CLIMATE VARIABILITY, AGRICULTURAL PRODUCTIVITY AND HOUSEHOLD WELFARE OUTCOMES IN UGANDA

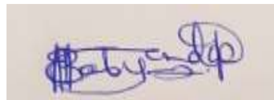
PETER BABYENDA

A THESIS SUBMITTED IN PARTIAL FULFILMENT FOR THE DEGREE OF DOCTOR OF PHILOSOPHY IN ECONOMICS IN THE DEPARTMENT OF ECONOMICS AND DEVELOPMENT STUDIES, FACULTY OF ARTS AND SOCIAL SCIENCES IN THE UNIVERSITY OF NAIROBI

2023

DECLARATION

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

Signature **:** 

BABYENDA PETER

Date : **13th September 2023**

This work has been submitted with our approval as university supervisors.

Signature **:** 

PROF. JANE KABUBO-MARIARA

Date : **13th September 2023**

Signature : 

DR. FREDRICK E. ODHIAMBO SULE

Date : **13th September 2023**

DEDICATION

I dedicate this work to my dear wife Roselyn and children Chloe, Israel, Elijah, and Josiah.

ACKNOWLEDGMENTS

I am forever grateful to my two supervisors, Prof. Jane Kabubo - Mariara and Dr. Fredrick E. Odhiambo Sule from the Department of Economics and Development Studies, Faculty of Social Sciences, University of Nairobi, Kenya for their time, patience, and dedicated guidance in the process of writing this dissertation. Special appreciation goes to the African Economic Research Consortium (AERC), Nairobi, Kenya for sponsoring my doctoral studies. I am thankful for the comments that helped to shape this dissertation from all faculty members at the Department of Economics, and Development Studies, University of Nairobi, Kenya; lecturers at the School of Economics, University of Dar Es Salaam, Tanzania, and the reviewers at the AERC biannual conferences especially my resource person, Dr. Precious Zikhali and the other AERC group E resource persons and researchers.

Heartfelt appreciation goes to my wife Roselyn, my children Chloe, Israel, Elijah and Josiah, my parents, and siblings for their words of encouragement, support, tolerance, and prayers throughout my academic journey. To all colleagues in the AERC PhD class 2017 across the African continent and friends too numerous to mention, I salute you for the inspiration, guidance, and support. I will always be thankful for your tremendous contributions and comforting messages. I also acknowledge the support from workmates in the School of Economics, College of Business and Management Sciences, Makerere University main campus and Makerere University Jinja Campus.

Above all, I am thankful to the Almighty God. He is my ultimate source of inspiration, creative energy, wisdom, and guidance; He has never lifted His eye off me. Without Him, completion of this thesis would not have been possible. May His Name be glorified forever and ever, Amen.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDIX TABLES AND FIGURES

LIST OF ABBREVIATIONS

AERC	:	African Economic Research Consortium
BBS	:	Bona Bagagawale Scheme
BoU	:	Bank of Uganda
CA	:	Conservative Agriculture
CO_2	:	Carbon dioxide
CV	:	Coefficient of Variation
ES	:	Entandikwa Scheme
ESR	:	Endogenous Switching Regression
EU	:	European Union
FAO	:	Food and Agricultural Organization
GDP	:	Gross Domestic Product
GoU	:	Government of Uganda
IMF	:	International Monetary Fund
IPCC	:	Intergovernmental Panel for Climate Change
MWE	:	Ministry of Water and Environment
NAADS	:	National Agricultural Advisory Services
NCEP	:	National Centre for Environmental Prediction
ND – GAIN	:	The Notre Dame Global Adaptation Initiative
NEMA	:	National Environmental and Management Authority

NOAA	:	National Oceanic and Atmospheric Administration
NPA	:	National Planning Authority
OLS	:	Ordinary Least Squares
OWC	:	Operation Wealth Creation
PEAP	:	Poverty Eradication Action Plan
PMA	:	Plan for Modernization of Agriculture
PMA	:	Plan for Modernization of Agriculture
RM	:	Ricardian Cross-Section Models
Sq. kms	:	Square Kilometres
Sd	:	Standard deviation
UBOS	:	Uganda Bureau of Statistics
UCAR	:	Uganda Climate Change Action Report
UNPS	:	Uganda National Panel Survey
USA	:	United States of America

ABSTRACT

Eighty-five percent of Ugandans depend largely on rain-fed agriculture to make a living. Thus, they are exposed to the effects of variability in climate. Evidence shows that changes in climate are taking place in all regions of Uganda with noticeable changes in precipitation and temperature including persistence of adverse weather occurrences such as prolonged drought, floods, landslides, and rising temperatures. According to the World Bank, climate variability is projected to cause a global agricultural production loss of about US$1.5 billion by the year 2050. This is likely to extend to Uganda's main foreign exchange earning crops (such as coffee and maize) leading to combined economic losses among farm households of about US$1.4 billion by the year 2050. Against this backdrop, this thesis investigates the effect of variability in climate on the productivity of agriculture and the welfare outcomes of households in Uganda. The thesis further explores the factors influencing the decision of households to adapt to variability in climate and assesses welfare differences between the adapting and non-adapting households.

The thesis uses two data types – historical climate variability data obtained from the United States National Oceanic and Atmospheric Administration (NOAA) and household level survey data sourced from six waves of the Uganda National Panel Survey (UNPS). The UNPS waves data is countrywide repeated cross-sectional data collected from 2009 to 2019 by the Uganda Bureau of Statistics (UBoS). The thesis used the total factor productivity approach to evaluate the effect of variability in climate on agricultural productivity in Uganda (Essay 1). Weighted pooled Ordinary Least Squares (OLS) and random effects models were used in Essay 2 to examine the effect of climate variability on household welfare outcomes (consumption expenditure). The Endogenous Switching Regression (ESR) model was applied to assess the difference in welfare outcomes between the adapting and non-adapting households (Essay 3).

Findings in Essay 1 show a significant U-shaped effect of the variability of precipitation on productivity of agriculture in Uganda with regional analysis indicating that relative to other regions of the country, Eastern Uganda is the region that is most prone to extreme occurrences because of the variability in climate. However, the findings further present that the negative effect of the variability of precipitation on the productivity of agriculture disappears with access and availability of extension services. In Essay 2, the results show that variability of climate has a significant nonlinear effect on households' welfare outcomes with prolonged variability in precipitation associated with household welfare loss. However, variability in the highest and lowest temperatures have different effects on household consumption expenditure. The findings show that variability in the lowest temperature results in reduced consumption, while variability in the highest temperature leads to an increase in household consumption expenditure. Essay two results further indicate that households' improved access to extension services and the level of education of the household head improve household welfare. The Essay 3 findings show that adaptation to climate variability by farm households is beneficial as it safeguards against welfare deterioration among the adapting households and that the households that practice farming are more inclined to adapt to variability in climate under extreme or continuous cases of precipitation variability as compared to under mild or a few cases of climate variability. The results from the three essays highlight the need to build resilience and design policies and interventions that are not only aimed at mitigating variability in climate but also at increasing productivity in agriculture across the country, enhancing household welfare outcomes and increasing adaptation among the farming households.

Based on the study findings, this thesis recommends the need for the Ugandan government and the other stakeholders including development partners to prioritise access and availability of extension services to all farmers across the country to empower farmers to deal with varying climate and its associated impacts. Secondly, there is a need to sensitise farmers on the benefits of adaptation and if possible, subsidise some of the adaptation mechanisms such as irrigation equipment, climate variability tolerant seed varieties, climate forecast information and availing water for irrigation.

Keywords: *Climate variability, agricultural productivity, welfare outcomes and panel data models*

CHAPTER ONE

INTRODUCTION

1.1 Background to the study

There are rising signals across the world that climate variability in form of varying temperatures, changing, and altered patterns of precipitation, incidences of dangerous weather events like floods, landslides and prolonged drought are happening in many countries across the globe including sub-Saharan Africa where Uganda belongs (Ayinde et al., 2017; Kontgis et al., 2019). These climatic alterations are likely to affect agricultural sector productivity, given that the sector largely depends on nature (Kabubo-Mariara & Mulwa 2019; Sabiiti et al., 2018). In Uganda, the variability of climate is predicted to not only affect agricultural sector productivity but also the welfare of those mainly engaged in agricultural activities (NEMA, 2016[1]; Mubiru et al., 2018).

Uganda's weather statistics show that both precipitation (rainfall) and surface temperature (minimum and maximum) have been varying over years (Appendix1) across the country. This is an indication of probable occurrence of climate variability in Uganda. In addition, across East Africa, climate and more specifically rainfall and temperature have been changing since the 1950s (Sabiiti et al., 2018). For example, surface temperature on the Indian ocean has increased by 1°C since 1950, rainfall amounts have reduced but with an increasing variability (Munshi, Call, & Gray, 2018). At the same time, the region has frequently experienced intense rainfall events, floods, and droughts (Shikuku et al., 2017; Kontgis et al., 2019). Given that Uganda's agricultural sector is largely nature dependent and rainfed, there is a high likelihood that these varying climatic patterns could affect its productivity and thus welfare given that majority of Ugandan depend on agriculture as a source of food, livelihood, and income (Guloba, 2014, Mwaura & Okoboi 2014).

Globally, agriculture remains a major source of food and a complementary sector to both the industrial and service sectors (FAO, 2018). In Africa, the sector accounts for about forty percent of her foreign exchange revenues and workforce (FAO, 2012). In Uganda, agriculture contributes about 25% of GDP and provides jobs to approximately 70 percent of the working population

[1] 2014 Uganda's state of environment report

(UBOS, 2018). However, agricultural contributions to Uganda's total GDP share have been declining over time; for instance, it decreased to Uganda Shillings 3241.55 billion in the fourth quarter from Uganda Shillings 4209.31 billion in the third quarter of the 2018/19 financial year (Bank of Uganda, 2019). It is not certain whether the decline in agricultural GDP share is due to climate variability and its effects or other factors.

However, according to Uganda Bureau of Statistics (UBOS), prolonged drought experienced in 2017 led to a decline in agricultural harvests, exposing about 11 million Ugandans to food insecurity especially in the Eastern and the Northern parts of the country (UBOS, 2017). During the same period, food price inflation increased from 5% in September 2016 to 23.1% in May 2017 forcing the government of Uganda, development partners and other stakeholders to intervene by providing food relief in the affected districts (IMF, 2017). Similarly, poverty levels among Uganda's farming households rose from 23% in 2012 to 36% in 2017 and this was partly attributed to unpredictable climatic conditions that the country experienced between 2012 and 2017 (UBOS, 2017). On the other hand, Uganda's mean monthly household expenditure marginally decreased from UGX 328,200 (US$94) in 2012/13 to UGX 325,800 (US$93) in 2016/17 (UBOS, 2017). A decline in consumption expenditure is associated with a decline in the welfare of the household members. However, in 2018, following increased rains and stable climatic conditions, there was an increase in agricultural yields harvested by farming households and other farms in the country leading to a fall in food inflation to 2.9% as of March 2019 (Bank of Uganda, 2019).

This has thus made many scholars, stakeholders, and various government agencies to attribute fluctuations in Uganda's agricultural productivity and welfare outcomes particularly household consumption expenditure and poverty dynamics largely to variations in climatic conditions (Guloba, 2014; UBOS, 2017). Their argument is based on the fact that Uganda's agriculture is largely rain fed and thus almost entirely depends on natural climatic conditions (Mwaura & Okoboi, 2014; Shikuku et al., 2017) and yet, it is still the backbone of the economy as clearly outlined in the Uganda's vision 2040 (NPA, 2015)[2].

In addition, about 84% of the Ugandans who stay in rural areas are involved in farming as their major economic activity although 68% of them still practice and depend on subsistence agriculture

[2] National Planning Authority – a national body responsible for Uganda's development plans and strategies.

(UBOS, 2017). As a result, many interventions have been introduced and implemented by the Ugandan government over time in the agricultural sector mainly geared at uplifting her people from poverty, subsistence agriculture and food insecurity (Hisali et al., 2011). Among them, include Poverty Eradication Action Plan (PEAP), *Entandikwa* (startup capital) Scheme (ES), Plan for Modernization of Agriculture (PMA), *Bona Bagagawale* (prosperity for all) Scheme (BBS), Conservation Agriculture (CA), Uganda National Agricultural Advisory Services (NAADS), Presidential Initiative on Poverty and Hunger (PIPH) and Operation Wealth Creation (OWC). On variability in climate, the Ugandan government designed, adopted, and started implementing the Uganda National Climate Change Policy and the National Adaptation Plan (MoWE, 2015; NPA, 2015). The government efforts on climate variability mitigation have been supplemented by the private sector and development partners including financing some of the adaptation mechanisms such as provision of climate variability resistant crop varieties (UBOS, 2017).

Adopting measures that not only increase agricultural productivity but also improve household welfare outcomes will aid Uganda as a country to produce enough to sustain the growing demand for food because of the growing population. It will also play a part in achieving the first two and the twelfth United Nations' sustainable development goals[3] and in improving the general living standards of Ugandans (FAO, 2018). Similarly, tackling climate variability and its effects is in line with the sixth and thirteenth United Nations' sustainable development goals, which are about guaranteeing accessibility and maintainable use of water and action against variability in climate and its effects (UNDP, 2019). However, adoption of any policy measure and its successful implementation requires the backing of the empirical research evidence or findings. In addition, Uganda is ranked by the Notre Dame Global Initiative Index on climate change adaptation (ND-GAIN) as the 9th most vulnerable country to climate change and the 27th lowest prepared country to adapt to climate variability effects among countries that were surveyed in 2015 (UCAR, 2017).

Thus, it is essential to study the potential effects of variability in climate on productivity of agriculture and household welfare outcomes to inform targeted policy formulation, actions and interventions or programs. This is because, although climate variability is assumed to have an impact on everybody in the world, it is the poor and those in susceptible situations such as rural

[3] Sustainable Development Goals (SDG) 1 and 2 are about reducing poverty, hunger, and food insecurity, improving diet and sustainable farming while SDG 13 is about taking urgent action to combat climate change and its impacts.

based small-scale farmers and those engaged in nature dependent activities, who might bear the brunt of it (IPCC, 2018). Therefore, this study contributes to the literature on how farming households are affected by variability in climate in terms of their productivity, welfare outcomes as measured by consumption expenditure and their adaptation efforts. The study further analyses how adaptation to climate variability influences household welfare outcomes, specifically, their consumption expenditure. The findings of this study, provides key insights on how best the farming households can respond to variability in climate and its effects through building resilience, improving productivity and adaptation efforts.

1.2 Statement of the problem

It is evident that today many areas in Uganda are experiencing climatic variations with noticeable alterations in precipitation levels, availability of water, season length and occurrences of life-threatening weather events such as prolonged scarcity of rain, floods, landslides, rising temperatures and changing agricultural seasons among others (Shikuku et al., 2017; UBOS, 2017; UNMA[4], 2019). Areas like Kabaale in southwestern Uganda and Wakiso in central Uganda that used to enjoy cold weather throughout the year are now heating up (Guloba, 2014; Cooper, 2018).

The varying climatic conditions are likely to affect Uganda's weather patterns and farming seasons, thereby affecting the agricultural sector, which is largely dependent on natural conditions. This may put the livelihoods of about 85% of Ugandans who depend on agriculture (such as farmers, rural people, agricultural traders, and agro industries among others) for survival and employment at risk. In addition, according to various IPCC reports including that of 2022, climate change and variability will likely reduce productivity of the agricultural sector in already fragile areas such as the sub-Saharan Africa where Uganda belongs. This may in turn result in increased absolute poverty, hunger, malnutrition, and food insecurity, making it difficult to achieve the Uganda vision 2040 and the various UN global sustainable goals by 2030.

Thus, understanding the factors that affect agricultural productivity is important not only for designing ways to boost agricultural productivity among the farming households but also for improving the welfare of households, nutrition, food security and poverty reduction. This is

[4] Uganda National Meteorological Authority (UNMA) report for 2019.

because productive agriculture is an effective way of reducing poverty, enhancing welfare, and ensuring food security in Uganda where agriculture is still the main means of survival, employment and income earning not only for farmers but also as the main source of food, revenue, and exports for the country at large. Designing appropriate and effective policies by the policy makers requires timely and up to date reliable evidence generated through a scientific or an empirical research process. There is a dearth of such evidence in Uganda where research in this area is still scanty and at an infancy stage.

Although, there are some scholars who have analysed agricultural effects of variability in climate in Uganda (for example see Ekiyar et al., 2010; Nabikolo et al., 2012; Sabiiti et al., 2018 among others), analysis of the effect of variability in climate on productivity and household welfare outcomes has received limited attention to date. Yet, productivity and welfare improvement concerns are becoming increasingly vital given the rising population size coupled with declining agricultural land per capita. Although Mwaura & Okoboi (2014) used time series data to examine the effect of the variability of climate on productivity of agriculture in Uganda, the authors ignored institutional and household characteristics of farming households.

