | 2.18<br>(-0.57%) | 2.13<br>(-0.23%) |
| TE: ΔTotal net revenue (Million US$) | -270.26 | -454.85 | 12.13 | 11.8 |

Overall, increases in warming and reduction in precipitation will incur heavy losses on the agricultural sector. The average losses or gains per hectare are multiplied by the total cultivable agriculture land in Malawi to develop country-wide impacts of a given change in climate variable. The assumption is that a rational farmer will choose crops that maximize returns under given climate conditions. If the climate becomes unfavourable for one crop, the farmers will switch to new crop choices that suit their climate to maximize returns. The uniform scenario shows that an increase in warming by 2.5°C will result in a loss of US$48.4 per hectare and US$270 Million for the country as a whole. The damages are overstated to be US$400 Million when the farms are inefficient. A further increase in warming to 5°C will result in more than proportionate increases in losses for the agriculture sector. An examination of the decrease in precipitation by 7% and 14% both shows that the sector will benefit about US$12.3 Million and US$11.8 Million, respectively. Although these are positive gains, it can be noticed that gains are decreasing in the direction of precipitation change.

#### *2.4.4 Projected climate change and impacts on agriculture using Global Circulation Models*

Evidence from an ensemble of 15 Global Circulation Models (GCMs) of type CMIP3 that were run for Malawi provides an indication of more warming for future climates compared to the historical baseline climate period of 1995 to 2015. Considering that climate change is a long-term phenomenon, the periods of analysis to observe future climate shifts are sliced into four climatological windows from 2020 to 2099, with each slice having a size of 20 years, namely 2020-2039, 2040-2059, 2060-2079, and 2080-2099 (See Taylor et al. (2012)). Over this time period, two different emissions scenarios are examined, A2 and B1 (IPCC, 2001). These are also widely used in literature.

**Table 2.7: Projected warming for Malawi by Global Circulation Models (GCM)**

| Name of the Model | Scenario A2 | | | | Scenario B1 | | | |
|---|---|---|---|---|---|---|---|---|
| | **2020 – 2039** | **2040 - 2059** | **2060 - 2079** | **2080 - 2099** | **2020 - 2039** | **2040 - 2059** | **2060 - 2079** | **2080 - 2099** |
| Base climate (22.4) | | | | | | | | |
| BCCR_BCM2_0 | 20.8 | 21.4 | 22.2 | 23.2 | 20.7 | 21.2 | 21.5 | 21.9 |
| CCCMA_CGCM3_1 | 21.8 | 22.6 | 23.5 | 24.5 | 21.4 | 21.8 | 22.4 | 22.6 |
| CNRM_CM3 | 21.0 | 22.0 | 23.1 | 24.3 | 20.9 | 21.3 | 21.7 | 21.9 |
| **CSIRO_MK3_5** | **26.8** | **27.5** | **28.4** | **29.7** | **26.7** | **27.3** | **27.7** | **28.1** |
| GFDL_CM2_0 | 22.2 | 22.9 | 24.0 | 25.0 | 22.2 | 22.4 | 22.9 | 23.2 |
| GFDL_CM2_1 | 22.1 | 22.8 | 23.7 | 25 | 21.8 | 22.4 | 22.9 | 22.9 |
| INGV_ECHAM4 | 23.8 | 24.5 | 25.3 | 26.2 | - | | | |
| INMCM3_0 | 21.1 | 21.3 | 22.7 | 23.6 | 21.0 | 21.2 | 21.8 | 22.1 |
| IPSL_CM4 | 24.4 | 25.1 | 26.1 | 27.4 | 24.5 | 24.9 | 25.3 | 25.6 |
| MIROC3_2_MEDRES | 21.3 | 21.7 | 22.9 | 24.1 | 21.1 | 21.6 | 22.2 | 22.7 |
| MIUB_ECHO_G | 22.6 | 23.3 | 24.2 | 25.3 | 22.4 | 23.1 | 23.3 | 23.9 |
| MPI_ECHAM5 | 24.3 | 24.9 | 26.4 | 27.8 | 24.0 | 24.9 | 25.7 | 25.9 |
| MRI_CGCM2_3_2A | 22.0 | 22.6 | 23.5 | 24.1 | 21.8 | 22.3 | 22.6 | 22.9 |
| UKMO_HadCM3 | 23.8 | 24.9 | 25.9 | 27.3 | 23.6 | 24.3 | 25.0 | 25.6 |
| UKMO_HadGEM1 | 22.2 | 23.1 | 24.3 | 25.6 | | | | |
| Mean for all models | 22.7 | 23.4 | 24.4 | 25.5 | 22.5 | 23.0 | 23.5 | 23.8 |

Taking the average climate outcome for all the examined GCMs, evidence shows that there will be a gradual decline of net farm revenues in the future due to warming. The climatological window averages are fitted into the Ricardian framework, and this attests to the fact that there will be a warming impact on net farm revenues. The finding shows that the impacts will intensify over the period 2060 to 2099. The projected impacts vary depending on the model and scenario in question. For all models, emissions scenario B1 has shown to have moderate warming impacts compared to scenario A2 (Table 2.7). With regard to precipitation, although there are mixed projected trajectories, the mean of the GCMs shows that the gains outweigh the losses because of the increase in the mean annual precipitation by 2099. As was the case with temperature impacts, the impacts for Scenario B1 are relatively lower than A2 (Table 2.8).

**Table 2. 8: Projected impacts of warming on Malawi's agriculture, in US$ Millions per year**

| | **Scenario A2** | | | | **Scenario B1** | | | |
|---|---|---|---|---|---|---|---|---|
| | **2020 – 2039** | **2040 - 2059** | **2060 - 2079** | **2080 – 2099** | **2020 - 2039** | **2040 - 2059** | **2060 - 2079** | **2080 - 2099** |
| BCCR_BCM2_0 | -54.5 | -98.8 | -157.8 | -231.7 | -47.1 | -84.0 | -106.2 | -135.7 |
| CCCMA_CGCM3_1 | -128.3 | -187.4 | -253.8 | -327.7 | -98.8 | -128.3 | -172.6 | -187.4 |
| CNRM_CM3 | -69.2 | -143.1 | -224.3 | -312.9 | -61.8 | -91.4 | -120.9 | -135.7 |
| **CSIRO_MK3_5** | **-497.5** | **-549.2** | **-615.6** | **-711.6** | **-490.1** | **-534.4** | **-564.0** | **-593.5** |
| GFDL_CM2_0 | -157.8 | -209.5 | -290.8 | -364.6 | -157.8 | -172.6 | -209.5 | -231.7 |
| GFDL_CM2_1 | -150.5 | -202.1 | -268.6 | -364.6 | -128.3 | -172.6 | -209.5 | -209.5 |
| INGV_ECHAM4 | -276.0 | -327.7 | -386.7 | -453.2 | | | | |
| INMCM3_0 | -76.6 | -91.4 | -194.8 | -261.2 | -69.2 | -84.0 | -128.3 | -150.5 |
| **IPSL_CM4** | **-320.3** | **-372.0** | **-445.8** | **-541.8** | **-327.7** | **-357.2** | **-386.7** | **-408.9** |
| MIROC3_2_MEDRES | -91.4 | -120.9 | -209.5 | -298.1 | -76.6 | -113.5 | -157.8 | -194.8 |
| MIUB_ECHO_G | -187.4 | -239.1 | -305.5 | -386.7 | -172.6 | -224.3 | -239.1 | -283.4 |
| **MPI_ECHAM5** | **-312.9** | **-357.2** | **-468.0** | **-571.3** | **-290.8** | **-357.2** | **-416.3** | **-431.0** |
| MRI_CGCM2_3_2A | -143.1 | -187.4 | -253.8 | -298.1 | -128.3 | -165.2 | -187.4 | -209.5 |
| UKMO_HadCM3 | -276.0 | -357.2 | -431.0 | -534.4 | -261.2 | -312.9 | -364.6 | -408.9 |
| UKMO_HadGEM1 | -157.8 | -224.3 | -312.9 | -408.9 | | | | |
| **Mean for all models** | -193.3 | -244.5 | -321.3 | -404.5 | -177.7 | -215.2 | -251.0 | -275.4 |

Different GCMs have shown divergent precipitation outcomes for the future. While others have projected a drier future, others have projected a wetter future compared to the baseline (historical) precipitation window of 1995 to 2015. Of the 15 GCMs examined, six have projected a relatively drier future. A further examination of the mean for the 15 GCMs shows that precipitation will increase in the future between 10% to 16% across different future time slices. Using monthly rainfall data over the period of analysis, rainfall trends over the months of the year have shown slightly different distribution patterns for the A2 Scenario and B1 Scenario (Figure 2.4). The B1 class projections have shown that there will be an earlier onset of rainfall around November with high mean precipitation in the off-season compared to the baseline. This might result in reduced costs of irrigation and, in turn, increased net farm revenues for farmers engaging in irrigated farming. The A2 class projections have shown increased precipitation in the months of November, December, January and February. There may be an early decline of precipitation towards the end of the rain season, which may require the adoption of shorter duration crop varieties to tally with shorter rain season.

**Table 2.9: Projected annual precipitation change (%) by Global Circulation Models (GCMs)**

| **Name of the Model** | **Scenario A2** | | | | **Scenario B1** | | | |
|---|---|---|---|---|---|---|---|---|
| | **2020 - 2039** | **2040 - 2059** | **2060 - 2079** | **2080 - 2099** | **2020 - 2039** | **2040 - 2059** | **2060 - 2079** | **2080 - 2099** |
| Base climate (1029.1*) | | | | | | | | |
| BCCR_BCM2_0 | 36.5 | 37.9 | 37.9 | 50.4 | 38.5 | 35.8 | 37.3 | 37.1 |
| **CCCMA_CGCM3_1** | **-8.9** | **-2.1** | **0.8** | **4.6** | **-0.5** | **5.0** | **-2.8** | **0.8** |
| CNRM_CM3 | 49.5 | 46.8 | 51.5 | 51.7 | 35.3 | 54.4 | 45.2 | 48.6 |
| CSIRO_MK3_5 | 11.0 | 12.8 | 22.7 | 13.6 | 14.7 | 10.4 | 13.6 | 10.9 |
| GFDL_CM2_0 | 23.5 | 35.6 | 36.8 | 26.1 | 31.9 | 29.5 | 38.7 | 35.2 |
| GFDL_CM2_1 | 25.9 | 17.4 | 23.3 | 25.3 | 20.6 | 22.5 | 14.5 | 17.8 |
| INGV_ECHAM4 | 25.4 | 29.9 | 33.4 | 32.8 | | | | |
| **INMCM3_0** | **-17.5** | **-12.8** | **-11.8** | **0.0** | **-20.2** | **-16.5** | **-16.1** | **-14.0** |
| **IPSL_CM4** | **-20.2** | **-13.4** | **-18.0** | **-10.4** | **-19.8** | **-23.4** | **-21.6** | **-14.8** |
| MIROC3_2_MEDRES | 13.7 | 14.1 | 18.2 | 18.9 | 7.8 | 11.3 | 11.3 | 10.3 |
| MIUB_ECHO_G | 14.7 | 17.0 | 24.1 | 33.9 | 15.4 | 17.8 | 21.2 | 21.0 |
| **MPI_ECHAM5** | **-26.4** | **-24.3** | **-26.8** | **-21.4** | **-26.1** | **-30.2** | **-31.2** | **-25.4** |
| MRI_CGCM2_3_2A | 30.8 | 33.1 | 24.7 | 27.3 | 25.6 | 28.5 | 32.0 | 27.6 |
| **UKMO_HadCM3** | **-12.1** | **-18.8** | **-14.5** | **-7.3** | **-13.9** | **-16.8** | **-20.3** | **-13.1** |
| **UKMO_HadGEM1** | **9.8** | **4.8** | **-4.4** | **-2.8** | | | | |
| Mean for all models | 10.4 | 11.9 | 13.2 | 16.2 | 8.4 | 9.9 | 9.4 | 10.9 |

*Baseline value in mm not %

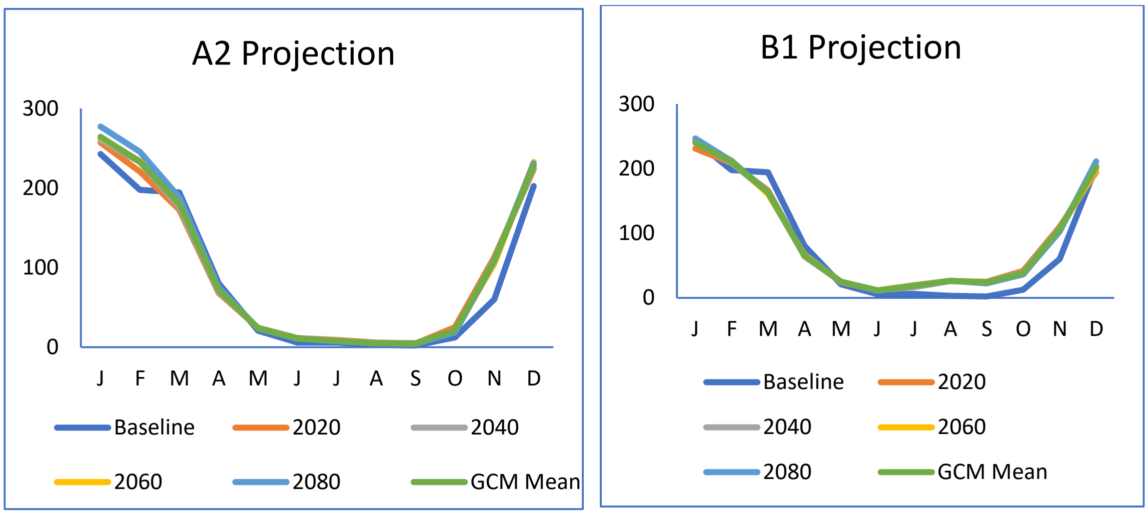


***Figure 2. 4: Projected change in the distribution of rainfall over a year***

Feeding various precipitation scenarios from GCMs into the Ricardian model yield the gains and losses presented in Table 2.10. The uncertainty of the future makes it a challenge to predict exactly what the climate will be like. However, from an ensemble of various state of the art GCMs we can get the mean projected precipitation to give a picture of what future climate will be like at the same time appreciate the sensitivity of climate impacts calibrated across various models. Overall, the mean of the GCMs shows that the gains outweigh the losses because of the increase in the mean annual precipitation by 2099. This corroborates with the finding of Andt et al. (2010) and Saka et al. (2012), who notes that future climate change will favour the agriculture sector. The CNRM_CM3 model projected the highest gains from change in precipitation, while we observed the worst damages projected from the MPI_ECHAM5 model. Using the mean of GCMs, by 2099, the agriculture sector will benefit US$3.8 Million per year from a change in precipitation. As was the case with temperature impacts, the impacts for Scenario B1 are relatively lower than A2.

**Table 2. 10: Projected impacts of precipitation change (US$ in Millions/year) for Malawi**

| Name of the Model | Scenario A2 | | | | Scenario B1 | | | |
|---|---|---|---|---|---|---|---|---|
| | 2020 - 2039 | 2040 - 2059 | 2060 - 2079 | 2080 - 2099 | 2020 - 2039 | 2040 - 2059 | 2060 - 2079 | 2080 - 2099 |
| ***Base climate (1029.1)** | | | | | | | | |
| BCCR_BCM2_0 | 8.49 | 8.83 | 8.82 | 11.74 | 8.98 | 8.34 | 8.70 | 8.65 |
| **CCCMA_CGCM3_1** | -2.08 | -0.48 | 0.19 | 1.07 | -0.12 | 1.16 | -0.66 | 0.18 |
| CNRM_CM3 | 11.54 | 10.89 | 12.00 | 12.04 | 8.21 | 12.67 | 10.53 | 11.32 |
| CSIRO_MK3_5 | 2.56 | 2.99 | 5.28 | 3.16 | 3.41 | 2.43 | 3.18 | 2.54 |
| GFDL_CM2_0 | 5.47 | 8.28 | 8.56 | 6.09 | 7.43 | 6.87 | 9.02 | 8.21 |
| GFDL_CM2_1 | 6.04 | 4.04 | 5.42 | 5.89 | 4.81 | 5.25 | 3.37 | 4.14 |
| INGV_ECHAM4 | 5.92 | 6.97 | 7.78 | 7.63 | | | | |
| **INMCM3_0** | **-4.08** | **-2.98** | **-2.75** | **0.00** | **-4.70** | **-3.84** | **-3.75** | **-3.25** |
| **IPSL_CM4** | **-4.70** | **-3.13** | **-4.20** | **-2.43** | **-4.62** | **-5.46** | **-5.03** | **-3.45** |
| MIROC3_2_MEDRES | 3.18 | 3.27 | 4.23 | 4.41 | 1.82 | 2.63 | 2.63 | 2.41 |
| MIUB_ECHO_G | 3.42 | 3.95 | 5.62 | 7.90 | 3.60 | 4.14 | 4.93 | 4.88 |
| **MPI_ECHAM5** | **-6.14** | **-5.65** | **-6.24** | **-4.99** | **-6.07** | **-7.04** | **-7.27** | **-5.92** |
| MRI_CGCM2_3_2A | 7.17 | 7.71 | 5.76 | 6.37 | 5.97 | 6.64 | 7.45 | 6.42 |
| **UKMO_HadCM3** | **-2.83** | **-4.37** | **-3.38** | **-1.71** | **-3.23** | **-3.91** | **-4.73** | **-3.04** |
| **UKMO_HadGEM1** | 2.27 | 1.11 | -1.02 | -0.65 | | | | |
| Mean for all models | 2.42 | 2.76 | 3.07 | 3.77 | 1.96 | 2.30 | 2.18 | 2.54 |

*Baseline value in mm not %

## 5. CONCLUSIONS AND POLICY IMPLICATIONS

The study assessed the current and potential impacts of climate change on agriculture in Malawi. Climate change will have diverse impacts on agriculture, meriting the need to understand the interaction between global climate shifts and the agricultural system. The results have shown that increases in rainfall will generate economic gains for the agriculture sector and may reduce the probability of farmers living below the poverty line. Warming will have detrimental impacts on the sector. A comparison of efficient and non-efficient farmers in their production shows that impacts could be exaggerated for the inefficient farmers. For the inefficient farms, the economic impacts could be idiosyncratic, comprising of true climate-related impacts and technical inefficiency impacts.

The future economic impacts of climate change will largely depend on the nature of the future climates. While many studies have viewed climate change to be detrimental to agricultural enterprise outcomes, our study finds that the agriculture sector will benefit from a wetter future, although there will be some losses from increased future warming. There is a general consensus across GCMs that the projected future climate for Malawi will be more warming than the baseline. The resulting economic, agricultural damages will be moderate in the short future but will be expected to increase in the medium (2060) to long term future (2080). The negative economic impacts from increased warming could be offset by shifting crop variety choices to adopting drought-tolerant varieties and reinforcing affordable irrigation systems and farm water conservation practices. These will generate positive marginal changes in economic gains of US$226 for drought-tolerant varieties and US$163 for irrigated farms per hectare per year compared to those who will not adopt.

There are uncertainties in the 15 GCMs about the direction of future precipitation for Malawi. However, the general consensus (mean) across the GCMs for A2 and B1 emission scenarios shows that there will be more precipitation relative to the baseline precipitation. As a result, Malawi will have positive economic gains, for the agriculture sector, from this future climate shift. However, the gains from precipitation changes are not enough to offset the impacts of warming unless the farmers employ systematic adaption strategies to moderate the negative impacts of future warming, Since the negative shifts in climate cannot be reversed easily if, at all they can, the plausible actions could be to mitigate the impacts through relevant adaptation strategies.

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# CHAPTER 3

# CLIMATE-INDUCED VULNERABILITY TO POVERTY

## 3.1 Introduction

### *3.1.1 Background*

The staggering effects of climate change on agrarian economies have deepened than ever. These effects continue to threaten economies that heavily depend on agriculture and forest sectors for rural livelihoods (Rosenzweig & Parry, 1993; Gbetibouo & Hassan, 2005; Kurukulasuriya, et al., 2006). The magnitude of the effects is skewed towards the rural population because a majority of the population resides in the rural and is mostly employed in subsistence rain-fed agriculture as their prime economic activity, and more than half of their earnings are spent on food (Cranfield, Eales, Hertel, & Preckel, 2003). Increased intensity of climate extremes such as droughts and floods will result in low agricultural productivity, negatively and directly impact their livelihoods (Easterling, et al., 2007). This will, in turn, weaken the efficacy of certain adaptation strategies, like irrigation, as low levels of precipitation will reduce the amount of water available for irrigated food production (FAO, 2003) in the off-rainfall season.

The developing regions like Sub-Saharan Africa (SSA) has been dominated by countries whose economies heavily rely on agriculture for employment and food security (Livingston, Schonberger, & Delaney, 2011). Although the agriculture sector has large numbers of small-scale farmers, they mostly produce under unfavourable climatic (low precipitation and high temperatures) and environmental (low soil fertility) conditions (Mutsvangwa, 2011). With regard to climate conditions, the need arises to understand the nature and extent of vulnerability and, in turn, resilience to the impacts on farming households in general to aid documentation and packaging of practical and workable strategies for enhancing communities' capacity to reduce vulnerability and to mitigate negative climate change impacts. In Malawi, the resilience of agriculture will depend on the capacity of producers to adapt their agriculture systems to changing environmental and economic conditions. This will be of particular importance as climate change alters the nature and magnitude of these environmental shocks. Those who may not adapt will incur economic losses over time, which will ultimately threaten the economic viability of their agriculture ventures.

Studies relating to climate change and agriculture in Malawi have taken divergent trajectories. Others have analysed factors affecting choices of climate adaptation strategies in agriculture (Pangapanga, Jumbe, Kanyanda, & Thangalimodzi, 2012) but did not quantify the vulnerability of farming households to climate stresses. Nordhagen and Pascual (2013) examined the impacts of shocks on the behaviour of farmers in seed markets. In order to understand the economic viability of the agricultural systems in Malawi under increasing climate variability, as proposed in climate change forecasts, it makes vulnerability studies much relevant as it is a precursor to bolster the agriculture sector's resilience. It is believed that climate variability will relay greater vulnerability on most of the farmers in developing countries, not because the level of climate variability is high, but because of over-dependence on rain-fed agriculture. Any minor variability will transmit great losses in agricultural output (Watson, Zinyowera, Moss, & Dokken, 1998), given that Malawi lies in the tropical region where temperatures are already high.

The term vulnerability refers to shocks and stresses of climate change and variability to which farming households are exposed and their adaptive capacity to withstand the resulting negative effects (IPCC, 2001; IPCC, 2007). IPCC (2007) define adaptive capacity as the ability of a system to adjust to a changed state of climate and moderate damages or cope with the associated consequences. The level of vulnerability of the households to climate-related hazards depends on first the magnitude of climate stresses and, second, on the resilience of those households to withstand climate-related shocks (NEST, 2004).

Empirical studies have revealed that climate change has an impact on agricultural land returns and that the agriculture sector is vulnerable to climate change both in terms of economic returns and total physical product (Gbetibouo & Hassan, 2005). Theories suggest that tropical regions in developing economies have indicated vulnerability when it comes to climate fluctuations (Hertel & Rosch, 2010). In the agriculture landscape, yields could be reduced considerably due to the climate-related stresses, having drastic consequences upon farmers' production and welfare, which is why individual farming units from the environmental-economical limelight needs to be analyzed in order to explore the possibility of strengthening resilience to climate change stresses.

### *3.1.2 Problem Statement*

Despite this importance, studies on the vulnerability of farming households to climate change are limited in the tropics. For Africa in general, a few studies have assessed the vulnerability of households to climate shocks (Mansour and Hachicha 2014, Dercon 2004, Dercon 2005, Hoddinott and Quisumbing 2003). While these studies are informative, their coverage is limited to a few countries. This presents an important limitation as their findings cannot be generalized to farming communities in the tropics or southern Africa. Countries with different levels of per capita income are expected to have different levels of vulnerability to poverty. In addition, the magnitude of the effects on different variables cannot be the same. Some variables could matter in one country and not in another country. Therefore, climate change requires an analysis to a level that would enhance policymakers at the country level to formulate policy options that would yield the intended results with a high level of precision (Klein, 2004).

An analysis of vulnerability is important because an efficient social policy needs to focus beyond poverty alleviation now and examine poverty prevention in the future. A poverty alleviation plan that ignores the transient nature of poverty ignores households that have a high likelihood of staying in a poverty trap and may instead devote scarce resources to households that are only poor in the short run and would exit the poverty trap without government assistance (Ellis & Freeman, 2005). Several researchers have done work around this area of poverty entry and exit before (Glewwe, Gragnolatti, & Zaman, 1999; McCulloch & Baulch, 2000; Neilson, Contreras, Cooper, & Hermann, 2008). One limiting factor about these studies is that they used multinomial logit models and failed to account for state dependency of poverty models resulting in cross equation correlation of the error terms. This study, therefore, seeks to contribute to earlier studies and fill the limitation of earlier studies in this area by using a Multivariate Probit that accounts for state dependency of poverty.

By understanding, preparing for, and adapting to climate-related stresses, farming families can leverage opportunities and reduce risks (Trinh, Rañola, Camacho, & Simelton, 2018). This is particularly necessary for Malawi, in which 80 percent of the population reside in the rural agrarian communities (NSO, 2008). More importantly, there lacks an analysis at the national scale regarding a climate-related vulnerability that could provide the longitudinal picture that is needed to understand how climate change is impacting the vulnerability of farming households to poverty in the country (Olayide & Alabi, 2018). It is against this background that this chapter sets forth to quantify the magnitudes and patterns of rural climate-induced vulnerability to poverty in Malawi.

### *3.1.3 Objective of the Study*

The overall objective of this chapter is to examine farmers' vulnerability to poverty under climate-induced stresses in Malawi. Specifically, the study seeks to:

- Quantify the magnitude of climate stress-induced vulnerability to poverty among farming households.
- To quantify the effects of ex-ante climate stress-induced vulnerability on ex-post poverty.
- To quantify the relative effects of climate-related stresses on poverty transition.

## 3.2 Literature Review

### *3.2.1 Defining Vulnerability*

In the current study's context, vulnerability refers to the manner and extent to which a farming system is prone to conditions that negatively affect the welfare of the system itself. In the climate change field, the IPCC defined vulnerability as "the degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes" (McCarthy, Canziani and Leary, et al. 2001). In contrast, the poverty and development knowledge archives has defined vulnerability as total measure of human welfare that integrates environmental, social, economic, and political exposure to a range of harmful perturbations (Bohle, Downing, & Watts, 1994). According to Yamin et al. (2005), the disaster community defined vulnerability as conditions that are triggered by physical, social, economic, and environmental factors or processes that increase the risk of a community to the impact of harmful perturbations. In the field of resilience, vulnerability is defined as a lack of ability to recover quickly after a shock (Hill & Wial, 2008).

In the literature on rural livelihoods, it is widely accepted that seasonal climate variations (including periodicity and precipitation) are one of the key drivers of vulnerability faced by farming families (Ellis & Freeman, 2005). Economic assets, capital resources, financial means, wealth, the economic condition of nations and technological advancement of groups clearly is a determinant of reducing vulnerability to climate stress (Kates 2000).

### *3.2.2 Measurement of Vulnerability*

Different disciplines conceptualize vulnerability differently based on the objectives and methodologies employed. Adger (1999), Füssel and Klein (2006), and Füssel (2007) have provided a good framework for measuring the vulnerability of households. In a broader view, the literature has categorized vulnerability into three; socio-economic, biophysical and integrated assessment approaches.

#### 3.2.2.1 Socioeconomic vulnerability assessment

Socioeconomic vulnerability focuses on the capacity of the system to withstand hazardous exposure given the social, economic and political characteristics of the individuals or social groups (Tompkins & Hurlston, 2006; Turner, et al., 2003; Burton & Cohen, 1993). The social capacity of the system is largely determined by income distribution, gender, ethnicity, social capital, local institutions, among others—the differences in these variables for a given population result in different outcomes of vulnerability. Thus, even before a shock or natural hazard occurs, vulnerability can be regarded as an internal state of the system (Allen, 2003). The impacts of such or natural hazardous are mediated by the internal characteristics of the system, including socio-economics, institutional and demographic factors. Thus, the impacts of shocks are better understood through the lens of social vulnerability. Within the study of social vulnerability, there are two variants: individual vulnerability and collective vulnerability. The former is largely determined by the social status of individuals or households and the latter by the institutional, infrastructural variables, although the two are intertwined (Adger, 1999).