Other studies such as Sabiiti et al. (2018) and Nabikolo et al. (2012) have low in-depth analysis in terms of coverage and focus and thus their findings may not be representative of the entire country since Uganda has many districts and regions. Findings of such studies may lead to misleading, unreliable, inappropriate, and temporary policy recommendations due to lack of adequate and concrete evidence. In addition, the analysis of the welfare differences between farming households that have practiced some adaptation to climate variability mechanisms and those who have not, has not yet been extensively carried out in Uganda.

It is thus vital to comprehend how the changing climate is affecting agricultural productivity and household welfare outcomes, and how best Ugandan farming households can cope with its effect on productivity and welfare. This provides evidence necessary for designing optimal, appropriate, and effective country wide, regional or crop specific policy measures aimed at combating climate variability and its effects. These measures may in turn aid Uganda to achieve its national targets

NDP III), regional targets, African Union agenda 2063[5] and a number (1, 2, 3, 6, 12 and 13) of the 2030 United Nations' SDGs on time.

1.3 Research questions

This study addresses three research questions:

(i) How does climate variability affect agricultural productivity in Uganda?

(ii) In what ways does climate variability affect household welfare outcomes (household consumption expenditure) in Uganda?

(iii) Does adaptation to climate variability affect household welfare outcomes (consumption expenditure) in Uganda?

1.4 Objectives of the study

The general objective of this study is to examine the impact of variability in climate on agricultural productivity and welfare outcomes of households in Uganda. The specific study objectives include:

(i) To investigate the effect of variability in climate on agricultural productivity in Uganda.

(ii) To examine the impact of variability in climate on household welfare outcomes (household consumption expenditure) in Uganda.

(iii) To assess the impact of adaptation to climate variability on household welfare outcomes (household consumption expenditure) in Uganda.

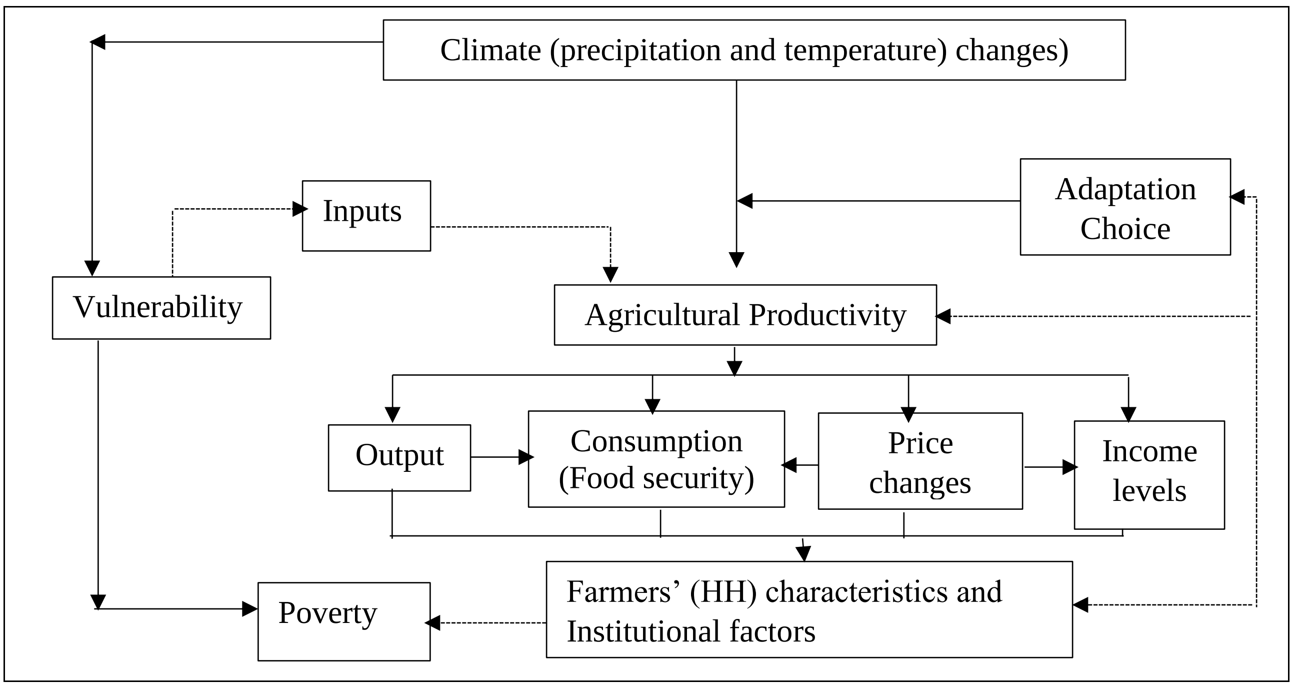
1.5 Conceptual framework of the study

The conceptual framework is founded on the works of FAO (2008) and Skoufias et al. (2011). This study is based on the argument that climate change affects agricultural productivity and household welfare outcomes (household consumption expenditure) through various channels as shown in Figure 2, while farming households respond to climate change and its effects. The framework follows from the theoretical proposition that declining inputs such as climate

[5] AU 2063 agenda stipulates the need for all Africans to have healthy and productive lives. This is in addition to AU's target of ending hunger and food insecurity in Africa in the year 2025, which is just six years away from now.

(precipitation and temperature) reduces productivity of farmers (reduces total output per given total input mix). This in turn reduces farmers' incomes and hence their expenditure levels especially for rain fed agriculture dependent farming households. This thus exposes farmers to poverty and food insecurity (FAO, 2016). Therefore, variabilities in precipitation and temperature are likely to affect agricultural productivity which will in turn affect the welfare of people in terms of their incomes and food security status (Munshi, Call, & Gray, 2018).

Figure 1: Conceptual framework of the study



Source: Adapted and modified from FAO (2008) and Skoufias et al. (2011)

From figure 1, we can see that climate variability influences welfare mainly via its effects on agricultural productivity and incomes. This is largely due to the established fact that approximately 85 percent of Ugandan households' livelihoods rely greatly on rain fed agriculture (UBoS, 2018). Thus, any climatic shock that adversely affects agricultural yields and thus, productivity and revenues, also affects household income (Skoufias et al., 2011). Subject to the household's capacity to adapt to changing agricultural yields and revenues due to climate variability, the outcome could be a decline in consumption, indicating welfare loss (Smit et al., 2016). Therefore, adaptation mechanisms (such as irrigation, planting improved crop varieties among others) undertaken by the farming households could be welfare improving.

1.6 Data types and sources

The study uses two types of data - household level survey data collected from 2009 to 2019 and long-term historical climate data ranging from 1979 to 2013. The household survey data used in the study are six Uganda National Panel Survey (UNPS), that is, the 2009/10, 2010/11, 2011/12, 2013/14, 2015/16 and 2018/19 waves, spanning over a period of 10 years. These data sets are national representative as they report on the entire country as collected by Uganda Bureau of Statistics (UBOS) in collaboration with the World Bank's Living Standards Measurement Study, also known as the Integrated Surveys on Agriculture (LSMS-ISA) program. Each data wave covers about 2,500 households giving a total of approximately 12,500 observations in the data set used under this study. The UNPS administers four modules to sampled households – the Socio-economic, Woman; Agriculture and Community modules collected over a period of 12 months (also known as a "wave"). This is largely to consider factors that are seasonal that affect the components of consumption expenditure and agriculture. Data collection in each wave is done in two visits to the same household (six months apart) to cater for the two-yearly farming seasons experienced in Uganda.

The long-term historical climate data on precipitation and temperature were sourced from the National Oceanic and Atmospheric Administration (NOAA) of the United States of America from its online website. This source provides high quality controlled historical climate data obtained on a daily, monthly, seasonal, or annual basis. The climate data was a 0.5° x 0.5° latitude and longitude grid based on each household GPS coordinates as provided in UNPS waves under study.

1.7 Contributions of the thesis

The thesis adds to the body of literature by examining empirically the effect of variations in climate on productivity of agriculture and welfare outcomes of households such as household consumption expenditure in Uganda. These are critical issues as they jointly account for 29 percent (5 out of 17) of the 2030 United Nations Sustainable Development Goals (SDGs). This shows that these issues are of great concern not only in developing states but also in developed nations and the entire world. Given the fact that the world's population is rising, and yet the agricultural land is not increasing, there is a need to increase agricultural productivity to produce more food (Mendelsohn, 2012; World Bank, 2018; FAO, 2018; UNDP, 2019). In addition, 39.5 percent of the farming households in Uganda are engaged in climatic sensitive subsistence agriculture for livelihood and survival (UBOS, 2017). Thus, given a dearth of evidence-based research, the thesis explores the climate variability effects on productivity in agriculture and the welfare outcomes of households, and recommends appropriate evidence-based measures to protect small-scale farmers against the adverse effects of variability in climate.

Secondly, existing studies in Uganda on the subject matter (see for instance Mwaura & Okoboi 2014) used time series data to analyse the effect of variability in climate on productivity of agriculture without considering institutional and household characteristics which are cross-sectional in nature. In the literature, it is noted that any study on agriculture, given its complexities, demands detailed considerations of socio-economic, institutional, and household specific factors. Omitting these factors in the analysis may lead to biased, inconsistent and inefficient model estimates (Green, 2012; Baltagi, 2013) that may yield misleading policy recommendations. To overcome these shortcomings, this thesis takes into consideration the social economic, household, and institutional factors combined with long-term climate data for over 30 years and covers the entire country. In addition, the study estimates total factor productivity derived from the stochastic production function. This accurately measures the farming household performance that is not due to inputs but other factors. Hence, the findings from this study provide important information for designing policies aimed at accelerating agricultural productivity in the presence of climate variability, given that agriculture is identified as the leading engine for poverty eradication among Uganda's rural population, especially farmers (NPA, 2015).

More so, the study extends its national analysis to regional and crop specific analyses for the four crops - maize, beans, cassava, and banana - which are commonly grown in all regions of Uganda. Through this kind of analysis, the thesis contributes to the understanding of which region and crop are more vulnerable to variabilities in climate and proposes necessary region and crop specific measures for improving agricultural productivity in the presence of climate variability. Knowledge about the climate variability impact on crop productivity provides timely and key information to policy actors, farming households and other stakeholders involved in Uganda's agricultural sector to increase per hectare yields from these crops and hence increase their income earnings and in turn improve their welfare outcomes such as consumption.

In addition, the study investigates the differences in household welfare outcomes in terms of per adult equivalent household consumption expenditures between the adapting and non-adapting farming households in Uganda. This does not only provide a deep understanding of the benefits associated with the adaptation to climate variability but also provides evidence to support the ongoing Uganda's National Adaptation Plan making process. Although the emphasis in this study is on climate variability related factors, both household and policy related factors are also considered. This is important for informing specific policy action on climate variability and welfare improvement in the country. The extant literature on poverty dynamics in Uganda had ignored the influence of climate related factors on household welfare outcomes (Mwungu et al., 2019). This study also addresses the econometric challenges of endogeneity and reverse causality by employing an endogenous switching regression model, estimated using the Full Information Maximum Likelihood (FIML) estimator. This produces consistent, efficient, and credible estimates, which are essential for the present and evolving policy design to address the effect of climate variability on welfare outcomes in Uganda.

1.8 Structure of the thesis

This work comprises five chapters. Chapter one presents a general introduction to the entire thesis. This is followed by chapter two that investigates the climate variability impact on agricultural productivity in Uganda. Chapter three assesses the climate variability impact on household welfare outcomes while chapter four analyses the difference in household welfare outcomes between the adapters and the non-adapters including identifying factors that determine adaptation to climate variability by the households. Finally, chapter five presents the summary of the key results of the study, conclusions, and policy recommendations from the study's findings.

References

Ayinde, O. E., Muchie, M., & Olatunji, G. B. (2017). Effect of Climate Change on Agricultural Productivity in Nigeria: A Co-integration Model Approach. *Journal of Human Ecology*, *35*(3), 189–194. https://doi.org/10.1080/09709274.2011.11906406

Baltagi, H. B. (2013). *Econometric Analysis of Panel Data, 5th edn. UK: John Wiley & Sons*.

Ekiyar, V., Jumbe, C., Mangisoni, J., & Mkwambisi. (2010). *Climate change impacts to agriculture in Uganda's semi-arid areas, farmers' means of adaptation: An application of cross-section data*. Second RUFORUM Bi-annual Meeting 20-24th September 2010, Entebbe, Uganda. RUFORUM Working Document Series pp 6: 27-31.

Green, H. (2012). *Econometric Analysis (7th ed.)*. USA, *Stern School of Business, New York University*

Guloba, M. (2014). *Analysis of Adaptation to Climate Variability and Change in Uganda: A Gender and Household Welfare Perspective*. https://doi.org/10.1016/0375-9601(73)90015-7

Hisali, E., Birungi, P., & Buyinza, F. (2011). Adaptation to climate change in Uganda: Evidence from micro level data. *Global Environmental Change*, *21*(4), 1245–1261. https://doi.org/10.1016/j.gloenvcha.2011.07.005

IPCC. (2018). *Summary for policymakers. In Global Warming of 1.5°C: An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty.* [Allen, M. R., Babiker, M., Chen, Y., de Coninck, H., Connors, S., van Diemen, R. & Zickfeld, K (eds.)]. Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press.

Kabubo-Mariara, J., Mulwa, R. M., & Falco, S. di. (2017). Adaptation to climate change and variability and its implications for household nutrition in Kenya. *Environment for Development Discussion Paper - Resources for the Future (RFF)*, *17*, 29–35. http://www.rff.org/files/document/file/EfD DP 17-05.pdf

Kontgis, C., Schneider, A., Ozdogan, M., Kucharik, C., Tri, V. P. D., Duc, N. H., & Schatz, J. (2019). Climate change impacts on rice productivity in the Mekong River Delta. *Applied Geography*, *102*(December 2018), 71–83. https://doi.org/10.1016/j.apgeog.2018.12.004

Mendelsohn, R. (2012). The Economics of Adaptation to Climate Change in Developing Countries. *Climate Change Economics*, *03*(02), 1250006. https://doi.org/10.1142/S2010007812500066

Mottet, A., Henderson, B., Opio, C., Falcucci, A., Tempio, G., Silvestri, S., Chesterman, S., & Gerber, P. J. (2017). Climate change mitigation and productivity gains in livestock supply chains: insights from regional case studies. *Regional Environmental Change*, *17*(1), 129–141. https://doi.org/10.1007/s10113-016-0986-3

Mubiru, D. N., Radeny, M., Kyazze, F. B., Zziwa, A., Lwasa, J., Kinyangi, J., & Mungai, C. (2018). Climate trends, risks, and coping strategies in smallholder farming systems in Uganda. *Climate Risk Management*, *22*(August), 4-21.

https://doi.org/10.1016/j.crm.2018.08.004

Mwaura, F. M., & Okoboi, G. (2014). *Climate Variability and Crop Production in Uganda*. *7*(2), 159–172. https://doi.org/10.5539/jsd.v7n2p159

Mwungu, C. M., Mwongera, C., Shikuku, K. M., Acosta, M., Ampaire, E. L., Winowiecki, L. A., & Läderach, P. (2019). *Household Welfare Effects of Stress- - Tolerant Varieties in Northern Uganda*. https://doi.org/10.1007/978-3-319-92798-5

Nabikolo, D., Bashaasha, B., Mangheni, M., & Majaliwa, J. (2012). Determinants of climate change adaptation among male and female headed farm households in eastern Uganda. *African Crop Science Journal*, *20*(2), 203–212.

Nuwagaba, A., & Namateefu, L. K. (2013). Climatic Change, Land Use and Food Security in Uganda: A Survey of Western Uganda. *Journal of Earth Sciences and Geotechnical Engineering*, *3*(2), 61–72.

Sabiiti, G., Prediction, I. C., Centre, A., Ininda, J., Ogalo, L., & Ouma, J. (2018). *Limits to Climate Change Adaptation*. *January*. https://doi.org/10.1007/978-3-319-64599-5

Shikuku, K. M., Winowiecki, L., Twyman, J., Eitzinger, A., Perez, J. G., Mwongera, C., & Läderach, P. (2017). Smallholder farmers' attitudes and determinants of adaptation to climate risks in East Africa. *Climate Risk Management*, *16*, 234–245. https://doi.org/10.1016/j.crm.2017.03.001

Skoufias, E., Rabassa, M., & Olivieri, S. (2011). *The poverty impacts of climate change: A review of the evidence*. *April*. https://doi.org/10.1596/1813-9450-5622

Smit, B., & Pilifosova, O. (2001). *Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Chapter 18: Adaptation to climate change in the context of sustainable development and equity*. 36. https://doi.org/10.1103/PhysRevD.87.106003

Smit, L. C. B. (2016). Climate change, food security, and livelihoods in sub-Saharan Africa. *Regional Environmental Change*, 385-399. https://doi.org/10.1007/s10113-015-0761-x

UBoS. (2018). *Uganda National Statistical Abstracts 2018.* Kampala, Uganda. Uganda Bureau of Statistics (UBOS).