The key weakness of this approach is that it focuses only on the variation in socioeconomic variables among individuals or community groups as the source of the differences in levels of vulnerability. While in an actual sense, the differences in the environment in which the households are living could bring divergent outcomes of the vulnerability levels. Apart from socioeconomic factors, some environments are more exposed or prone to natural shocks than others. Similarly, different environments are endowed with resources differently such that when a shock strikes, households from different environments would naturally be presented with different coping mechanisms.

#### 3.2.2.2 Biophysical vulnerability assessment

The biophysical approach focuses on how environmental change transmits damages on biological and social systems. This approach has been identified differently by different disciplines. In the medical field, they have called it a dose-response relationship; in environmental economics, they have called it a damage function; in geography, it is called a hazard-loss relationship (Füssel, 2007).

The literature is not short of this approach. For example, economic impacts of climate change have been assessed using relationships between climate variables and crop income (Füssel, 2007; Mendelsohn, Nordhaus, & Shaw, 1994; Polsky & Esterling, 2001). Others have studied the relationship between biophysical (crop yield, land use and environment) and climate variables (Reeves, Bagneb, & Tanakac, 2017). In the same stream of literature, we have impacts of climate changes on water and food supplies (Gohar & Cashman, 2016), and ecosystem disturbance (Dwire, Mellmann-Brown, & Gurrieri, 2018). The parameters of the biophysical prediction models are used to forecast or predict future impacts by simulating future climate variables (Kurukulasuriya & Mendelsohn, 2008).

The biophysical approaches have one key limitation. They have tended to focus much on the physical damages as a result of environmental stress. For example, the approach can be used to calibrate the impacts of climate change on crop yields. Although the level of damages for different social groups might be the same, the corresponding impacts on their welfare depend on their internal socioeconomic characteristics, which moderate their adaptive capacities. Poor farmers would suffer greatly from the impact of droughts due to their weak adaptive capacity, while better-off farmers would easily smoothen their consumption - permanent income hypothesis.

#### 3.2.2.3 Integrated vulnerability assessment approaches

This approach builds on the fact that the earlier two approaches were reciprocal in terms of their strength and weakness. Thus, this approach is a hybrid of the socio-economic and biophysical approaches. Many researchers have been applying this approach to different research problems. In the recent past, Wei, et al. (2017) used the approach to identify the vulnerabilities of the animal husbandry to snow disasters at a spatial scale in order to refine disaster mitigation and adaptation strategies. Karagiorgosa et al. (2016) applied it to study vulnerability to flash floods in Greece.

Although the integrated vulnerability assessment is relatively a new concept, Fussel (2007) argued that the IPPC (2001) definition of vulnerability reflected the multidimensional nature of the approach. The key elements of the definition included exposure, sensitivity, adaptive capacity. In Fussel (2007) framework, the sensitivity in the definition corresponds to the biophysical approach. In contrast, the adaptive capacity corresponds to the socioeconomic approach. Hence the blend of the two approaches might bring outcomes that are in line or very close to the definition of vulnerability by IPPC (2001).

Although the integrated assessment approach is more robust than each of the discussed approaches, it comes with some limitations. The literature lacks a standardized way of combining the socioeconomic and biophysical indicators when implementing the integrated assessment. Furthermore, it is not clear what relative weights should be put on socioeconomic and biophysical vulnerability or on each of the variables in the model. Second, the approach does not account for the dynamic nature of adaptation and coping mechanisms as new opportunities arise in the presence of environmental shocks.

### *3.2.3 Econometrics based methods to vulnerability assessment*

Within the above-discussed approaches to vulnerability assessment, there are econometrics-based methods and indicator methods. What is common to these methods is the treatment of poverty. In measuring vulnerability, several researchers have suggested the use of poverty as a proxy for household welfare and measure the magnitude to which households are not able to cope with negative effects of climate-related stress, which is usually reflected as a change in the level of poverty or poverty depth (Calvo & Dercon, 2005; Kamanou & Morduch, 2005; Ligon & Schechter, 2003). This is concerned with assessing the role of risk in the economics of poverty (Alwang, Siegel, & Jorgensen, 2001).

Thus, this section explores the body of literature on econometric methodologies used in assessing vulnerability which is of interest for this study. Econometric approaches for measuring vulnerability uses household data to assess the level of vulnerability for disaggregates of social groupings. Hoddinot and Quisumbing, (2003) put three different methodologies used to assess vulnerability. These include vulnerability as uninsured exposure to risk (VER), vulnerability as the low expected utility (VEU) and vulnerability as expected poverty (VEP). All three methods construct a measure of welfare loss attributed to shocks.

### 3.2.2.1 Vulnerability as low expected utility

Ligon and Schechter (2003) define vulnerability as the deviation of the expected utility from the utility of consumption level that is at vulnerability cut-off point and above. Putting it differently, it is the difference between the expected consumption and the certainty equivalence of consumption. This can mathematically be defined as:

$$V^i = U^i(z) - E[U^i(c^i)]$$

Where $z$ is the certainty equivalence consumption or the poverty cut-off point, if the household's consumption equates or exceeds $z$, then it is considered as non-vulnerable. Taking an expectation of a well-behaved consumption expenditure function will cause the vulnerability not to depend on mean consumption only but also on the variation of consumption. With this, vulnerability can be decomposed to comprise of poverty and risk.

$$V^i = U^i(z) - U^i\big(E[c^i]\big)] \qquad \text{Poverty}$$

$$+\big\{U^i\big(E\big[c^i\big]\big) - E\big[U^i\big(E\big[c^i\big|\bar{\mathbf{x}}\big]\big)\big]\big\} \qquad \text{Aggregate risk}$$

$$+\{E[U^i(E[c^i|\bar{\mathbf{x}}])] - E[U^i(c^i)]\} \qquad \text{Idiosyncratic risk}$$

The function $U(.)$ follows a constant rate of risk aversion (CRRA) function form $U(c) = (c^{1-\gamma})/(1-\gamma)$ during estimation, where $\gamma \in \mathbb{R}_{++}$. Using panel data, the expectation of consumption is parameterized as $E(c_t^i|\bar{\mathbf{x}}_t, \mathbf{x}_t^i) = \alpha^i + \eta_t + \mathbf{x}_t^{i\prime}\boldsymbol{\beta}$, with $\theta = (\alpha^i, \eta_t, \boldsymbol{\beta}')$ a vector of parameters to be estimated. Ligon and Schechter (2003) applied this method to a panel dataset obtained from Bulgaria in 1994 and found that poverty and risk played roughly equal roles in reducing welfare. However, the key flaw of this method is the failure to factor in an individual's risk behaviour about uncertain outcomes since individuals have asymmetric information about their preferences for such outcomes (Kanbur, 1987).

3.2.2.2 Vulnerability as uninsured exposure to risk

This method is applied after the shock has happened to determine the magnitude of welfare losses (not probabilities) or reduction in the level of consumption as a result of the effect of shock on the individuals (Hoddinott and Quisumbing 2003). The impact of a shock is analyzed using a panel dataset to compare consumption levels ex-ante and ex-post shock. The welfare losses are analysed relative to observed shocks. Skoufias (2003) analyzed the effects of shocks in Russia using the same methods. The assumption is that when there is no risk management strategy, shocks result in welfare losses on individuals, which is observable through their reduction in consumption bundles. The value of welfare loss is equivalent to the insurance value that an individual would be willing to pay prior to the occurrence of the shock in question. The major drawback of this approach is the difficulty to find a panel for which to compare consumption levels. There have been debates that cross-sectional data induces some biases in the estimates (Skoufias, 2003).

3.2.2.3 Vulnerability as expected poverty

The expected poverty group of measures identifies vulnerable households as those trapped below an agreed-upon poverty line with particular probability (Alwang, Siegel, & Jorgensen, 2001). This approach views vulnerability as the expected poverty while income expenditure is used as a surrogate for well-being. Hence it models the probability of a given household falling below the cut-off or minimum expenditure (poverty line) if the household was above the poverty line. In the case that the household was already trapped in poverty before the shock, the model estimates the probability of that household's failure to exit the poverty trap (Chaudhuri, Jalan, & Suryahadi, 2002).

A recent application of this method comes from Deressa et al. (2009) in a study in which they estimate the likelihood of the income of households falling below a poverty line and characterizes vulnerable households as those with more than 0.5 probability of falling below or staying in the poverty trap. The authors were able to characterize the share of vulnerable households in different regions and differentiate between poor, vulnerable households and non-poor vulnerable households. One important observation was that the probability of being poor was quite sensitive to the poverty line used.

## 3.3 Methodology

### *3.3.1 Theoretical Framework*

The theoretical framework of vulnerability can be understood by assuming that there is a representative farm household. This household is affected by different factors, some of which are exogenous, like the environment in which the household is placed. The other factors are idiosyncratic to the household, such as socioeconomic characteristics and resource endowments. Using a certain and right mix of its resource endowments towards different economic activities given the environmental setting they are in the household can produce goods and services which in turn earns it income. The outcome, which is income, is the key determinant of vulnerability.

The asset endowment that a household has can be summarized as capital and labour. Capital includes natural capital (land), physical capital (livestock, agricultural implements), social capital (affiliation to community groupings like village savings and loans association (VSLAs)[1] and farmer groups), financial capital (their deposits at VSLAs, cash at hand), human capital (agricultural knowledge, skills and health). On the other hand, labour endowment is the potential labour that a household can supply to own production or sell to enterprises external to the household. Given its asset endowment, the representative farm household will seek to maximize a joint utility function of consumption ($c_i$) and leisure ($l_i$) as:

$$\max U(c_i, l_i) \tag{1}$$

subject to budget, commodity balance, resource and non-negativity constraints

$$p_c \sum c_i + wL^h + rA^h \leq p_y \sum_i^k F(A, L, S) + wL^m + rA^m \tag{2}$$

$$L = \sum L_i^f + L^h \tag{3}$$

[1] These are community savings and lending groups where members save their earnings or borrow at an affordable interest rate.

$$A = A^f + A^h \quad (4)$$

$$E^A = A^f + A^m,\ E^L = L^f + L^m + l \quad (5)^2$$

$$c_i, l_i, L_i^m, A^f, A^m \in \mathbb{R}_+ \quad (6)$$

The farmer maximizes utility by choosing the level of consumption ($c_i$), leisure ($l_i$) given the household's endowment of hired labour ($L^h$), hired land ($A^h$), household labour supplied to market ($L^m$), land supplied to the market ($A^m$), household labour for own production ($L_i^f$) and household land for own production ($A^f$). The farm household produces agricultural goods according to a well-behaved production function, *F*(*A*, *L*, *S*) for agricultural and non-agricultural activities, where *A* is farmland area, *L* is labour. The production function, *F*(.) is the monotonic non-increasing function in climate shocks, *S*. Equation (2) is a full income constraint which implies that the sum of consumptions, wages for hired labour and rental payment for hired land cannot exceed the sum of the value of output, wage earnings from labour supply and earnings from land rented out. Equations (3) to (5) are the farmer's resource constraints that define the farmer's risk management plan, and equation (6) is a collection of non-negativity constraints on consumption, leisure and farm inputs. The allocation of resources to different production activities depends on the farmer's perceived variability of returns for each activity. Thus, a farmer will engage in activities that are perceived to have less variability to climate shocks, or they will engage in the production of several activities that embody different levels of susceptibility to climatic shocks, which have an impact on their returns.

[2] Total land endowment ($E^A$) is the sum of own farmland for own production ($A^f$) and farmland rented out ($A^m$). Total labour endowment ($E^L$) is the sum of own labour supply ($L^f$), labour supplied to the market ($L^m$), and leisure ($l$).

The relationship between resource endowment, enterprise choice and returns are affected by the likelihood of shocks occurring (Heitzmann, Canagarajah, & Siegel, 2002). The shocks may impact the resource endowment or returns to investment. For example, prolonged droughts and floods may destroy physical capital. After a shock, households engage in ex-post disaster management. These include selling their labour force, borrowing from credit markets, drawing on savings resources (i.e. livestock and financial savings, or other household assets), self-select into social support programs like public works, cash transfer in order to smoothen their consumption.

However, the success of ex-post disaster management largely depends on the nature and magnitudes of the disasters, availability of savings, the functioning of the credit markets, the presence of government social support programs. If these ex-post shock management mechanisms are weak or non-existence, there is a high likelihood of a household having their consumption below their expected levels.

### *3.3.2 Empirical framework for Modeling household vulnerability to climate change*

This study will adopt the vulnerability to expected poverty (VEP) approach to analyze the vulnerability of households to climate change impacts. Climate change impacts through climate extreme events enter household welfare function through the production function as specified in the theoretical framework above. Although most of the empirical studies of vulnerability analysis have used cross-section data (Chaudhuri, Empirical Methods for Assessing Household Vulnerability to Poverty, 2000; Chaudhuri, Jalan, & Suryahadi, 2002; Chaudhuri, 2003; Suryahadi & Sumarto, 2003; Appiah-Kubi & Oduro Abena, 2008; Azam & Imai, 2009), they have one common limitation. These studies make a sweeping assumption that spatial variation in consumption (variation across household) proxies inter-temporal variation in consumption. Tesliuc and Lindert (2002), with experiences from Guatemala, note errors that go with cross-sectional studies. Disasters are very prevalent in Guatemala. In their study, they found out that at the time of data collection, some households were still recovering from the impacts of disasters that had happened several years back. Thus, the use of cross-section data from a year that had no disasters might result in understating the level of consumption vulnerability.

The literature has a growing number of articles that have estimated vulnerability to poverty using panel data which is more robust compared to vulnerability measures using cross-sectional data. Following Chaudhuri (2000), the probability of a given household being consumption poor at time t+j is given as;

$$V_{ht} = \Pr(\ln C_{h,t+j} < \ln Z) = \int_{c}^{z} f\left(C_{ht+j}\right) dc \qquad (7)$$

Where, $V_{ht}$ represents the vulnerability of farm household $h$ at time $t$, $C_{h,t+j}$ is the consumption of household $h$ at time t+j, and $z$ is the poverty cut off point of household consumption. The vulnerability of a farmer to climate shock is proportional to the length of time period $j$. Given $j$ time periods, the vulnerability of a household in $j$ periods (Risk or R(.)) is the probability of observing at least one spell of climate-related shock on agriculture. This probability is given by one less the probability of $j$ episodes of shocks (Pritchett, Suryahadi, & Sumarto, 2000):

$$R_h(n, z) = 1 - [(1 - (\Pr\left(c_{h,t+1}\right) < z), \ldots, (1 - (\Pr\left(c_{h,t+j}\right) < z))] \qquad (8)$$

Given threshold probability, $p$, and an indicator function $\Lambda(.)$, which equals one if the indicator function is true and zero if otherwise, Pritchett et al. (2000) define a household as vulnerable if the risk in *j* periods exceeds the threshold probability, *p*.

$$V_{ht}(p, n, z) = \Lambda(R_{ht}(n, z) > p) \quad (9)$$

The consumption generating process can be specified as a multilevel process, as suggested by Günther and Harttgen (2009). The Multilevel Mixed-Effects ML regression is specified as:

$$\ln C_{ij} = \beta_{0j} + \mathbf{X}_{ij}\boldsymbol{\beta}_{\mathbf{1j}} + \varepsilon_h \quad (10)$$

Where $C_{ht}$ is the consumption expenditure per capita for household $h$, $\boldsymbol{X}_h$ is the observable vector of household characteristics (demographic characteristics, physical capital, human capital, demographic factors) and climate shocks (i.e. droughts and floods), $\boldsymbol{\beta}$ is a vector of parameters, and $\mathcal{E}_h$ is a zero-mean disturbance term that captures household's eccentric attributes accounting for variation in per capita consumption for households that has not been explained by the model. For consistent and unbiased estimates of parameters, the error term must satisfy the following expectations:

$$E(\varepsilon_{ht}|\mathbf{X}) = 0$$

$$E\left(\varepsilon_{ht}, \varepsilon_{jt}\middle|\mathbf{X}\right) = \begin{cases} \sigma_e^2 \ \forall \ h = j \\ 0 \ \ \forall \ h \neq j \end{cases} \quad (11)$$

$$E(\varepsilon_{ht}, \varepsilon_{hs}|\mathbf{X}) = 0 \ \forall \ t \neq s$$

$$E(\varepsilon_{ht}\mathbf{X}) = 0$$

$$\varepsilon_{ht} \sim N(0, \sigma_e^2)$$

Equation 10 yields the first moment of consumption for given farmer i, in district j. District specific factors that affect the intercept and the propensity to consume can be included in equation 10 in the determination of the variance of consumption. The intercept and the propensity to consume in equation 10 can be decomposed into:

$$\beta_{0j} = \gamma_{00} + \sum \gamma_{01} Z_j + u_{0j} \quad (12)$$

$$\beta_{1j} = \gamma_{10} + \sum \gamma_{11} Z_j + u_{1j} \quad (13)$$

Substitution of equation 12 and 13 into equation 10 yield an estimable form of equation specified as:

$$\ln C_{ij} = \gamma_{00} + \gamma_{01} Z_j + \mathbf{X}_{ij}\left(\gamma_{10} + \sum \gamma_{11} Z_j\right) + u_{1j}\mathbf{X}_{ij} + u_{0j} + \varepsilon_i \quad (14)$$

Where the first three terms in the right and side of the equation form the deterministic part of the model, the last three terms are the stochastic component. The stochastic part is decomposed into two; $u_{1j}\mathbf{X}_{ij} + u_{0j}$ measures the variance of consumption across districts that are not accounted for and $\varepsilon_i$ measures variance of consumption within district that is not accounted for. The consumption variance is set to be a function of both farmer characteristics and community and incidence of climate-related stresses. The consumption variance takes the form:

Idiosyncratic variance: $\varepsilon_{ij}^2 = \phi_0 + \sum \phi_1 X_{ij} + \sum \phi_2 Z_j$ (15)

Covariate variance: $u_{0j}^2 = \tau_0 + \sum \tau_1 Z_j$ (16)

Total variance: $\left(\varepsilon_{ij} + u_{0j}\right)^2 = \theta_0 + \sum \theta_1 X_{ij} + \sum \theta_2 Z_j$ (17)

From the preceding equation, the expectation of consumption ($ln\ \hat{C}_{ij}$) and the components of variance of consumption are determined from equations 14 to 17.

Any given household $i$, with characteristics **X** can then have the vulnerability to poverty level calculated using the estimated coefficients such that

$$\hat{V}_{it} = \widehat{Pr}(\ln C_{i,t+j} < \ln Z \,|X_i) = \Phi\left(\frac{\ln z - \ln \hat{C}_{ij})}{\sqrt{\hat{\sigma}_{ij}^2}}\right) \tag{18}$$

Where $\hat{V}_{it}$ is estimated vulnerability to expected poverty (i.e. this is essentially the likelihood of a consumption per capita being below the poverty cut off point given the household-specific attributes), $\Phi(.)$is the cumulative density function of the standard normal distribution, and $\sigma$ is the standard error from equation (14). Where lnZ is the log of the minimum consumption/income level beyond which a household would be called poor. Using the assumption that the log of consumption is normally distributed, the estimates from the above equation can be used to derive the probability of a household being vulnerable. However, vulnerability estimates will also depend on the poverty line, the expected log of consumption and its variance. Vulnerability to expected poverty decreases with increased variability in expected consumption.

Several studies that studied household consumption patterns assumed that the random error term is a result of measurement error and that its variance is constant across all households. This is a weak assumption in that it results in inefficient parameter and vulnerability estimates (Chaudhuri, 2003). This problem can be resolved by estimating model coefficients using a maximum likelihood approach (Amemiya, 1977).

The predictor variables adopted in this study follow those that have commonly been used in previous studies (Chaudhuri, Jalan, & Suryahadi, 2002; Tesliuc & Lindert, 2002; Sarris & Karfakis, 2006; Shewmake, 2008). Table 1 below presents definitions of the variables included in the model.

Having derived the vulnerability of farmers to climate stresses, there is a need to compose it into various measures to understand its various facets at length. The purpose of decomposing vulnerability is to satisfy three principles as has been applied in poverty measurement: First, a measure of vulnerability should be able to identify the proportion of the population that is vulnerable. Second, should be sensitive to the distribution across the population being studied and lastly, should be able to capture the severity of the vulnerability. These three classes of vulnerability can be measured following Foster et al. (1984), which decomposes vulnerability as:

$$V_\alpha = \frac{1}{n}\left[\sum_{i=1}^{q}(W_0 - \frac{W_i}{W_0})^\alpha\right] \qquad (19)$$

Where, $V_\alpha$ is the vulnerability measure, $W_0$ is the threshold of vulnerability, $W_i$ is the actual vulnerability of farmer i, *n* is the total number of farmers in the analysis, $q$ is the number of farmers above the vulnerability threshold, $\alpha$ is the sensitivity indicator and takes on a value of 0 for head count vulnerability, a value of 1 for vulnerability gap or depth, and a value of 2 for severity of vulnerability or the distribution pattern of the vulnerability among the vulnerable.

The vulnerability to poverty in the future as a result of climate shocks is calculated at two points in time, 2013 and 2016, with 2010 as the baseline for 2013 and 2013 as the baseline for 2016. The vulnerability index is bounded between 0 and 1. Unlike poverty, vulnerability is an ex-ante concept, it is not possible to compute it for 2010 as this year is the first wave of the panel data used in this study. Following Chaudhuri et al. (2002), the vulnerability threshold is set at an arbitrary value of 0.5. Those households with a vulnerability index of above 0.5 are taken to be vulnerable. An index of 0.5 means that the household has 50% likelihood of becoming poor in the future.

The first step in the derivation of the vulnerability stand of the farmers is to estimate the expectation of their per capita consumption and the variance of the same. Since the interest is to assess the level of vulnerability that is induced by climate-related stresses, a number of stresses or shocks are included in the consumption model. Two consumption models are fitted, one for 2013 and another for 2016. The 2013 consumption function uses per capita consumption in 2013, climate shock variables for 2013 and farmer specific characteristics for 2010. Similarly, the consumption function for 2016 used per capita consumption for 2016 as a response variable, climate shock variables for 2016 and farmer specific characteristics for 2013. Thus, the farmers' characteristics now (in period $t$) will influence the resilience capacity to poverty in the future (in period $t+1$) as climate stresses intensify.

### 3.3.3 Modeling interplay between poverty and vulnerability

Another important step after determining the probability of future poverty (vulnerability) is to determine the determinants of poverty and, in a way, ascertain the role of vulnerability to actual future poverty state. The question is, does vulnerability trap farmers into poverty.

To implement this piece, the poverty state is first determined at two points; for 2013 and 2016 for each farmer. A binary variable for poverty, $p$, is developed by setting $p$ = 1 if the log of per capita food consumption, $ln\, C_{ht}$ falls short of the poverty line, $ln\, Z,$ $(ln\, C_{ht} < ln\, Z\, |X_h)$ given the farmer's characteristics, the presence/absence of climate shocks in 2013 and 2016, and poverty, $p$ = 0 for otherwise. Mixed-Effects Probit model, $\Pr(P_i = 1) = \Phi(X_h \psi')$, is used to estimate the effect of different covariates of the poverty state of a farmer. Where $\Phi$ is the cumulative standard normal distribution. Vulnerability to poverty in 2010 is used as input into the poverty regression for 2013. Similarly, vulnerability to poverty in 2013 is used as an argument in the 2016 poverty function.

Further analysis is done to understand the poverty transition dynamics between 2010 to 2016. There are four sets of states of poverty transition over the period of analysis, which can be decomposed at two time periods; 2010 to 2013 and 2013 to 2016. The four sets of poverty transition outcomes that we observe over these two periods are;

- Poor in 2010 and poor in 2013
- Poor in 2010 and non-poor in 2013
- Non-poor in 2010 and poor in 2013
- Non-poor in 2010 and Non-poor in 2013

For the second period of analysis (2013 – 2016) we have:

- Poor in 2013 and poor in 2016
- Poor in 2013 and non-poor in 2016
- Non-poor in 2013 and poor in 2016
- Non-poor in 2013 and Non-poor in 2016

For each period of analysis, we have outcomes that are mutually exclusive. Thus, it could be theoretically tempting to think that the candidate model to use in this scenario is the Multinomial Logit Model (MLM) as others have used before (Glewwe, Gragnolatti, & Zaman, 1999; McCulloch & Baulch, 2000; Neilson, Contreras, Cooper, & Hermann, 2008). However, given that the current state of poverty is not independent of the previous states of poverty, MLM may not be appropriate as it imposes a strong assumption of independence of invariant alternatives. This assumption implies that there is no cross-equation correlation of error terms. If the data does not conform to this assumption, having error terms correlated across equations, use of MLM will result in sample selectivity bias due to the initial condition dependency problem (Heckman, 1981). Even if the logit models were modelled as separate equations for each outcome, still it would take the initial state as exogenous. Failure to correct these problems will result in biased estimates (Kassie, Jaleta, Shiferaw, Mmbando, & Mekuria, 2013) and misorient the shape of relevant policy interventions.

To remedy the problem associated with MLM, this study uses the Multivariate Probit model which allows for error terms to be freely correlated across equations (Newman & Canagarajah, 2000). Specification of the poverty transition multivariate probit, we begin by specifying the farmer's consumption function:

$$f_1(Y_{i,1}) = \chi_{i,1}\beta_1 + \varepsilon_{i,1} \qquad (20)$$

Where *Y* is the per capita farm household consumption, *X* is a vector of farmer specific characteristics associated with per capita consumption, $\varepsilon$ is the random error term, $f_1$is a monotonic transformation indicator that ensures that the random error term follows a standard normal distribution. Therefore, four possible poverty transition outcomes emanate from the consumption function, which in turn define the dependent variables for the multivariate probit model. The probability of each possible transitioning from state *i* of poverty to state *j* (let's define it as outcome *k*) is given by a system of multivariate probit equations specified as:

$$\Pr(P_k = k) = \Pr(Y_t \leq z \mid Y_{t-1} \leq z) = \Phi(f_1(Y) - x\beta) \tag{21}$$

$$\Pr(P_k = k) = \Pr(Y_t \leq z \mid Y_{t-1} \geq z) = \Phi(f_1(Y) - x\beta) \tag{22}$$

$$\Pr(P_k = k) = \Pr(Y_t \geq z \mid Y_{t-1} \leq z) = \Phi(f_1(Y) - x\beta) \tag{23}$$

$$\Pr(P_k = k) = \Pr(Y_t \geq z \mid Y_{t-1} \geq z) = \Phi(f_1(Y) - x\beta) \tag{24}$$

Where Φ is the standard normal distribution of the probability of a given transition, which results in a probit model, $z$ is the poverty threshold, $Y_t$ is the per capita consumption level in period *t* and $Y_{t-1}$ is the previous period per capita consumption. The associated variance-covariance matrix of the system of equations is given by:

$$\sum = \begin{bmatrix} 1 & \dots & Rho14 \\ \vdots & \ddots & \vdots \\ Rho41 & \dots & Rho44 \end{bmatrix}$$

Where Rho is the cross-equation correlation of the error term, the model system is estimated using the simulated maximum likelihood approach in R software. In all models, I use Chi-square for F-statistic for overall significance of the model, t-statistics or the p-values for the individual significance of variables, Variance Inflation Factor (VIF) to check orthogonality. Table 3.1 presents a summary statistic for the variables that are included in the empirical models. The table presents the means along with associated standard errors in parenthesis.