World Bank Group. (2016). World Bank Group Climate Change Action plan 2016-2020. *World Bank Group*. https://doi.org/10.1111/1467-8322.12302

Wulf, K. (2008). Climate Change and Food Security: A Framework Document. Food and Agriculture Organization of the United Nations Rome, 2008. *Food and Agriculture Organization of the United Nations Rome, 2008*, 93. http://rstb.royalsocietypublishing.org/content/360/1463/2139.short

CHAPTER TWO

CLIMATE VARIABILITY AND AGRICULTURAL PRODUCTIVITY IN UGANDA

2.1.0 Introduction

2.1.1 Background to the study

The nexus between variations in climate and agriculture continues to arouse debate across the globe among different stakeholders including scholars. It is predicted that climate change is expected to impact agricultural productivity in developing nations, where the majority of farming households are involved in rain-fed agricultural activities (Kahsay & Hansen, 2016; Huong et al., 2018; IPCC, 2018; Kontgis et al., 2019). The impact may be less felt in developed countries due to their capacity to quickly forecast and adapt to the vagaries of changes in climate, technology, and appropriate safety nets for their citizens to rely on other than agriculture (Mubiru et al., 2018). For developing countries such as Uganda, where 68 percent of farming households are engaged in traditional subsistence farming (UBoS, 2018), variations in climate might have a substantial impact not only on agricultural yields but also on their productivity (Mwaura & Okoboi, 2014).

This is because climate variability is likely to intensify the occurrence of extreme precipitation conditions, prolonged dry seasons, and floods (Banerjee et al., 2019), which greatly influences agricultural outcomes especially in subsistence agriculture (Lee et al., 2012; Sheng & Xu, 2019). Thus, appreciating the impact of variability of climate on agricultural productivity is important to back up the making of policies that stimulate the implementation of long-term adaptation mechanisms (Reed et al., 2017; Huong et al., 2018). This also facilitates the assessment of the degree of vulnerability of the country's economy as well as the farming households and their dependents to variability in climate and its associated effects. It also fits well in the planning aspirations of the farmers, government and all those stakeholders engaged in agricultural activities.

Despite its declining GDP share, the agricultural sector is still Uganda's economic backbone and the chief employer of most Ugandans (World Bank, 2019). The sector employs around 70 percent of the country's total labour force, contributes around 25% to GDP, and accounts for about 45% of the country's total exports (UBoS, 2017). Agriculture as a sector, therefore, has the potential to steer Uganda's development agenda, as outlined in the country's vision 2040 and the corresponding National Development Plans (I, II, III[6] - NPA, 2015). It provides opportunities for economic inclusion, especially for women and youth, who are the main participants in the sector (UBoS, 2018). However, the sector remains vulnerable to climate shocks such as prolonged drought and unreliable rainfall, as it largely depends on natural conditions (Mwaura & Okoboi, 2014; Abidoye et al., 2017).

In addition, farming households in the subsistence sector lack adequate capacity, timely climate and weather forecast information, skills, and resources required to mitigate or adapt to climate variability (Guloba, 2014). Thus, it is vital to comprehend climate variability effects on the productivity of Uganda's agricultural sector to generate evidence to design appropriate measures to minimise and mitigate its risks. Failure to do so may expose farming households to food insecurity and poverty, given the inadequate non-farm opportunities, especially in rural Uganda coupled with the rising population size (Mwaura & Okoboi, 2014; Ochieng et al., 2016).

Uganda's government designed and started the implementation of the National Adaptation Plan for the Agricultural Sector (NAP-Ag) in 2018 (Adade et al., 2019; Mubiru et al., 2018). This was largely aimed at minimising the effects of variability in climate on farmers across the country (MAAIF, 2018). It was done in response to increasing instances of intense and prolonged dry spells in some areas of the country, droughts, floods, rise in temperature and increased incidences of pests and diseases caused by the climate variability in the country (Mubiru et al., 2018; UBOS, 2019). In addition, Uganda's agricultural sector performance has been varying over time (UBOS, 2018; World Bank, 2019).

Climate variability in Uganda is largely attributed to the continuous destruction of the environment and nature by human activities such as deforestation[7], and use of poor farming techniques by some farmers (Abid et al., 2016; UBOS, 2019). Other causes include increasing industrialization in the country, poor disposal of plastics and polythene bags, increasing electronic wastes, and oil exploration activities in the Albertine region (MoWE, 2012; IPCC, 2018).

[6]These are five-year national development plans, designed in line with the country's vision 2040 (NPA, 2015). The country is currently implementing the National Development Plan (NDP) III (2020 – 2025).
[7]Uganda's forest cover has decreased drastically since independence, from 42% in 1962 to about 9% in 2016 (UBoS, 2018) largely due to the need for more land for agriculture, settlement, and industrialisation.

Several scholars have studied the effects of variability of climate on agriculture throughout the world including Africa and East Africa in particular. Among them include Alam et al. (2014), Kontgis et al. (2019), Ludena & Mejia (2012), Mamane & Malam (2015), Mendelsohn (2011), Mendelsohn & Nordhaus (2010), Mottet et al. (2017) and Mwaura & Okoboi (2014) among others. Majority of these studies have been conducted in developed countries although they are currently on an increase in developing nations including African states (Kabubo-Mariara et al., 2016). This shows the value attached to analysing the effect of variability of climate on agriculture by various stakeholders, governments, and scholars all over the world. Additionally, most of these studies (see for instance Mendelsohn & Nordhaus, 2010; Mottet et al., 2017) have largely concentrated on analysing climate variability impacts on agricultural yields and incomes as opposed to analysing agricultural productivity implications of climate variability. Impacts of climate variability are likely to vary across countries, regions and from one crop to another and thus the need for a Ugandan specific study.

2.1.2 Problem Statement

Uganda is already experiencing extreme meteorological conditions including prolonged dry seasons, altered planting seasons, floods, landslides, altered rainfall patterns and strong winds. While these climatic events might increase yields of some crops or productivity in some areas of the world, on average, climate variability is anticipated to affect the agricultural sector negatively especially in developing countries like Uganda due to limited adaptation capacity and over reliance on nature.

So far, lack of an in-depth and a countrywide study that combines household level and long-term climate data to analyse the effect of variability of climate on productivity of agriculture has curtailed the decision-making and planning process among the farming households, government, and other participants in the sector. This study fills these gaps by estimating the total factor agricultural productivity function derived from the stochastic production function in a panel setting at national level, regional level and for the four crops commonly grown in Uganda – maize, beans, banana, and cassava.

2.1.3 Objectives of the Study

The major objective of this chapter is to evaluate the effect of variability in climate on agricultural productivity in Uganda. The specific objectives of the study include:

(i) To analyse the effect of the variability of climate on agricultural productivity in Uganda.

(ii) To assess the effect of non-climatic factors on the productivity of agriculture in Uganda.

2.1.4 Contributions of the study

This study makes three key contributions to literature. First, existing studies in Uganda on the subject matter (see for instance Mwaura & Okoboi, 2014) used time series data to analyse the effect of climate variability on the productivity of agriculture and thus did not take into consideration the institutional and household characteristics which are cross-sectional in nature. Any study on agriculture, given its complexities, demands detailed considerations of socio-economic, institutional, and household specific factors. Omitting these factors in the analysis may lead to biased, inconsistent and inefficient model estimates (Green, 2012; Baltagi, 2013), leading to misleading policy conclusions. Others such as Orlove et al. (2010), Egeru (2012) and Shikuku et al. (2017) combined climate data with household cross section data in investigating the effect of climate variability on agriculture, but they were limited in scope and focus. Their climate data covered a shorter period and only covered specific areas and not the entire country.

In addition, the studies did not examine agricultural productivity concerns due to climate variability. In this case, therefore, their study findings may not depict the true picture of variability of climate impacts on agricultural productivity in the entire country. To overcome these shortcomings, this paper takes into consideration the social economic, household, and institutional factors combined with long-term historical climate data for over 30 years and covers the entire country. In addition, the study estimates total factor productivity derived from the stochastic production function. This accurately measures the farming household performance that is not due to inputs but other factors. Hence, the findings from this study provide crucial information for designing policies aimed at accelerating agricultural productivity even in the presence of climate variability across the country. Improving agricultural productivity is timely, given that agriculture is identified as the leading engine for poverty eradication especially among Uganda's rural population and the farmers (NPA, 2015).

The second contribution of this paper is that unlike other previous studies such as Mwaura & Okoboi (2014), this chapter extends the national analysis to regional and crop specific analyses for the four crops - maize, beans, cassava, and banana which are grown in all regions of Uganda. Through this kind of analysis, this study identifies which region and crop is more vulnerable to variabilities in climate and thus proposes measures that are both region and crop specific, necessary to improve productivity of agriculture in the presence of variability in climate.

The last contribution of the paper is on methodology used. The paper uses the total factor productivity approach to identify the effect of climate variability on the overall productivity of the agricultural sector and the selected common crops grown in Uganda. This is novel for Uganda as the existing studies have either used descriptive statistics to analyse cross-section survey data collected in a specific region for example Mubiru et al. (2018) in Karamoja region or simply estimated the production function using standard time series such as Mwaura & Okoboi (2014). Estimating a total factor productivity function using panel data solves the challenges faced by the traditional Ricardian model such as failure to cater for the time component of climate variables, non-stability of the model estimates and measurement errors (Massetti & Mendelsohn, 2011). In this chapter, the study combines six waves of the UNPS collected by Uganda Bureau of Statistics (UBOS) over ten years with the historical climate data (1979 – 2019) inserted at the level of the household using the household GIS information contained in the UNPS data. Studies of such nature are not common in Uganda as most of the previous studies have concentrated mainly on analysing climatic trends and people’s opinions on climate change (see for instance Egeru, 2012).

2.1.5 Structure of the chapter

Chapter two of this study is organised in the following way. In the next section, relevant literature on the link between variability in climate and agricultural productivity and the resulting gaps are discussed. This is followed by a methodology section that explains the methods and procedures employed to achieve the study objectives. In section four, the empirical results and their interpretations are discussed and finally, section five summarises the entire chapter with conclusions, recommendations for policy formulation and potential areas for further research.

2.2.0 Literature Review

2.2.1 Theoretical Literature

Nature dependent sectors including agriculture are quite sensitive and prone to climate variability (Wulf, 2008; Wang et al., 2009; Mendelsohn & Massetti, 2017). This is largely because agriculture involves natural processes that require fixed amounts of nutrients, temperatures, and precipitation for proper growth of both crops and animals (Vuren et al., 2009; Gornall et al., 2010; Mamane & Malam, 2015). According to Nastis et al. (2012), Limantol et al. (2016) and Ali & Erenstein (2017), climatic attributes that are anticipated to have a direct effect on productivity of agriculture include variability in temperature and changes in the occurrence and intensity of precipitation levels such as rainfall. Others are variability in incidences of extreme weather conditions (for example prolonged dry seasons, water overflows, and landslides), and changes in carbon dioxide (CO_2) levels available for plant photosynthesis process.

It has been established in the literature that crop production varies strongly with variability in temperature, wind and rainfall amounts received in each area (Baya et al., 2019; Sheng & Xu, 2019). However, this relationship depends on the crop type and the location where the crop is grown (Ayinde et al., 2017; Rötter et al., 2018). Altered rainfall patterns not only affect crop growth but also decrease the amount of water available for irrigation by some farming households (Mwangi & Kariuki, 2015; Arshad et al., 2017). Variations in temperature and moisture levels indirectly affect crops' capacity to absorb manure and other soil reserves that are key in influencing crop output and thus productivity (Cotter et al., 2010; Alam et al., 2014). Variability in climate is thus likely to influence the kinds, incidences, and occurrences of crop pests and diseases; affect accessibility, timing, and availability of water for irrigation; and increase cases of soil erosion (Ochieng et al., 2016; Arslan et al., 2017; MAAIF, 2016).

Climate variability is projected to increase yields of some crops (Debaeke et al., 2017; Seo & Mendelsohn, 2008) – for instance, by increasing the regularity and amount of rainfall in some areas, thereby lengthening crop seasons. Rising concentrations of carbon dioxide caused by variability of climate can raise the productivity of the agro-ecosystems – but also vice versa (Wang et al., 2009). However, the global effect of variability in climate on productivity is projected to be negative in the aggregate terms, and the negative impact will be borne more in developing countries (Ayinde et al., 2017; Huong et al., 2018; Kontgis et al., 2019; Kumar et al., 2016; Sheng & Xu, 2019; Silvestri et al., 2012; Urgessa, 2015). This paper, therefore, establishes the actual effect of variability in climate on Uganda's agricultural productivity and selected crop yields.

There are basically three methods used to analyse the impact of climate changes on productivity of agriculture - the agronomic models, the Ricardian models, and the stochastic production function models (Salvo et al., 2013; Zhang et al., 2017). Agronomic models are biophysical models that integrate soil, plants, and climate processes to evaluate the impact of climate changes on productivity of agriculture (Jones et al., 2017). These models are mainly based on simulation experiments and remote sensing and not necessarily on theory or raw data (Arshad et al., 2018). Agronomic models, however, neglect the economic dimensions of the effect of variability in climate on productivity of agriculture (Salvo et al., 2013).

Stochastic production functions on the other hand assume that yields from agriculture are a function of climate and soil related variables (Kumar et al., 2016). Climate and soil factors are considered as explanatory variables in the empirical estimation of the agricultural production function (Ochieng et al., 2016). In this method, the economic factors are not highly regarded but are included in the analysis (Salvo et al., 2013). The main shortcoming of this approach is that it is mainly suitable for crop and locational specific studies and does not cater for probable adaptation mechanisms that farming households can adopt as a way of dealing with variability in climate and its effects (Mendelsohn et al., 1996; Kabubo-Mariara & Karanja, 2007). To solve these shortcomings, Mendelsohn et al. (1994) proposed a Ricardian approach.

The Ricardian approach of estimating climate variability – agriculture nexus is based on the proposition that rents from land show the anticipated agricultural productivity (Ricardo, 1817). The approach therefore investigates how the observed cross-sectional changes in land values (or net revenues from land investments such as agriculture) are caused by changes in climate and other variables including adaptation mechanisms, for example, irrigation (Mendelsohn, 2014; Salvo et al. 2014). The Ricardian approach is credited for taking into consideration the farming households' ability to adapt[8] (Nelson et al., 2010; Bozzola et al., 2018). However, the cross-sectional Ricardian model estimates have been criticised for being unstable over time (Greenstone & Deschenes, 2011;

[8] In Ricardian estimation, adaptation measures such as irrigation can be included in the model.

De Salvo et al., 2014). However there have been modifications to estimate the Ricardian model with panel data (Luis & Orlando, 2015; Massetti & Mendelsohn, 2011; Abidoye et al., 2017).

2.2.2 Empirical Literature

Existing related empirical studies on the impact of variability in climate on productivity of agriculture can be distinguished based on analytical methods used (Salvo et al., 2013). For example, Kabubo-Mariara & Karanja (2007), studied the economic effects of climate variability on crop agriculture in Kenya, using a seasonal Ricardian model and a crop simulation model in 38 out of 46 former districts and now counties of Kenya. The study used several data types including long-term precipitation and temperature seasonal averages; long-term monthly average hydrological data; soil types and, cross-sectional household survey. Their findings indicate that variability in climate impacts on crop revenues, with a rise in winter (June-August) temperatures leading to increased crop revenues while a rise in summer (March-May) temperatures contributing to a reduction in crop revenues. Their study further uncovers a non-linear impact of climate (temperature and precipitation) change on crop revenues. Their findings corroborate with those of some earlier studies such as Abidoye et al. (2017) and Kurukulasuriya & Mendelsohn (2017).

However, studies that use traditional Ricardian approach and rely only on cross-sectional data have been criticised on the grounds that their estimated coefficients are unstable over time (Massetti & Mendelsohn, 2011). This led to the modification of the traditional Ricardian approach to one that is estimated using panel data (Luis et al., 2015; Kabubo-Mariara et al., 2016; Massetti & Mendelsohn, 2011). For example, Luis et al. (2015) estimated a Ricardian model with panel data in Mexico to establish the impact of variability in climate on agricultural activities. The study found out that farms that depend on irrigation are vulnerable to variability in temperature while rainfed farms are prone to precipitation changes and adverse climatic events such as floods. This study however, based its analysis only on farm revenues and ignored productivity concerns that are of more interest given the rising population – land ratio. On the other hand, Kabubo-Mariara et al. (2016) concentrated on food and nutrition security. Therefore, this chapter addresses these gaps by focusing on productivity impacts of climate variability in Uganda using panel data and estimating a total factor productivity derived from the estimated stochastic production function.