**Table 3.1: Variables in included in the empirical models**

| Variables | 2010 | 2013 | 2016 |
|---|---|---|---|
| | Mean (std Error) | | |
| Log of per capita consumption | 10.4970 | 10.8757 | 11.1083 |
| | (0.0220) | (0.0223) | (0.0231) |
| Household size | 5.1186 | 5.7481 | 5.9911 |
| | (0.0713) | (0.0685) | (0.0656) |
| Literacy (1/0) | 0.6977 | 0.7320 | 0.7291 |
| | (0.0114) | (0.0112) | (0.0114) |
| Years of schooling | 7.1417 | 7.1716 | 6.9019 |
| | (0.1294) | (0.1260) | (0.1204) |
| Female share in household | 0.8267 | 1.0552 | 1.3648 |
| | (0.0096) | (0.0164) | (0.0246) |
| Age of farmer | 43.300 | 46.0839 | 47.3989 |
| | (15.624) | (14.45) | (15.034) |
| Members age 0 to 9 | 1.8080 | 2.1875 | 2.3363 |
| | (0.0423) | (0.0455) | (0.0541) |
| Members age 10 to 17 | 0.9698 | 1.3675 | 1.7172 |
| | (0.0358) | (0.0401) | (0.0452) |
| Female Members age 18 to 59 | 1.0965 | 1.4888 | 1.7841 |
| | (0.0179) | (0.0290) | (0.0371) |
| Male Members age 18 to 59 | 1.0241 | 1.4291 | 1.6682 |
| | (0.0216) | (0.0337) | (0.0386) |
| Members age 60 or greater | 0.1719 | 0.2957 | 1.0018 |
| | (0.0148) | (0.0190) | (0.0554) |
| Married (1/0) | 0.8492 | 0.8871 | 0.9037 |
| | (0.0113) | (0.0097) | (0.0088) |
| Dependency ratio | 1.1489 | 1.1412 | 1.0931 |
| | (0.0281) | (0.0248) | (0.0227) |
| Waged occupation (1/0) | 0.3246 | 0.4263 | 0.5352 |
| | (0.0178) | (0.0244) | (0.0288) |
| Off-farm enterprise (1/0) | 0.1849 | 0.2612 | 0.2507 |
| | (0.0123) | (0.0134) | (0.0130) |
| Large ruminant livestock (1/0) | 0.0312 | 0.0541 | 0.0562 |
| | (0.0055) | (0.0069) | (0.0069) |
| Small ruminant livestock (1/0) | 0.2844 | 0.3461 | 0.4193 |
| | (0.0143) | (0.0145) | (0.0147) |
| Poultry (1/0) | 0.4241 | 0.5280 | 0.5343 |
| | (0.0157) | (0.0153) | (0.0149) |
| Agriculture land (ha) | 3.9693 | 1.9789 | 2.1488 |
| | (2.2573) | (0.0667) | (0.0759 |
| Distance to road network (km) | 7.6524 | 7.7901 | 8.1784 |
| | (0.2793) | (0.2799) | (0.2804) |
| Distance to district center (km) | 59.0189 | 21.6381 | 23.0009 |
| | (0.9051) | (0.4963) | (0.5203) |
| Droughts (1/0) | 0.4010 | 0.3144 | 0.4273 |
| | (0.0155) | (0.0142) | (0.0148) |
| Floods (1/0) | 0.0442 | 0.1446 | 0.1142 |

| Variables | 2010 | 2013 | 2016 |
|---|---|---|---|
| | Mean (std Error) | | |
| | (0.0065) | (0.0107) | (0.0095) |
| Crop pests (1/0) | 0.0724 | 0.2043 | 0.1392 |
| | (0.0082) | (0.0123) | (0.0103) |
| Livestock disease (1/0) | 0.0724 | 0.2174 | 0.1285 |
| | (0.0082) | (0.0126) | (0.0100) |
| Irregular rains (1/0) | | 0.5000 | 0.7012 |
| | | (0.0153) | (0.0137) |
| *N* | 995 | 1,072 | 1,121 |

I also compute the probability of entering and the existing vulnerability trap. From the transition matrix of bivariate movements into and out of vulnerability, we can calculate the associated probability of entering (E) or leaving (L) the vulnerability spell as follows:

$$p(E) = \frac{E_t \in NV_{t-1}}{NV_{t-1}} \in [0,1]$$

$$p(L) = \frac{L_t \in V_{t-1}}{V_{t-1}} \in [0,1]$$

Where in the above two equations, $E_t \in NV_{t-1}$ is the set of farmers that are entering the vulnerability spell in period t; which is given by the subset of farmers that are vulnerable in period t, from within a set of farmers that were not vulnerable in period t-1. $NV_{t-1}$ is the set of farmers that are not vulnerable in period *t*-1. $L_t \in V_{t-1}$ is the set of farmers leaving vulnerability spell in period *t*, given by the subset of farmers that are not vulnerable in period *t*, from within a set of farmers that were vulnerable in period *t* -1.

### *3.3.4 The Data sources*

This study uses a panel component of Living Standards Measurement Survey (LMSM) data that was collected by Malawi's National Statistical Office with support from World Bank. The first wave of the data was collected from March 2010 to March 2011 under the umbrella of the World Bank Living Standards Measurement Study. A sub-sample of the first wave comprising of 204 enumeration areas (EAs) out of 768 EAs was selected prior to the start of the first wave field work with the intention to (i) to track and resurvey these households in 2013 as a second wave as part of the Integrated Household Panel Survey (IHPS) and (ii) visit a total of 3,246 households in these EAs twice to reduce recall associated with different aspects of agricultural data collection. At baseline, the IHPS sample was selected to be representative at the national. Once a split-off individual was located, the new household that he/she formed/joined since 2010 was also brought into the IHPS sample. In view of the tracking rules, the final IHPS sample, therefore, includes a total of 4,000 households that could be traced back to 3,104 baseline households. In parallel with the fourth integrated household survey (IHS4) operations, also implemented the Integrated Household Panel Survey 2016 as a third wave or follow up to the IHPS. The IHPS 2016 subsample covered a national sample of 102 EAs (out of the 204 baseline IHS3 panel EAs), and was conducted during the first half of IHS4 fieldwork.

The IHPS consisted of four questionnaire instruments; the household questionnaire, the agriculture questionnaire, the fishery questionnaire, and the community questionnaire. Of interest for this study were the agriculture and household questionnaires. The agriculture questionnaire allows, among other things, for extensive agricultural productivity analysis through the diligent estimation of land areas, both owned and cultivated land, labour and non-labour input use and expenditures, and production figures for main crops and livestock. The household questionnaire encompassed economic activities, demographics, welfare and other sectoral information of households. It covers a wide range of topics, dealing with the dynamics of poverty (consumption, cash and non-cash income, savings, assets, food security, health and education, vulnerability and social protection). Geospatial data on climate variables (rainfall and temperature) geographical variables (altitude) were also compiled for all waves of the panel.

## 3.4 Results and Discussion

### *3.4.1 Vulnerability levels*

As a common practice with econometric approaches, I first implement house cleaning to check for the presence of multicollinearity in the variables to be included in the models so that variables that may posit redundant information about the dependent variable is controlled out. I use the Variance Inflation Factor (VIF) and eigenvalues to ascertain the level of collinearity in the variables for the 2013 and 2016 consumption functions, respectively. The results for the collinearity diagnostics are presented in Appendix 1 and 2.

The diagnostics results show that all variables embodied a tolerable level of collinearity. The rule of thumb is that VIF should not exceed 10, and in our case, all the VIF values are far to 10. The reported condition indices are also within the tolerable range, not exceeding a threshold of 30. None of the eigenvalues is close to 0 on another front, showing that the estimates from the model are stable and that minor changes in the data values would transmit large changes in the estimated coefficients. Table 3.2 presents the results of the multilevel mixed-effects maximum likelihood model for future consumption and its variance conditioned on future climate stresses and current farmer characteristics.

**Table 3. 2: Multilevel Mixed-Effects ML regression model for per capita consumption**

| | 2013 ($t$ =2010) | | 2016 ($t$ = 2013) | |
|---|---|---|---|---|
| | $E(lnC\|X_h)$ | $Var(lnC\|X_h)$ | $E(lnC\|X_h)$ | $Var(lnC\|X_h)$ |
| Household size (*t*) | -0.06969 | 0.05168 | -0.05318 | -0.04336 |
| | (-6.83)** | (1.38) | (-4.98)** | (-1.19) |
| Literacy level (*t*) | 0.00014 | 0.17191 | 0.05129 | 0.28705 |
| | (0.00) | (0.81) | (0.75) | (1.23) |
| Schooling years (*t*) | 0.05862 | 0.05311 | 0.04712 | 0.00587 |
| | (10.21)** | (2.51)* | (7.60)** | (0.28) |
| Share of females (*t*) | -0.17898 | -0.22396 | -0.17487 | -0.43039 |
| | (-0.60) | (-0.20) | (-1.23) | (-0.89) |
| Age of farmer (*t*) | 0.03299 | -0.06030 | 0.06466 | 0.06662 |
| | (2.74)** | (-1.36) | (4.28)** | (1.29) |
| Age squared (*t*) | -0.00028 | 0.00097 | -0.00070 | -0.00064 |
| | (-1.74) | (1.62) | (-3.48)** | (-0.93) |
| Married (*t*) | 0.01802 | -0.30778 | 0.04766 | 0.14378 |
| | (0.29) | (-1.33) | (0.65) | (0.57) |
| Dependency Ratio (*t*) | -0.06916 | -0.09703 | -0.04351 | -0.05392 |
| | (-3.02)** | (-2.07)* | (-3.53)* | (-4.41)** |
| Female share squared (*t*) | 0.15378 | 0.09851 | 0.08729 | 0.15173 |
| | (0.90) | (0.16) | (1.76) | (0.89) |
| Off-farm enterprise (*t*) | 0.25568 | -0.03411 | 0.28194 | 0.17392 |
| | (5.02)** | (-0.18) | (5.71)** | (1.03) |
| Own Livestock (*t*) | 0.00397 | 0.22692 | 0.07791 | -0.07805 |
| | (3.10)** | (1.48) | (4.68)** | (-0.49) |
| Drought (*t*+3) | -0.15548 | -0.02483 | -0.00681 | 0.11201 |
| | (-3.35)** | (-0.15) | (-0.14) | (0.69) |
| Floods (*t*+3) | -0.02174 | 0.25866 | -0.06966 | 0.43976 |
| | (-0.38) | (1.24) | (-0.88) | (1.63) |
| Crop pests (*t*+3) | -0.03318 | -0.52845 | -0.13436 | -0.48306 |
| | (-0.59) | (-2.55)* | (-1.63) | (-1.72) |
| Livestock disease (*t*+3) | -0.06761 | 0.74731 | -0.03570 | -0.37342 |
| | (-1.20) | (3.62)** | (-0.43) | (-1.32) |
| Irregular rains (*t*+3) | -0.02796 | -0.20007 | -0.11370 | 0.12289 |
| | (-0.66) | (-1.28) | (-2.34)* | (0.74) |
| Constant | 10.40803 | -2.11291 | 10.2626 | -2.49588 |
| | (4.24)** | (-2.27)* | (6.07)** | (-2.56)* |
| **Random-effects Parameters** | | | | |
| SD district Level | 0.17024 | 0.16430 | 0.1975 | 0.1643 |
| | (5.157) | (4.212) | (2.1544) | (4.345) |
| SD individual Level | 0.5508 | 2.0461 | 0.2566 | 2.0461 |
| | (0.1286) | (3.442) | (4.775) | (3.212) |
| Wald Chi-Square | 341.88** | 41** | 297.76** | 142.41** |
| *N* | 973 | 973 | 1,032 | 1,032 |

Source: Author's calculation from LSMS 2010, 2013, 2016, t statistics in parentheses. * $p<0.05$; ** $p<0.01$

The Wald Chi-Square for all the models are large enough and significant ($p<0.05$), providing evidence that the joint effect of covariates on the dependent variable was not neutral. I used the sandwich estimator of standard errors to insure against possible heteroskedasticity in the models. Adequacy of the variables included in the models was tested using the Ramsey RESET test for omitted variables. All four models reported an F-statistic of $p<0.01$, alluding to rejection of the null hypothesis of omitted variables.

The results show that the size of farming households has a negative effect on future consumption for both models of 2013 and 2016. With larger a house size, the farmer's propensity to save decreases. Savings are necessary to cushion future consumption when in times of climate-related shocks. Small household sizes will have enough savings, which the farmer's household can draw on to smoothen consumption in times of climate shocks. The effect of years of schooling was positive and significant, meaning that more years of schooling will have a positive effect on future consumption.

The age of the farmer has a positive effect on consumption. Younger farmers are energetic and are usually early adopters of new agricultural innovations. As they become more experienced with ageing, they earn more income and hence increase consumption until their age reaches an inflexion point. As they become older, their productivity decreases and, in turn, decreases their consumption, as shown by the squared variable for the age of the farmer, having negative coefficients. Dependence was computed based on age group distribution in the household. Dependents outside the household were not captured in the data. Dependency burden has a decreasing effect on consumption, regardless of the amount of income the farmer earns, with more dependents, the per capita consumption drops. On the other hand, with fewer dependents, the farmer will be able to save surplus disposable income for future consumption in times of shocks.

Off-farm enterprise ventures have a positive effect on consumption. Off-farm income is usually resilient to climate-related stresses compared to agriculture enterprises. Thus, when climate-related stresses intensify in the future, those farmers who solely rely on agriculture face a decrease in consumption, while those engaging in other non-farm income-generating activities maintain their consumption path. Similarly, livestock ownership positively influenced future consumption. Livestock assets can quickly be converted into liquid capital to smoothen climate-induced income shocks. As such, it has a minimizing effect on the variance of consumption for the farmer.

Using the regression estimates for the consumption and variance of consumption in Table 3.1 and the 2013 and 2016 poverty line, respectively, I derive the vulnerability to expected poverty scores for 2013 and 2016. The scores are derived from the status of the household in 2010 (2016) and the economic condition of the household in 2013 (2016), given the idiosyncratic and covariate climate-related shocks facing the farmer in 2013 (2016), respectively. Figure 3.1 is output from R software showing the distribution of farmers vulnerability to expected poverty given the future climate-induced stresses.

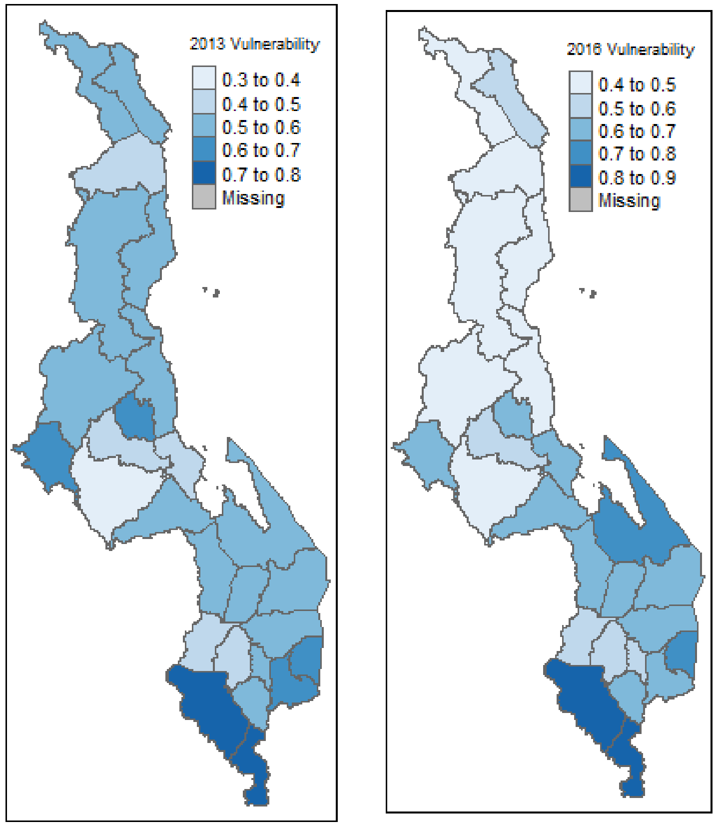
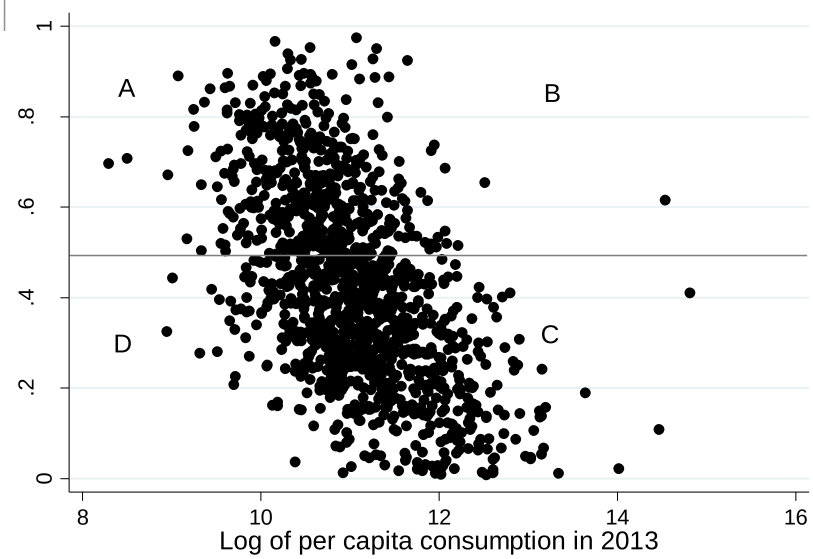



***Figure 3.1: Geospatial distribution of vulnerability across Malawi***

The figure shows that vulnerability is more concentrated towards the south, with the general decline in invulnerability in the north over analysis periods. The two districts at the bottom, Chikwawa and Nsanje, maintain high vulnerability scores. This result is not surprising because these are the districts that are often hit by droughts and floods.

Figure 3.2 is a scatter plot of vulnerability to expected poverty scores and log of per capita consumption in the future. The horizontal strike inside the scattered space shows the vulnerability threshold of 0.5. The vertical strike is the food consumption poverty line. The food poverty line represents the cost of a food bundle that provides the necessary energy requirements per person per day. First, the daily calorie requirement was set at 2,400 kilocalories per person. Second, the price per calorie was estimated from the population in the fifth and sixth deciles of the per capita consumption distribution. Last, the food poverty line was calculated as the daily calorie requirement per person multiplied by the price per calorie, following (WorldBank, 2018)




Source: Author's own plot (2019)

***Figure 3. 2: Household vulnerability to poverty in 2013***

The scatter plot in space is divided into four quadrants; A, B, C and D. Each quadrant presents a unique combination of vulnerability to a deficient levels of per capita consumption in the future. Quadrant A shows a cluster of currently poor households and are expected to remain poor in the future. Quadrant B shows households that is currently poor but is expected to transition out of poverty in the future. Quadrant C presents households that are currently not poor, and their consumption will be resilient to future climate-related shocks. Finally, quadrant D include households that are not poor now but will have a weak resilience capacity in future to climate-related shocks. Similarly, in Figure 3.3, the same analogy applies to quadrants A, B, C and D.

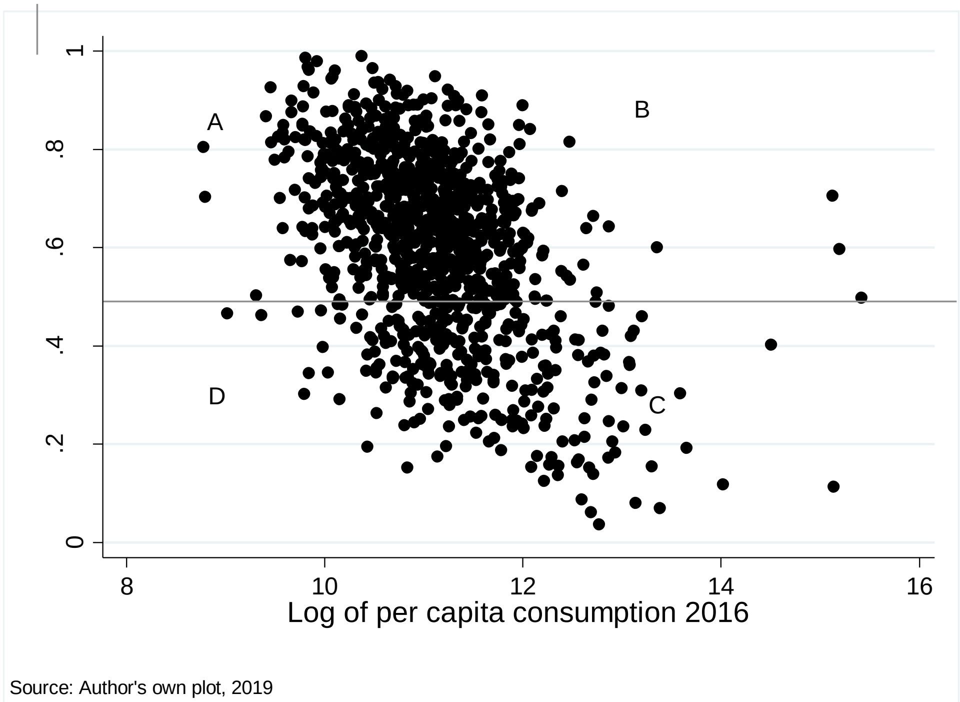



***Figure 3.3: Household vulnerability to poverty in 2016***

### *3.4.2 Vulnerability transition*

The study looked at the vulnerability change across time for the surveyed farmers. Table 2 shows the numbers of farmers that are vulnerable to climate stresses at various points in time, as defined by a vulnerability threshold of 0.5. A score of at least 0.5 means that a farmer is vulnerable, and a score of fewer than 0.5 shows non-vulnerable. A quick synopsis shows that vulnerability headcount to expected poverty has had an increasing trend over the period of analysis. At first baseline, that is the year 2010, 47% of the farmers were vulnerable to future climate stresses of 2013. In 2013 (baseline for 2016), the number of vulnerable farmers to 2016 climate-related stresses increased to 58%. I conducted further analysis to check the vulnerability of farmers in 2010 to long-run climate-related shocks (in 2016). The data shows that such vulnerability is still high but less than the level triggered by 2013 climate stresses. This shows that short-run climate stresses will have a high impact on vulnerability than long-run climate stresses will do, which provides a bit more time for farmers to prepare. The increasing trend in the vulnerability headcount over time is in line with the direction of the intensity of shocks over time (Poterie, et al., 2018). In 2013, 61% of farmers experienced climate-related shocks, whereas, in 2016, 79% of farmers experienced the shocks.

The vulnerability gap (VG), defined by the mean distance below the vulnerability threshold as a proportion of that threshold, is usually interpreted as a measured of depth of vulnerability (Gordon & Abrams, 2021).

**Table 3. 3: Temporal vulnerability change**

| | | **Vulnerability trigger** | |
|---|---|---|---|
| **Base** | **Vulnerable indicator** | **2013 shocks** | **2016 shocks** |
| **2010** | Vulnerability headcount | 0.47 | 0.29 |
| | Vulnerability gap | -0.53 | -0.36 |
| | Severity of vulnerability | 0.48 | 0.43 |
| | Vulnerability headcount | - | 0.58 |
| | Vulnerability gap | - | -0.60 |
| **2013** | Severity of vulnerability | - | 0.74 |

The vulnerability gap of the farmers was 53% for 2013, 70% for 2016 and 36% for the long run. Finally, the severity of vulnerability computed for 2013 was 48%. This implies that there is a distinction in the distribution of vulnerability among those who are vulnerable. It shows that vulnerability is skewed towards the most vulnerable. The assumption with the vulnerability gap is that a transfer to the vulnerable farmers would have the same welfare effect on farmers' vulnerability as that gained by the less vulnerable farmers. This may result in disoriented equity outcomes of a policy aimed at reducing the vulnerability of the farmers to climate stresses. As such, this merits the need to take into account the severity of vulnerability among the study population.

It is also interesting to study how farmers are entering and exiting the vulnerability spell over time. That is, are those vulnerable at baseline continue to be vulnerable in future, or they exit the spell and vice versa. Table 3.4 shows the vulnerability transition for individual farmers and the associated probability of transition. The analysis shows that 38.7% of the studied farmers were vulnerable at baseline (2010) and remained vulnerable in 2013 (Total vulnerable were about 58% in 2013). This shows that a large percent of those vulnerable have remained in the vulnerability trap over the period of analysis. A very small percent of farmers (8.8%) who were in the vulnerable set at the baseline escaped the spell in 2013. We further see that 19.3% of the farmers who were not vulnerable at baseline are entering the vulnerability trap in 2013. About 33.2% seem to be resilient to climate-related stresses and maintain their non-vulnerability status between the baseline and 2013. The movements across the four sets of analysis show that vulnerability was a net absorber of farmers. The greatest change in movement is noticed in moving from vulnerability set into the same set. The second absolute largest change is coming from farmers who have been resilient to the vulnerability traps. Non-vulnerability set is less absorptive in net terms.

**Table 3. 4: Temporal transition into and out of vulnerability trap**

| Status in 2013 | Status in 2016 (% of farmers) | | |
|---|---|---|---|
| | **Vulnerable** | **Non-vulnerable** | **Total** |
| Vulnerable | 38.7 | 8.8 | 47.5 |
| Non-vulnerable | 19.3 | 33.2 | 52.5 |
| Total | 58.0 | 42.0 | 100 |
| **Probability of entering and leaving vulnerability** | | | |
| | Entering | Leaving | |
| 2013 – 2016 | 0.37 | 0.19 | |

Source: Author computation from Malawi IHSP panel

In this study, transition probabilities are computed for each ordered pair of years on which vulnerability indices were computed. The probability of entering poverty (0.37) is much large than the probability of leaving poverty (0.19), ( $p(E) > p(L)$), about 2 times larger (Table 3.4).

### *3.4.3 Determinant of poverty*

Table 3.5 reports parameter estimates for the mixed-effects probit models for 2013 and 2016 poverty. Within the same model, I present the impact of the ex-ante vulnerability on ex post poverty. That is, vulnerability in 2010 is regressed on both 2013 poverty and 2016 poverty. Vulnerability in 2013 is regressed on 2016 poverty. Since probit coefficients cannot be interpreted directly as an effect of covariates, only the marginal effects are presented for plausible interpretation of the coefficient estimates. Results for the collinearity diagnostics are presented in Appendix A3.1 to A3.2. The variables included in the model did not show any serious level of multicollinearity as determined by VIF, Condition index and eigenvalues. One problematic variable in both models was crop diversification which indicated a VIF of more than 10, an eigenvalue of close to zero, and a condition index of greater the 30. For this reason, the crop diversification variable was dropped from both models.

The results provided evidence that ex-ante vulnerability in 2010 and 2013 translated into ex-post poverty for 2013 and 2016, respectively. For the first case of the 2013 poverty model, the results show that a unit increase in the vulnerability to poverty in 2010 increased the probability of actual poverty in 2013 by 19%. Whereas unit change in vulnerability in 2013 translated into 17% of actual poverty in 2016.

These capture the short-run impact of vulnerability on ex-post poverty. The long-run impact of the vulnerability is captured by regressing 2010 vulnerability on 2016 poverty. The result shows similar effects, but the magnitude of the impact dies off over time. While the same vulnerability had an impact of 19% on poverty in the short run, in the long run, the impact reduced to 8%.

Farmers' age shows that it is a negative correlate of poverty, but this is true only for the young population of farmers. As farmers are growing in age at earlier years, poverty tends to go down. However, the squared age of farmers shows a reversal of the effect. This implies that in the old years of farmers, further ageing results in increased poverty. With ageing, farmers tend to grow feeble, and their marginal productivity of labour and managerial skills tend to decline. Not only does the age of the farmer alone plays an important role in poverty determination but also that of other household members and

**Table 3. 5: Multilevel Mixed-Effects Probit Model for Determinants of Poverty**

| Variable | Poverty in 2013 Coefficients | | Poverty in 2016 Coefficients | |
|---|---|---|---|---|
| Vulnerability in 2010 | 0.1987 | (5.51)** | 0.0806 | (2.67)** |
| Vulnerability in 2013 | - | - | 0.1732 | (5.18)** |
| Household size | -0.1155 | (2.48)* | 0.0641 | (3.30)** |
| Years of Schooling | -0.0234 | (1.40) | -0.0150 | (1.60) |
| Farmer's age | -0.0333 | (2.52)** | -0.0462 | (2.74)** |
| Farmer's age squared | 0.0430 | (1.21) | 0.0060 | (1.80) |
| Dependency share | -0.0152 | (0.58) | -0.0299 | (0.46) |
| No. individuals in hh aged 0 - 9yr | 0.0187 | (10.3)** | 0. 0155 | (7.05)** |
| No. individuals in hh aged 10 - 17 | 0.0102 | (5.35)** | 0.0094 | (9.08)** |
| No. females in hh aged 18 - 59 | -0.0431 | (2.51)* | -0.0342 | (1.01) |
| No. males in hh aged 18 - 59 | -0.1151 | (1.39) | -0.1535 | (2.41)* |
| No. individuals in hh aged ≥ 60 | 0.0291 | (0.97) | 0.0069 | (0.50) |
| No. individuals with industry occupation | -0.1328 | (13.8)** | -0.1175 | (3.20)** |
| Large ruminants livestock (0/1) | -0.0131 | (0.32) | -0.2439 | (2.76)** |
| Small ruminants livestock (0/1) | -0.1004 | (2.59)** | -0.0520 | (2.53)** |
| Poultry (0/1) | -0.0962 | (7.34)** | 0.0710 | (11.3)** |
| Off-farm enterprise | -0.0309 | (0.80) | -0.1748 | (2.83)** |
| Safety nets | 0.0435 | (0.95) | 0.0522 | (0.91) |
| Drought (0/1) | 0.3297 | (14.1)** | 0.2102 | (12.3)** |
| Floods (0/1) | 0.1589 | (2.24)* | 0.2555 | (2.68)** |
| Crop pest infestation (0/1) | 0.0979 | (0.16) | 0.1743 | (1.79) |
| Livestock disease infestation (0/1) | 0.0140 | (0.36) | 0.0102 | (0.00) |
| Irregular rains (0/1) | 0.1218 | (6.80)** | 0.1266 | (4.44)** |
| Distance to road network | 0.0013 | (0.79) | 0.0095 | (2.47)* |
| Distance to agricultural market | 0.0016 | (1.08) | 0.0026 | (1.16) |
| Distance to district market | 0.4687 | (3.51)** | 0.0023 | (1.12) |
| **Random-effects Parameters** | | | | |
| SD district Level | 0.2248 | 2.8312 | 0.3929 | 5.1092 |
| SD individual Level | 0.5797 | 3.7303 | 0.3870 | 3.8279 |
| Wald Chi-square | 204.2** | | 138.1** | |
| *N* | 973 | | 1,032 | |

* $p$<0.05; ** $p$<0.01, Absolute t-statistics in parenthesis

concentration of household members in a given age class. Thus, I look at how various age groups coupled with gender concentration affect the poverty of the farming household.

The number of individuals aged 0 to 9 years in the household is positively related to the poverty state of the household. When one child in that age group is added to the household, the farming household's poverty probability increases by about 1.7 percentage points. The reason is that individuals in this age group are net consumers and still young to supply labour for the household production activities. The number of individuals aged 10 to 17 years in the household was also a positive determinant of poverty but with a lesser magnitude than that of the younger age group. The net effect of an added member of 10 to 17 years is around 1% percentage points. The effect is relatively smaller because apart from consumption, they are old enough to provide labour support to some of the household's productive activities, which indirectly have a bearing on its poverty stand. Another interesting age block is between 18 to 59, which is considered a productive age group. Disaggregating it by gender shows that adding a female member to a household in that age group will result in decreased poverty, although the levels of significance are marginal. Adding a male member has a greater effect on poverty reduction than female addition. This is expected especially because male members have better access to economic opportunities compared to their female counterparts within the same productive age group. Statistically, the result is indecisive for individuals aged 60 and above. However, economically the coefficient shows that members above 60 years are positively associated with poverty in the farming household. This corroborates Chen et al. (2016), who established that the ageing population had become the key issue of Chinese rural poverty.

The number of individuals who have a wage primary industry occupation has the greatest effect on poverty reduction. As they earn wages, their contribution to the household's food basket is more direct. A result is noticed for the off-farm enterprises. Results further show that ownership of livestock plays an important role in reducing poverty probability. Since livestock is so broad and each type can present different poverty outcomes, three common categories are examined; large ruminants, small ruminants (including pig) and poultry. Poultry was the most significant determinant of poverty reduction, with a marginal effect of 7 – 9%. Probably the ease with which poultry can be sold (low unit price) compared to other types of livestock makes it an important livestock type for reducing poverty probability in the face of climate shocks. Keeping small ruminants also reduced the risk of poverty while large livestock was significant only for 2016 and inconclusive for 2013. It is usually difficult to secure markets for large livestock, especially during periods of intensified climate stresses as compared to poultry (small livestock) from a unit value perspective. In general, the finding is in line with (Alary, Corniaux, & Gautier, 2011)

Poverty was strongly associated with droughts, floods and irregular rainfall. Droughts have been shown to have the greatest impact on farmers welfare loss, followed by floods. Farmers who faced droughts in 2013 were 32% poorer compared to those who didn't, and there were 21% poor in 2016 than those who were not exposed. Similarly, those who faced flood episodes in 2013 (2016) were 15% (25%) poor than those who were not impacted. Floods tend to destroy crops, farmers physical assets and displace them. The results are not significant for crop pests and livestock disease infestation. However, irregular rains accounted for 12% poverty difference when compared with farmers who did not face irregular rains.

### *3.4.4 Determinants of Poverty Transition*

The results of Table 3.6 present the determinants of entry into and exit from the poverty trap, between 2010 and 2013. Further results for the poverty transition between 2013 and 2016 are presented in Appendix 6. However, both results are similar in terms of the direction they are taking. Overall, the included regressors in the model well jointly significant in explaining the poverty mobility ($p < 0.01$). Further still, the estimates of rho were significant, showing that there were significant interactions of the error terms across the equations in the multivariate system. This salutes the suitability of multivariate probit as opposed to multinomial logit, which cannot stand the assumption of the initial condition dependency problem.

I first look at the effect of previous vulnerability to expected poverty on poverty transition. The effect size on each poverty trajectory is different. The result points to the largest positive relationship between previous vulnerability and being consistently trapped in poverty. In contrast, those who escape poverty face a pullback effect by their previous state of vulnerability. Even the non-poor to maintain their welfare above the poverty line are negatively impacted by the state of vulnerability in the previous period. In net terms, vulnerability has a stronger effect on pushing farmers into poverty in the future than the effect on those who are non-poor to switch states.

Another set of factors that affect mobility across poverty states are covariate shocks. The first covariate shock is drought. The results show that drought increases the probability of poor households remaining poor and those non-poor slipping off into poverty. However, the drought did not explain the movement from poor to non-poor. Floods are also noticed to increase the probability of remaining poor or pulling the non-poor into poverty. It further limits the chances of those who are poor to shift above the poverty threshold. Livestock disease shock is an important factor in constraining the already poor farmers to cross the threshold.

**Table 3. 6: MV Probit for Determinants of Poverty Transition (2010 – 2013)**

| Variable | Poor → Poor | Poor → Non-Poor | Non-Poor → Poor | Non-Poor → Non-Poor |
|---|---|---|---|---|
| VEP | 4.0477 | -1.6186 | 3.4342 | -2.5892 |
| | (8.27)** | (4.98)** | (2.90)** | (2.79)** |
| Household hold size | 0.1942 | -0.2724 | -0.1476 | -0.0211 |
| | (3.77)** | (2.94)** | (2.80)** | (0.29) |
| Literacy | -0.3587 | -5.2608 | -0.5677 | -0.4939 |
| | (2.47)* | (0.04) | (3.43)** | (1.56) |
| Years of Schooling | -0.1032 | 0.0348 | -0.0127 | 0.1659 |
| | (6.20)** | (1.61) | (0.88) | (8.37)** |
| Female share | 0.7209 | 0.2965 | 0.5257 | -0.4099 |
| | (1.91) | (0.55) | (1.40) | (1.10) |
| Male share | -0.2960 | -0.0292 | -0.3693 | 0.3588 |
| | (1.95) | (0.18) | (2.51)* | (2.73)** |
| Age | 0.0173 | 0.1353 | -0.2015 | 0.1221 |
| | (0.38) | (1.57) | (4.81)** | (2.44)* |
| Age squared | -0.0007 | -0.0024 | 0.0022 | -0.0009 |
| | (1.08) | (1.95) | (4.12)** | (1.41) |
| No. individuals in hh aged 0 - 9yr | 0.1371 | 0.0392 | -0.0851 | -0.3071 |
| | (1.87) | (0.32) | (1.14) | (2.84)** |
| No. individuals in hh aged 10 - 17 | 0.0107 | 0.3682 | 0.0134 | -0.3061 |
| | (0.18) | (3.87)** | (0.22) | (3.55)** |
| No. females in hh aged 18 - 59 | -0.2593 | -0.1243 | 0.2809 | -0.2052 |
| | (2.94)** | (0.80) | (3.08)** | (1.69) |
| No. males in hh aged 18 - 59 | 0.0110 | 0.0626 | 0.0582 | -0.0613 |
| | (0.18) | (0.55) | (0.92) | (0.69) |

| Variable | Poor → Poor | Poor → Non-Poor | Non-Poor → Poor | Non-Poor → Non-Poor |
|---|---|---|---|---|
| No. individuals in hh aged ≥ 60 | -0.0094 | 0.3768 | 0.2018 | -0.7654 |
| | (0.09) | (2.08)* | (1.81) | (4.59)** |
| Married | -0.3319 | 0.6301 | 0.3902 | 0.2177 |
| | (1.96)* | (1.35) | (2.06)* | (1.00) |
| Dependency share | 0.1595 | -0.0608 | -0.0781 | -0.1760 |
| | (1.78) | (0.24) | (0.80) | (0.95) |
| No. indi. with industry occupation | -0.0663 | -0.0238 | -0.0393 | -0.0064 |
| | (0.84) | (0.18) | (0.52) | (0.07) |
| Off-farmer enterprise | -0.5538 | 1.1121 | -0.2972 | 0.7329 |
| | (4.85)** | (5.54)** | (2.60)** | (5.33)** |
| Large ruminants | 0.1389 | 0.5761 | -0.0264 | -0.4097 |
| | (0.66) | (1.64) | (0.12) | (1.32) |
| Small ruminants | 0.0033 | -0.2432 | 0.2214 | 0.2423 |
| | (0.03) | (1.06) | (2.09)* | (1.62) |
| Poultry | 0.0540 | -0.4945 | 0.1354 | 0.1210 |
| | (0.54) | (2.44)* | (1.36) | (0.90) |
| Agriculture land | 0.0270 | 0.0715 | -0.0105 | 0.0941 |
| | (1.17) | (1.41) | (0.45) | (3.30)** |
| Distance to road network | 0.0026 | -0.0015 | -0.0154 | -0.0002 |
| | (0.46) | (0.13) | (2.59)** | (0.02) |
| Distance to agricultural market | 0.0163 | -0.0031 | -0.0059 | 0.0101 |
| | (4.12)** | (0.40) | (1.58) | (1.81) |
| Distance to district market | -0.0095 | -0.0034 | 0.0105 | -0.0050 |
| | (2.34)* | (0.53) | (3.16)** | (1.02) |
| Drought | 0.1268 | -0.3311 | 0.0203 | -0.0142 |
| | (4.23)** | (11.60) | (9.20)** | (0.10) |
| Floods | 0.3578 | -0.3810 | 0.1615 | 0.1204 |
| | (2.97)** | (2.33)* | (3.96)** | (0.50) |
| Crop pest infestation | -0.0477 | -0.6186 | 0.4342 | -0.5892 |
| | (0.27) | (1.98)* | (2.30)* | (2.29)* |
| Livestock diseases | 0.0087 | -0.6549 | 0.1796 | -0.2744 |
| | (0.05) | (2.76)** | (0.99) | (1.06) |
| Irregular rainfall | 0.2431 | 0.0727 | 0.0833 | -0.4528 |
| | (2.21)* | (0.35) | (3.77)** | (3.17)** |
| Constant | -0.7376 | 1.6468 | 2.4002 | -2.8560 |
| | (1.04) | (0.01) | (3.46)** | (3.08)** |
| Rho21 | 0.0343 | | | |
| | (2.22)* | | | |
| Rho 31 | 0.8719 | | | |
| | (10.17)** | | | |
| Rho 41 | 0.1107 | | | |
| | (10.11)** | | | |

| Variable | Poor → Poor | Poor → Non-Poor | Non-Poor → Poor | Non-Poor → Non-Poor |
|---|---|---|---|---|
| Rho 32 | 0.0337 | | | |
| | (1.29)* | | | |
| Rho 42 | 0.2958 | | | |
| | (3.05)** | | | |
| Rho 43 | 0.4160 | | | |
| | (3.75)** | | | |
| Model Wald Chi-square | 592** | | | |
| Rho Chi-square | 199.57** | | | |
| *N* | 1,038 | | | |

* $p<0.05$; ** $p<0.01$, Absolute t-statistics in parenthesis

### 3.5 Conclusions and Recommendations

The chapter has examined the farmers' vulnerability to expected poverty under climate-induced stresses in Malawi. Specifically, the study sought to: i) Quantify the magnitude of climate stress-induced vulnerability to poverty among farming households; ii) quantify the effects of ex-ante climate stress-induced vulnerability on ex-post poverty and; iii) To quantify the relative effects of climate-related stresses on poverty transition. The study used a panel version of Living Standards Measurement Survey data collected over the period of 2010 to 2016 in Malawi.

Using a vulnerability threshold of 0.5, 47% of the farmers were vulnerable to future climate stresses in 2013. In 2013, the number of vulnerable farmers to 2016 climate-related stresses increased to 58%. Further analysis to check the vulnerability of farmers to long-run shocks (in 2016) shows that such vulnerability is lower and different from the vulnerability in 2013 to 2016 climate-related shocks. The implication is that current vulnerability will be associated strongly with short-run climate stresses and less so with the long-run climate-related chocks.

This chapter has also examined the determinants of poverty using a multilevel mixed-effects probit. In the result, I find that there is a significant linkage between ex-ante vulnerability and ex-post poverty. Vulnerability increases the probability of actual poverty in the short run. The effects of vulnerability on actual poverty lessen with time in the long run. Similarly, climate-related stresses worsened the welfare of farming households. Poverty was accelerated by droughts, floods and irregular rainfall. Droughts had the greatest impact on farmers welfare loss, followed by floods. The finding from this study has shown that there is a statistically significant correlation of the error terms across various poverty transition equations. This implies that the current poverty outcome is dependent on the previous state of poverty of a farmer. As such previous studies that have used multinomial categorial models risked obtaining biased estimates. Using the multivariate probit model that takes the previous state of poverty endogenously to correct for flaws of previous studies, the study finds that vulnerability is a sharp predictor of poverty persistency and entry or exit of poverty. Secondly, Climate-related stresses played an important role in farmers transition across poverty states between time periods.

The study underscores the importance the livestock in buffering against poverty through serving a safety net. This suggests that the inclusion of livestock in the shaping of climate management policies for farmers is crucial. Sustainable livestock promotion programs like livestock pass-on schemes can help to reach many farmers at low cost in the long run while mitigating the impacts of climate-related stresses on poverty outcomes—small livestock like poultry act as the best safety net, but the resulting welfare growth opportunities thin.

Large livestock provides both a safety net and growth opportunities. However, the promotion of livestock should go concurrently with support of access to and function of the livestock markets. Secondly, although the rural economy is highly dependent on agriculture, switching sectors may not be possible for developing economies. However, diversification into off-farm income-generating activities offers prospects for poverty reduction and growth.

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## Appendix

### Appendix A3.1: Test for Multicollinearity in 2013 Consumption Model

| Variable | Tolerance | VIF | Square root VIF | Eigen values | Condition Index |
|---|---|---|---|---|---|
| Household size | 0.746 | 1.341 | 1.158 | 1.241 | 1.000 |
| Literacy level | 0.773 | 1.293 | 1.137 | 0.854 | 0.829 |
| Schooling years | 0.733 | 1.365 | 1.168 | 0.803 | 0.804 |
| Share of females | 0.448 | 2.230 | 1.493 | 0.715 | 0.759 |
| Age of farmer | 0.287 | 3.481 | 1.866 | 0.625 | 0.709 |
| Age squared | 0.320 | 3.122 | 1.767 | 0.433 | 0.591 |
| Married | 0.789 | 1.268 | 1.126 | 0.400 | 0.568 |
| Dependency Ratio | 0.427 | 2.341 | 1.530 | 0.378 | 0.551 |
| Female share squared | 0.480 | 2.082 | 1.443 | 0.304 | 0.495 |
| Off-farm enterprize | 0.513 | 1.949 | 1.396 | 0.183 | 0.384 |
| Own Livestock | 0.718 | 1.392 | 1.180 | 0.163 | 0.363 |
| Drought | 0.441 | 2.268 | 1.506 | 0.091 | 0.271 |
| Floods | 0.945 | 1.058 | 1.029 | 0.753 | 0.779 |
| Crop pests | 0.705 | 1.418 | 1.191 | 0.201 | 0.403 |
| Livestock disease | 0.736 | 1.360 | 1.166 | 0.414 | 0.578 |
| Irregular rains | 0.864 | 1.158 | 1.076 | 0.259 | 0.457 |

### Appendix A3.2: Test for Multicollinearity in 2016 Consumption Model

| Variable | Tolerance | VIF | Square root VIF | Eigen values | Condition Index |
|---|---|---|---|---|---|
| Household size | 0.798 | 1.25 | 1.1196 | 1.730 | 1.000 |
| Literacy level | 0.780 | 1.28 | 1.1321 | 0.755 | 0.660 |
| Schooling years | 0.716 | 1.40 | 1.1819 | 0.686 | 0.630 |
| Share of females | 0.380 | 2.63 | 1.6221 | 0.610 | 0.594 |
| Age of farmer | 0.259 | 3.86 | 1.9636 | 0.528 | 0.553 |
| Age squared | 0.289 | 3.46 | 1.8610 | 0.470 | 0.521 |
| Married | 0.835 | 1.20 | 1.0944 | 0.339 | 0.443 |
| Dependency Ratio | 0.477 | 2.10 | 1.4483 | 0.309 | 0.422 |
| Female share squared | 0.480 | 2.08 | 1.4432 | 0.267 | 0.393 |
| Off-farm enterprize | 0.694 | 1.44 | 1.2004 | 0.176 | 0.319 |
| Own Livestock | 0.940 | 1.06 | 1.0313 | 0.135 | 0.279 |
| Drought | 0.838 | 1.19 | 1.0924 | 0.083 | 0.219 |
| Floods | 0.731 | 1.37 | 1.1699 | 0.751 | 0.659 |
| Crop pests | 0.558 | 1.79 | 1.3388 | 0.187 | 0.328 |
| Livestock disease | 0.600 | 1.67 | 1.2906 | 0.964 | 0.746 |
| Irregular rains | 0.446 | 2.24 | 1.4973 | 0.021 | 0.111 |

**Appendix A3.3: Test for Multicollinearity in 2013 Poverty Model**

| | Tolerance | VIF | Square Root VIF | Eigenvalue | Condition Index |
|---|---|---|---|---|---|
| Vulnerability in 2010 | 0.568 | 1.76 | 1.33 | 7.638 | 1.000 |
| Household size | 0.329 | 3.04 | 1.74 | 1.403 | 2.333 |
| Years of Schooling | 0.144 | 6.95 | 2.64 | 1.155 | 2.572 |
| Farmer’s age | 0.253 | 3.96 | 1.99 | 1.063 | 2.680 |
| Farmer’s age squared | 0.762 | 1.31 | 1.15 | 1.012 | 2.748 |
| Dependency share | 0.128 | 7.81 | 2.80 | 0.801 | 3.087 |
| No. individuals in hh aged 0 - 9yr | 0.721 | 1.39 | 1.18 | 0.761 | 3.167 |
| No. individuals in hh aged 10 - 17 | 0.214 | 4.67 | 2.16 | 0.666 | 3.387 |
| No. females in hh aged 18 - 59 | 0.416 | 2.40 | 1.55 | 0.597 | 3.577 |
| No. males in hh aged 18 - 59 | 0.268 | 3.73 | 1.93 | 0.580 | 3.629 |
| No. individuals in hh aged ≥ 60 | 0.452 | 2.21 | 1.49 | 0.457 | 4.087 |
| No. individuals with industry occupation | 0.491 | 2.04 | 1.43 | 0.429 | 4.218 |
| Large ruminants livestock (0/1) | 0.852 | 1.17 | 1.08 | 0.401 | 4.365 |
| Small ruminants livestock (0/1) | 0.516 | 1.94 | 1.39 | 0.362 | 4.592 |
| Poultry (0/1) | 0.404 | 2.48 | 1.57 | 0.349 | 4.681 |
| Off-farm enterprise | 0.697 | 1.43 | 1.20 | 0.319 | 4.893 |
| Safety nets | 0.173 | 5.79 | 2.41 | 0.271 | 5.305 |
| Drought (0/1) | 0.498 | 2.01 | 1.42 | 0.192 | 6.308 |
| Floods (0/1) | 0.762 | 1.31 | 1.15 | 0.144 | 7.288 |
| Crop pest infestation (0/1) | 0.620 | 1.61 | 1.27 | 0.115 | 8.143 |
| Livestock disease infestation (0/1) | 0.553 | 1.81 | 1.35 | 0.101 | 8.705 |
| Irregular rains (0/1) | 0.406 | 2.46 | 1.57 | 0.075 | 10.068 |
| Distance to road network | 0.436 | 2.29 | 1.51 | 0.061 | 11.146 |
| Distance to agricultural market | 0.157 | 6.35 | 2.52 | 0.027 | 16.667 |
| Distance to district market | 0.181 | 5.54 | 2.35 | 0.018 | 20.746 |
| Crop diversification | 0.057 | 17.49 | 4.18 | 0.002 | 70.964 |

**Appendix A3.4: Test for Multicollinearity in 2016 Poverty Model**

| Variable | Tolerance | VIF | Square Root VIF | Eigenvalue | Condition Index |
|---|---|---|---|---|---|
| Vulnerability in 2010 | 0.649 | 1.540 | 1.24 | 15.738 | 1.000 |
| Vulnerability in 2013 | 0.354 | 2.824 | 1.68 | 1.788 | 2.967 |
| Household size | 0.460 | 2.176 | 1.48 | 1.288 | 3.495 |
| Years of Schooling | 0.151 | 6.615 | 2.57 | 1.033 | 3.904 |
| Farmer’s age | 0.486 | 2.058 | 1.43 | 0.847 | 4.312 |
| Farmer’s age squared | 0.222 | 4.514 | 2.12 | 0.738 | 4.619 |
| Dependency share | 0.158 | 6.324 | 2.51 | 0.713 | 4.699 |
| No. individuals in hh aged 0 - 9yr | 0.118 | 8.502 | 2.92 | 0.570 | 5.254 |
| No. individuals in hh aged 10 - 17 | 0.277 | 3.609 | 1.90 | 0.532 | 5.441 |
| No. females in hh aged 18 - 59 | 0.122 | 8.174 | 2.86 | 0.482 | 5.714 |
| No. males in hh aged 18 - 59 | 0.157 | 6.370 | 2.52 | 0.459 | 5.854 |
| No. individuals in hh aged ≥ 60 | 0.635 | 1.574 | 1.25 | 0.353 | 6.679 |
| No. individuals with industry occupation | 0.450 | 2.221 | 1.49 | 0.337 | 6.834 |
| Large ruminants livestock (0/1) | 0.818 | 1.223 | 1.11 | 0.326 | 6.953 |
| Small ruminants livestock (0/1) | 0.419 | 2.385 | 1.54 | 0.318 | 7.040 |
| Poultry (0/1) | 0.319 | 3.139 | 1.77 | 0.277 | 7.536 |
| Off-farm enterprise | 0.722 | 1.385 | 1.18 | 0.259 | 7.796 |
| Safety nets | 0.181 | 5.521 | 2.35 | 0.186 | 9.202 |
| Drought (0/1) | 0.471 | 2.122 | 1.46 | 0.175 | 9.473 |
| Floods (0/1) | 0.595 | 1.680 | 1.30 | 0.136 | 10.740 |
| Crop pest infestation (0/1) | 0.446 | 2.241 | 1.50 | 0.123 | 11.293 |
| Livestock disease infestation (0/1) | 0.465 | 2.149 | 1.47 | 0.113 | 11.802 |
| Irregular rains (0/1) | 0.291 | 3.436 | 1.85 | 0.097 | 12.724 |
| Distance to road network | 0.480 | 2.084 | 1.44 | 0.095 | 12.890 |
| Distance to agricultural market | 0.139 | 7.186 | 2.68 | 0.084 | 13.716 |
| Distance to district market | 0.187 | 5.336 | 2.31 | 0.078 | 14.191 |
| Crop diversification | 0.066 | 15.050 | 3.88 | 0.006 | 51.363 |

**Appendix A3.5: MV Probit for Determinants of Poverty Transition (2013 – 2016)**

| | Poor → Poor | Poor → Non-Poor | Non-Poor → Poor | Non-Poor → Non-Poor |
|---|---|---|---|---|
| VEP | 3.7442 | -5.0020 | 1.2535 | -7.4069 |
| | (7.31)** | (6.55)** | (3.46)** | (12.10)** |
| Household hold size | 0.1253 | -0.1329 | -0.0661 | -0.1035 |
| | (3.82)** | (1.89) | (1.56) | (2.06)* |
| Literacy | 0.0239 | -0.4291 | -0.1558 | -0.4773 |
| | (0.18) | (1.52) | (1.07) | (2.37)* |
| Years of Schooling | -0.0532 | -0.0190 | 0.0031 | 0.0620 |
| | (3.48)** | (0.77) | (0.21) | (4.04)** |
| Female share | 0.1105 | -0.3274 | 0.3900 | -0.2026 |
| | (4.58)** | (0.96) | (2.07)* | (0.99) |
| Male share | 0.0048 | -0.0657 | 0.0571 | 0.0129 |
| | (0.10) | (0.88) | (1.41) | (0.29) |
| Age | 0.0097 | 0.0563 | -0.1076 | 0.1012 |
| | (0.25) | (0.68) | (2.55)* | (2.32)* |
| Age squared | 0.0004 | -0.0013 | 0.0012 | -0.0009 |
| | (5.83)** | (1.15) | (2.18)* | (1.62) |
| No. individuals in hh aged 0 - 9yr | 0.0085 | -0.0585 | 0.0824 | -0.0147 |
| | (0.19) | (0.66) | (1.54) | (0.25) |
| No. individuals in hh aged 10 - 17 | 0.0239 | 0.1815 | -0.0508 | -0.1136 |
| | (0.54) | (2.64)** | (1.03) | (1.97)* |
| No. females in hh aged 18 - 59 | 0.1351 | 0.0028 | 0.1898 | -0.1635 |
| | (2.00)* | (0.02) | (2.57)* | (1.90) |
| No. males in hh aged 18 - 59 | -0.0940 | 0.1516 | -0.0067 | 0.0165 |
| | (6.68)** | (5.78)** | (9.12)** | (0.27) |
| No. individuals in hh aged ≥ 60 | -0.1046 | 0.0557 | 0.0093 | -0.0290 |
| | (1.18) | (0.95) | (0.26) | (0.62) |
| Married | 0.0821 | 0.5014 | 0.1280 | -0.1925 |
| | (0.54) | (1.17) | (0.75) | (1.07) |
| Dependency share | 0.3337 | -0.0758 | 0.0504 | 0.0415 |
| | (4.51)** | (0.34) | (0.51) | (0.32) |
| No. indi. with industry occupation | -0.0850 | -0.0251 | -0.0666 | 0.0387 |
| | (1.22) | (0.27) | (1.02) | (0.60) |
| Off-farmer enterprise | -0.3477 | 0.1254 | 0.0513 | 0.0736 |
| | (3.23)** | (0.73) | (0.48) | (0.61) |
| Large ruminants | -0.2195 | 0.0214 | -0.1331 | 0.4483 |
| | (1.11) | (0.07) | (0.64) | (1.73) |
| Small ruminants | -0.0809 | 0.0202 | -0.1859 | 0.1365 |

| | Poor → Poor | Poor → Non-Poor | Non-Poor → Poor | Non-Poor → Non-Poor |
|---|---|---|---|---|
| | (0.82) | (0.11) | (1.87) | (1.17) |
| Poultry | -0.0901 | 0.3504 | -0.1326 | 0.0093 |
| | (0.93) | (2.07)* | (1.33) | (0.08) |
| Agriculture land | -0.0175 | 0.0410 | -0.0179 | 0.0288 |
| | (4.80)** | (5.17)** | (0.72) | (31.18)** |
| Distance to road network | 0.0052 | -0.0067 | -0.0126 | -0.0051 |
| | (0.97) | (0.62) | (2.13)* | (0.73) |
| Distance to agricultural market | 0.0147 | -0.0083 | 0.0041 | -0.0015 |
| | (3.78)** | (1.17) | (1.05) | (0.32) |
| Distance to district market | -0.0076 | 0.0017 | 0.0082 | -0.0027 |
| | (2.04)* | (0.30) | (2.43)* | (0.64) |
| Drought | 0.1356 | -0.1715 | 0.0402 | -0.0449 |
| | (5.37)** | (7.94)** | (4.38)** | (0.37) |
| Floods | 0.3980 | -0.3477 | 0.1888 | -0.0561 |
| | (2.40)* | (7.40)** | (1.14) | (6.30)** |
| Crop pest infestation | 0.0913 | -0.7259 | -0.3246 | 0-.6452 |
| | (0.53) | (2.62)** | (1.72) | (3.31)** |
| Livestock diseases | 0.0445 | -0.6940 | 0.1442 | -0.2934 |
| | (0.26) | (2.08)* | (0.80) | (8.49)** |
| Irregular rainfall | 0.2450 | -0.1810 | 0.0555 | -0.2676 |
| | (2.33)* | (5.01)** | (0.52) | (2.81)** |
| Constant | -1.6325 | -1.6323 | 1.0247 | 1.4267 |
| | (2.68)** | (1.14) | (1.39) | (1.54) |
| Rho21 | 0.2263 | | | |
| | (1.94) | | | |
| Rho 31 | 0.6727 | | | |
| | (8.96)** | | | |
| Rho 41 | 0.3409 | | | |
| | (3.88)** | | | |
| Rho 32 | 0.0107 | | | |
| | (0.12) | | | |
| Rho 42 | 0.1708 | | | |
| | (1.83) | | | |
| Rho 43 | 0.2371 | | | |
| | (3.12)** | | | |
| Model Wald Chi-square | 406.95** | | | |
| Rho Chi-square | 222.13** | | | |
| *N* | 1,021 | | | |