The second category consists of those studies that have applied crop simulation models. An example is a world study by Rötter et al. (2018) and Oort & Zwart (2018). Rötter et al. (2018) analysed the impact of variability in climate on five crops - maize, rice, wheat, potatoes, and vegetables. The study found out that changes in climate result in reduced yields for all the five crops and yet these are key food crops consumed globally. The study further predicted that the trend would worsen by the year 2050 across the world if nothing is done currently to tame the varying climate and its effects. However, the key limitation of Rötter et al.'s study and other studies that use crop simulation models such as Oort & Zwart (2018) is that they base their analysis only on simulated data obtained using assimilation methods grounded on cross section models and remote sensing instead of real data estimated using economic models. For more robust and concrete evidence to guide accurate policy formulation, cross-sectional simulation models need to be combined with models that are based on economic theories and principles.

The third category of the existing similar empirical studies involve those that have estimated stochastic production functions in the form of Cobb-Douglas production function. These include among others Nastis et al. (2012), Ademe et al. (2017), Kumar et al. (2016) and Geng et al. (2019) among others. For instance, Nastis et al. (2012) estimated a production function using secondary time series data and Ordinary Least Squares (OLS) with Newey-West standard errors for twenty-eight years (1980-2007) in Greece. The findings of their study indicated that variability in both temperature and precipitation negatively affects agricultural yields. However, this study omitted the social economic household and farm specific characteristics in their analysis. Omission of such variables might cause a problem of endogeneity that affects the accuracy and validity of the model estimates (Greene, 2012). On the other hand, Kumar et al. (2016) assessed the effect of climate variations on productivity of land considering main food and non-food crops in India using panel data collected over thirty years from 1980 to 2009 for 15 crops in 13 key agricultural states of India. The results show that productivity of land reduces with a rise in the yearly mean maximum temperatures. Using simulations, they projected a decrease in land productivity of 48.6% by the year 2100 that will greatly affect farmers' crop productivity and their income levels.

Similarly, Geng et al. (2019) applied a structural Cobb-Douglas production function and secondary time series data from 1981 to 2016 to investigate the effect of variations in climate on wheat yields in Northern China during winter season. The study found out that a rise in temperature impacts negatively on per unit wheat harvested. However, the study only concentrated on one element of climate variability (temperature) and only one crop ignoring other dimensions of variability in climate including changes in rainfall and other crops that equally can be affected by the varying climate. Secondly, the study only focused on one region of China thus its findings cannot be generalised across China. In addition, as noted by Aydinalp and Cresser (2008) and Ayinde et al. (2011), agricultural productivity effects of variability in climate might vary across the world and thus called for the country specific studies investigating the impact of variability in climate on agriculture, since the impact might depend largely on the existing local conditions.

In Uganda, Mwaura & Okoboi (2014) analysed time-varying ARCH approach to investigate the impact of variability in climate on Uganda's production of crops. The paper established that variations in temperature and rainfall from their long-run averages (climate variability) significantly affect crop yields with an exponential rise in rainfall having the largest negative impact on Uganda's crop yields. The study, however, did not consider the socio-economic, household, and institutional factors and yet this is the only nationwide study on the subject matter in Uganda. Previous studies for example Egeru (2012), Nabikolo et al. (2012 and Shikuku et al. (2017) did not cover the whole country and largely used descriptive statistics and trend analysis in their analysis. In addition, these studies ignored productivity concerns and instead concentrated on crop yields. These gaps are what this study addresses by using a nationally representative data set to investigate the climate variability implications on Uganda's agricultural productivity.

2.2.3 Summary of the Literature

From the review of the related literature, there are two arguments on the likely effect of variability in climate on productivity in agriculture. The first argument is that variability in climate might result in a rise in yields of some crops (Debaeke et al., 2017; Seo & Mendelsohn, 2008). For example, Debaeke et al. (2017) argue that variability in climate will increase the regularity, patterns, and amount of rainfall in some areas by lengthening crop seasons leading to high crop yields. However, the study is silent on agricultural productivity effects of climate variability. The second argument which is more popular in the literature stipulates that variability in climate will impact agriculture negatively (for example see Ayinde et al., 2017; Huong et al., 2018; Kontgis et al., 2019; Kumar et al., 2016; Sheng & Xu, 2019; Silvestri et al., 2012; Urgessa, 2015 among others). Ayinde et al. (2017) and Huong et al. (2018) project that, the negative effects are likely to be more felt in the less developed countries due to over dependence on nature for their agricultural activities, limited non-farm activities and lack of adequate capacity to invest in adaptation and mitigation mechanisms, although the impact might vary from one country to another. However, in Uganda, such studies are still at an infancy stage and scarce, yet agriculture accounts for over 70% of the working labour force and is the backbone of the economy. The few existing studies have either covered a smaller part of the country (for example see Egeru, 2012) or have not used household level data (such as Mwaura & Okoboi, 2014). The present study thus addresses these gaps in the existing literature by focusing on productivity as opposed to output, on a countrywide basis, over time and includes some adaptation mechanisms adopted.

2.3.0 Methodology

2.3.1 Theoretical framework of the study

This chapter estimates the Total Factor Productivity (TFP) derived from the stochastic Cobb – Douglas production function (Saliola & Bank, 2012; Sheng & Xu, 2019; Smith, 2019). Given that climate variability is not a direct input of agricultural production process, estimating total factor productivity function is the appropriate framework to establish the impact of variability in climate on Uganda's productivity of agriculture (Islam et al., 2016; Kumar et al. (2016). This is because total factor productivity establishes how efficiently and intense the factor inputs are utilised in the production and thus, it is a better measure of productivity (Şeker & Saliola, 2018; Sheng & Xu, 2019).

Consider a Cobb – Douglas production function below:

$$Y = AK^{\alpha}L^{\beta}Z^{\theta} \quad \dots \dots \dots (3.1)$$

Where Y is the total agricultural output, A is the intercept which is a measure of productivity. K is capital input, L is labour input while Z is land input. α, β and θ are input elasticities.

Total factor productivity (A) which is described as the ratio of total output to weighted input index is therefore estimated using the following formula:

$$A = \frac{Y}{K^{\alpha}L^{\beta}Z^{\theta}} \quad \dots \dots \dots (3.2)$$

Taking natural logs on both sides of equation (2) yields:

$$lnA = lnY - (\alpha lnK + \beta lnL + \theta lnZ) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (3.3)$$

Introducing time dimension gives:

$$lnA_t = lnY_t - (\alpha lnK_t + \beta lnL_t + \theta lnZ_t) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (3.4)$$

Taking first difference gives the total factor productivity as:

$$\frac{A_t - A_{t-1}}{A_{t-1}} = lnA_t - lnA_{t-1} = \frac{Y_t - Y_{t-1}}{Y_{t-1}} - \left(\alpha \frac{K_t - K_{t-1}}{K_{t-1}} + \beta \frac{L_t - L_{t-1}}{L_{t-1}} + \theta \frac{Z_t - Z_{t-1}}{Z_{t-1}}\right) \ldots (3.5)$$

Econometrically, this can be estimated as:

$$lnlnY_t = \hat{\alpha} lnK_t + \hat{\beta} lnL_t + \hat{\theta} lnZ_t + \hat{\gamma} t + \varepsilon_t \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (3.6)$$

$\hat{\gamma}$ gives total factor productivity (TFP)[9] estimates. The obtained estimates are thus used as the dependent variable for assessing the impact of climate variability on agricultural productivity.

Following other studies such as Muendler (2004), Şeker & Saliola (2018) and Sheng & Xu (2019), total factor productivity (TFP) is a function of climate factors (C), household factors (H), social economic factors (S) institutional factors (I) and Locational factors (G). Putting these together yields a theoretical model for the study as follows:

$$TFP = f(C, H, S, I, G) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (3.7)$$

3.3 Empirical model and estimation procedure

Following the theoretical model and other earlier studies such as Muendler (2004) and Sheng & Xu (2019), the empirical model is specified as:

$$TFP\ (\hat{\gamma}) = \alpha_0 + \alpha_1 C_{it} + \alpha_2 H_{it} + \alpha_3 S_{it} + \alpha_4 I_{it} + \alpha_5 G_{it} + u_{it} \ldots \ldots \ldots \ldots \ldots (3.8)$$

Where C is a vector of climate factors, H is a vector of farming household inputs, S is a vector of social economic factors, I is a vector of institutional factors and G are locational factors (residential and regional location). A quadratic specification for variability in precipitation and temperature

[9] TPF was calculated from the residuals of the estimated standard Cobb-Douglas total agricultural production function. Total agricultural output is provided by Uganda Bureau of Statistics (UBOS).

terms caters for the non-linearity and extreme impacts of variability in climate (Mendelsohn & Massetti, 2011; Bozzola et al., 2018).

Next, precipitation variability is interacted with availability of extension services to test whether extension services empower households to overcome climate variability challenges over time.

$$TTF\ (\hat{\rho})_{it} = \alpha_0 + \alpha_1 Temp_{it} + \alpha_2 Ppt_{it} + \delta_1 {T^2}_{it} + \delta_2 {Ppt_{it}}^2 + \alpha_3 H_{it} + \alpha_4 I_{it} + \alpha_5 (Ppt_{it} * Ext_{it}) + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.9)$$

Where Ext_{it} represents availability of extension services to household i at time t.

This model is estimated using the two panel data models of fixed effects and random effects. To select between fixed effects and random effects, the Hausman specification test is used with the null hypothesis – random effects is the preferred model (Baltagi, 2013). The results are also compared with those from pooled OLS. The study corrects errors for potential heteroskedasticity and tests for multicollinearity using Observed Information Matrix (OIM).

The paper further estimates models for each region and for the four commonly grown crops - maize; beans; cassava and banana. These crops were selected because they are the common crops grown by the majority of Ugandans and across all regions of the country (UBOS, 2017, 2018).

3.4 Study Variables

Dependent Variables: The main dependent variable of the study is Total Factor Productivity (TFP) which is defined as a fraction of output that is not caused by the amount of inputs used in the process of production (Şeker & Saliola, 2018; Sheng & Xu, 2019). The same applies for regional and crop specific estimated models.

Independent Variables: Explanatory variables used in the analysis have been classified into three categories. Climate variability factors - precipitation and temperature – are in the first category. Household characteristics for example age, gender, marital status, size of the household, household head education level and location of the household fall in the second category. Institutional variables such as availability of extension services as well as access to market for crops are included in the third category.

Table 1: Definition and measurement of variables

Variable	Definition and measurement	Expected sign	Literature Source
Total factor Productivity	Measure of productivity	Dependen t variable	(Şeker & Saliola, 2018; Sheng & Xu, 2019).
Climate Variability			
Precipitation Variability	Coefficient of variation of precipitation for a period of at least 30 years.	**+/-**	Alem, et al., (2010) and Arshad et al., (2018)
Temperature Variability	Coefficient of variation for (Minimum and Maximum) Temperature for a period of 30 years.	**+/-**	Arslan et al. (2017); Nkegbe & Kuunibe (2014).
Household Characteristics			
Household head Age	Complete years	+	Guloba (2014); Hisali et al., (2011)
Household head Education level	Number of years of school	+/-	Kabubo-Mariara & Mulwa (2019); Reed et al. (2017)
Gender of household head	Dummy 1 = Male, 0 otherwise	+	Ademe et al. (2017)
HH head Marital status	Dummy 1 = Married, 0, Otherwise	+/-	Zhang & Chen (2017)
HH equipment value	In Uganda shillings, a measure of capital input.	+	Kumar et al. (2016)
Household size (labour)	Number of people in the household, a measure of labour input	+/-	Luis & Orlando (2015)
Location of a household	Dummy 1 = Urban, 0, Otherwise	-	Shikuku et al. 2017) Van Passel et al. (2017)
Institutional factors			
Extension services	Dummy 1 = Available, 0 otherwise	+/-	Baya et al. (2019)
Access to Market	Dummy 1 = Yes, 0 otherwise	+	Zhang & Chen (2017)

2.3.5 Data Sources

The study uses long-term daily climate data (1979-2013) obtained from the United States National Oceanic and Atmospheric Administration (NOAA)[10]. This data set has been credited for producing accurate climate observations over time (Massetti & Mendelsohn, 2011; Bozzola et al., 2018). In this chapter, data on climate are converted first to monthly data and then to annual data before getting the coefficients of variation for both precipitation and temperature. The study relies on the coefficient of variation of each climate variable as a measure of variability. Information on household and institutional factors was obtained from the Uganda National Panel Surveys spanning a period of 10 years from 2009 to 2019.

Total agricultural output is obtained from the summation of all major crop yields that are captured by Uganda Bureau of Statistics (UBOS) after standard conversion into one unit of measurement. These data sets are nationally representative, and the study utilises six waves of UNPS (2009/10, 2010/11, 2011/12, 2013/14, 2015/16 and 2018/19) with each covering on average 2,500 households, giving a total pool of about 15,000 observations. This data set is large and reliable enough to ensure precision of the model estimates. The data on climate are matched with data at the household[11] level using household GPS information as provided in the UNPS data sets.

2.4.0 Empirical Findings

2.4.1 Descriptive Statistics

Figure 2 below shows an increasing trend of both average precipitation and temperature is noticeable with the annual increase in average temperature being much smaller than that of average precipitation. A similar trend on Uganda's climate was established by Lazzaroni (2012) and Guloba (2014) who also found an upward trend in Uganda's climatic variables of precipitation and temperature. However, although average rainfall amounts are rising, the pattern is unreliable, altered and is unevenly distributed across the country (Egeru, 2012; UBOS, 2018). In figure 3, both precipitation and temperature vary as shown by the three-line graphs and a non-zero coefficient of variation. The trend analysis across the various regions of the country between 1978

---

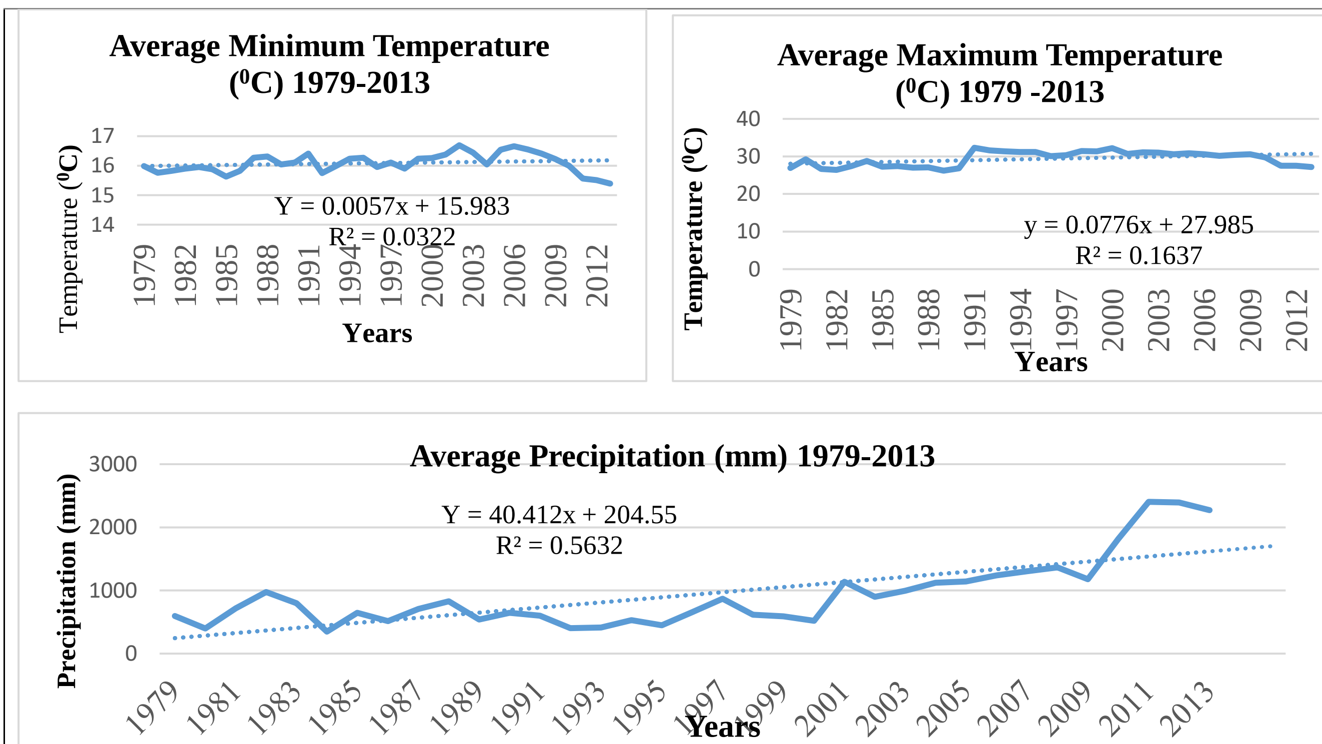
[10]More information on this climate data is available at http://www.esrl.noaa.gov/psd. The climate data is made available by NOAA/OAR/ESRL PSD, Boulder, Colorad USA.

[11]All households without GPS coordinates and those who did not farm any crop were dropped from the data set.

and 2014 are shown in the maps (see Figures A1, A2 and A3 in appendix). The trends clearly support the existence of climate variability in all parts of the country over the period under analysis.