* $p$<0.05; ** $p$<0.01

**Appendix A3.6: Derivation of Vulnerability to Expected poverty in R Software**

```
#       VULNERABILITY OF SMALLHOLDER FARMERS TO CLIMATE CHANGE
#          Assa M. Maganga
#         University of Malawi
#         Department of Economics
#       Date Last Modified: 5 April 2019
# --------------------------------------------------------------
#DERIVING VULNERABILITY TO COVARIATE SHOCKS SCORES.

#FITTING THE MULTILEVEL MODEL
 #step 1: calculate ex ante mean
    Model_1 <- lme(fixed = lnC ~ hhsize_10 +  Literacy_10  +
Schooling_10   +  femaleshare_10  +  age_10  +  age_square_10  +
married_10  +  depratio_10  +  femaleshare2_10  +  enterprize_10
+   Livestock_10 +  drought_13  +  floods_13  +  croppests_13  +
livestockdisea_13  +  irreg_rains_13, random=~1|district/HHno,
correlation = corAR1(),   data = VEP, na.action=na.exclude)

#summary(Model_1)

#step2: calculate ex ante variance
  VEP$yhat   <- fitted(Model_1)
  VEP$res   <- resid(Model_1)
  VEP$lnres2[!is.na(VEP$res)] < log((VEP$res[!is.na(VEP$res)])^2)
  Model_1a <- lme(fixed = lnres2 ~ hhsize_10 +  Literacy_10  +
Schooling_10   +  femaleshare_10  +  age_10  +  age_square_10  +
married_10  +  depratio_10  +  femaleshare2_10  +  enterprize_10
+   Livestock_10 +  drought_13  +  floods_13  +  croppests_13  +
```

```
livestockdisea_13  +  irreg_rains_13, random=~1|district/HHno,
correlation = corAR1(),   data = VEP, na.action=na.exclude)

VEP$plnres2 <- fitted(Model_1a)
  VEP$eplnres2 <- exp(VEP$plnres2)
  VEP$sd2 <- sd(!is.na(VEP$eplnres2))

  #   step 3: calculate Score
VEP$z1 <- ((VEP$z -VEP$yhat) /VEP$sd2) # Z-score
VEP$vep <-  pnorm(VEP$z1)
summary(VEP$vep2)
```

# CHAPTER 4

# WILLINGNESS TO PAY FOR INDEX INSURANCE FOR STAPLE FOOD CROP

## 4.1 Introduction

### *4.1.1 Background*

Crop agriculture has a heavy reliance on weather and is negatively impacted by periodic episodes of droughts and floods. These have an inverse relationship with farm output (Akhtar, et al., 2019). The presence of droughts and floods will trap agriculture out in a vicious cycle: These shocks will reduce farm output and have a negative effect on the economic lives of farming households. As a result, these farmers will migrate to urban areas to recover their fragile livelihoods. With urbanization, farm output is expected to remain low in the subsequent periods (Hongo, 2010).

Uncertainty in climate is associated with risks that expose farmers to high vulnerabilities, affecting their livelihood. This risk emanates from weather-related extreme events (Hellmuth, et al., 2007). Thus, weather outcomes are either below or above the normal threshold. As such, agriculture risk management is becoming a contemporary issue as variability in climate is predicted to worsen in the future, which will pose further increasing uncertainties on agriculture output and performance of the agriculture sector in general (Antón, et al., 2013). Extreme climate events obstruct the economic lives of the farming households, whose livelihoods are agriculture-based, and retards progress towards the achievement of the Sustainable Development Goals. These arise because most of African Agriculture is dependent on rain-fed moisture, and in Sub-Saharan Africa (SSA) in particular, agriculture is one of the most important sectors as it contributes about 29 percent to Gross Domestic Product and provides employment to 86 percent of the population (Nnadi, et al., 2019; World Bank, 2008). This will make risk management to remain a relevant option as it provides farmers with a buffer in the face of climate-related unanticipated extreme events, thereby strengthening the resilience of the agriculture sector (Someshwar, 2008).

It is believed that the effects of climate-related extreme events on the economic lives of farming households have intensified in recent years, most significantly due to global warming (Barnett, et al., 2007). In certain parts of Africa, research findings have shown that countries have already experienced a persistent fall in GDP by 1 to 3 percent yearly as a result of droughts and floods. There are also predictions that there will be further losses of 1 to 2 percent of GDP in the short terms and this will worsen to a range of 5 to 10 percent by 2030 (Smith, et al., 2012), meriting the need for a plausible solution that could cushion farmers in the face of impeding climate-related risks.

Of the climate-related shocks, those that have been commonly reported in African Context include droughts and floods. Cole et al. (2013) note that about 89% of the surveyed households in developing countries reported that variability in rainfall was the most important weather risk they were facing. Africa, in particular, based on both farmers reports and empirical evidence, rainfall shocks was the most worrying weather shock that farmers faced in Ethiopia (Dercon, et al., 2011). A review of the International Disaster Database for the past four decades shows a historical record of 1000 natural disasters in Africa affecting around 330 million individuals. Of these disasters, although floods were frequent, it happened that droughts affected 83% often the victims and resulted in 40% of the registered economic damages (EMDAT, 2010). With time, these events tend to intensify in frequency (Dilley, et al., 2005). With exposure to these shocks, farmers to find alternatives that they can use to manage the aftermath of these shocks.

In developing countries, weather index crop insurance has emerged as one potential sustainable risk management strategy for farmers that transfers climate triggered risks from farmers to insurance brokers (Barnett, et al., 2007). It is a better option than traditional crop insurance because of its underlying challenges with paying indemnities according to the actual losses experienced by the farmer. Index insurance reduces the risk of adverse selection in which farmers are inclined to subscribe to insurance if they are at high risk. Farmers subscribe to an insurance based on terms, conditions and payouts that are uniform for all farmers in a designated location, hence, mitigating the problem of adverse selection by insurance brokers. The second advantage is that it reduces the problem of moral hazard. In traditional insurance, farmers may influence payouts by altering their farm management behaviour into one that can induce losses in order to trigger a payout. Whereas, with index insurance, payouts are dependent on variables that are exogenous to the farmers, such as weather outcomes (World Bank, 2011). Therefore, the provision of index-based crop insurance to farmers is a sustainable risk management strategy that can cushion or offer long-run income growth for farmers in low-income countries (Cole, et al., 2013).

Poor and vulnerable farmers in developing countries face income risk due to climate-related shocks. The concept of risk management in agriculture is not new among farmers. Farmers already engage in a number of risk mitigation strategies that tend to smoothen their consumption path in order to minimize the effects of the shocks. These could include livelihood diversification, sale of assets, draws on savings, among others (Dercon, 2002). The effectiveness of these strategies is depended on the scale of the risks. Without a doubt, these strategies are effective for idiosyncratic shocks. However, when shocks are covariate in nature – affecting the entire community, some of the strategies, especially those that rely on the proper functioning of community markets, tend to be no longer effective. Studies have found that the impact of idiosyncratic shocks on consumption is not significant suggesting that there is usually intra-household resource distribution when one household is stricken by such shocks. On the other hand, covariate shocks are mostly correlated with consumption decay (Harrower, et al., 2005). For such shocks, a formal agriculture insurance policy for farmers becomes more plausible to manage such agricultural risks (Dercon, 2002; Mechler, et al., 2006). Designing an insurance policy that meets the needs of farmers in times of climate-related covariate shocks is a step forward toward the management of agricultural production risks (Clarke, et al., 2012).

### *4.1.2 Problem Statement and justification*

Weather index insurance, being a new concept in Malawi, has not received much attention from researchers at the country scale. It is not surprising that previous studies that have had to do with the management of climate risk in agriculture have mostly been to do with adaptation (preventive measures) of impact mitigating technologies such as conservation agriculture technologies and others (Chidanti-Malunga, 2011;

Pangapanga, et al., 2012; Assa, et al., 2017). As efforts to help farmers to manage climate risks through subscription to weather index insurance are in infancy, an initial understanding of the farmers' willingness to pay a premium for the insurance services is a first step to shape proper packaging of the weather index policy. To the author's knowledge, there is no study to date that has examined the demand side of weather index insurance in Malawi. The information will be much needed by the insurance companies and the Ministry of Agriculture in shaping the direction of the agriculture insurance market in Malawi. As such, this study uses cross-sectional data from 10 districts to employ contingent valuation methods to weather index insurance potential in Malawi.

#### *4.1.3 Objective of the study*

The general objective of this study is to generate the demand side information from farmers who are the major victims of climate-related shocks. Thus, the prime concern of this study is to elicit farmers' willingness to pay for weather index insurance in Malawi for maize crops. The specific objectives of the study are:

- To identify the determinants of the willingness of farmers to pay for Weather Index Insurance
- To estimate the mean Willingness to Pay for weather index insurance.
- To compare Willingness to pay estimates from parametric and non-parametric methods.
- To develop a framework for designing weather index insurance

## 4.2 Literature Review

This section provides the background to risk management and the concept of insurance. In turn, it presents a review of the theoretical construct of the contingent valuation methods.

### *4.2.1 Risk and risk management*

Risk can be defined as the potential damage for loss, damage as a result of the interplay among vulnerability, exposure to hazards and the probability of its occurrence (IPCC, 2018). In agriculture, farmers are faced with output, price risks which in turn affect their incomes from time to time. Teshome and Bogale (2015) have characterized risks into three; 1) those that affect households, 2) those that affect the community, 3) those that affect region and nation. The individual risk could range from illness, loss of family members, loss of non-farm income source and others. Community or regions risks could include floods and droughts. In agriculture, these risks are somehow intertwined. Community risks like droughts or floods could affect agriculture output and, in turn, alter region prices for some communities (Cervantes-Godoy, et al., 2013).

With missing markets for contract pricing and crop insurance in developing countries until the recent past, farmers have been engaging in self-insurance so as to minimize the negative effects of shocks on their livelihood (Davies, 1993). Some of the effects of the shocks and the shocks themselves are not strange to farmers. Farmers can anticipant and predict certain shock occurrences and at the same time engage in ex-ante risk management strategies to minimize the effects of those shocks or engage in ex-post risk coping strategies to smoothen their consumption. Some of the risk coping strategies could have a lasting impact on the lives of the farmers (Machetta, 2011; Kwadzo, et al., 2013). These could include sell of household assets, reducing food intake and school dropout of children. Reduction in food intake could have a negative long-run effect on a child's cognitive ability (Jones, et al., 2009). Dropping out of school could also affect the supply of skilled human capital in the future. Deciphering from these effects, it can be depicted self-insurance might not be the best option for the households and the nation in the long term. This makes the presence of crop insurance products more relevant to the farming society if farmers are to remain better off in times of weather shocks.

### *4.2.2 Agriculture Insurance*

Agriculture insurance builds on the same principle as other forms of insurance like health insurance or property insurance. The key principle is that it entails paying a regular sum of money to an insurance agency in return for an irregular payback that happens when there is unforeseen loss (Kwadzo, et al., 2013). Subscription to an insurance policy does not reduce the likelihood of a shock from happening. However, what it does is smoothen the economic stand of the farmer should they experience a shock (Danso-Abbeam, et al., 2014). This empowers the farmers to manage the shocks effectively. Agriculture insurance can largely be categorized into two: 1) indemnity-based insurance and 2) index-based insurance.

#### 4.2.2.1 The Indemnity-based crop insurance

Indemnity-based crop insurance is a type that covers individual farmers from a given hazard. Its focus is on the actual losses such that a farmer will claim the actual loss experience. The insurance can cover either one type of hazard or several hazards, depending on what is specified in the contractual agreement. Any loss that is triggered by any hazard which is specified in the agreement qualifies for a farmer to file a claim.

The total premium for the farmer is calculated based on the total production cost or the estimated revenue from production (Tsikirayi, et al., 2013).

Indemnity-based insurance is challenged by a number of weakness that might affect its sustainability and effectiveness, especially when it is to do with cover for small scale farmers (Newbery, et al., 1983). These challenges include moral hazard and adverse selection, which in turn results increase costs of administration as the insurance providers try to bridge the gap of asymmetric information. In moral hazard, insured farmers may have less incentive to work hard as they would without insurance, hence, increasing the chances of losses. Alternatively, insured farmers may declare losses that could be costly for the insurance agent to verify. With regard to adverse selection, fewer risk farmers may not bother to subscript for an insurance policy, while high-risk farmers will crowd out the insurance policy. As such, on average increases the probability of losses to the insurance provider. This will result in a failure of the insurance market with time, as Akerlof puts it as the market for lemons (Akerlof, 1970). These challenges provide evidence that the traditional crop insurance in developing countries will not only be ineffective but will also kill the insurance markets. This seeks a modified type of insurance that can ably handle these kinds of challenges.

#### 4.2.2.2 Index-based crop insurance

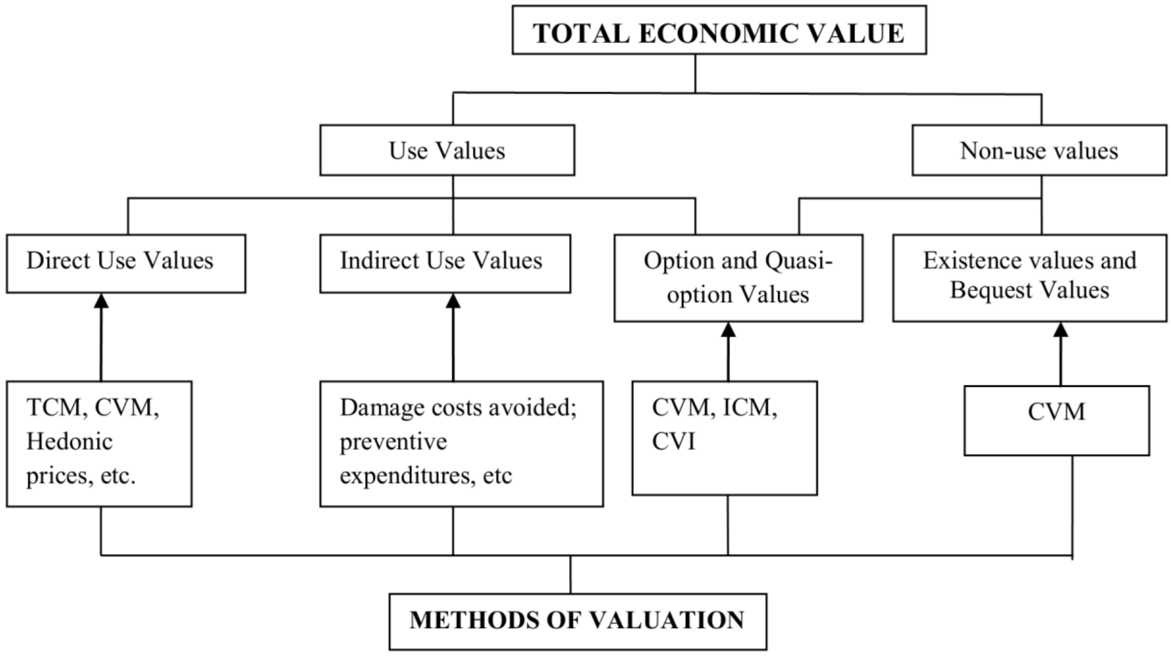
Index-based insurance is a step ahead of traditional insurance. It can be contraction at individual, community or regional level. One of its distinguishing characteristics is that it disconnects actual individual losses from the payout. Instead of using actual losses, it uses an index that is exogenous to the farmer’s behaviour. When certain variables exceed certain agreed thresholds, the payout is triggered. For example, in Malawi, they have used rainfall amount, in Peru, they have used location area yield data, and in India, they have used mortality rate of livestock (ILO, 2011; Cole, et al., 2012). The index used data (droughts, floods) that is usually compiled at weather stations for a given community. The major drawback of this policy, from the farmers perspective, is that a farmer as an individual may have losses at his farmer by may not file a claim if the index did not exceed the agreed threshold. This is why, in the design of the index, the yield should be highly correlated with the index used.

### *4.2.1 Economic valuation of non-market goods*

Pricing goods and services that are currently not offered on the market is generally imagined as they have no economic value. Over time, beyond neoclassical economics, there has been development and evolution of techniques that can be used to peg prices or economic value on goods or services which cannot currently be accessed on the market by using stated preference (Hoyos, et al., 2010). In this regard, economic value is the opportunity cost of forgoing other goods or services in order to access the good/service that is not currently offered on the market. This money metric welfare representation is constructed using Willing to Pay (WTP) in order to minimize losses that are incurred as a result of changing climate. This willingness to pay is an extremum that an individual is willing to pay, in our case, crop insurance subscription, in order to maintain their level of welfare despite the occurrence of floods and droughts (Douglas, et al., 1998). Estimation of economic value through valuation, therefore, enables us to determine the marginal returns of non-market goods to the individual’s utility.

Valuation of non-market goods is not an end product but rather a tool or methodology that aids decision making in the provision of related goods and services. It is usually amalgamated with financial instruments within a given institution setting to derive the economic value on non-market goods (Jean-Michael, 2011). To derive this economic value, the decomposition of the Total Economic Value (TEV) approach is used. This is based on the premise that the economic value of a good or service has different components of values depending on its attributes. These components of value are based on whether the value can directly be measured through tangibly deriving benefits from the product or indirectly. Thus, Total Economic Value can be decomposed into Direct Use Value, Indirect Use Value, and Non-use.

Direct use value is a value of a stream of benefits that are realized by directly consuming the good. Indirect use-value is a stream of benefits that accrual from consumption of the services from a given good. Non-use values are twofold: Option and existence values. The option value is an intrinsic benefit enjoyed by individuals by deciding not to consume the good today but keep it for the future. Existence value is the value attached to a good by an individual who likes to enjoy seeing the existence of that good without directly deriving benefit from it (Zhang, et al., 2010). Figure 1 illustrates the decomposition of these values.




Source: Adapted from Edward et al., (1997)

***Figure 4. 1: Conceptual framework for understanding the economic valuation of non-market goods***

The non-use values pose a greater difficulty in quantification. Non-use values are intrinsic; they may not relate to either current or future consumption by individuals in question. These are based on subjective value judgement (Edward, et al., 1997).

The above approach has mostly been used in empirical environmental economics to quantify the cost of providing a given quality of an environmental good. In the analysis, the focus is usually on how a change in the attribute or quality of an environmental good would transmit changes into the utility of an individual. i.e gains or losses in welfare of an individual. The assessment is driven by two key questions: 1). How much is an individual willing to give up on other goods in order to avert damages caused by environmental or climate changes; 2) How much better off will the benefiting individual be if a non-market good was provided to enhance averting damages caused by the environmental or climate change. These are the two questions that this current study seeks to respond to. The former relates to the quantification of the affordable price for weather index crop insurance. The latter relates to the welfare changes as a result of subscribing to weather index insurance.

Valuation of non-market goods has its roots in the field of welfare economics, building on the concepts of consumer and producer surplus to aid efficient pricing of the provision of non-market goods (Douglas, et al., 1998), in this case, price of insurance products to minimize damages caused by floods and droughts.

In order to evaluate the money metric welfare shifts due to worsening climate events, with the goal of maintaining a fixed level of welfare during pre and post-disaster periods, two measures have been suggested in literature; these are equivalent variation and compensated variation (Latham, 1999). Equivalent variation is the amount of money that must be adjusted from an individual in order to maintain their initial level of utility (welfare) regardless of the presence of the climate shocks. If the policy change results in an individual's improvement, then the measure is called compensated variation (Nyborg, 1996).

For a proposed provision of insurance products that increases resilience of an individual's welfare, compensation variations could define the income change necessary to maintain the individual's initial level of utility throughout episodes of droughts and floods. This will be the maximum amount from his income that an individual will be ready to give up in order to maintain his level of welfare; in environmental economics, this amount is called Willingness to Pay (WTP). Considering a change in the provision of climate risk management goods from $q_0$ to $q_1$, in which $q_1$ is a vector of goods that includes crop insurance, compensated variation is given by $u_0(m_0 - WTP, q_1) = u_0(m_0, q_0)$, where $u_0$ is the initial level of utility an individual is capable of realizing given that his income is $m_0$ and climate risk management strategies $q_0$. With the provision of $q_1$, an individual's utility does not drop in the face of climate shocks. Without taking off any income from the individual, his utility of income goes up. As such, to maintain the same level of utility as at the initial, an amount equivalent to *WTP* must be taken away from an individual (Hanemann, et al., 1991; Cook, 2011).

By definition, WTP is the amount an individual is willing to pay for the desired level of a good or payment to avert the effects of undesirable outcomes of environmental changes (Charles 2000). The choice between the use of WTP or Willingness To Accept on the rights that are vested by the individual who is concerned. WTP works when the person who suffer damage does not have the right to stop it. On the other hand, WTA works when the rights are vested in the concerned individual and therefore must be compensated for any damage he may suffer. For the insurance products, since we are dealing with climate shocks for which rights cannot be applied, and as such, the individual does not have rights over nature, WTP is a plausible option (Nyborg, 1996; EDIEN, 2002). Thus, WTP is appropriate for this study and has been highlighted as one of the most conservative approaches compared to WTA (Arrow, et al., 1993), it avoids over estimation that is common with WTA approaches.

### *4.2.2 Methods in the valuation of non-market Goods*

In a broader spectrum, there are two key methods that are used to derive values for non-market goods. These include stated preference and revealed preference methods. The following sub-sections unpack each of these methods.

#### *4.2.2.1 Revealed Preference*

The theory of revealed preference is traced back in the Samuelson (1948) novel work when he was trying to derive a utility function using minimum quantities of goods and price information such that the consumer could consistently choose the same consumption bundles in line with the original data. Varian (1992) makes a solid presentation of the theory of revealed preference. This approach draws statistical inference on the actual choices people make in the marketplace. It proceeds from observing actual quantities purchased at given prices. There are tw0 commonly used methods under this approach: Travel cost methods and hedonic pricing method (Adarnowicz, et al., 1994).

##### *4.2.2.1.1 Travel Cost Method*

The travel cost method has been used to establish values of a recreation site accruing from environmental amenities. This can take two forms: it can be used to value recreation loss from, for instance, closure of beach due to oil spillage, or alternatively, recreation gains from a particular improvement in water quality or environmental scenery. The economic values established by this method are use-values since it entails the elicitation that depends on the observed behaviour of the participants (Cameron, 1992). The method of travel cost is further categorized into whether the focus is on estimating demand for one site or multiple sites (Pokki, et al., 2018).

A single-site model is a demand model that estimates the number of trips achieved to a given recreation site over a defined period of time. In this demand model, quantity demand is the number of trips a person achieved to a recreation site for a given season; the price is the total actual cost of travel, cost of time and on-site expenses (Cameron, 1992; Bockstael, 1994). The general form of the model is

$$r \ = f(tc_r, y, z)$$

Where $tc_r$ is the cost of a trip to a recreation site, $r$ is the number of trips, $y$ is the income of the person, $z$ is a vector of socio-demographic characteristics. Economic theory postulates a negative relationship between the number of trips and the cost of the trip. Thus, those individuals living further from the site will report fewer trips than those within a close radius of the site (Bertram, et al., 2017). The data on trips costs and the number of trips can be used to plot a downward sloping demand curve. The area above the actual cost and the choke price will be the consumer surplus or the benefit to the individual. Mathematically this is represented as:

$$\Delta w = \int_0^{choke} f(tc_r, y, z) dtc_r$$

Thus, if the recreation site is closed for a given period, the welfare loss to the individual would be equivalent to the consumer surplus.

For the multiple-site scenario, the Random Utility Maximization model is the most commonly used model (Bockstael, et al., 1989). This model considers a discrete choice of a recreation site from an array of different competing sites (Hanemann, 1999). The driving factor for the choice of a given site is a set of attributes embodied by the site. A revealing choice for a site says much about the trade-off that an individual makes for one site against the other, given varying characteristics of the sites. At times the, Random Utility Model is used to model several sites simultaneously.

Given so many sites that a person is faced with to make a decision on which one to go to, the choice is moderated by the level utility that can be realized by visiting a site (McConnell, 1995). Each site will have its own level of utility, and as a rational economic agent, a person will choose to visit a site that will maximize the utility, *v*i. Utility level for each site is a function of the trip cost and the site-specific characteristics (Parsons, et al., 2003):

$$v_i = \beta_{tc} tc_i + \beta_q q_i + e_i$$

Where *tc* is the cost of visiting site *i*, $q$ is a vector of characteristics for site *i*, $e$ is the stochastic error component of the model to account for unobserved factors. Trip cost is inversely related to the utility of the site. An individual, therefore, seeks to maximize given several sites:

$$U = max(v_1, v_2, \ldots v_i)$$

When one of the sites is closed, the loss in welfare to the individual with be the difference in utility maximization for before and after closure (McConnell, et al., 1995).

4.2.2.1.2 Hedonic Pricing Method

Products that are similar in type offered in one market would still face different prices because of the level of product differentiation that each one of them has. The hedonic pricing method relies on the difference in prices for the differentiated products to derive value for a particular attribute of a product (Veronika, et al., 2018). For instance, if two products only vary in terms of one aspect, the price differential will reflect the sacrifice consumers are willing to make for the additional characteristic that one of the goods has. In this case, the researcher does not directly observe the value the consumer presses on the given characteristic, but rather through observing market transactions, and it is possible to decipher the value the consumers peg on a characteristic.

Hedonic pricing has been applied in research since Waugh's (1928) analysis of the determinants of asparagus pricing. The application has covered a broad spectrum ranging from automobile, health sector, housing and agriculture (Beach, et al., 1993; Nimon, et al., 1999; Danzon, et al., 2000). However, the method has gained strong roots in the housing industry.