For precipitation variability, the coefficient of variation ranges between 0.3 and 1.3. Extreme variability in precipitation is observable in areas of Karamoja, Southwestern (Kigezi and Kasese) and Albertine regions of Uganda, with the highest variability in precipitation experienced in Karamoja region between 1981 and 2013. The coefficient of variation ranged between 1.00 and 1.60 in the Karamoja region during this period. No area has precipitation coefficient of variation below 0.1 (the threshold), hence confirming precipitation variability in Uganda (Arshad et al., 2017). High variability in temperature was experienced in the areas surrounding Lake Victoria (Wakiso, Mpiji and Mukono) and the Kabaale areas in Southwestern Uganda. This has been largely attributed to the changing rainfall patterns, swamp reclamation and deforestation in these areas (Egeru, 2012; Guloba, 2014). For the rest of the country, the variability ranged between 0.01 and 0.18. Variability in maximum temperature is slightly lower than that of minimum temperature although an overall non-uniform trend in temperature variability across the country is observable.

Figure 2: Trend analysis of the Uganda's historical climate variables from 1979 to 2013



Source: Author's own Calculations based on Global Weather Data downloaded from NOAA (2019)

The summary statistics for all study variables used in this study are presented in table 3 below.

Table 2: Summary Statistics

Study Variables	**Mean**	**Std. Dev.**	**Min**	**Max**
Total Factor Productivity	2.99	3.57	1.72E-06	36.81
Precipitation Variability	0.33	0.17	0.002	1.55
Minimum Temperature Variability	0.05	0.02	0.02	0.19
Maximum Temperature Variability	0.08	0.01	0.05	0.16
Access to extension services	0.44	0.50	0	1
Access to credit	0.81	0.40	0	1
Household head Age	48.42	15.01	14	100
Gender of HH head (1 = male)	0.70	0.46	0	1
Location (1 = urban, 0 = rural)	0.13	0.33	0	1
Marital status (=1 Married)	0.74	0.44	0	1
Education (Years of education)	5.34	3.82	0	17
Household size (Labour Input)	11.09	13.02	1	72
Household Asset (Capital Input)	48039.78	252531.4	0	16700000

Source: Author's calculations based on UNPS data sets (2009-2019) and World climate data

The summary statistics show that climate variability variables (precipitation and temperature) have non-zero mean implying that indeed there is existence of variability in climate as earlier shown in the trend analysis (Figure 2). On average, farming household heads in the data set had reached a minimum of five years of education, an equivalent of some primary education. Many of the farmers (56%) were not accessing agricultural extension services given that only 46% had access to extension services. This is of great concern given the importance of extension services in agriculture and their perceived role in empowering farmers to improve their productivity and build resilience against climate variability and its effects (Lazzaroni, 2012). Hence the need for more efforts by the government to provide extension services through the ministry of Agriculture, Animal Industry and Fisheries. 81% of the households had access to the market for their crop products. The statistics also show that a greater number of the farming household heads (76%) were married with 70% of the households being male headed.

2.4.2 Empirical results

The study starts by estimating the stochastic Cobb-Douglas production function to derive the total factor productivity. Total Factor Productivity (TFP) refers to the part of output growth that is not accounted for by input growth (Sheng & Xu, 2019). It shows the change in output made possible by the passage of time, holding input quantities constant. It is thus interpreted as the average rate of agricultural productivity change between periods t-1 and t. The results are presented in table 3 below.

Table 3: Estimated Stochastic Agricultural Production Function

Variables	Total Agricultural Output
Capital	0.25***
	(0.01)
Labour	0.00***
	(0.00)
Land	0.01***
	(0.00)
Time	-0.28***
	(0.01)
Constant	2.59***
	(0.15)
Observations	12,706
R-squared	0.08

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

Source: *Author's calculations based on UNPS data sets (2009-2019) and World Climate data*

The time estimates are now used as the dependent variable in the estimation of the total factor productivity model. In this estimation, all factor input measures or indicators are not included. The standard errors have been corrected for any suspected serial correlation and heteroscedasticity. The Observed Information Matrix results (Appendix 3) confirm the absence of multicollinearity among regressors. The chow test results indicate that the estimated models are statistically significant, implying that the included variables jointly explain changes in agricultural productivity as measured by total factor productivity. The Roy-Zellner test results shows that the error term is spherical implying that the random error term is uncorrelated with the model regressors (Baltagi, 2013). This thus confirms that our model estimates are robust, consistent, efficient, and thus reliable and valid for policy recommendations.

Table 4: Regression Results

Dependent Variable (Total Factor Productivity)	**Fixed Effects**	**Random Effects**	**Pooled OLS**
Precipitation variability	-4.22***	-4.14***	-4.14***
	(1.42)	(1.35)	(1.42)
Precipitation squared	2.24**	2.36**	2.36**
	(1.10)	(1.04)	(1.11)
Min temp variability	11.80*	13.61**	13.61**
	(6.67)	(6.43)	(6.19)
Minimum temp squared	-75.70	-92.30	-92.30*
	(59.59)	(57.40)	(54.17)
Max temp variability	-25.60*	-25.32*	-25.32
	(15.54)	(14.94)	(15.78)
Max temp squared	144.45	146.42*	146.42
	(92.62)	(88.90)	(95.18)
Household Age	-0.02	0.03	0.03
	(0.03)	(0.02)	(0.02)
Household Age Squared	-0.00	-0.00*	-0.00
	(0.00)	(0.00)	(0.00)
Gender of Household head (Male)	0.72***	0.22*	0.22
	(0.20)	(0.13)	(0.17)
Location (1 = urban, 0 = rural)	-0.62***	-0.77***	-0.77***
	(0.21)	(0.13)	(0.16)
Marital status (Married)	0.80***	0.59***	0.59***
	(0.21)	(0.14)	(0.18)
Education of household head (years)	0.10***	0.03**	0.03*
	(0.02)	(0.01)	(0.02)
Access to extension services	0.02**	0.02	0.02
	(0.03)	(0.23)	(0.25)
Access to market	0.06	0.05	0.05
	(0.07)	(0.07)	(0.07)
Precipitation variability*extension services	0.98**	0.84**	0.84**
	(0.42)	(0.40)	(0.42)
Constant	5.78***	3.73***	3.73***
	(1.14)	(0.87)	(0.95)
Observations	12,706	12,706	12,706
Number of Households	2,947	2,947	2,947
Haussman test (chi2(14))	101.83***		
Chow Test (F (2946, 9744))	3.91***		
Roy-Zellner Test	2018.02***		

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Source: *Author's calculations based on UNPS data sets (2009-2019) and World Climate data*

2.4.3 Discussion of results

The Hausman specification test results suggest that fixed effects model results are consistent with the data set. This is because the test statistic rejects the null hypothesis that the random effects model is the preferred model at 1% level of significance and hence only fixed effects model results are interpreted and discussed.

The results show a nonlinear significant link between precipitation variability and agricultural productivity in Uganda. This is because the coefficients of both the quadratic and the linear terms of precipitation are statistically significant. The coefficient of the linear precipitation variability term is negative and statistically significant while that of the squared term is positive and statistically significant. This finding implies that as the intensity of precipitation variability increases, the farmers' productivity starts to increase as well. The turning point is observed when the coefficient of precipitation variability is 1.88.

This U-shaped relationship between variability in precipitation and total agricultural factor productivity is consistent with the results of the earlier papers (such as Ademe et al., 2017; Baya et al., 2019; Mendelsohn, 2014; Abidoye et al., 2017). For example, Baya et al. (2019) argues that, as precipitation variability increases, farming households understand the weather changes and start to practice some measures aimed at copying up, sometimes unintended. Similarly, Ali & Erenstein (2017) note that, as climate continues to vary, farmers resort to early planting and sometimes, planting alternating crops that are tolerant to precipitation variability including construction of valley dams and other water catchment areas. This, just as our study findings, tend to imply that some farmers adapt to varying climatic conditions unknowingly (autonomous adaptation) while others adapt knowingly or intended (planned adaptation).

However, this study finding contradicts those of Lazzaroni (2012), who found a non-significant relationship between rainfall variability and agriculture in Uganda. Lazzaroni argued that the adverse effect of deviations in Uganda's rainfall levels was being offset by land productivity and thus the arguments in the literature that rainfall variability reduces agricultural productivity were being exaggerated. His findings were surprising given the over-reliance of Uganda's agricultural sector on natural conditions, with few farming households using irrigation as an alternative for rainfall variability and unreliability. However, his finding could be due to the time scope (one year) of the weather data used and the fact that the study only considered rainfall as opposed to precipitation that combines many components other than rainfall such as humidity, fog, and moisture, all these play a big role in influencing productivity of the agricultural sector. Our study findings also corroborate the predictions of Burgess et al. (2011) that variability in precipitation levels is expected to have a substantial adverse effect on productivity of agriculture in developing countries, which, like Uganda, are in the tropics, thus very sensitive to changes in climate.

The study uncovers a statistically weak significant impact of minimum and maximum temperature variability on productivity of agriculture in Uganda. The findings are mixed with the coefficients of variability in minimum temperature suggesting a weak positive impact while that of maximum temperature suggesting a weak negative impact. These findings tend to support those of Arslan et al. (2017) in Tanzania who established that changes in temperature only affects agricultural yields or productivity if the increasing temperature exceeds the threshold of crop-specific heat stress. These results further suggest that Uganda’s temperature is changing and thus measures should be devised to overcome the likely negative effects on agricultural activities, which until now is the largest employer of Ugandans and the main source of foreign exchange.

The study further investigates the impact of key selected household variables on productivity of the agricultural sector. This follows the argument by Hlahla et al. (2019) that the agricultural productivity effects due to climate variability are shaped by household specific and social economic factors, for example, the household head’s education level, measured by years spent at school and the location of the household. The results show that agricultural productivity increases with the education level of the household head. This corroborates the findings of the previous studies such as Seo & Mendelsohn (2008), Reed et al. (2017) and Sheng & Xu (2019) among others. Reed et al. (2017) argues that education is important in enabling farming households to adopt better methods of farming, correctly predict the climatic conditions, and thus plan accordingly, which in turn increases their productivity in comparison to the uneducated farmers. More so, education increases the probability of an individual getting a non-farm employment such as in the industrial and service sectors, unlike their counterparts, the uneducated, who have to depend on agricultural or nature-based activities. The study results further indicate that agricultural productivity is likely to be lower if the farming household is in an urban locality as opposed to being in a rural area. This contradicts the results of research done by Alam et al. (2014), who established that farmers in urban or peri urban areas tend to be more productive than those in rural areas. They argued that farmers in relatively urban areas use advanced farming methods and tend to practise intensive agriculture due to limited available farmland in urban areas, which is uncommon among rural farmers. For Uganda's case however, agriculture is largely a rural based sector and thus all programs and interventions aimed at enhancing agricultural productivity target mainly the rural farmers (UBOS, 2018). This could partly explain why the results of this research reveal that rural based farmers are more productive than their counterparts in urban areas. However, the study shows that total factor productivity increases when the farming household head is married as opposed to being unmarried.

The results show that the availability of extension services increases agricultural total productivity in Uganda by 0.02 percentage points, other factors held constant. This outcome is in line with Reed et al. (2017) who argued that availability of extension services increases farm productivity among farmers. This supports our earlier argument that the Ugandan government should avail extension services to all farmers throughout the country.

In addition, interacting precipitation variability and availability of extension services in the model yields a significant positive effect on productivity. This finding implies that provision of extension services offsets the negative impact of precipitation variability on agricultural productivity of the farming households. This is true following the arguments of earlier authors such as Urgessa (2015) and Folayan (2017) who argued that extension services can help to mitigate adverse effects of variability in climate through the skills and ways that are offered to farmers in the form of extension services. Farmers can easily learn how to improve their productivity despite the presence of variability in climate.

2.4.4 Results by region

Separate models for each of the four main regions of Uganda – central, eastern, western, and northern regions are estimated with an aim of identifying the region that is most prone to climate variability with a view to informing targeted aid policy formulation, implementation, and planning.

Table 5: Regression results by region (Dependent variable: Total Factor Productivity)

Variables	Central	Eastern	Western	Northern
Precipitation variability	-6.11**	-7.50**	-4.73*	-3.40*
	(3.70)	(2.94)	(2.51)	(2.00)
Precipitation variability squared	4.61	3.20	3.27*	2.95*
	(2.90)	(2.29)	(1.87)	(1.54)
Min temp variability	15.20	22.79	1.52	-0.61
	(11.11)	(14.45)	(16.73)	(8.37)
Min temp variability squared	-118.16	-162.97	33.70	-1.87
	(88.01)	(128.52)	(158.61)	(67.85)
Maximum temp variability	-34.60	-71.20**	9.75	-10.92
	(33.67)	(32.78)	(38.20)	(20.74)
Max temp variability squared	196.95	393.32**	-38.81	42.34
	(199.70)	(195.63)	(238.26)	(120.42)
Age of HH head	-0.13	-0.28**	0.16	0.00
	(0.09)	(0.13)	(0.11)	(0.07)
Age squared	0.00	0.00	-0.00*	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Gender of HH head (male)	1.03	2.58***	-0.94	0.31
	(0.64)	(0.75)	(0.74)	(0.42)
Household Location (urban)	-1.03	1.48***	0.70	-1.00**
	(0.70)	(0.47)	(0.77)	(0.44)
HH head Marital status (married)	1.25**	-1.66**	1.64	-0.28
	(0.59)	(0.78)	(1.13)	(0.43)
HH head Education level (years)	0.22***	0.02	0.04	0.07
	(0.08)	(0.07)	(0.08)	(0.06)
Access to extension services	0.60**	0.97**	0.58**	0.03**
	(0.46)	(0.51)	(0.50)	(0.30)
Access to market	0.27	-0.14	-0.16	0.19**
	(0.17)	(0.15)	(0.12)	(0.09)
Precipitation variability*extension services	1.24	1.86**	0.18	0.21
	(1.11)	(0.87)	(0.87)	(0.54)
Constant	11.08***	17.53***	-0.53	2.28
	(3.00)	(3.93)	(3.19)	(2.17)
Observations	3,259	3,090	3,181	3,176
R-squared	0.07	0.04	0.03	0.01
Number of households	790	744	764	762

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Source: *Author's computations based on UNPS data sets (2009-2019) and World Climate Data*

The regional results (table 5) show that the size of the effect of precipitation variability on productivity of agriculture in Uganda is not uniform across her four regions. The findings show that the impact is greater in Eastern Uganda followed by the Central region. This implies that in comparison to other regions, Eastern Uganda is more vulnerable to climate variability. Eastern Uganda occasionally faces severe occurrences of prolonged drought, landslides, and floods in comparison to other regions (UNMA, 2019). These severely affect agriculture in terms of the realized yields per hectare (Guloba, 2014). The results further show that availability of extension services increases farmers' productivity across all regions of the country and if it is well applied in Eastern Uganda, it would help to offset the impact of variability in precipitation on productivity in the region.

2.4.5 Results by major crops

The study further estimates separate models for the four common crops grown by most of the farmers in Uganda as per Uganda Bureau of Statistics records. The crops include maize, beans, bananas (locally known as '*matooke*') and cassava. The dependent variable for each crop is total factor productivity derived from estimating the stochastic production function of each crop. Table 6 presents the results of the estimated crop specific stochastic production function.

Table 6: Estimated Stochastic Production Function Models for each Crop.

Variables	Cassava	Maize	Beans	Banana
Capital	0.19***	0.13***	0.19***	0.07***
	(0.02)	(0.03)	(0.03)	(0.01)
Labour	0.01**	0.01***	0.01**	0.00**
	(0.00)	(0.00)	(0.00)	(0.00)
Land	-0.01***	-0.00	-0.00	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Time	-0.13***	-0.06***	-0.05***	0.25***
	(0.02)	(0.02)	(0.02)	(0.01)
Constant	2.37***	0.39	-1.71***	-2.77***
	(0.24)	(0.30)	(0.29)	(0.11)
Observations	5,731	7,164	7,492	6,493
R-squared	0.02	0.01	0.01	0.23

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

Source: Author's calculations based on UNPS data sets (2009-2019) and World Climate data

Next, the study presents the crop specific productivity implications of climate variability. The standard errors are robust and clustered at the household level to cater for heteroscedasticity.