Elicitation with hedonic pricing follows two steps. In the first stage, a hedonic price function is estimated. This is estimated as price as a function of product characteristics. The coefficient on each characteristic depicts the marginal value or implicit price of that characteristic. The first stage is more direct to implement, while the second stage is more data demanding and complex. Rosen's (1974) novel work was very vital in laying the utility theory so as to bridge the link between consumer preference for differentiated products and the equilibrium price function in the hedonic model.

Although the revealed preference approach mirrors the actual observed behaviour of the implied consumers, it has registered its own shortcomings. First is that the economic values are derived from observing consumers behaviour only record use-value. Non-use values cannot be implied by observing the consumer's market transactions. Larson (1992) tried to challenge this shortfall, but his claims have not received credence in the literature on non-market valuation. Second, the revealed preference approach is not able to capture the value of environmental change that has not yet been experienced by consumers. This is kind of problematic for policy makers to shape future interventions condition on what the quality of the environment will be then. Third, travel cost methods are limited to estimated values for a single-day trip, whereas in practice, consumers may have several destinations or sites on a single day.

#### 4.2.2.2 Stated Preference

Stated preference methods fall within a class of surveys that seek to quantify the people's value judgements for products that are difficult to value, using a hypothetical market scenario (Grip, et al., 2019). There are two variant methods under stated preference that are commonly used: contingent valuation and choice experiment. For a while, these methods have been applied to measure preference for products and services that cannot be measured directly using revealed preference as observed through market transactions. The linking thread in all these methods is that they require setting up a hypothetical market through which preference behaviour is analyzed (Boudon, 1996).

##### 4.2.2.2.1 Contingent valuation method

World Bank (2002) has defined contingent valuation as a method of tagging values on goods that are not sold in the market, usually environmental goods and health. This valuation method offers individuals questions to make economic decisions of choice for a product that the market is not currently offering. The valuation outcome is based on a simulated market scenario with which the individual is presented. The advantage of this method is that it is able to capture non-use values, unlike other methods. Depending on the aspect being studied, contingent valuation elicits an individual's willingness to pay to prevent loss of a certain welfare level or willingness-to-accept to compensation for a given level of welfare loss (Abdul-Rahim, 2005).

In theory, the method of contingent valuation methods was first pioneered by Wantrup (1947) with the aim of modelling non-market good. However, practically the method was first applied by Davis (1963), who commissioned a study to estimate the value that tourists placed on wilderness zones. The method was not popular until it was applied to quantify the effects of Exxon Valdez oil spillage USA in 1989 (Piatt, et al., 1990). Although the method began to get popular at that time, it met resistance from other researchers, especially when it came to using its findings to shape the policy landscape. In 1993, the debate was heated, the National Oceanic and Atmospheric Administration commissioned a panel of discussions by renowned economists of the time to establish whether the results of the methods could be trusted upon for decision making (Arrow, et al., 1993). The key conclusion from the panel of discussion was that the method was robust in yielding economic estimates of value that can be trusted, provided that the survey is carefully designed and the experimental setting is controlled for (Arrow, et al., 1993).

The contingent Valuation technique requires the use of a structured questionnaire as the main tool for data collection. The questionnaire is administered to a representative random sample from a given population (Geleto, 2011). Three key systematic steps are followed:

First, the hypothetical scenario is explained to the respondents to enhance their thorough understanding of the product at hand. The interviewer explains to the respondent what the product is, its attributes, who is going to pay for it, and by what mode of payment. Second, the respondents are given the opportunity to consider the market context of the hypothetical good. In the third step, the respondents critically analyse the market scenario and make a statement about their preference for the product by indicating their willingness to pay or willingness to accept depending on the good in question (Geleto, 2011). There are various elicitation methods to arrive at the respondents' willingness to pay or to accept.

Open-ended: In this approach, respondents are asked an open-ended question to state their willingness to pay for a product (Finco, et al., 2010). This produces a continuous variable of willingness to pay on which various statistical methods can be applied. It has several advantages over other elicitation techniques. The method is easy to explain and get understood by respondents; the continuous bid provides for easy computation of the mean willingness to pay. Finally, the method is efficient in terms of the time taken to administer the questionnaire to the respondents (Venkatachalam, 2004). However, this method is criticized for being prone to respondent systematic biases (Mitchell, et al., 1989).

Single bounded Dichotomous choice: In this method, the respondent is asked to confirm if they are willing to pay a predetermined amount of money in a close-ended format. This produces a discrete variable with yes or no responses. This requires sophisticated statistical computation methods (Bishop, et al., 1980). Although this approach is simple to implement, its major short-coming is that it is less efficient and requires a very large sample to achieve a given level of precision (Hanemann, 1991).

Double bounded dichotomous choice: This technique was developed by Carson et al. (1986) and Hanemann (1984). It results in a dichotomous outcome in a multi-stage format. This is an improvement of the single choice dichotomous choice earlier looked at. In the second state, another yes-no question is asked with a higher or a lower bid depending on the response to the first bid. The initial bid is iterated among the respondents in order to establish the true willingness to pay by respondents. Due to the reported statistical efficiency of this method, it has gained more superiority over the single dichotomous choice experiment (Cooper, et al., 2002). However, literature has shown that there is usually inconsistency between the first response and the follow-up response. The follow-up question usually is not known to the respondent in advance and comes as a surprise. Others have argued that it is this surprise that is responsible for inconsistent responses (Cooper, et al., 2002). Hanemann et al. (1991) are able to show that the method is asymptotically efficient than its counterpart single bounded dichotomous choice experiment.

In order to remedy the potential bias associated with the double bounded dichotomous technique, (Cooper, et al., 2002), formulated the one- and one-half dichotomous choice technique while maintaining the efficiency gains that come with multiple dichotomous choice techniques. In the technique, two prices are presented upfront. The exact willingness to pay is not known, but it’s believed to lie between the bounds of the two prices. One of the two prices is selected at random and presented to the respondent. The follow-up question and the second price are only applicable if doing so would be consistent with the response of the first question. Through this, it is believed that the method eliminates the bias that might emanate from the surprise of a follow-up question. However, the methods result in loss of information from the second question that is often not asked conditional on the outcome of the first question. For this reason, this study adopted the double bounded dichotomous choice experiment.

#### 4.2.2.2.2 Choice Experiment

The discrete choice experiment has become one of the widely used research tools across different disciplines of social sciences. It is used in studies that involve studying consumer choices of goods that have different sets of attributes (Hanley, et al., 2002). The choices consumers make reveal their values that they peg on the attribute differential across the goods in question. As these kinds of situations often arise times in our lives, many disciplines have adopted these methods of Discrete Choice Experiment (DCE).

In DCE, individuals are presented with two or more hypothetical goods, each one of which is defined with a different set of attributes. The value which the individual places on each set of attributes moderates their choice of one good over the other. Cost attribute is usually included in the attribute set, and this allows to elicit the individual willingness to pay depending on which attribute set the individual has chosen (Hanley, et al., 1998; Louviere, et al., 2000; Bennett, et al., 2001).

In Environmental Economics, DCE has been used to elicit values of resources or resource-related products and services by studying individuals' choices given the trade-off between costs and benefits they bear. For example, in natural resource management, Adamowicz et al. (1998) applied it to wildlife, Scarpa et al. (2007) used it to study water economics, and Johnston and Duke (2007) applied it to land markets. The method has also been widely used in recreation activities, including water-based activities, hunting and hiking (Adamowicz, et al., 1994; Hanley, et al., 2002; Boxall, et al., 1996). Others have also applied it to study product and services markets i.e. for the energy sector, fuels and product recycling (Roe, et al., 2001; Susaeta, et al., 2010; Karousakis, et al., 2008).

## 4.3 Methodology

### *4.3.1 Building Theoretical Framework of Economics of crop insurance*

4.3.1.1 Hypothetical weather index insurance design

Given the missing markets for index insurance for agriculture in Malawi, we designed a hypothetical version building on one that was previously piloted by World Bank in the same country in 2007. The weather index is constructed using rainfall data from all weather stations throughout the country. This index is based on the Malawi Meteorological Services Department's (MMSD) national maize yield assessment model, used by the Government since 1992 to produce national maize production forecasts each February. The MMSD (and weather index) model uses daily rainfall as the only varying input to predict maize yields and, therefore, production throughout the country. In this way, the model, and therefore the index, isolates the impact of only rainfall variability on maize production. Based on a water balance calculation, the model captures not only the total amount of rainfall received at each station but also its distribution during the agricultural season and how rainfall deficits impact maize yields. By using such a model, a contract can be structured to reflect conditions that would impact national maize production and, therefore, food security. The contract has a trigger level of 95 percent, i.e., a pay-out is only made if at the end of the agricultural season in April the index is calculated to be below the 95 percent trigger level (meaning that the season's index value is less than 95 percent of its long term average, implying the total national maize production is also down due to deficit rainfall-related losses). If the index is above 95 percent at the end of April, no payment is made.

#### 4.3.1.2 The basic Model

Micro-insurance markets for agriculture risk management are relatively new in Malawi. Efforts are at the tender stage to scale-out the adoption of micro-insurance. Given the missing agriculture insurance markets, it poses a normative economic challenge to estimate the demand for insurance among smallholder farmers. With the evolution of the environmental economics discipline, there are methods that have been developed to estimate demand for products whose markets have not yet formed (Fonta, et al., 2010).

In essence, the farmer faces two states of the world; with a spell or without a spell. The farmer has income endowment $m$, call it to the state of contingent wealth. If there is a climate shock, the associated economic loss is given by $L$. In the absence of an insurance market, the farmer will have income $m$ if there is no spell or alternatively $m - L$ if there is a spell. A farmer will purchase insurance to alter his income pattern over the varying states of nature. For a farmer who has purchased insurance, in the presence of a loss, he will receive a compensation equivalent to C, depending on the magnitude of $L$. This is after the farmer purchased insurance at a premium, $P$, at a rate of $\alpha$ of the total compensation C, such that $\alpha C = P$.

We consider the simplest version of a model where we have one production cycle ahead, with two possible states; having a loss or not having a loss. We denote the loss probability by $\pi$. The farmer's expected wealth without an insurance policy is given by:

$$\bar{m} = (1-\pi)m + \pi(m-L) = m - \pi L \tag{1}$$

Given this equation, the expected utility of farmer's income, in a case of no insurance policy, is given by:

$$\bar{\psi} = (1-\pi)\psi(m) + \pi\psi(m-L) = \psi(m-\pi L) \tag{2}$$

Where $\psi$ (.) is the indirect utility function, this equation defines farmers uncertainty in their income when there is no insurance cover. The insurance company will offer a cover equivalent to $C$ going at a premium rate of $\alpha[0,1]$, while the actual premium is $P = \alpha C$. An insurance contract will yield a value $E[\psi(\pi, P, C)] = (1-\pi)\psi(m) + \pi\psi(m - L - P + C)$. A farmer can iterate between purchasing insurance or not purchasing. However, the decision to purchase will only be rational if: $E[\psi(\pi, P, C)] \succcurlyeq E[\psi(\pi, 0)] = E[\psi(\pi, m, m - L)]$. We denote expected utility, $E[.]$ as $\bar{\psi}$ to economize on space. The farmer seeks to solve the following problem:

$$\max_{P\geq 0} \bar{\psi} = (1-\pi)\psi(m-P) + \pi\psi(m-L-P+C) \qquad (3)$$

Subject to: $P = \alpha C$

I first substitute the constraint into the farmer's objective function and take the first-order conditions using the Kuhn – Tucker process.

$$\bar{\psi}_P(P^*) = -(1-\pi)\psi'(m-P^*) + (\frac{1}{\alpha} - 1)\pi\psi'(m - L - P^* + \frac{P^*}{\alpha}) \leq 0 \qquad (4)$$

$$P^* \geq 0, \; \bar{\psi}_P(P^*) \otimes P^* = 0$$

The second-order maximization hypothesis will be;

$$\bar{\psi}_{PP}(P^*) = (1-\pi)\psi''(m-P^*) + \left(\frac{1}{\alpha} - 1\right)^2 \pi\psi''\left(m - L - P^* + \frac{P^*}{\alpha}\right) < 0 \qquad (5)$$

The utility function will be strictly concave in $P$ at $\forall\, C \in \mathbb{R}^{++}$. Thus, the first-order condition, $\bar{\psi}_P(P^*) \otimes P^*$Will be both necessary and sufficient condition for optimal premium, $P^* > 0$. If we take for the case of optimal premium (Willingness to Pay) being greater than 0, $P^* > 0$, which is the case when farmers are willing to pay for insurance:

$$P^* > 0 \Rightarrow \frac{\alpha(1-\pi)}{(1-\alpha)} = \pi \frac{\psi'(m-L-P^*+\frac{P^*}{\alpha})}{\psi'(m-P^*)}$$

$$\frac{\alpha}{(1-\alpha)} = \frac{\pi}{(1-\pi)} \frac{\psi'(m-L-P^*+\frac{P^*}{\alpha})}{\psi'(m-P^*)}$$

(6)

The case where $P^* = 0$, which is the case when farmers are not willing to pay for insurance:

$$P^* = 0 \Rightarrow \frac{\alpha(1-\pi)}{(1-\alpha)} > \pi \frac{\psi'(m-L)}{\psi'(m)}$$

$$\frac{\alpha}{(1-\alpha)} > \frac{\pi}{(1-\pi)} \frac{\psi'(m-L)}{\psi'(m)} \qquad (7)$$

In the above two cases, equation 6 implies that the farmer will be willing to pay for crop insurance if the ratio of premium rate to the rate of net compensation is equal to the ratio of the expected marginal utility of income after compensation to expected income from no compensation (no climate shock). In equation 7, the farmer will not be willing to pay for insurance if the ratio of the premium rate to rate of net compensation is greater than the ratio of expected marginal utility of his income after compensation to the expected marginal utility of his income under no compensation.

#### 4.3.1.3 An Extended Model

Considering the complexity of the weather index insurance, I extend the basic model to incorporate several scenarios. For the purpose of specificity, I use the Constant Absolute Risk Aversion (CARA)[3] utility function form. There are four scenarios that an insured farmer will face that will also be helpful in increasing the precision of the approximated expected utility of an individual under weather index insurance policy.  In the first case, the farmer will suffer a loss with a probability of $\pi_1$, and receive a payout for the loss, having a utility of $b - e^{-a(m-\pi_\theta C+C-L)}$. Where $\pi_\theta$ is the probability of reimbursement. In the second case, the farmer may not suffer a loss and never get any payout. The probability of jointly not suffering a loss and not receiving compensation is given by

[3] This is a utility function that is given by $U = b - e^{-ax}$, where u is parametric utility, $b$ >0 is a constant, $a$>0 define the risk aversion factor, $x$ ≥0 is the net wealth of an individual at a given state.

$\pi_2$. The associated utility is $b - e^{-a(m-\pi_\theta C)}$. There are two additional cases that might occur if the index is weakly correlated with the loss. First, a farmer suffers a loss, but the registered index does not meet the threshold such that there is no payout. I give this one a probability $\pi_3$, and hence utility of $b - e^{-a(m-\pi_\theta C-L)}$. The last state is when chance favours the farmer, in which case, he doesn't have a loss but the index points that there should be compensation. This has a probability of $\pi_4$ and a utility function $b - e^{-a(m-\pi_\theta C+C)}$. From these possible outcomes, the expected utility of the farmer is given by:

$$\bar{\psi} = \pi_1[b - e^{-a(m-\pi_\theta C+C-L)}] + \pi_2[b - e^{-a(m-\pi_\theta C)}] + \pi_3[b - e^{-a(m-\pi_\theta C-L)}] + \pi_4[b - e^{-a(m-\pi_\theta C+C)}] \tag{8}$$

The insurer will find the optimal level of production by choosing the optimal level of $C^*$ from:

$$\frac{\partial\bar{\psi}}{\partial C} = \pi_1\left[b - \frac{\partial}{\partial C}e^{-a(m-\pi_\theta C+C-L)}\right] + \pi_2\left[b - \frac{\partial}{\partial C}e^{-a(m-\pi_\theta C)}\right] + \pi_3\left[b - \frac{\partial}{\partial C}e^{-a(m-\pi_\theta C-L)}\right] + \pi_4\left[b - \frac{\partial}{\partial C}e^{-a(m-\pi_\theta C+C)}\right] = 0$$

#### 4.3.1.4 Supply side optimal Insurance Pricing

The demand for insurance facing each insurer will be a function of its own price and the price of other insurers. The assumption is the insurers set prices simultaneously while producing a homogenous product. In the case of Malawi, where insurance markets are not fully developed, and only a limited number of insurance companies operate, the market may mirror the oligopoly structure. That is, the demand for the product for each insurer will be a proportion of market demand defined by a share of farmers that may contract with a given insurer. The expected profit for the insurer will be given by:

$$\overline{\Pi} = D\otimes z(p_i, p_{\overline{m}})(p_i - vc - \pi C) - FC$$

Where, $p_{\overline{m}}$ is the aggregate premium for all other insurers except for insurer *i*, $p_i$ is the premium offered by *i*, *vc* is the variable cost, *C* is the compensation payout, $\pi$ is the probability of a weather index falling below a threshold and *FC* is the fixed cost, *D* is the market demand, and *z* is the market share for insurer *i*. The first-order condition to the insurer's profit maximization problem will be:

$$\frac{\partial\overline{\Pi}}{\partial p_i} = \frac{\partial z_i}{\partial p_i}(p_i, p_{\overline{m}})D(p_i - vc - \pi C) + Dz_i = 0$$

Remembering price elasticity of demand is given by $\epsilon = \frac{\partial Qz(p_i,p_{\overline{m}})}{\partial p_i} . \frac{p_i}{Qz(p_i,p_{\overline{m}})} \Longrightarrow \frac{\partial Qz(p_i,p_{\overline{m}})}{\partial p_i} = \epsilon \frac{Qz(p_i,p_{\overline{m}})}{p_i}$. Using this concept in the first-order condition, we get:

$$\frac{z_i}{p_i}\epsilon D(p_i - c - \pi C) + Dz_i = 0$$

Thus,

$$-\epsilon(p_i, p_{\overline{m}}) = \frac{p_i}{p_i - c - \pi C}$$

The right side shows that it depends on $p_i$ only while the left-hand side depends on both $p_i$ and $p_{\overline{m}}$. Representing these two in a two-dimension space will show where they intersect. The intersection point is the premium price that is the best response for insurers *i*. Each insurer will continue to alter their reaction function based on other insurers prices until there is no more incentive for profit from changing the premium. The best reaction function will yield an equilibrium price, *p**, for which case, $p_i = p_{\overline{m}} = p^*$. Therefore, from the above equation, the equilibrium premium price will be given by:

$$-\epsilon(p^*, p^*) = \frac{p^*}{p^* - c - \pi C} \Rightarrow p^* = \frac{(c + \pi C)\epsilon(p^*, p^*)}{\epsilon(p^*, p^*) + 1}$$

### *4.3.2 Econometric Model Construction*

4.3.2.1 Estimating the determinants of Willingness to Pay Model

The objective here is to estimate the relationship between predetermined farmer specific characteristics and the Willingness to Pay for Weather Index Insurance. For a given amount of willingness to pay in money metric subtracted from the farmer's income, the farmer will either be in apposition to say no to a dichotomous choice question of Contingent Valuation Method or accept a specified bid for a willingness to pay value. This choice problem can be modelled by extending what was proposed by Hanemann (1984). The farmer's expected utility function is given by:

$$\bar{\psi} = \pi_1[b - e^{-a(m-\pi_\theta C+C-L)}] + \pi_2[b - e^{-a(m-\pi_\theta C)}] + \pi_3[b - e^{-a(m-\pi_\theta C-L)}] + \pi_4[b - e^{-a(m-\pi_\theta C+C)}] \quad (9)$$

Where the arguments are as earlier defined, a farmer is faced with two parallel worlds, first, the expected profitability of the agriculture venture without an insurance policy, and second, the expected profitability of an agriculture venture with a subscription to an insurance policy.

We notice that farmer's income is the most limiting asset at the farmer's disposal. The farmer, therefore, will be willing to pay an insurance premium in such a way as to maximize utility under certain conditions otherwise reject:

$$\bar{\psi}_1 = \left[\pi_1\left[b - e^{-a(m-\pi_\theta C+C-L)}\right] + \pi_2\left[b - e^{-a(m-\pi_\theta C)}\right] + \pi_3\left[b - e^{-a(m-\pi_\theta C-L)}\right] + \pi_4\left[b - e^{-a(m-\pi_\theta C+C)}\right]\right] \gtrsim \left[\pi_1\left[b - e^{-a(m-L)}\right] + \pi_2\left[b - e^{-a(m)}\right]\right] = \bar{\psi}_0 \quad (10)$$

Where, $\pi_\theta C$, is the BID, or the insurance premium per hectare for the climate risk management, $e_1$ and $e_0$ are the random error components with an expectation of zero, and they are independently distributed. Therefore, the probability that a farmer will decide to pay for the crop insurance is the probability of observing a conditional expected indirect utility function for the proposed policy change (with insurance) being greater than the expected indirect utility function for the status quo (without insurance).

In practice, we do not observe utility. The utility is a latent variable and can be studied by observing farmers' choices for or against insurance, and the associated choice reflects the rational choice given the unobservable utility levels. The utility of the farmer is a function of the observable characteristics, including household characteristics, institutional, socio-demographic and the stochastic component, *e*.

$$\bar{\psi} = f(x) + e \qquad (11)$$

Where f(.) is a function of factors that are hypothesized to affect choices around insurance, from the literature survey, these factors include the age of the farmer, gender, education, income, household size, land size, farming experience, livestock ownership, access to credit, extension contact. Other specific variables that will also be tested include previous experience of shocks, remittances, the recent history of food security, and the use of drought-tolerant seed varieties.

Equation (11) is a choice modelling problem that seeks to establish the probability of accepting an initial bid. A rational farmer is constrained to accept an initial bid if $\bar{\psi}_1(.) \gtrsim \bar{\psi}_0(.)$. This narrows down from latent to an observable dichotomous choice modelling problem of outcome *y*, where:

$$Y = \begin{Bmatrix} 1 \; if \; \bar{\psi}_1(.) + e_1 \geq \bar{\psi}_0(.) + e_1 \\ 0 \; if \; otherwise \end{Bmatrix} \qquad (12)$$

From this, the probability that a given farmer is willing to pay for crop insurance is given by

$$Prob(Y = 1) = Prob(\bar{\psi}_1(.) \geq \bar{\psi}_0(.)) \tag{13}$$

If we substitute equation (13) into equation (11) we get:

$$Prob(Y = 1) = Prob(\alpha_1 X + e_1 \geq \alpha_0 X + e_0) \tag{14}$$

By rearranging equation 14 we get:

$$Prob(Y = 1) = Prob((e_1 - e_0) \geq X(\alpha_0 - \alpha_1)) \tag{15}$$

We can constrain the stochastic component and the parameters according to $\varepsilon = e_1 - e_0$, and $\beta = \alpha_0 - \alpha_1$, the equation that is estimable becomes;

$$Prob(Y = 1) = Prob(\varepsilon \geq X\beta) = G(X; \beta) \tag{16}$$

This is a cumulative probability distribution function. It provides a structural model for the estimation of the probability of subscribing to a crop insurance policy. The model can either be estimated using logit or probit formulation depending on the assumptions made about the stochastic component (Greene, 2002). It is assumed that the stochastic component is normally distributed with a zero mean. In such a case, the logit model could best explain the data generation process. The logit model for willingness to pay for an insurance policy is specified following Hanemann et al. (1991) as:

$$Y *= X\beta + \varepsilon \tag{17}$$

Where $Y = 1 \; if \; Y * \in \mathbb{R}^{++}$and $Y = 0 \; if \; Y * \in \mathbb{R}^{-}$. Where coefficient vector to be estimated is given by $\beta$, $X$ is a vector of determinants of willingness to pay, Y* is farmer's unobservable (latent) willingness to pay for crop insurance, Y is a Bernoulli response of willingness to pay by farmers, $\varepsilon$ is a normally distributed random error term with constant variance.

#### 4.3.2.2 Parametric Estimation of Willingness to Pay for Weather Index Insurance

The study designed a hypothetical insurance market that was presented to a farmer as is the case with contingent valuation methods. The following statement was read to the farmer before presenting bids for willingness to pay:

> "I would like to ask you a number of questions related to the potential of introducing a new index-based maize crop insurance scheme in your area. The nature of the proposed scheme is as follows: you pay a fixed amount of money for the next one year (an insurance premium) to a designated insurance company to cover your maize crop against droughts in the production season. This amount is supposed to be paid at the beginning of the rain season to cover rain season agriculture production, only in the case of an officially acknowledged drought (Rainfall below what maize crop requires for optimum yield) occurrence that you will get compensated for any losses incurred on your farms. In case the disaster is not officially recognized, you will not be compensated. However, if there is a registered drought disaster and you did not experience losses, you will get the compensation still. Similarly, you will not get compensation if you experience losses, but there is no registered drought. The meteorological experts will determine rainfall amount".

From equation 9, the farmers' expected utility from index insurance will either be 0 or positive and this moderates farmers' willingness to pay for index insurance. Those with positive expected indirect utility will indicate a positive willingness to pay, while those with a non-positive expected utility will not be willing to pay for the index insurance. We let the $w^0$ be the first bid premium, and $w^+$ is the follow-up higher bid premium conditional on acceptance of the first bid and $w^-$ is the follow-up lower bid premium conditional on the rejection of the first bid. Thus, if a farmer is affirmative to the first bid, the second bid $w^+$ is formulated to be higher than $w^0$; otherwise, if the farmer says no to the first bid, then $w^-$ is formulated to be lower than the $w^0$. This multi-stage bidding game will have the four outcomes; $\pi^{yy}, \pi^{nn},\ \pi^{yn}, \pi^{ny}$. The probability that a farmer answers yes to both the first and the second bid is given by:

$$\pi^{yy}(w^0, w^+) = Pr(w^0\ \leq max\ WTP \wedge w^+ \leq max\ WTP) \quad (18)$$

$$= Pr\{w^0\ \leq max\ WTP |\ w^+ \leq max\ WTP\} Pr\{\ w^+ \leq max\ WTP\}$$

$$= Pr\{w^+\ \leq max\ WTP\} = 1 - G(w^+; \beta)$$

It follows from the above that with $w^0 < w^+$, $Pr\{w^0\ \leq max\ WTP |\ w^+ \leq max\ WTP\} \equiv 1$. Similarly, with $w^- < w^0$, $Pr\{w^-\ \leq max\ WTP |\ w^+ \leq max\ WTP\} \equiv 1$, Therefore;

$$\pi^{nn}(w^0, w^-) = Pr(w^0\ > max\ WTP \wedge w^- > max\ WTP\}\ = G(w^-; \beta) \quad (19)$$

When a farmer accepts the first bid and rejects the second higher bid, we will have $w^+ > w^0$, and:

$$\pi^{yn}(w^0, w^+) = Pr(w^0\ \leq max\ WTP\ \ \leq w^+\}\ = G(w^+; \beta)\ - G(w^0; \beta) \quad (20)$$

When a farmer rejects the first bid and accepts the second lower bid, we will have $w^- < w^0$, and:

$$\pi^{ny}(w^0, w^-) = Pr(w^0\ \geq max\ WTP\ \ \geq w^-\}\ = G(w^0; \beta)\ - G(w^-; \beta) \quad (21)$$

In the above derivations, there are two sets of equations; Equations 18 and 19 are single bounded and allow the research to lower the bound for upper bound and to raise the bound for the lower bound. Whereas equation set 20 and 21 are double bounded and allow the researcher to fix an upper and lower bound on the true *WTP*, which is unobservable. With bids, $w^0$, $w^+$, and $w^-$, the log-likelihood function for estimation is:

$$lnL^D(\beta) = \sum_{i=1}^{n}\{d_{\mathrm{i}}^{yy} ln\pi^{yy}(w^0, w^+) + \mathrm{d}_i^{nn}(w^0, w^-) ln\pi^{nn}(w^0, w^-)$$

$$+ d_{\mathrm{i}}^{yn} ln\pi^{yn}(w^0, w^+) + \ d_{\mathrm{i}}^{ny} ln\pi^{ny}(w^0, w^-)\} \qquad (22)$$

Where d* are the dichotomous valued indicator variables. For example, $d_{\mathrm{i}}^{yy}$ Is equal to one if the respondent answered yes to both the first and the second bid, and it's zero if otherwise. Their corresponding probabilities are as earlier presented in Equations 18 to 19. With some assumptions of the G(.), the model can be parametrized using the maximum likelihood technique. The maximum likelihood estimator is the solution to the first-order differentiation; $\partial lnL^D(\beta)/\partial\beta = 0$. If G(.) is the standard logistic CDF, equations 18 to 21 becomes:

$$\pi^{yy}(w^0, w^+) = 1 - G(w^+;\beta)$$

$$= \frac{1}{exp(-\alpha + \beta w^+)}$$

$$= exp(\alpha \ - \ \beta w^+) \qquad (23)$$

$$\pi^{nn}(w^0, w^-) = G(w^-;\beta)$$

$$= 1 - \frac{1}{exp(-\alpha + \beta w^-)}$$

$$= 1 - exp(\alpha \ - \ \beta w^-) \qquad (24)$$

$$\pi^{yn}(w^0, w^+) = G(w^+;\beta) \ - \ G(w^0;\beta)$$

$$= \left\{1 - \frac{1}{exp(-\alpha + \beta w^+)}\right\} - \left\{1 - \frac{1}{exp(-\alpha + \beta w^0)}\right\}$$

$$= exp(\alpha \ - \ \beta w^0) - exp(\alpha \ - \ \beta w^+) \qquad (25)$$

$$\pi^{yn}(w^0, w^-) = G(w^0;\beta) \ - \ G(w^-;\beta)$$

$$= \left\{1 - \frac{1}{exp(-\alpha + \beta w^0)}\right\} - \left\{1 - \frac{1}{exp(-\alpha + \beta w^-)}\right\}$$

$$= exp(\alpha - \beta w^-) - exp(\alpha - \beta w^0) \quad (26)$$

The corresponding log-likelihood function is given by:

$$ln\, L = \sum_{n=1}^{N}\left[d_i^{yy}\, ln\{\exp(\alpha - \beta w^-)\} + d_i^{nn} ln\{1 - exp(\alpha - \beta w^-\} + d_i^{yn} ln\{\exp(\alpha - \beta w^0) - \exp(\alpha - \beta w^+)\} + d_i^{ny} ln\{\exp(\alpha - \beta w^-) - \exp(\alpha - \beta w^0)\}\right] \quad (27)$$

The asymptotic variance-covariance for the estimator is given by;

$$V^D(\hat{\beta}^D) = \left[-E\,\frac{\partial^2 lnL^D\left(\hat{\beta}^D\right)}{\partial\beta\,\partial\beta'}\right]^{-1} \equiv I^D(\hat{\beta}^D)^{-1} \quad (28)$$

The model was estimated using the DCchoice R packages in the R environment. This package provides functions for analyzing single-, one-and-one-half-, and double-bounded dichotomous choice contingent valuation (CV) data. (Aizaki et al., 2014). The Likelihood Ratio Chi-square statistic, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to test the goodness of fit of the model. Table 4.1 lists all the variables that were included in the estimation of the willingness to pay along with their prior expected signs.