Table 7: Regression results per major crop grown in Uganda (Dependent variable: Total factor productivity for each Crop)

Variables	Maize	Beans	Cassava	Banana
Precipitation variability	0.79	2.93*	-3.22**	1.55**
	(1.86)	(1.64)	(1.28)	(0.63)
Precipitation variability squared	-0.59	-2.39*	2.34**	-0.81*
	(1.45)	(1.25)	(1.01)	(0.47)
Min temp variability	3.08	0.70	-0.01	-4.03*
	(6.10)	(5.52)	(7.94)	(2.32)
Min temp variability squared	-48.32	-7.14	19.79	38.37*
	(47.48)	(44.20)	(74.65)	(20.13)
Maximum temp variability	-5.68	-15.56	8.39	-7.27
	(19.37)	(16.86)	(14.81)	(6.87)
Max temp variability squared	38.45	67.31	-46.67	31.13
	(116.71)	(101.99)	(88.88)	(41.28)
Age of HH head	0.10*	0.13*	-0.02	0.03
	(0.06)	(0.08)	(0.06)	(0.02)
Age squared	-0.00	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Gender of HH head (male)	-0.29	0.41	-0.01	-0.26*
	(0.42)	(0.32)	(0.43)	(0.15)
Household Location (urban)	-0.11	-0.16	-0.50	0.32**
	(0.44)	(0.33)	(0.47)	(0.15)
HH head Marital status (married)	0.10	-0.52	0.60	0.28
	(0.46)	(0.37)	(0.37)	(0.23)
HH head Education level (years)	0.05	0.00	0.08*	0.01
	(0.05)	(0.04)	(0.05)	(0.02)
Access to extension services	0.01**	0.16**	0.56**	0.37***
	(0.03)	(0.02)	(0.24)	(0.11)
Access to market	-0.13	-0.03	0.04	0.07**
	(0.09)	(0.08)	(0.06)	(0.03)
Precipitation variability*extension services	0.47	0.22	-0.04	0.51**
	(0.52)	(0.48)	(0.42)	(0.20)
Constant	-2.57	-3.32	1.13	-1.34*
	(1.92)	(2.16)	(1.72)	(0.77)
Observations	7,164	7,492	5,731	6,493
R-squared	0.01	0.01	0.03	0.02
Number of Households	2,091	2,067	1,779	1,654

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: *Author's calculations based on UNPS data sets (2009-2019) and World Climate data*

The results in table 7 show that precipitation changes have a significant inverted U-shaped relationship with total factor productivity for beans and banana and a significant U-shaped relationship with that of cassava, but no significant relationship with that of maize. These outcomes are in tandem with those of Adhikari et al. (2015) who noted that changes in climate would likely affect crops such as maize, cassava, banana, and beans if farmers of these crops fail to adapt to these changes in time. Similarly, our findings support the arguments of Van Asten et al. (2011) who noted that bananas, unlike other crops, require consistent supply of water to sustain its green vegetation and its shallow root system. Therefore, prolonged changes in water patterns might negatively affect banana yields and thus productivity. According to Arslan et al. (2017), during the flowering period, beans and maize require relatively less water, as more rain or water destroys the flowering process. This greatly affects yields realised and hence productivity returns. However, Sheng & Xu (2019) established a large drop in yields of many crops including maize due to climate variability in Asia and in China which contradicts our study findings that found a non-significant impact of all climate variability components on the productivity of maize.

Changes in the minimum temperature have a significant U-shaped relationship with banana productivity but have no significant impact on productivity of maize, beans, and cassava. This implies that variations in minimum temperature only alters banana yields and not those of maize, beans, and cassava. Beans and maize require relatively higher temperatures during the flowering stage while cassava is relatively tolerant to changes in temperature including a rise in temperature (Dhakal, 2016). The findings on banana productivity in response to variability in minimum temperature are like those of Van Asten et al. (2011) who established that a rise in the temperature because of prolonged drought is one of the major causes of banana yield loss in the East African region. Similarly, Adhikari et al. (2015) found out that a rise in temperature might lead to a 10% loss in the banana yields. Therefore, the results of this chapter seem to imply that banana, as a crop, requires relatively higher temperatures to achieve higher yields per hectare.

As earlier predicted by previous studies, access to extension services increases productivity of all crops under study in this chapter. Extension services are important in providing advice and imparting skills and knowledge to the farmers on various issues. In addition, access to extension services offsets the negative impact of precipitation variability on banana productivity, other factors remaining constant. This is shown by the statistically significant positive coefficient of the interaction term between precipitation variability and access to extension services. The results further show that productivity of all crops under study in this chapter are not sensitive to the level of the education of the head of the household with the exception of cassava. This is quite surprising given that education is expected to increase the farmers' productivity and thus for all crops (Dhakal, 2016; Arshad et al., 2018). However, most of the farmers learn on the job from their experiences, peers, or government agricultural officials such as commercial, production and extension officers. The government of Uganda has initiated many programs including a plan for modernization of agriculture, national agricultural advisory services, and operation wealth creation, all aimed at equipping farmers with necessary skills and information to improve their productivity especially in the four crops under study in this essay. This could therefore explain why the level of household education level has no significant role in the per hectare yields for beans, maize, cassava, and banana.

2.5.0 Summary, Conclusions and Policy implications

2.5.1 Summary

The majority (about 68%) of Ugandans are absorbed in the agricultural sector either directly or indirectly, yet the sector is quite prone to variability in climate and its effects given its reliance on natural climatic conditions and nature. However, the actual effect of variability in climate on the productivity of agriculture in the country remains unclear due to lack of in-depth countrywide empirical studies, a gap that this essay addresses. In this chapter, the impact of variability in climate on the productivity of agriculture and the selected crop productivity is analysed using the total factor productivity derived from estimating a stochastic production function. The chapter utilises long-term historical climate data from 1979 to 2013 interpolated at the level of the household and merged with data from the Uganda National Panel Survey (UNPS) collected over ten years from 2009 to 2019 using household GPS information contained in each wave.

The analysis and the findings in this chapter shed light on the vulnerability of Uganda's farming households, regions and selected key crops to climate variability. The descriptive statistics in this chapter show that on average the farming household heads had 5.3 years of education (some primary education as per UBOS classification). However, 56 percent of the farming households were not accessing agricultural extension services, although 81 percent of the farming households had access to credit facilities. On the other hand, the trend analysis supports the existence of climate variability in all regions of Uganda from 1979 to 2013 as shown by a non-zero coefficient of variation for the two components of climate variability – precipitation and temperature. Coefficients of variation is the most recognized statistical measure for variability in most statistical and empirical studies on variability (Gorst et al., 2018).

The empirical regression results show that precipitation variability has a non-linear U-shaped (convex) relationship with Uganda's agricultural productivity while access to extension services positively increases agricultural productivity and that of selected crops under study in this chapter. On the other hand, regional analysis indicates a non-uniform effect of variability in climate on productivity of agriculture across the four regions of the country with the eastern region being the most affected region. The crop-specific results show that beans and bananas are more susceptible to variability in climate as compared to maize and cassava. This implies that maize and cassava in comparison to beans and bananas are more resilient to climate variability and its effects. Availability of extension services and household's head education level have positive impacts on agricultural productivity. Gender, marital status, and the household's head age had a statistically insignificant impact on productivity.

2.5.2 Conclusion

This chapter has investigated the climate variability impacts on Uganda's agricultural productivity by estimating a total agricultural factor productivity model using panel data. The results show that climate variability is not only taking place, but also significantly affecting agricultural productivity across Uganda. A U-shaped relationship between precipitation variability and agricultural productivity as established in this chapter suggests that as precipitation variability increases, productivity may instead improve due to probable autonomous adaptation by farmers.

This follows the fact that as precipitation variability persists, farming households become aware of both the presence and the impact of variability in climate on their activities and, thus, start to devise ways of dealing with it and its effects (Codjoe et al., 2011). The spontaneous and autonomous adaptation to climate variability by some farming households may improve agricultural productivity. The positive significant coefficient of the interaction term - precipitation variability with availability of extension services confirms the importance of these extension services in offsetting the adverse effects of precipitation variability.

Regional analysis indicates that the Eastern region is likely to suffer more consequences of climate variability as compared to other regions of Uganda – Central, Western and Northern regions. In addition, regional findings show that access to extension services might save Eastern Uganda from the negative effect of precipitation changes on their farm activities. Considering crop specific analysis, the findings indicate that climate variability will affect beans and banana crops more compared to maize and cassava. The results also predict cassava to be the crop least affected by varying climatic conditions in Uganda. According to the existing empirical literature, cassava and maize are drought resistant crops in comparison to bananas and beans. To protect farmers' welfare and livelihoods including employment and food security, there is a need for clearly laid out plans, actions, and programs to counter climate variability. This is because many Ugandans across all regions depend on banana plantations and beans for both income and food.

This chapter, thus, adds to the literature on the impact of climate variability on agricultural productivity by combining both the household level survey data and long-term climate data. This is important in accounting for agricultural seasonal complexities and solves model selection bias that may lead to inconsistent, and unreliable model estimates, which usually results when household specific characteristics are omitted in the analysis. In addition to national and regional analysis, the study conducts crop specific analysis for common crops grown across the four regions of Uganda. The findings from this kind of analysis provide important information for targeted policy interventions required to accelerate productivity of agriculture in the presence of variability in climate. This is vital for job creation, reducing poverty and ensuring food security among the farming households in the country. This chapter finally provides a methodological innovation where a total factor productivity is derived from estimating a stochastic production function. This innovation is aimed at establishing the actual impact of changes in climate on total productivity of agriculture and of specific crops in Uganda.

2.5.3 Policy Implications

Following the study findings, the government of Uganda should design and adopt policies and measures aimed at combating variabilities in climate and their effects across the entire country.

For example, there is a need for deliberate efforts geared at providing extension services for all farming households in the country. This is because the study findings show that access to extension services improves farmer productivity even in the presence of climate variability. Therefore, development partners such as the Food and Agricultural Organization (FAO), non-governmental organisations and community-based organisations can as well complement government efforts in providing extension services by either providing technical resources or funds to finance extension programs. Through extension services, farming households can be empowered and sensitised on how to deal with climate variability and its associated impacts. This enables them to adequately plan on how to alleviate and cope up with them. Extension services can also be in the form of timely information on climate variability and weather forecasts to enable farmers to prepare in time and adjust their farming practices, including the type of crops grown.

Secondly, the negative impact of precipitation variability on the productivity of agriculture and crop yields can be minimised through frequent farmer education programs. This follows the fact that education improves productivity of farmers (Nagasha et al., 2019). Through education, farmers can learn ways of adapting to climate variability including how to apply irrigation, planting drought resistant crops, construction of valley dams among others.

2.5.4 Areas for Further Research

This study has made an important input to research on the effect of variability in climate on the productivity of agriculture. However, this study did not incorporate the effect of soil related factors because of data limitation. Further research should analyse the effect of soil-related factors such as soil fertility, type, and PH level. This is because soil related factors might play a big role in determining land or agricultural productivity. Another potential area of further research is analysing the effect of variability in climate on farmers' decisions to invest in agriculture. The findings of such a study will show whether farmers incorporate changes in climate in their farming investment decisions and thus plan of time.

References

Abid, M., Schneider, U. A., & Scheffran, J. (2016). Adaptation to climate change and its impacts on food productivity and crop income: Perspectives of farmers in rural Pakistan. *Journal of Rural Studies*, *47*, 254–266. https://doi.org/10.1016/j.jrurstud.2016.08.005

Abidoye, B. O., Kurukulasuriya, P., Reed, B., & Mendelsohn, R. (2017). Structural Ricardian Analysis of South-East Asian Agriculture. *Climate Change Economics*, *08*(04), 1792001. https://doi.org/10.1142/s2010007817920014

Abidoye, B. O., Mendelsohn, R., Ahmed, S., Amanullah, S., Chasidpon, C., Baker, L., Dobias, R., Ghosh, B., Gunaratne, L. H. P., Hedeyetullah, M. M., Mungatana, E., Ortiz, C., Simões, M., Kurukulasuriya, P., Perera, C., Sooriyaarachchi, A., Supnithadnaporn, A., & Truong, T. (2017). South-East Asian Ricardian Studies: Bangladesh, Sri Lanka, Thailand, and Vietnam. *Climate Change Economics*, *08*(03), 1740004. https://doi.org/10.1142/s2010007817400048

Adade, P., Crespo, O., & Abu, M. (2019). Climate Risk Management Adapting to changing climate through improving adaptive capacity at the local level – The case of smallholder horticultural producers in Ghana. *Climate Risk Management*, *23*(September 2018), 124–135. https://doi.org/10.1016/j.crm.2018.12.004

Ademe, A. S., Belay, K., & Mwanjalolo, M. (2017). *Impact of Climate Variability on Cool Weather Crop Yield in Ethiopia*. *December*.

Adhikari, U., Nejadhashemi, A. P., & Woznicki, S. A. (2015a). *Climate change and eastern Africa: a review of impact on major crops*. https://doi.org/10.1002/fes3.61

Adhikari, U., Nejadhashemi, A. P., & Woznicki, S. A. (2015b). Climate change and eastern Africa: A review of impact on major crops. In *Food and Energy Security* (Vol. 4, Issue 2). https://doi.org/10.1002/fes3.61

Alam, Md Mahmudul. Siwar, C., Talib, B., & Toriman, M. E. (2014). Impacts of Climatic Changes on Paddy Production in Malaysia: Micro Study on IADA at Northwest Selangor. *Research Journal of Environmental and Earth Sciences*, *6*(5), 251–258.

Ali, A., & Erenstein, O. (2017). Assessing farmer use of climate change adaptation practices and impacts on food security and poverty in Pakistan. *Climate Risk Management*, *16*. https://doi.org/10.1016/j.crm.2016.12.001

Arshad, M., Amjath-Babu, T. S., Aravindakshan, S., Krupnik, T. J., Toussaint, V., Kächele, H., & Müller, K. (2018). Climatic variability and thermal stress in Pakistan's rice and wheat systems: A stochastic frontier and quantile regression analysis of economic efficiency. *Ecological Indicators*, *89*, 496–506. https://doi.org/10.1016/j.ecolind.2017.12.014

Arshad, M., Kächele, H., Krupnik, T. J., Amjath-Babu, T. S., Aravindakshan, S., Abbas, A., Mehmood, Y., & Müller, K. (2017). Climate variability, farmland value, and farmers' perceptions of climate change: implications for adaptation in rural Pakistan. *International Journal of Sustainable Development and World Ecology*, *24*(6), 532–544. https://doi.org/10.1080/13504509.2016.1254689

Arslan, A., Belotti, F., & Lipper, L. (2017). Smallholder productivity and weather shocks: Adoption and impact of widely promoted agricultural practices in Tanzania. *Food Policy*, *69*, 68–81. https://doi.org/10.1016/j.foodpol.2017.03.005

Ayinde, O. E., Muchie, M., & Olatunji, G. B. (2017). Effect of Climate Change on Agricultural Productivity in Nigeria: A Co-integration Model Approach. *Journal of Human Ecology*, *35*(3), 189–194. https://doi.org/10.1080/09709274.2011.11906406

Baltagi, H. B. (2013). *Econometric Analysis of Panel Data, 5th edn. UK: John Wiley & Sons*.

Banerjee, S. (2019). *Building capacities of women for climate change adaptation: Insights from migrant-sending households in Nepal*.

Baya, B. B., Nzeadibe, T. C., Nwosu, E. O., & Uzomah, N. L. (2019). *Climate change, food insecurity and household adaptation mechanisms in Amaro Ward, Southern Region of Ethiopia*. *May*. https://doi.org/10.5897/JAERD2019.1042

Bozzola, M., Massetti, E., Mendelsohn, R., & Capitanio, F. (2018a). A Ricardian analysis of the impact of climate change on Italian agriculture. *European Review of Agricultural Economics*, *45*(1), 1–23. https://doi.org/10.1093/erae/jbx023

Bozzola, M., Massetti, E., Mendelsohn, R., & Capitanio, F. (2018b). *A Ricardian analysis of the impact of climate change on Italian agriculture*. *45*(November 2017), 57–79. https://doi.org/10.1093/erae/jbx023

Chen, S., Chen, X., & Xu, J. (2016). Impacts of climate change on agriculture: Evidence from China. *Journal of Environmental Economics and Management*, *76*, 105–124. https://doi.org/10.1016/j.jeem.2015.01.005

Cotter, J., Tirado, R., & Apoteker, A. (2010). *Biodiversity is the answer*. *2*, 2010.

Debaeke, P., Casadebaig, P., Flenet, F., & Langlade, N. (2017). Sunflower crop and climate change: vulnerability, adaptation, and mitigation potential from case-studies in Europe. *Ocl*, *24*(1), D102. https://doi.org/10.1051/ocl/2016052

Dhakal, S., Sedhain, G., & Dhakal, S. (2016). Climate Change Impact and Adaptation Practices in Agriculture: A Case Study of Rautahat District, Nepal. *Climate*, *4*(4), 63. https://doi.org/10.3390/cli4040063

Dzanku, F. M. (2015). Household Welfare Effects of Agricultural Productivity: A Multidimensional Perspective from Ghana. *Journal of Development Studies*, *51*(9), 1139–1154. https://doi.org/10.1080/00220388.2015.1010153

Egeru, A. (2012). *Role of Indigenous Knowledge in Climate Change Adaptation: A case study of the*. *11*(April), 217–224.