Several measures of Willingness to Pay estimates can be derived in the course of the model estimation procedure. First, the mean willingness to pay (MWTP) was derived as:

$$mean\, WTP = \int_0^\infty [1 - G(w)]dw \quad (29)$$

In equation 29, the integration runs to infinity, meaning that there are some individual respondents whose willingness to pay is greater than their income. This goes against the

**Table 4.1: Description of the variables included in the parametric estimation of WTP**

| Variable | Description | Expected sign |
|---|---|---|
| Age | Age of a farmer in years | + |
| Age squared | Squared Age of a farmer in years | - |
| Gender | 1= farmer is male<br>0= farmer is female | + |
| Education | Number of completed years in school | + |
| Experience of climate shocks | 1= Experience a climate shock last 12 moths<br>0= Otherwise | + |
| Access to extension service | 1= Received advice on weather<br>0= Otherwise | + |
| Household income | Average monthly income (MK) | + |
| Family size | Number of household members | - |
| Maize Farm size (Ha) | Size of maize field (Ha) | +/- |
| Farming experience | Number of years in farming | +/- |
| Remittances received | 1= Receive remittances<br>0= Otherwise | +/- |
| Use of DT Variety | 1= Used DT maize variety<br>0= Otherwise | +/- |
| Livestock ownership (poultry) | 1= Household has small livestock<br>0= Otherwise | + |
| Livestock ownership (Large) | 1= Household has lager livestock<br>0= Otherwise | + |
| Previous Food Security Status | 1= Experience food shortage in past year<br>0= Otherwise | + |
| Bid price | Bid in amount (MK) of willingness to pay | - |

standard economic theory, as no one would pay for something that costs more than their income. To overcome this problem, a truncated mean at the maximum bid in the survey is used. Boyle et al. (1988) proposed a normalization routine of the probability density function (PDF) with the assumption that $F(w) = 0,\ if\ \ w\ > w_{max}$. It is necessary to normalize so that the statistical properties are preserved even after truncation. Thus, the truncated mean WTP was calculated as:

$$\int_0^{t_{max}} \frac{[1-G(w)]}{F(w_{max})} dw \tag{30}$$

The last measure is the median WTP which is more robust to the influence of outliers (Hahnemann, 1984). This estimate is given by:

$$median\, WTP \; = \; F^{-1}(0.5) \tag{31}$$

4.3.2.3 Non-Parametric Estimation of the Willingness to Pay

As has been noticed in the previous sections, parametric estimations require a priori specification of the distribution of WTP. The parametric approach uses the maximum-likelihood method, which will yield consistent estimates of WTP only when the specified probability distribution is correct. However, in practice, it is difficult to correctly specify the probability distribution. This requires checking the robustness of the estimates using a non-parametric approach that does not impose any prior distribution. The only restriction that is imposed on non-parametric is the weak monotonicity.

This study applied the Kaplan–Meier–Turnbull estimator (Carson, et al., 2005) to estimate the non-parametric mean of WTP for the farmers. Given that farmers were issued bids $C_{j,}$ such that j=1,2,…M denotes the index for the order of the bids. In addition, $C_j > C_k$ for any j >K and $C_0 = 0$. The probability that the farmer's willingness to pay is in the interval $C_{j-1}$ and $C_j$ is $P_j$. Thus,

$$P_j = \Pr(C_{j-1} < WTP < C_j\,) \forall\, j = 1{,}2, .. M + 1$$

The cumulative distribution is given by:

$F_j = \Pr(WTP > C_j)$ for $j$ = 1, …, M+1

Where $F_{M+1} = 1$ and $F_0 = 0$.

And $Pr_j = F_j - F_{j-1}$

The Turnbull likelihood is expressed as probability and the cumulative distribution function:

$$L(F;N,Y) = \sum_{j}^{M}\left[N_j \ln(F_j) + Y_j \ln(1 - F_j)\right]$$

$$L(P;N,Y) = \sum_{j}^{M}\left[N_j \ln\left(\sum_{i=1}^{j} P_J\right) + Y_j \ln\left(1 - \sum_{i=1}^{j} P_j\right)\right]$$

Where $N_j$ is the number of people who respond No to $C_j$ and $Y_j$ is the number of people who respond yes to $C_j$.. Considering first and second bids: $\mathrm{Pr}_1 = \frac{N_1}{N_1+Y_1}$ and $\mathrm{Pr}_2 = \frac{N_2}{N_2+Y_2} - \mathrm{Pr}_1$. Thus, $\mathrm{Pr}_2$ will only be positive if $\frac{N_1}{N_1+Y_1} < \frac{N_2}{N_2+Y_2}$. However, if the opposite is true, then the unconstrained estimate of $\mathrm{Pr}_2$ will tend to be negative. The Kuhn-Turker outcome of binding non-negativity constraint for $P_j$ is summing jth and (j – 1)th cells. This is defined as $N_j^* = N_j + N_{j-1}$, similarly, $Y_j^* = Y_j + Y_{j-1}$ and then Pr is re-estimated as:

$$\mathrm{Pr}_j = \frac{N_j^*}{N_j^* + Y_j^*} - \sum_{k=1}^{j} P_k$$

This algorithm yields the constrained maximum of the likelihood function using the Kuhn-Tucker conditions. It searches for the largest number of cells within a monotonic increasing CDF. An and Ayala (1996) uses the iterative technique. The above procedure is used to derive survival curves. But, then the probability mass is derived for each bid, inter bid curve can be realized by interpolation. Various interpolation procedures have been used previously. Scarpal et al. (1998) use a kernel estimation to connect points by the weak concept of continuity. Kristom (1990) uses linear interpolation and solves the mean willingness to pay by finding the area and the interpolated line. This study uses a more conservative approach to interpolating between successive bids. In this approach, the survival curve between two adjacent bids, $C_{j+1}$ and $C_j$ is interpolated with $\hat{S}(C_j)$, which is the lower of the two probabilities. The mean willingness to pay corresponds to the area under the step function:

$$meanWTP_{KMT} = \sum_{j=1}^{J} \hat{S}(C_j)(\, C_{j+1} - C_j)$$

This estimate is called Kaplan–Meier–Turnbull (Carson, et al., 2005). The Kaplan–Meier–Turnbull is a step function making it impossible to have a point estimate of the median WTP, but rather an interval estimate in which the point estimate is likely to be (Carson, et al., 1990).

### *4.3.3 Data and sampling strategy*

#### 4.3.3.1 Study area

The study was conducted in five districts of Mzimba, Nkhata-Bay (both from the Northern Region), Nkhotakota, Ntchisi, Kasungu, Lilongwe, Dowa, Mchinji (all from Central Region) and Zomba, Machinga (Southern Region). The choice of the district is based on the NASFAM district, where a project on weather index insurance was to be implemented. The map below (Figure 4.2) shows the spatial distribution of the study districts. To the right, it shows where the specific sites are geo-referenced on the map of Malawi.

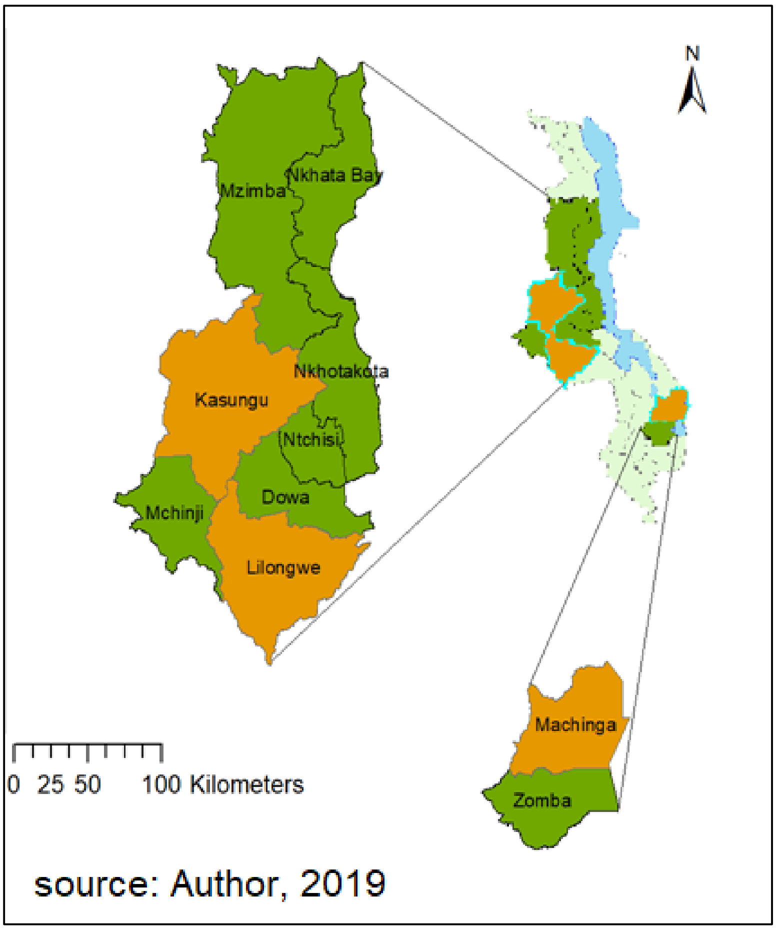



***Figure 4. 2: Map of the study districts***

4.3.3.2 Sample size

Computation of the optimal sample size requires an initial specification of assumptions on parameters of the sample size formula. The first parameter is the confidence interval of 95%. As the study was a clustered face-to-face survey, it was expected that there would be an intra-cluster (farmer club) correlation for the key variables. This is because farmers within the same cluster were sharing the same soils, pests, market access, indigenous knowledge etc., which results in these farmers achieving similar results to farmers in clusters that are far apart where conditions between them are very different. The amount of new information that each new survey farmer provides from within the same sampled cluster would be less than that of a new farmer. This loss of independence between multiple observations within the cluster was taken into account by multiplying the base sample size by a design effect of 2 (Edriss, 2012). Using the following sampling parameters: Minimum statistically significant difference in maize yield of 25%; 95% level of significance; population size of 100,000; Design Effect of 2 for correction of clustering effect; resulted in a sample size of 1170.

The sampling frame for the farmer's universe included all farmers in the five districts who belonged to farmer clubs which was obtained from the National Association of Farmers in Malawi. Farmers were organised in clubs of 10 farmers. Therefore, the procedure used was to proportionately allocate the sample clubs according to the population of farmers in the study district, as shown in Table 2. In total, 117 clubs were sampled. Within each club sampled, members were randomly divided into primary and secondary (replacement) farmers. Primary farmers were the ones that were targeted to

**Table 4.2: Sample distribution across zones**

| District | Sample size | Clusters |
|---|---|---|
| Dowa | 47 | 6 |
| Kasungu | 217 | 27 |
| Lilongwe | 318 | 40 |
| Machinga | 50 | 6 |
| Mchinji | 289 | 36 |
| Mzimba | 55 | 7 |
| Nkhatabay | 16 | 2 |
| Nkhotakota | 71 | 9 |
| Ntchisi | 53 | 7 |
| Zomba | 54 | 7 |
| Total | 1170 | 146 |

be interviewed from the sampled club, while secondary ones were those that served as replacements where the target for the primary was not met for a club due to member absence or other reasons. The number of sampled farmers from each cluster was 8, and this left two other farmers within the cluster to act as replacements when any of the primary sample farmers were not available. The achievement was possible because of the replacement farmers that were put in place during the design of the data collection. One of the reasons to replace sample farmers included attrition of club members. Overall, the interviews comprised of 89% primary respondents and 11% replacement. Fortunately, all respondents that were available for the interview consented to participate in the study.

A number of data quality procedures were put in place to ensure minimal errors as much as possible. Highlighting some of these; First, the questionnaire was programmed on tablets with necessary skip patterns and consistency checks. Where inconsistent entries were done, the tablet could flag an error message so as to alert the interviewer before proceeding with the interview. Before deploying the teams into the field, they were thoroughly trained in the tool coupled with preliminary piloting to get them to familiarize with it and iron out some bottlenecks in the question wording, translations and pre-coded responses.

### 4.4. Results and Discussion

This section presents the key findings of the current study. It starts by presenting the background characteristics of the studied farmers. In turn, the parametric econometrics results of the model used are presented for the farmers' willingness to pay for weather index insurance. Lastly, the economic value of the weather index insurance is presented based on the willingness to pay.

### *4.4.1 Characteristics of the sampled farmers*

4.4.1.1 Socio-demographic characteristics

The sociodemographic characteristics of the surveyed farmers are presented in Table 4.3. The summary shows that the average age of the farmers was about 45 years. This age is within the economically active age group of 15 to 65 for Malawi as a country. The implication is that with the adoption of the weather index insurance, this economically active population could smoothen their agriculture enterprise performance in the face of shocks. Most of the households were headed by males. In total, the male-headed households comprised 78% of the total surveyed farmers. This is consistent with the national ratio of household headship to 75% male-headed households (NSO, 2017).

**Table 4.3: Sociodemographic characteristics of sampled farmers**

| **Characteristic** | **Statistics** | **Std Deviation** |
|---|---|---|
| Age of household head (years) | 44.5 | 14.3 |
| Gender of household head (1/0), Male=1 | 0.783 | 0.41 |
| Education level of household head (1/0) | | |
| None | 0.16 | 0.10 |
| Std 1 to 5 | 0.29 | 0.45 |
| std 6 to 8 | 0.36 | 0.48 |
| Form 1 to 2 | 0.10 | 0.30 |
| Form 3 to 4 | 0.08 | 0.28 |
| Adult literacy | 0.01 | 0.07 |
| Tertiary | 0.00 | 0.00 |
| Household size | 5.09 | 1.781 |
| Dependency ratio | 0.47 | 0.22 |

| **Characteristic** | **Statistics** | **Std Deviation** |
|---|---|---|
| Income level (MK/Month) | 28,317.51 | 20,066 |
| Food security (1/0) | 0. 32 | 0.12 |
| Marital status (1/0) | | |
| Married Monogamous | 0.79 | 0.41 |
| Married Polygamous | 0.06 | 0.24 |
| Divorced | 0.06 | 0.23 |
| Separated | 0.01 | 0.10 |
| Total farm area (Ha) | 1.376 | 0.68 |
| Maize Farm size (Ha) | 0.537 | 0.23 |
| Experience of climate shocks (1/0) | 0.51 | 0.21 |
| Access to extension service (1/0) | 0.28 | 0.10 |
| Farming experience (Years) | 16 | 7.20 |
| Remittances received (1/0) | 0.21 | 0.11 |
| Previous Food Security Status (1/0) | 0.35 | 0.19 |

The education level of farmers is very crucial in understanding new and emerging agriculture technologies and innovations. The study registered 16% of farmers who have not attended any formal education system. Most of the farmers have gone to a level of junior and senior primary school. Around 18% of the farmers went as far as to attend secondary education. None of the farmers attended professional post-secondary education training. Not surprising, as those who have the opportunity to attend tertiary education have expanded opportunities to grab off-farm jobs elsewhere in urban areas. On average, each household had five members. This translates into a dependence ratio of 0.47. Given their mean monthly income of MK28,317, it implied that per capita income was less than a dollar per day. This explains the levels of vulnerability the surveyed farmers are hooked in due to shocks that can have an impact on their consumption function. Although these households are farming families, only 32% reported having adequate food reserves to run them through the entire year before the next harvest. The average agriculture landholding size (natural capital) that was currently in agriculture use at the time of the survey was 0.7 hectares against the national average of 0.57 (NSO, 2017).

#### 4.4.1.2 Livestock endowment

Livestock can be a source of income, food and nutrition security to households. Livestock provides a safety net, helping keep poor households from falling into poverty. It can be traded off to meet emergency family and health needs. It can also provide the household's coping capacity to impending shocks.

The most common livestock type kept by farmers was indigenous chickens (Table 4.3). Some have nicknamed it "village land rover", alluding to its resilient characteristics. It was owned by 75% of farmers. The indigenous chicken breed is widely preferred to exotic because of its resilience to diseases and low management cost through a free-range system of production. The hybrid breed was by none of the farmers. Goats were owned by about 42% of farmers. It is becoming a common practice in most communities in Malawi that when community members share Villages Savings and Loans (VSL) proceeds, they purchase goats which they use to start livestock pass-on schemes. This has facilitated most of the farmers to have access to goats through the informal savings groups. Pigs were the third commonly owned livestock enterprise as 24% of farmers reported keeping pigs. Further analysis showed that any farmer who owned livestock had at least a local chicken. Cattle production was not common, and higher ownership was found in districts of Northern Malawi, where it is usually used to pay for bride price in their marriage system.

**Table 4.4: Percentage of farmers owning various livestock types**

| Livestock type | Female | Male | Total |
|---|---|---|---|
| Cattle | 3.9% | 6.9% | 6.4% |
| Goats | 45.5% | 41.7% | 42.3% |
| Sheep | 3.9% | .6% | 1.1% |
| Pigs | 18.2% | 25.3% | 24.0% |
| Local chickens | 81.8% | 73.6% | 75.1% |
| Hybrid chickens | 0.0% | 0.0% | 0.0% |
| Any livestock | 81.8% | 73.6% | 75.1% |

### 4.4.2 Existing climate risk management strategies

Even in the absence of weather index insurance, farmers do invest in other pre-and post-disaster management strategies. A number of these strategies and their statistics are presented in Table 4.5. The statistics show that farmers are working their best to employ various technologies to reduce the effects of climate risks on their capital. The percentage of farmers who adopted more than three Climate Smart Agriculture (CSA) technologies was 64%. Those who adopted conservation agriculture, defined as those who adopted minimum tillage, mulching and crop mixes (either intercropping or agroforestry) was reported to be 9%. The percentage of farmers who practised irrigation farming was 13%. Most of the farmers (45%) are switching to Drought Tolerant (DT) Maize varieties to withstand harsh weather conditions.

**Table 4. 5: Percentage of farmers who adopted climate smart agriculture (CSA) technologies**

| CSA Technologies | Female | Male | Total |
|---|---|---|---|
| Minimum tillage | 15.7% | 9.9% | 11.0% |
| Crop residues | 81.1% | 77.4% | 78.1% |
| Intercropping | 7.1% | 12.6% | 11.7% |
| Manure | 44.9% | 34.6% | 36.5% |
| Agroforestry | 59.8% | 63.6% | 63.0% |

| CSA Technologies | Female | Male | Total |
|---|---|---|---|
| Irrigation | 4.7% | 7.9% | 7.3% |
| DT Maize variety | 37.0% | 47.0% | 45.0% |
| Diversified crop/livestock farming | 62.2% | 64.6% | 64.2% |
| Conservation agriculture package[4] | 14.2% | 7.7% | 8.8% |
| At least one CSA Technology of the above | 100.0% | 100.0% | 100.0% |
| At least three CSA technologies | 62.2% | 64.6% | 64.2% |

### 4.4.3 Estimation of Willingness to pay for Weather Index Insurance

#### *4.4.3.1 Description of the Willingness to pay*

The key thrust of this study was to estimate the willingness to pay for weather index insurance by smallholder farmers using a dichotomous choice technique with a follow-up. Farmers were assigned random bids, which were programmed to be randomly assigned within the data collection tablet gadgets. A collection of these random bids was drawn from a pilot study of 60 farmers. These farmers were served with an open-ended question on what maximum amount they would be willing to pay for weather index insurance for a hectare of maize farmland after thoroughly explaining to them about the hypothetical market. Table 4.6 gives a summary of the random assigned initial bids and their follow-up bids.

Given the first question of the bidding game, the first row for each bid summarizes the responses that were affirmative, and the second row summarizes those who rejected the

[4] Conservation agriculture consists of minimum tillage, mulching (soil cover) and crop rotation or crop mixes

first bid. Thus, each outcome for the randomly assigned first bid is summarized per row according to its response. In total, 32% of the farmers were affirmative to the first bid. Particularly, 12% were willing to pay MK2000, 9% for MK4000, 5% for MK6000, and 6% for MK8000. For the farmers who answered "yes" to the first bid, a follow-up bid hiked by 100% was presented. For those that answered "no" the second bid was cut by half.

**Table 4.6: Summary of Double-Bounded Dichotomous Responses**

| Initial bid | Follow-up bid | **First Question** | | **Second question** | |
|---|---|---|---|---|---|
| | | **Yes to initial Bid** | **No to Initial Bid** | **Yes to Follow-up** | **No to Follow-up** |
| MK 2000 | MK 4000 | 12% | 0% | 4% | 8% |
| MK 2000 | MK 1000 | 0% | 18% | 2% | 16% |
| MK 4000 | MK 2000 | 9% | 0% | 5% | 9% |
| MK 4000 | MK 8000 | 0% | 14% | 4% | 5% |
| MK 6000 | MK 12000 | 5% | 0% | 1% | 4% |
| MK 6000 | MK 3000 | 0% | 15% | 4% | 11% |
| MK 8000 | MK 16000 | 6% | 0% | 1% | 4% |
| MK 8000 | MK 4000 | 0% | 21% | 5% | 17% |

For the second bid, we have another, either a "yes" or a "no", regardless of their response to the first question. Some who responded "yes" to the first bid gave a "no" response to the second bid. Similarly, some who answered "no" to the first bid, when presented with the lower follow-up bid they answered a "yes". About 5% of the farmers were willing to pay MK4000, regardless of the rejection to pay MK8000 in the initial bid. In the same vein, those who accepted to pay MK8000, when followed up with a doubled value of bid (MK16000), 1% of the farmers were still willing to pay the amount. A similar analysis applies to the other values of the second bid.

Further analysis is done to unpack the joint distribution of the outcomes of the initial and follow-up bid. Four possible outcomes are presented. These are a yes-yes, yes-no, no-yes and a no-no outcome. The result for this is exiled in Table 4.3 of the Annex.

4.4.3.2 Parametric Estimation of the Willingness to Pay

Mean willingness to pay and the determinants of willingness to pay (which was the willingness to pay for a pre-determined bid for weather index insurance) were jointly estimated using a Double Bounded Log-Logistic regression model. The model included independent variables that could help to explain farmers' willingness decision to engage with agriculture insurance markets. These included both continuous and dummy variables i.e. socio-economic and institutional variables. A priori inspection was implemented to ensure that the model satisfied certain requirements. First, the variables included in the model were checked for multicollinearity if at all present was within the tolerable range. This was done using the Variance Inflation Factor (VIF), for which results are presented in Table 1 of the Appendix. The results showed that all variables included in the model, not embody a serious level of multicollinearity. All variables registered a VIF value which was far from the cut-off point of 10. Further analysis of the association of dummy variables (Table 2 of Appendix) did not warrant a serious level of association.

After the aforementioned tests, the double bounded log-logistic regression was implemented in R Environment using the DCchoice package. The results of the model

**Table 4. 7: Determinants of the willingness to pay for weather index insurance**

| Predictor | Coefficient | Std Error | p-value | Margin Effects | P-value |
|---|---|---|---|---|---|
| Constant | 8.870 | 0.493 | 0.000 | - | - |
| Age | 0.3750 | 0.4710 | 0.212 | 0.1293 | 0.212 |
| Age squared | -0.4423 | 0.5532 | 0.212 | -0.1510 | 0.212 |
| **Gender** | -0.0660 | 0.0260 | 0.006 | -0.0220 | 0.006 |
| **Education** | 0.4160 | 0.0780 | 0.000 | 0.1434 | 0.000 |
| **Experience of climate shocks** | 0.2221 | 0.0123 | 0.000 | 0.0716 | 0.000 |
| **Access to extension service** | 0.3850 | 0.1700 | 0.012 | 0.1328 | 0.012 |
| **Log(Household income)** | 0.3487 | 0.0710 | 0.000 | 0.1224 | 0.000 |
| Family size | -0.0201 | 0.0371 | 0.295 | -0.0069 | 0.295 |
| **Maize Farm size (Ha)** | 0.5410 | 0.2140 | 0.006 | 0.1866 | 0.006 |
| **Farming experience** | 0.2650 | 0.0740 | 0.000 | 0.0883 | 0.000 |
| **Remittances received** | -0.2322 | 0.0410 | 0.000 | -0.0774 | 0.000 |
| **Use of DT Variety** | 0.5313 | 0.1282 | 0.000 | 0.1660 | 0.000 |
| **Livestock ownership (poultry)** | 0.3744 | 0.1369 | 0.003 | 0.0013 | 0.003 |
| **Livestock ownership (Large)** | -0.4244 | 0.1121 | 0.000 | -0.1458 | 0.000 |
| **Previous Food Security Status** | -0.5516 | 0.1467 | 0.000 | -0.1839 | 0.000 |
| **log(bid)** | -1.1761 | 0.0485 | 0.000 | -0.1307 | 0.000 |
| Observations (N) | 1170 | | | | |
| AIC (BIC) | 1897 (1928) | | | | |
| LR statistic | 54.2 | | 0.000 | | |
| **WTP Estimates** | | | | | |
| **Point Estimate** | **Estimate** | **Confidence Interval** | | | |
| | | **LB** | **UB** | | |
| Mean | 10,885.6 | 7,554.6 | 21,432.3 | | |
| Truncated Mean | 6,785.4 | 6,537.1 | 7,066.6 | | |
| Adjusted truncated Mean | 7,084.2 | 6,774.9 | 7,466.0 | | |
| Median | 4,847.3 | 4,658.2 | 5,040.7 | | |

are presented in Table 4.7. The model had a Likelihood Ratio Chi-square statistic of 54, which was significant at 1%. This measures the overall significance of the model. This result shows that variables included in the model were jointly explaining the variation in farmers WTP for weather index insurance with a high level of goodness of fit. Worth mentioning that in the family of probit and logit, the coefficients that are directly reported by the model do not explain the magnitude of the effects of the variables on the dependent variables. They only show the direction of effect, as such, cannot be reasonably interpreted directly. For that reason, the model presents both the coefficients and the marginal effects that are derived from the model. Green (2002) interprets marginal effects as the expected probability of choosing a particular choice given that there is a unity change in the given independent variable while holding all other factors constant. The second column in the table presents the coefficient estimates, and the last but one presents the marginal effects for the regressors. A total of 16 variables were included in the model. Out of these, 13 variables were significant in explaining farmers' WTP.