Ewert, F., Bindi, M., Webber, H., Trnka, M., Kersebaum, K. C., Olesen, J. E., Van Ittersum, M. K., Janssen, S., Rivington, M., Semenov, M. A., Wallach, D., Porter, J. R., Stewart, D., Verhagen, J., Gaiser, T., Palosuo, T., Tao, F., Nendel, C., Roggero, P. P., … Asseng, S. (2015). Crop modelling for integrated assessment of risk to food production from climate change *. *Environmental Modelling and Software*. https://doi.org/10.1016/j.envsoft.2014.12.003

Folayan, A. (2017). Rural Accessibility Theory of Agricultural Productivity. *International Journal of Transport Economics / Rivista Internazionale Di Economia Published by: Accademia Editoriale Stable*, *12*(2), 165–174. http://www.jstor.org/stable/

Geng, X., Wang, F., Ren, W., & Hao, Z. (2019). *Climate Change Impacts on Winter Wheat Yield in Northern China*. *2019*.

Gorst, A., Dehlavi, A., & Groom, B. (2018). Crop productivity and adaptation to climate change in Pakistan. *Environment and Development Economics*, *23*(06), 679–701. https://doi.org/10.1017/s1355770x18000232

Green, H. (2012). *Econometric Analysis (7th ed.)*.

Greenstone, M., & Deschenes, O. (2011). The Economic Impacts of Climate Change: Evidence from Agricultural Profits and Random Fluctuations in Weather. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.876929

Guloba, M. (2014). *Analysis of Adaptation to Climate Variability and Change in Uganda: A Gender and Household Welfare Perspective*. https://doi.org/10.1016/0375-9601(73)90015-7

Hlahla, S., Nel, A., & Hill, T. R. (2019). Assessing municipal-level governance responses to climate change in KwaZulu-Natal, South Africa. *Journal of Environmental Planning and Management*, *0*(0), 1–19. https://doi.org/10.1080/09640568.2018.1466693

Huong, N. T. L., Bo, Y. S., & Fahad, S. (2018). Economic impact of climate change on agriculture using the Ricardian approach: A case of northwest Vietnam. *Journal of the Saudi Society of Agricultural Sciences*. https://doi.org/10.1016/j.jssas.2018.02.006

IPCC. (2018). *Summary for Policymakers. In: Global warming of 1.5°C. An IPCC Special Report on the impacts of global warming*. https://www.ipcc.ch/

Jat, M. L., Dagar, J. C., Sapkota, T. B., Yadvinder-Singh, Govaerts, B., Ridaura, S. L., Saharawat, Y. S., Sharma, R. K., Tetarwal, J. P., Jat, R. K., Hobbs, H., & Stirling, C. (2016). Climate change and agriculture: Adaptation strategies and mitigation opportunities for food security in South Asia and Latin America. In *Advances in Agronomy* (Vol. 137). Elsevier Inc. https://doi.org/10.1016/bs.agron.2015.12.005

Jones, J. W., Antle, J. M., Basso, B., Boote, K. J., Conant, R. T., Foster, I., Godfray, H. C. J., Herrero, M., Howitt, R. E., Janssen, S., Keating, B. A., Munoz-Carpena, R., Porter, C. H., Rosenzweig, C., & Wheeler, T. R. (2017). Brief history of agricultural systems modelling. *Agricultural Systems*, *155*, 240–254. https://doi.org/10.1016/j.agsy.2016.05.014

Kabubo-Mariara, J, Di Falco, S. & Mulwa, R. (2016). The impact of climate change on food calorie production and nutritional poverty: evidence from Kenya. *Environment for Development Discussion Paper - Resources for the Future (RFF), March*, 35 pp.

Kabubo-Mariara, J., & Karanja, F. K. (2007). *The economic impact of climate change on Kenyan crop agriculture: A Ricardian approach ☆*. *57*, 319–330. https://doi.org/10.1016/j.gloplacha.2007.01.002

Kahsay, G. A., & Hansen, L. G. (2016). The effect of climate change and adaptation policy on agricultural production in Eastern Africa. *Ecological Economics*, *121*, 54–64.

https://doi.org/10.1016/j.ecolecon.2015.11.016

Kontgis, C., Schneider, A., Ozdogan, M., Kucharik, C., Tri, V. P. D., Duc, N. H., & Schatz, J. (2019). Climate change impacts on rice productivity in the Mekong River Delta. *Applied Geography*, *102*(December 2018), 71–83. https://doi.org/10.1016/j.apgeog.2018.12.004

Kumar, A., Sharma, P., & Joshi, S. (2016). Assessing the impacts of climate change on land productivity in Indian crop agriculture: Evidence from panel data analysis. *Journal of Agricultural Science and Technology*, *18*(1), 1–13.

Lazzaroni, S. (2012). Weather variability and food consumption: Evidence from Uganda. MA Research Paper, *International Institute of Social Studies*, The Hague, The Netherlands.

Lee, J., Nadolnyak, D., & Hartarska, V. (2012). *Impact of Climate Change on Agricultural Production in Asian Countries: Evidence from Panel Study*. 0–18.

Limantol, A. M., Keith, B. E., Azabre, B. A., & Lennartz, B. (2016). Farmers' perception and adaptation practice to climate variability and change: a case study of the Vea catchment in Ghana. In *SpringerPlus* (Vol. 5, Issue 1). Springer International Publishing. https://doi.org/10.1186/s40064-016-2433-9

Ludena, C., & Mejia, C. (2012). Climate Change, Agricultural Productivity, and its Impacts on the Food Industry: A General Equilibrium Analysis. *International Association of Agricultural Economists (IAAE) Triennial Conference, Foz Do Iguacu, Brazil,18-24 August,2012*. http://ideas.repec.org/p/ags/iaae12/126851.html

Luis, M. G., Orlando, R., & Alatorre, J. E. (2015). Climate change, irrigation, and agricultural activities in Mexico: A Ricardian analysis with panel data. *Journal of Development and Agricultural Economics*, *7*(7), 261–272. https://doi.org/10.5897/jdae2015.0650

MAAIF. (2018). *The National Adaptation Plan for the Ugandan Agricultural Sector*. *November, 2018. The Republic of Uganda through the Ministry of Agriculture, Animal Industry and Fisheries (MAAIF).* Kampala, Uganda.

Mamane Bello, G. H., & Malam Maman, M. N. (2015). A Ricardian Analysis of the Impact of Temperature and Rainfall Variability on Ag-riculture in Dosso and Maradi Regions of Niger Republic. *Agricultural Sciences*, *06*(07), 724–733. https://doi.org/10.4236/as.2015.67070

Massetti, E., & Mendelsohn, R. (2011). Estimating Ricardian models with panel data. *Climate Change Economics*, *2*(4), 301–319. https://doi.org/10.1142/S2010007811000322

Mendelsohn, R. (2008). The impact of climate change on agriculture in developing countries. *Journal of Natural Resources Policy Research*, *1*(1), 5–19. https://doi.org/10.1080/19390450802495882

Mendelsohn, R. (2014). The impact of climate change on agriculture in Asia. *Journal of Integrative Agriculture*, *13*(4), 660–665. https://doi.org/10.1016/S2095-3119(13)60701-7

Mendelsohn, R., & Nordhaus, W. (2010). The Impact of Global Warming on Agriculture: A Ricardian Analysis: Reply. *American Economic Review*, *89*(4), 1046–1048. https://doi.org/10.1257/aer.89.4.1046

Mendelsohn, R., Nordhaus, W., & Shaw, D. (1996). Climate impacts on aggregate farm value: Accounting for adaptation. *Agricultural and Forest Meteorology*, *80*(1), 55–66. https://doi.org/10.1016/0168-1923(95)02316-X

Mendelsohn, R. O., & Massetti, E. (2017). The Use of Cross-Sectional Analysis to Measure Climate Impacts on Agriculture: Theory and Evidence. *Review of Environmental Economics and Policy*, *11*(2), 280–298. https://doi.org/10.1093/reep/rex017

Mottet, A., Henderson, B., Opio, C., Falcucci, A., Tempio, G., Silvestri, S., Chesterman, S., & Gerber, P. J. (2017). Climate change mitigation and productivity gains in livestock supply chains: insights from regional case studies. *Regional Environmental Change*, *17*(1), 129–141. https://doi.org/10.1007/s10113-016-0986-3

MoWE. (2012). *Uganda National Climate Change Policy. Ministry of Water and Environment (MoWE). July* 2012, 1–48.

Mubiru, D. N., Radeny, M., Kyazze, F. B., Zziwa, A., Lwasa, J., Kinyangi, J., & Mungai, C. (2018). Climate trends, risks, and coping strategies in smallholder farming systems in Uganda. *Climate Risk Management*, *22*(August), 4–21. https://doi.org/10.1016/j.crm.2018.08.004

Mwangi, M., & Kariuki, S. (2015). Factors Determining Adoption of New Agricultural Technology by Smallholder Farmers in Developing Countries. *Journal of Economic and Sustainable Development*, *6*(5), 208–216. www.iiste.org

Mwaura, F. M., & Okoboi, G. (2014). *Climate Variability and Crop Production in Uganda*. *7*(2), 159–172. https://doi.org/10.5539/jsd.v7n2p159

Nabikolo, D., Bashaasha, B., Mangheni, M., & Majaliwa, J. (2012). Determinants of climate change adaptation among male and female headed farm households in eastern Uganda. *African Crop Science Journal*, *20*(2), 203–212.

Nagasha, J. I., Ocaido, M., & Kaase-bwanga, E. (2019). *Theoretical and conceptual framework for gender analysis of attitudes and adaptation mechanisms to climate change for sustainable livelihoods in Uganda*. *11*(June), 51–57. https://doi.org/10.5897/JASD2019.0532

Nelson, R., Kokic, P., Crimp, S., Martin, P., Meinke, H., Howden, S. M., de Voil, P., & Nidumolu, U. (2010). The vulnerability of Australian rural communities to climate variability and change: Part II-Integrating impacts with adaptive capacity. *Environmental Science and Policy*, *13*(1), 18–27. https://doi.org/10.1016/j.envsci.2009.09.007

Niggol Seo, S., & Mendelsohn, R. (2009). A Ricardian Analysis of the Impact of Climate Change on South American Farms. *Chilean Journal of Agricultural Research*, *68*(1). https://doi.org/10.4067/s0718-58392008000100007

Nii, S., Codjoe, A., & Owusu, G. (2011). *Climate change / variability and food systems: evidence from the Afram Plains, Ghana*. 753–765. https://doi.org/10.1007/s10113-011-0211-3

NPA. (2015). Uganda National Vision 2040. National Planning Authority (NPA), *Kampala, Uganda.*

Nuwagaba, A., & Namateefu, L. K. (2013). Climatic Change, Land Use and Food Security in Uganda: A Survey of Western Uganda. *Journal of Earth Sciences and Geotechnical Engineering*, *3*(2), 61–72.

Ochieng, J., Kirimi, L., & Mathenge, M. (2016). Effects of climate variability and change on agricultural production: The case of small-scale farmers in Kenya. *NJAS - Wageningen Journal of Life Sciences*, *77*(2016), 71–78. https://doi.org/10.1016/j.njas.2016.03.005

Oort, P. A. J. Van, & Zwart, S. J. (2018). *Impacts of climate change on rice production in Africa and causes of simulated yield changes*. *July 2017*, 1029–1045. https://doi.org/10.1111/gcb.13967

Orlove, B., Roncoli, C., Kabugo, M., & Majugu, A. (2010). Indigenous climate knowledge in southern Uganda: The multiple components of a dynamic regional system. *Climatic Change*, *100*(2), 243–265. https://doi.org/10.1007/s10584-009-9586-2

Reed, B., Mendelsohn, R., & Abidoye, B. O. (2017). The Economics of Crop Adaptation To Climate Change in South-East Asia. *Climate Change Economics*, *08*(03), 1740002. https://doi.org/10.1142/s2010007817400024

Reed, M. S., Podesta, G., Fazey, I., Geeson, N., Hessel, R., Hubacek, K., Letson, D., Nainggolan, D., Prell, C., Rickenbach, M. G., Ritsema, C., Schwilch, G., Stringer, L. C., & Thomas, A. D. (2013). Combining analytical frameworks to assess livelihood vulnerability to climate change and analyse adaptation options. *Ecological Economics*, *94*, 66–77. https://doi.org/10.1016/j.ecolecon.2013.07.007

Rötter, R. P., Hoffmann, M. P., Koch, M., & Müller, C. (2018). Progress in modelling agricultural impacts of and adaptations to climate change. *Current Opinion in Plant Biology*, *45*, 255–261. https://doi.org/10.1016/j.pbi.2018.05.009

Salvo, D. (2013). Measuring the effect of climate change on agriculture: A literature review of analytical models. *Journal of Development and Agricultural Economics*, *5*(12), 499–509. https://doi.org/10.5897/jdae2013.0519

Salvo, M. De, Begalli, D., & Signorello, G. (2014). *The Ricardian analysis twenty years after the original model: Evolution, unresolved issues, and empirical problems*. *6*(3), 124–131. https://doi.org/10.5897/JDAE2013.0534

Seo, S. N., & Mendelsohn, R. (2008a). A *Ricardian Analysis of the Impact of Climate Change on South American Farms*. *68*(MARCH), 69–79.

Seo, S. N., & Mendelsohn, R. (2008b). A structural Ricardian analysis of climate change impacts and adaptations in African agriculture. *Agricultural Economics*, *38*(2), 151–165.

Sheng, Y., & Xu, X. (2019). The productivity impact of climate change: Evidence from Australia's Millennium drought. *Economic Modelling*, *76*(July), 182–191. https://doi.org/10.1016/j.econmod.2018.07.031

Shikuku, K. M., Winowiecki, L., Twyman, J., Eitzinger, A., Perez, J. G., Mwongera, C., & Läderach, P. (2017). Smallholder farmers' attitudes and determinants of adaptation to climate risks in East Africa. *Climate Risk Management*, *16*, 234–245. https://doi.org/10.1016/j.crm.2017.03.001

Silvestri, S., Bryan, E., Ringler, C., Herrero, M., & Okoba, B. (2012). Climate change perception and adaptation of agro-pastoral communities in Kenya. *Regional Environmental Change*, *12*(4), 791–802. https://doi.org/10.1007/s10113-012-0293-6

Srinivasan, J. T., Sekhara, C., & Nuthalapati, R. (2019). *Groundwater Extraction, Agriculture and Poverty in Godavari River Basin*. *2*(July), 45–74.

Taraz, V. (2017). Adaptation to climate change: historical evidence from the Indian monsoon. *Environment and Development Economics*, *22*(05), 517–545. https://doi.org/10.1017/s1355770x17000195

UBOS. (2017). *The 2016/17 Uganda National Household Survey (UNHS).* Kampala, Uganda: Uganda Bureau of Statistics (UBOS).

UBOS. (2012). *Agricultural Sector statistics.* Kampala, Uganda: Uganda Bureau of Statistics (UBOS).

Urgessa, T. (2015). The Determinants of Agricultural Productivity and Rural Household Income in Ethiopia. *Ethiopian Journal of Economics*, *24*(2). https://www.ajol.info/index.php/eje/article/viewFile/146625/136151

Vachani, S., Usmani, J., & Lewis, J. I. (2014). Assessing climate change impacts and adaptation strategies in China. *Adaptation to Climate Change in Asia*, *January 2012*, 93–116. https://doi.org/10.4337/9781781954737.00010

Van Asten, P. J. A., Fermont, A. M., & Taulya, G. (2011). Drought is a major yield loss factor for rainfed East African highland banana. *Agric. Water Manag. 98*(5), 541– 552.