Gender of the household head proved to be negatively related to Willingness to Pay for weather index insurance. Gender is a dummy variable, with Male coded one and females coded 0. Both the coefficient and its marginal effect are significant. The meaning is that keeping all other variables constant, being male decreased the probability of Willingness to Pay for weather index insurance by 2%. This is an expected result for weather insurance that focuses on food crops like maize. The results show that men were more risk-averse to paying for weather insurance for maize crop. This is in line with what other studies have established that women are concentrated on food crop production while men's attention goes much to high-value cash crop production (Hill, et al., 2014). For this reason, there is likely to be intrahousehold resource competition towards the crop type the draws the attention of each gender category. Women will seek investments that increase the resilience of their food crops, like weather index insurance, while men would like to allocate the same resources to their cash crops. The result goes against Dong et al. (2003), who established that men were more willing to pay for community-based insurance in Burkina Faso

Level of education was another predictor of Willingness to Pay. The coefficient of education for the model shows that education was important in explaining willingness to pay for weather index insurance positively. This result was in line with prior expectations (Senapati, 2020). Similarly, the marginal effect was positive and significant. This implied that holding other factors constant, the education level of the farmer will positively influence adoption behaviour for weather index insurance. This is so because an educated person is able to calculate the potential losses in the event that there is a weather shock and compare with that they can trade of as an insurance premium and what they could get in return as a payout. In the same vein, access to extension advice was positively related to Willingness to Pay. Those who had access to extension advice were 13% likely to be willing to pay for weather insurance. Just like education, extension advice informs the farmers about weather shocks and risk management strategies. As such, those farmers who interface with extension officers tend to be more knowledgeable and willing to pay for weather index insurance. This becomes consistent with their rationality as utility-maximizing economic agents. Similar to this is the years of experience in farming. This was defined as the number of years the farmer has been farming as an independent unit. Model results show that a marginal increase in years of experience will trigger an 8% probability increase in the willingness to pay for weather index insurance. Experience is the best teacher, through which a farmer not only hears about the negative effects of weather-related shocks on their crop production but rather experience the effects. This triggers them to take remedial actions towards weather-related shocks proactively than someone who is a first-timer in crop agriculture. The results are in line with  Fahad et al. (2018) for the key factors influencing farmers crop insurance decisions in Pakistan.

The average monthly earnings of the farmer was a strong predictor of willingness to pay. This is expected as the payment vehicle for the hypothetical insurance market presented to the farmers was cash which directly draws from their earnings. From the marginal effects for average income earnings (in log terms) variable, it shows that income has a positive marginal effect on the farmers choice of insurance uptake. An increase in income of the farmers will shift their budget constraint outwards at both pivotal ends as such insurance product becomes a monotonic increasing function of farmers income. Farmers can thus, easily substitute other products for insurance products and still remain on the same indifference curve.

Farmers as rational agents operate within the framework of their knowledge and past experiences. Specific in this study was the experience of climate shocks in the past two years. The result shows a positive relationship between having experienced climate shocks recently and the willingness to pay for weather index insurance. The farmers that reported to have experienced droughts or floods in the past two years were more willing to pay for insurance than those who had never recently experienced such shocks. Those who experienced shocks must have been more aware of the negative consequences of weather shocks on crop output and hence more willing to invest in risk management strategies that would help them smooth out the post-disaster food security situation in future.

Family size, that is, the number of persons in the farming households, has a negative relationship with Willingness to Pay. The effect is not significant, and its magnitude is not big. Every additional member to the household reduces the probability of willingness to pay for weather index insurance by 0.6%. The increasing number of members in the household puts pressure on the household's resources. As such, the resources cannot be easily allocated to uses that have medium to long-run returns when there is a dependency burden in the household requiring more expenditure financing now.

The study also explored the effect of maize farm size on farmers willingness to subscribe for weather index insurances. This factor was significant both for the coefficient and the marginal effect in the positive direction. When maize farm size increases by a hectare, the probability of willingness to sign up for weather index insurance increases by 18%. This result makes sense in such a way that farmers with big maize fields have high anticipated economic losses compared to farmers who have smaller maize fields in terms of costs of production and also the potential yield. A weather shock on a small maize field will result in a lower level of economic losses. As such, there is less incentive for farmers' interest in weather index insurance. The result could also mean that farmers with smaller maize fields have more diversified crop agriculture, and the risk of total crop failure due to droughts is minimized, whereas those farmers with big maize fields will be more specialized toward one main crop and the risk of total crop failure is high. In that regard, they find it more rational to hedge against such by sharing the risk with insurance companies.

Remittances play a vital role in smoothening household consumption. In this study, remittances were found to be negatively related to the farmer's decision to pay for weather index insurance. That is, farmers who were receiving remittances were less likely to be willing to subscribe for weather insurance compared to those who were not receiving any remittance. Given these two types of farming households, in the presence of a weather shock on their crop production, those who have inflows from remittances will easily use it to substitute failed crop production and maintain their food security stand. At the same time, those with no access to remittances will have to sell out their labour to get some more earnings which could compensate for their failed production (attain their lost utility). As such, the latter households will be more willing to pay for the weather index, so they remain on the same utility point, without trading their labour, when a weather shock strikes.

The use of weather insurance is not the only option that farmers can do to minimize the risk of weather shocks on crop production. The study found that some farmers are using Drought Tolerance (DT) maize varieties which are more resilient to droughts and dry spells. Further analysis of DT maize varieties uptake showed that the adopters of these varieties were 18% more likely to be willing to pay for weather insurance. Adoption of DT varieties in the first place shows that someone is informed about the effects of weather shocks, and by adopting, they are trying to minimize those risks. As such, it is not strange to see that there is more willing to pay for weather insurance products by the adopters than non-adopters.

Livestock endowment is also an important predictor of willingness to pay for weather insurance. Livestock is of two types: small livestock, which includes poultry, and big livestock includes ruminant and non-ruminant livestock. These two types of livestock have divergent outcomes in shaping willingness to pay for weather index insurance. Farmers who are engaged in small livestock keeping were more willing to pay for weather index insurance than those who keep large livestock. In magnitude terms, the likelihood of big livestock keeping farmers not being willing to pay for weather insurance outweighed the likelihood of small livestock farmers' willingness to pay for the insurance product. The reason could be; most farmers who keep large livestock use it as a safety net in times of shocks. They can easily liquidate it and use the cash to compensate for the agriculture output loss. On the other hand, for small livestock, the farmer usually keeps these for emergency expenses not big enough to cover agriculture output loss.

Lastly, the food security history of the household was very important in explaining willingness to pay for weather index insurance. Households that did not experience a food insecurity spell in the last production season were not as willing to pay for weather index insurance compared to those who had fresh memories of their food insecurity experience.

The estimates of Willingness to Pay for weather index insurance have been derived using different algorithms. The results of these estimates are presented in the lower panel of Table 7 of results. First, the expected Willingness to Pay computed was based on the unmodified error distribution. This yielded the highest willingness to pay an estimated MK10,885.6. The confidence interval for the estimates are presented in the last two columns, both the lower bound and the upper bound. The second estimate of willingness to pay is based on the assumption that the error distribution is truncated at the maximum bid. This yielded an estimated MK5,785.4. Slightly similar to this measure is the Adjusted truncated mean (MK7,084), which is adjusted following the Boyle et al. (1988) routine. The final estimate of the willingness to pay is the median which is estimated to be MK4,847.3.

#### 4.4.3.3 Non-Parametric Estimation of the Willingness to Pay

The Kaplan–Meier–Turnbull survival probability estimates of Willingness to pay are estimated and summarized in Figure 4.3. Three estimates of the WTP estimates are reported. These include; the Kaplan–Meier mean estimate, the Spearman–Karber mean estimate, and the median estimate. Essentially, these estimates are based on the area under the empirical survival function, Figure 2. For the Kaplan–Meier estimate, it is computed as a rectangular area under the empirical survival curve all the way to the maximum bid. For Spearman–Karber estimates, it is computed as the area under the survival curve up to the x-intercept. The results yielded a Kaplan–Meier means of MK4,487, a Spearman–Karber of MK5,602 and a median of the interval of MK4000 to MK6000 (Table 8). These estimates can be compared with their parametric counterparts reported in the previous section (Table 4.8). I find that these estimates are more conservative than the parametric estimates. These could be considered as the legal minimum WTP in the context of weather index crop insurance.

**Table 4. 8: Non-parametric Estimates of Willingness to Pay (MK/Ha Maize)**

| Estimator | Point Estimate | Interval Estimate | |
|---|---|---|---|
| | | Lower Bound | Upper Bound |
| Kaplan–Meier | 4,487 | | |
| Spearman–Karber | 5,602 | | |
| Median | - | 4000 | 6000 |

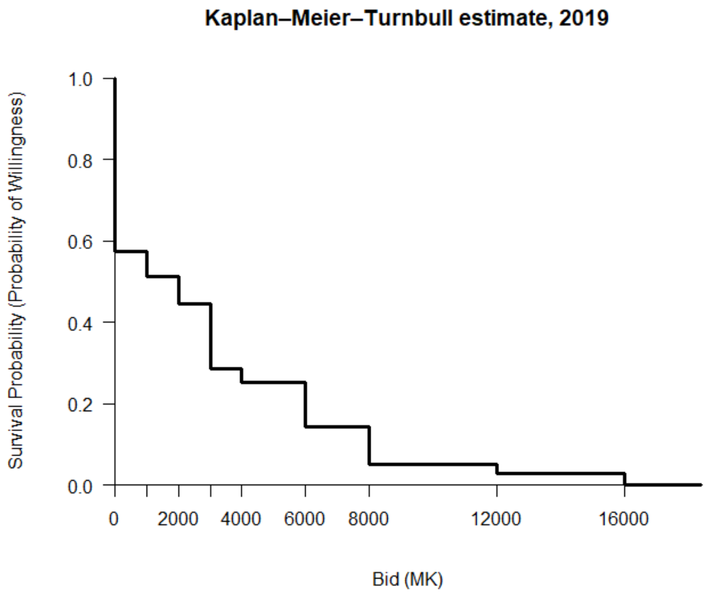



***Figure 4. 3: Kaplan–Meier–Turnbull estimate of the empirical survival function for Willingness to Pay***

### 4.5 Conclusions and Recommendations

Agriculture, especially cereal production in the tropics, are marred by several risks, mostly those related to climate change. The common of these include droughts and floods. When communities record episodes of these covariate risks, the existing coping mechanisms do not work due to a failed market system at the community level, unlike idiosyncratic shocks that are specific to households. In view of this, several countries in the tropics have embarked on pilot programs for crop insurance. Nevertheless, uptake of the insurance will depend on farmers' willingness to pay for the cost of this risk management strategy is to be sustainable. In Malawi, the concept of crop insurance is still infant despite being first piloted more than a decade ago. It remains unclear whether farmers would be interested in purchasing weather insurance products. This study, therefore, was set out to assess the demand side of weather index insurance for maize, which is one of the major food crops that define food security in Malawi. This study employed contingent valuation methods to explore the willingness of farmers to pay for weather index insurance for a hectare of maize.

The study used double-bounded questions and a semi-structured questionnaire to compile information about the surveyed farmers. A total of 1170 complete interviews were conducted distributed across six districts in all regions of Malawi. To reinforce understanding of willingness to pay and underlying factors, econometrics-based methods were used. The study employed a double bounded contingency valuation technique which used a log-logistic regression model. Four variants of willingness to pay estimates were computed, all of which point to the potential for weather index insurance markets in Malawi.

The descriptive statistics showed that most of the farming families surveyed were headed by men, married, attended some level of primary education and were low-income earners. It furthers shows that risk management in agricultural practices is not a new concept. Farmers are already engaging in a number of climate-smart agricultural practices to mitigate against the potential risks that come as a result of the climate-related shocks. These risk management strategies included the adoption of minimum tillage, crop residues, intercropping, agroforestry, irrigation, drought-tolerant varieties, crop diversification, conservation agriculture. Some farmers are even using a combination of several of these risk mitigation strategies to make sure that they deepen their production resilience capacity.

The results have shown that weather insurance product is a normal good with a well behaved downward sloping demand schedule. With the increase in premium, the demand is expected to go down. Willingness to pay for weather index insurance was found to be affected by a number of demand factors. The most important factors included gender, education, the previous record of climate shocks, extension contact, family size, experience in farming, access of remittances, current use of drought-tolerant varieties, household food security history and livestock endowment. Both parametric and non-parametric estimates of willingness to pay were within the same range of shots between MK4000 to MK7000. Although they fall within the relatively same interval, I find that the non-parametric estimates are more conservative than the parametric estimates.

Having established the mean willingness to pay by farmers for the weather index insurance, it only provides the demand-side analysis. Further studies need to be commissioned to undertake an analysis from the supply side and establish the optimal pricing rate. This optimal pricing rate could be compared with what the farmers are currently willing to pay. If the optimal pricing rate is higher than what the farmers are willing to pay, the government can think of rolling out a subsidy programme for weather index insurance. It could begin with weather shocks hotspots, and scale-out along the way to other areas. Alternatively, the government can support the subsidy component of the insurance policy by engaging the interested farmers in public works programs where they can provide labour, and instead of receiving cash for their labour, the government could make transfers directly to the insurance company for a well-defined weather index insurance product.

Education level of farmers, extension contact, previous episodes of shocks and experience in farmers were positive predictors of willingness to pay. All these factors point to the level of knowledge that the farmer has accumulated through various forms. To take advantage of these factors, the government and development actors could leverage the presence of extension officers in the marketing and delivery of weather index insurance products. As farmers deepen their knowledge of weather index insurance, including its benefits, we could see more farmers willing to purchase the product and, in turn, minimize the negative effects of weather-related shocks that are covered by weather index insurance policy.

The income of the farmers was also a very important factor in determining willingness to pay. They are already a number of initiatives by the government that focus on boosting farmers income. There is a need for streamlining these initiatives and focus efforts so that as farmers income increase, there will be a corresponding increase in demand for weather index insurance products. For non-farm sources of income, it is expected that it would be coming to the farmer in bits, and it may not be easy for the farmer to raise the amount for insurance subscriptions at once. As such, it is imperative to link the concept of crop insurance with the community-saving groups (commonly known as Village Savings and Lending Associations). Through these, farmers can have targets to gradually save the amount equivalent to the insurance premium fees such that as the time approaches the beginning of the cropping season, farmers will have saved enough to purchase crop insurance.

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# Appendix

## Appendix A4.1. VIF Test of multicollinearity

| Variable | VIF | 1/VIF |
|---|---|---|
| Age | 1 | 1.000 |
| Age squared | 1.69 | 0.592 |
| Gender | 1 | 1.000 |
| Education | 1.3 | 0.769 |
| Experience of climate shocks | 1.16 | 0.862 |
| Access to extension service | 1.01 | 0.990 |
| Log(Household income) | 1.64 | 0.610 |
| Family size | 1.29 | 0.775 |
| Maize Farm size | 1.16 | 0.862 |
| Farming experience | 1.05 | 0.952 |
| Remittances received in past 12 months | 1.03 | 0.971 |
| Use of DT Variety | 1.39 | 0.719 |
| Livestock ownership (poultry) | 1.18 | 0.847 |
| Livestock ownership (Large) | 1.25 | 0.800 |
| Previous Food Security Status | 1.23 | 0.813 |
| Average | 1.23 | 0.816 |

**Appendix A4.2. Contingency Coefficient for Dummy Variables.**

| Variable | Gender | Experience of climate shocks | Access to extension service | Remittances received in past 12 months | Use of DT Variety | Livestock ownership (poultry) | Livestock ownership (Large) | Previous Food Security Status |
|---|---|---|---|---|---|---|---|---|
| Gender | 1 | | | | | | | |
| Experience of climate shocks | 0.084 | 1 | | | | | | |
| Access to extension service | 0.149 | 0.179 | 1 | | | | | |
| Remittances received in past 12 months | 0.127 | 0.217 | 0.059 | 1 | | | | |
| Use of DT Variety | 0.219 | 0.149 | 0.239 | 0.166 | 1 | | | |
| Livestock ownership (poultry) | 0.214 | 0.2 | 0.181 | 0.081 | 0.239 | 1 | | |
| Livestock ownership (Large) | 0.135 | 0.144 | 0.058 | 0.156 | 0.076 | 0.099 | 1 | |
| Previous Food Security Status | 0.103 | 0.192 | 0.066 | 0.152 | 0.191 | 0.077 | 0.15 | 1 |

**Joint distribution of the Dichotomous choice responses**

As can be depicted from the Table, the No-No comprises the largest proportion of the sample followed by a yes-no. About 21% of the respondents answered yes in first place and no in the follow-up question. Ten percent of the farmers did not reject any bid in both stages of the game. About 14% of the farmers started by rejecting the bid but were comfortable with the follow-up bid. The presence of some farmers who are willing to pay for the product signifies that weather index insurance market has potential in the studied districts.

**Table 3. Joint distribution of the willingness to pay for weather index insurance**

| **Willingness Outcome** | **Frequency** | **Percentage** |
|---|---|---|
| Yes – Yes | 121 | 10.34 |
| Yes – No | 253 | 21.62 |
| No – Yes | 174 | 14.87 |
| No – No | 622 | 53.16 |
| Total | 1170 | 100 |

# CHAPTER 5

# GENERAL CONCLUSIONS

## 5.1 Conclusions and implications

In agriculture production, growing season temperature and rainfall are two primary factors determining crop yield outcomes. This thesis has analyzed three different areas relating to climate impacts on agriculture production.

The focus of chapter 2 was on the economic impacts of climate change on agriculture. This chapter examined the current and potential economic impacts of global warming and precipitation change on Malawi's agricultural production based on Ricardian analysis based on a three-year panel for Living Standards Measurement Survey (LSMS) data from 3,531 farming households. The model estimates showed that more warming negatively affects agriculture returns on the one hand, while more precipitation generates gains on the other hand. Additionally, simulation with Global Circulation Models showed that impacts from global warming would be more important than those from precipitation change. The impacts are heterogenous to production efficiency, with technically efficient farmers having moderate impacts in magnitude relative to inefficient farmers. With strategic climate adaptation choices, results show potential to abate some of the damages and enhance positive gains from future climate change.

Chapter 3 examined the farmers' vulnerability to expected poverty under climate-induced stresses in Malawi. Specifically, the study sought to i) Quantify the magnitude of climate stress-induced vulnerability to poverty among farming households; ii) quantify the effects of ex-ante climate stress-induced vulnerability on ex-post poverty and; iii) To quantify the relative effects of climate-related stresses on poverty transition. The study also used a panel version of Living Standards Measurement Survey (LSMS) data collected over the period of 2010 to 2016 in Malawi. I find that 47% of the studied farmers were vulnerable to climate stresses in 2013, and 58% of farmers were vulnerable to 2016 climate-related stresses. Expanding the time slice of analysis shows that vulnerability will be associated strongly with short-run climate stresses and less so with the long-run climate-related chocks. The study also finds that there is a significant linkage between ex-ante vulnerability and ex-post poverty. Similarly, the effects of vulnerability on actual poverty lessen with time to spell occurrence. Using a method that corrects selection bias, unlike previous studies, we find that Climate-related stresses worsened the welfare of farming households and affected the transition of farmers out of poverty. The study underscores the importance of livestock and off-farmer income diversification in buffering against poverty through serving a safety net.

Chapter 4 assessed the demand side of weather index insurance for maize, which is one of the major food crops that define food security in Malawi. I employed contingent valuation methods to explore the willingness of farmers to pay for weather index insurance for a hectare of maize. A total of 1170 complete interviews were conducted distributed across six districts in all regions of Malawi. The results showed that farmers are already engaging in a number of climate-smart agricultural practices to mitigate against the potential risks that come as a result of the climate-related shocks. These risk management strategies included the adoption of minimum tillage, crop residues, intercropping, agroforestry, irrigation, drought-tolerant varieties, crop diversification, conservation agriculture. Willingness to pay for weather index insurance was found to be affected by a number of demand factors. The most important factors included gender, education, the previous record of climate shocks, extension contact, family size, experience in farming, access of remittances, current use of drought-tolerant varieties, household food security history and livestock endowment. It was also established that, on average, farmers would be willing to pay MK10,885.6 for a hectare of maize field in a given cropping season. There are already a number of initiatives by the government that focus on boosting farmers' income. There is a need for streamlining these initiatives and focus efforts so that as farmers' income increase, there will be a corresponding increase in demand for weather index insurance products. It is also imperative to link the concept of crop insurance with the community-saving groups.

Finally, while this study focused on the farm level to explain national-level dynamics of climate and agriculture nexus, some more study needs to be conducted focusing on the macro-level. The new study could use general equilibrium models to explore how climate change is affecting the agriculture sector and how other sectors are helping to reproof resilience of the same. Furthermore, another trajectory would be to explore climate impacts on non-crop livelihoods for the studied farmers.

# APPENDIX 1 : Abstract of Peer Reviewed Publications 1

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## Climate induced vulnerability to poverty among smallholder farmers: Evidence from Malawi

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A R T I C L E I N F O

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A B S T R A C T

Assessment of farmers' climate change induced vulnerability is an important step for enhancing the understanding and decision-making to reduce such vulnerability. Using panel version of Malawi Living Standards Measurement Survey data of 2010, 2013 and 2016, this paper examines the magnitude of climate induced vulnerability to expected poverty among farming households and how climate change relates to ex-post poverty and poverty transition. We find that vulnerability is strongly associated with short-run climate stresses and less so with the long-run climate related shocks. The effects of vulnerability on actual poverty lessen with time in the long run. Similarly, climate related stresses worsen the welfare of farming households. Droughts, floods and irregular rainfall exacerbates poverty with droughts showing the greatest impact on farmers welfare loss, followed by floods. The study underscores the importance of livestock, in buffering against poverty through serving a safety net, and off-farm income-generating activities. This suggests that the inclusion of livestock in shaping of climate management policies for farmers is crucial.

### 1. Introduction

The developing regions like sub-Saharan Africa (SSA) have been dominated by countries whose economies heavily rely on agriculture for employment and food security (Livingston et al., 2011). The staggering effects of climate change continue to deepen and threaten economies that put heavy reliance on agriculture and forest sectors (Gbetibouo & Hassan, 2005; Kurukulasuriya et al., 2006). The magnitude of the effects is skewed towards the rural areas where majority of the population resides and are mostly employed in subsistence rain-fed agriculture as their primary economic activity. In addition, more than half of their earnings are spent on food (Cranfield et al., 2003). The amplified intensity of climate extremes such as droughts and floods will result in low agricultural productivity which will negatively and directly impact rural livelihoods (Easterling et al., 2007). This, in turn, will weaken the efficacy of certain adaptation strategies, like irrigation, as low levels of precipitation will reduce the amount of water available for irrigated food production (FAO, 2003) in the off-rainfall season.

Studies relating to climate change and agriculture in Malawi have assumed divergent trajectories. Pangapanga et al (2012) analyzed factors affecting choices of climate adaptation strategies in agriculture but did not quantify the poverty vulnerability of farming households to climate stresses. Similarly, Nordhagen and Pascual (2013) examined the impacts of shocks on the behavior of farmers in seed markets but did not account for farmers vulnerability the shocks could cause. In order to understand the economic viability of the agricultural systems under increasing climate variability, as proposed in climate change forecasts (Kurukulasuriya et al., 2006) it makes climate vulnerability studies much relevant to inform resilience building.

Currently, studies on the vulnerability of farming households to climate change are limited in the tropics. For Africa, in general, a few studies have assessed the vulnerability of households to climate shocks (Mansour et al., 2014; Dercon, 2004; Ligon & Schechter, 2003). While these studies are informative, they are limited by their geographical coverage as they only considered countries like Tunisia, Ethiopia and Kenya which have different climates from those of tropics and different per capita incomes. This presents an important limitation as their findings cannot be generalized to farming communities in a broader context. Countries with different levels of per capita income are expected to have different levels of vulnerability to poverty in the face of climate related stresses. Perhaps, the magnitude of the effects on different variables cannot be the same. Some variables could matter in one country and not

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## APPENDIX 2: Abstract of Peer-Reviewed Publications 2

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# Parametric and non-parametric estimates of willingness to pay for weather index insurance in Malawi

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ABSTRACT

As climate-related shocks on agriculture production intensify, weather index crop insurance has emerged as one potential risk management strategy for farmers. Nevertheless, sustainable uptake of this risk management strategy will largely depend on farmers' willingness to pay for the associated premiums. This study identifies various socio-economic factors that influence farmers' purchase of index insurance for staple food in rural Malawi. It further establishes an associated willingness to pay per hectare per cropping season. We use a hypothetical rainfall index insurance program to estimate insurance demand. The study highlights several determinants of willingness to pay for an index insurance product. Results suggest that gender, the previous record of climate shocks, extension contact, and access to remittances significantly influence willingness-to-pay for weather index insurance for a staple food crop. Both parametric and non-parametric estimates of willingness-to-pay are in the range of US$5.5 to US$15 per hectare per cropping season. At the infancy stage, government subsidies for insurance premium and linkage of premium payments to Village Savings Groups will be crucial.

### 1. Introduction

Crop agriculture in the tropics has a heavy reliance on the weather, making it suffer negative impacts from periodic episodes of droughts and floods. These have an inverse relationship with farm output [1]. The presence of unmanaged risks of droughts and floods exposes farmers to high vulnerabilities and affects their livelihood. These shocks have the potential to trap agriculture out in a vicious cycle. They can reduce farm output and lead to capital shrinkage due to the lost farm profits. In turn, farm output can remain low in subsequent production periods [2,3]. These make agriculture risk management a contemporary issue, given that climate variability is predicted to worsen in the future [4].

Extreme climate events are an obstruction to the economic lives of farming households, whose livelihoods are agriculture-based, and retard progress towards achievement of the Sustainable Development Goals. These, for example, have reduced agriculture output by 9–10% globally between 1964 and 2007 [5]. Although in the face of increasing droughts, African Agriculture is still dependent on rain-fed moisture. It is one of the most critical sectors in the African economies. In Sub-Saharan Africa (SSA), it contributes about 29% to Gross Domestic Product and employs about 86% of the population [6,7]. Therefore, there is a need for plausible risk management strategies. These will provide farmers with a buffer in unanticipated climate-related shocks, thereby strengthening the resilience of the agriculture sector [8].

Of the climate-related shocks, those that have are most common in Africa include droughts and floods. Cole et al. [9] note that about 89% of the surveyed households in developing countries report variability in rainfall as the most worrying weather shock that farmers face [10]. A review of the International Disaster Database shows a historical record of 1000 natural disasters in Africa affecting around 330 million individuals. Of these disasters, although floods were frequent, droughts affected 83% of individuals and resulted in 40% economic damages. These events have intensified in frequency and space [11]. With exposure to such shocks, farmers need to find alternatives to manage the aftermath of the same.

Risk management in agriculture, in general, is not new among farmers. Farmers already engage in several risk mitigation strategies that tend to smoothen their consumption path to minimise the effects of the shocks. These include livelihood diversification, sale of assets, draws on savings, among others [12]. The effectiveness of these strategies will depend on the scale of risks. These strategies are effective for idiosyncratic (individual) shocks. However, when shocks are covariate

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