Van Passel, S., Massetti, E., & Mendelsohn, R. (2017). A Ricardian Analysis of the Impact of Climate Change on European Agriculture. *Environmental and Resource Economics*, *67*, 725–760. https://doi.org/10.1007/s10640-016-0001-y

Wang, J., Mendelsohn, R., Dinar, A., Huang, J., Rozelle, S., & Zhang, L. (2009). The impact of climate change on China's agriculture. *Agricultural Economics*, *40*(3), 323–337. https://doi.org/10.1111/j.1574-0862.2009.00379.x

Wulf, K. (2008). Climate Change and Food Security: A Framework Document. Food and Agriculture Organization of the United Nations Rome, 2008. *Food and Agriculture Organization of the United Nations Rome, 2008*, 93. http://rstb.royalsocietypublishing.org/content/360/1463/2139.short

Zhang, P., Zhang, J., & Chen, M. (2017). Economic impacts of climate change on agriculture: The importance of additional climatic variables other than temperature and precipitation. *Journal of Environmental Economics and Management*, *83*. https://doi.org/10.1016/j.jeem.2016.12.001

CHAPTER THREE

CLIMATE VARIABILITY AND HOUSEHOLD WELFARE OUTCOMES IN UGANDA

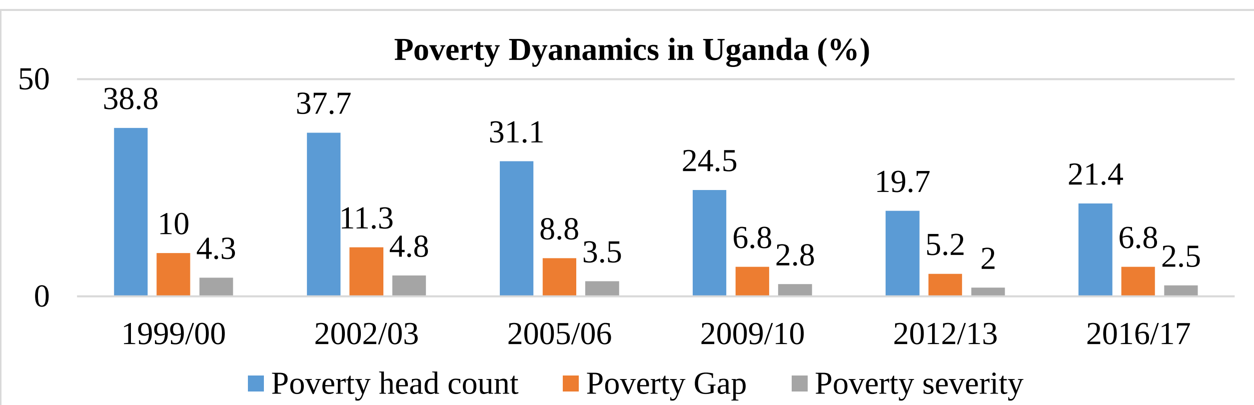
3.1.0 Introduction

3.1.1 Background to the study

Recent empirical studies show that global changes in climate are expected to intensify environmental tragedies such as variability in temperature and precipitation among others (IPCC, 2012; 2018)[12]. Countries in East Africa are experiencing variability in climate, as are many other countries in the tropics. For instance, Uganda for the past two decades has experienced a number of climatic upheavals such as floods, rising temperatures, changes in rainfall patterns, landslides and protracted droughts (Mubiru et al., 2018; UBOS, 2019). These climatic shocks are expected to affect natural resources as well as agriculture and human beings since they depend on these natural resources (Adhikari et al., 2015; Sam et al., 2021).

The variations in climate are expected to increase hardships to the already vulnerable groups especially the households involved in rural farming becoming a serious impediment to them making a living and the aspirations of development of the country (Arslan et al., 2017; Lazzaroni, 2012). For instance, although Uganda had a decreasing poverty headcount ratio from 1999/00 to 2012/13, a rising trend was observed between 2012/13 and 2016/17 as shown in figure 3 below.

Figure 3: Changes in poverty status: Dynamic perspective



Source: Uganda Bureau of Statistics (2018)

---

[12] Various Intergovernmental Panel on Climate Change (PCC) reports on Uganda's climate situation show an increasing trend in temperature and altered rainfall patterns (IPCC, 2012; 2014; 2018).

The rise in Uganda's headcount poverty ratio between 2012 and 2017 was heavily driven by the unfavourable climatic circumstances particularly the protracted drought in 2011 that prevailed in many areas of the country (Ssewanyana & Kasirye, 2014; UBoS, 2017). These weather events had a negative effect on agricultural yields and income levels of many farming households leading to a rise in the country's overall poverty levels (UBOS, 2018; Bank of Uganda, 2019).

By the same token, as per the Uganda National Panel Survey report for 2018/19, 338,520 (8.4 per cent) out of the estimated 40.3 million Ugandans were pushed back into poverty in the financial year 2018/19 alone. Wider and deeper analysis needs to be carried out to interrogate the causes of the rising poverty in the country. The results would yield data and evidence necessary to put in place suitable policy actions, programs and interventions that are sensitive to climate variability, and its effects. This will improve the welfare outcomes of households.

3.1.2 Problem statement

Between 1992 and 2012, Uganda scored highly in reducing household poverty levels in Sub-Saharan Africa. As a result, Uganda's national poverty level declined from 56.4% in 1992 to 19.7% by the year 2012 (World Bank, 2019), representing a 65% reduction in household poverty levels in a period of twenty (20) years. This success story in poverty reduction was largely attributed to a favourable climate in terms of reliable rainfall patterns that led to increased agricultural yields (UBOS, 2012; Guloba, 2014). Therefore, given that there are confirmed cases of climate variability in the country, it is timely and appropriate to assess their likely effect on household welfare to aid the ongoing debate on welfare implications of climate variability. This follows the predictions in the existing literature that, variability in climate could expose millions of the most vulnerable people in the world including Ugandans and mainly the rural population to hunger and extreme poverty, decelerating both global and national endeavours to attain sustainable development goals 1 and 2[13] (IPCC, 2018; Sam et al., 2021).

Although there exists a large body of literature on poverty, there is a gap in the research on the implications of variability in climate on the welfare of households, especially in developing

[13] The UN Sustainable Development Goals (SDGs) were adopted in 2015 by United Nations (UN) member countries during the UN general assembly to be achieved by the year 2030. SDG 1 is about eliminating poverty while SDG 2 is about erasing hunger in the world by the year 2030.

countries such as Uganda. This study addressed this gap by using cross-sectional household survey data pooled over a period of 10 years and long-term (over 30 years) historical climate data to evaluate the implications of climate variability on household welfare including the effect of the former on household consumption expenditure in Uganda.

3.1.3 Objectives of the Study

The major aim of this study is to evaluate the climate variability impact on household welfare outcomes in Uganda. The specific objectives of the study are:

(i) To analyse the impact of climate variability on household consumption expenditure as an indicator of household welfare outcomes in Uganda.
(ii) To provide evidence-based policy recommendations for improving household welfare outcomes in Uganda in the face of climate variability

3.1.4 Contributions of the Study

With the increasing evidence of climate variability and given Uganda's dependence on agriculture and nature, it is proper and timely to evaluate how changes in climate affect household welfare, to devise ways of addressing the resulting consequences. This is because understanding the impact of variability in climate on household welfare outcomes makes it easy to design targeted policy instruments aimed at improving household welfare through alleviating poverty and ending extreme hunger in Uganda's households. It also facilitates timely achievement of the country's vision 2040 and the various UN Sustainable Development Goals. The study findings are vital for building welfare resilience among households engaged in farming by putting into place pro poor policy actions to mitigate variability in climate and adaptation measures that are welfare enhancing.

In addition, this chapter adds to the body of knowledge in a few ways: first, the study uncovers how variability in climate affects household welfare outcomes such as consumption. The study also establishes non-climatic factors such as household characteristics and institutional factors that significantly influence welfare of the households. Such a study is important for informing policy actions and interventions for welfare improvement in the face of climate variability. The existing literature on Uganda's poverty dynamics has paid limited attention to the influence of climate related factors on household welfare outcomes particularly household consumption expenditure

(Mwungu et al., 2019). Secondly, the essay uses per household adult equivalent consumption expenditure as an indicator for household welfare outcomes. This welfare indicator is preferred because it captures both the monetary and the non-monetary household welfare components (Skoufias et al., 2011; Mulwa & Visser, 2020).

The inclusion of both climate, household and policy related institutional variables is instrumental in solving the problem of endogeneity that might arise due to omission of some key variables (Green, 2012). Further, the essay uses a series of nationally representative georeferenced Uganda National panel surveys that are part of the World Bank Living Standard Measurement Studies with detailed household, locational and institutional factors combined with climate data for the respective households. This is important for analysing changes in household welfare outcomes over time and the knowledge acquired is vital for aiding action-oriented policy interventions to improve household welfare outcomes over time. The data set used in this chapter is unique and can thus be used as a reference for further research.

3.1.5 Structure of the Chapter

The rest of the chapter is structured this way: The literature review begins next, followed by the methodology. Then the empirical results are presented in section four, while the fifth section concludes, and presents recommendations for policy and potential areas for further research.

3.2.0 Literature Review

3.2.1 Theoretical Literature Review

In theory, variability in climate affects the welfare outcomes of households via channels that are direct and indirect (Slesnick, 1998; Skoufias et al., 2011). Variability in climate directly affects welfare outcomes of households via market responses and biophysical changes (Leichenko & O'Brien, 2008). Examples of biophysical changes are prolonged dry seasons and excessive floods that are adverse and hence affects peoples' welfare (Lekobane & Seleka, 2017; Jha et al., 2017). The market response comes from changes in the farmers' yields caused by these extreme climatic conditions (Amare et al., 2018). This outcome in turn changes prices, especially food item prices and consequently the levels of income of those who rely on agricultural activities for a living (Hertel et al., 2010; Asfaw et al., 2016). The price changes and variations in household income levels directly affect their welfare outcomes including food security, consumption smoothing, and poverty status (Azzarri & Signorelli, 2020; Herrera et al., 2018; Vu & Glewwe, 2011).

Conversely, the indirect channel is largely argued from the perspective of the vulnerability framework where variability in climate makes households susceptible to welfare changes and other livelihood aspects (Yonas & Jonathan, 2013; Dzanku, 2015). It has been argued that countries that rely heavily on a rain-fed agricultural sector are prone to negative economic consequences caused by climate shocks such as drought and erratic rainfall patterns (Dell et al., 2012; Auffhammer & Schlenker, 2014). This is because extreme variability in climate occurrences including lengthy periods of drought considerably lower crop yields, reduce total agricultural production and hence revenues, thus decreasing consumption and other welfare measures and resulting in a rise in poverty (Yonas & Jonathan, 2013).

That is, variability in climate results in fluctuations in incomes where households cannot be sure of their returns more so from the agricultural sector. This reality can best be explained using the optimal expectations theory (Brunnermeier & Parker, 2005; Yonas & Jonathan, 2013) where households care about both their present and future welfare (utility). The latter is mainly influenced by their beliefs about how their circumstances in the future will be (Wossen et al., 2018). The greater effect is expected to be felt by the farming households in rural areas whose welfare relies greatly on the timely and reliable rain, do not have insurance, and have little or no adaptive capacity (Skoufias et al., 2011; Mulwa & Visser, 2020).

3.2.2 Empirical Literature

There exists a good amount of empirical research on how variability in climate affects welfare. For example, Skoufias et al. (2011) found that changes in temperatures and precipitation affect the various sources of income of the households in rural Mexico including agricultural incomes. As a result, welfare outcomes of households are affected, that is consumption, health, poverty, and food security and the household members experience losses in welfare. Skoufias et al. (2011)'s study also predicted that climate variabilities will derail global poverty reduction efforts, particularly in tropical countries and lead to increased levels of poverty. Skoufias & Vinha (2013) used ordinary least squares and established the impact of variability in climate on poverty to affect more poor people than rich people in Mexico. On the other hand, Yonas & Jonathan (2013), Herrera et al.

(2018) and Azzarri & Signorelli (2020) established both food and non-food per capita household expenditures to be susceptible to climate variability.

In addition, Skoufias & Vinha (2013) showed that encountering a drought or flood in an agricultural season results in huge drops in food and non-food consumption among households. However, the drop in consumption depends on the season when adverse climatic conditions have occurred and the climatic zone of the area where the household is located. Kabubo-Mariara et al. (2016) evaluated the effect of variability in climate on nutrition and food security in Kenya using three waves of panel data (2004, 2007 and 2010). The authors used a Ricardian approach to show a nonlinear effect of variability in climate on the welfare outcomes of households. Their findings further showed that the welfare outcomes of small-scale farmers were more negatively affected in comparison to large scale farmers. This was attributed to limited resources and adaptation capacity among the small-scale farmers. The authors recommended that farmers could adopt advanced techniques in farming as a way of adapting to variability in climate. Earlier, Kabubo-Mariara (2009) had found long run changes in climate to worsen poverty, increase vulnerability and cause loss of livelihoods among Kenyans. Nonetheless, their study did not consider the households that carry out farming for a living.

In Uganda, Bagamba et al. (2012) using the trade-off examination model examined the impact of variability in weather patterns on the living conditions of people in three regions of Uganda. These regions included the greater Masaka, Central, and Southwestern Uganda. The results of their study show that weather variability negatively affected the living conditions of between 70-97 percent of the households within the area of the study. In terms of vulnerability, their results indicate the most affected region to be Southwestern Uganda where a number of small-scale farmers reside. Their study, however, did not consider other regions of the country such as Eastern and Northern Uganda.

Earlier, Matovu & Buyinza (2010) used the Computable General Equilibrium (CGE) methodology to examine how the growth and welfare of Uganda is affected by variability in climate. The authors combined household level survey data, the Uganda's Social Accounting Matrix (SAM) and climate data from the Uganda National Meteorological Authority (UNMA). They found that rising temperatures and unreliable rainfall affect farmers' income negatively, because of reduced agricultural yields. The study also predicted rural poverty to rise by 0.6%, because of variability in climate. Nonetheless, this study uses poverty as an indicator of household welfare (Skoufias et al. 2011; Lekobane & Seleka, 2017).

Asfaw et al. (2016) used nationally representative data from the Uganda National Panel Survey (UNPS) and a set of climate change indicators to investigate how weather shocks affect outcomes of household welfare. They analysed the data by use of the Generalised Least Squares (GLS) random effects and quantile regression models. They established that weather shocks affect households' consumption and income smoothing behaviour negatively. Likewise, Beliyou et al. (2018) analysed how variability in climate affects the monthly per capita expenditure of households in rural areas of Ghana, Tanzania, and Uganda. Their research combined three data sets - monthly precipitation data from 1981-2013, monthly temperature data from 1950 to 2013, and household survey data dated between 1998 and 2014. But their research did not consider other forms of precipitation, for example moisture, which also contributes to agricultural output, and this may have affected their model estimates.

Nkegbe & Kuunibe (2014) used trend equations and Ricardian approach and determined that climate variability negatively affects incomes and revenues from agricultural activities in Ghana and leads to loss of household welfare. Their results agree with those of Wossen & Berger (2014) who used stimulation experiments for the Northern Ghana region. The two studies proposed that households diversify their economic activities to protect themselves against risks posed by climate variability.

In Ethiopia, Yayeh & Leal (2017) found climate variability to negatively affect the level of income of an estimated 80 percent of households engaged in farming due to reduced agricultural yields. Their results show the importance of tailoring studies on climate variability to a particular country to ascertain areas and groups that are more susceptible to variability in climate and its effects. This approach could make it easier to come up with targeted policies to ease the likely adverse effects of climate variability. Coromaldi (2020) examined the impact of variability in climate on rural farmers' welfare using a socio-economic data from Ethiopia Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) 2011/12 and historical re-analysis data on temperature and rainfall obtained from two sources - NOAA and the European Centre for Medium-

Range Weather Forecasts (ECMWF). Using an instrumental variable technique, the study results show that both rainfall variability and maximum temperature variability negatively affect household welfare measures of food security, consumption expenditure and poverty. The authors' research, however, did not consider other components of temperature including the minimum temperature, which determine the overall surface temperature.

Ahmed et al., (2009), applied a new structure of economic-climate investigation to assess effects of variability in climate on poverty in sixteen developing countries. He found that variability in climate increases poverty in all the sixteen countries with rural areas more adversely affected as compared to the urban areas. Srinivasan et al. (2019) analysed data from 825 farming households in India's Godavari River basin and found that climate variability lowers households' welfare, worsens poverty and widens the income inequality between the agricultural and non-agricultural households. However, the study evaluated only one indicator of variability in climate, that is, the decreasing in the water levels of Godavari River and did not consider the other indicators of variability in climate such as changes in precipitation and temperature.

3.2.3 Summary of the literature

The theoretical literature establishes that variability in climate affects household welfare outcomes directly by affecting changes in biophysical and market conditions and indirectly affects household welfare outcomes by making them vulnerable to agricultural yields and income uncertainties. On the other hand, the existing empirical studies project rising risks of adverse effects of variability in climate on the welfare outcomes of households, particularly patterns of consumption and expenditure. This therefore calls for fresh country specific evidence to increase the knowledge on the effects and aid in formulation of appropriate policies for the specific country. Some studies, for instance Bagamba et al. (2012) did not analyse statistical data but relied on people's views about variability in climate while Matovu & Buyinza (2010) used a different indicator of household welfare outcomes other than the household consumption expenditure.

Looking at those outside Uganda, Kabubo-Mariara et al.'s (2016) study in Kenya did not analyse the impact of climate variability on the welfare of crop dependant farmers while others such as Srinivasan et al. (2019) and Coromaldi (2020) did not consider key components of climate variability such as temperature and precipitation variability. Other studies such as Asfaw &

Maggio (2017), have no conclusive results on household welfare implications of climate variability. Therefore, this chapter analyses the extent and direction of effect of variability in climate on Uganda's household welfare outcomes.

3.0 Methodology

3.3.1 Theoretical framework of the study

Theoretically, the effect of the variability of climate on the welfare outcomes of farming household's is based on the theory of maximisation of utility as outlined by Deaton (1989). Under this, it is assumed that a representative household maximises his or her utility (welfare) subject to his or her budget constraint and climate variations (Lekobane & Seleka, 2017; Vu & Glewwe, 2011). This therefore implies that farming household welfare outcome is given by a utility function as described below (Deaton, 1989):

$$W_i = U_i = f(X_i, q_i) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (3.1.1)$$

Where W_i is the total farming household welfare outcomes, U_i is the utility level of a given farming household, X_i represents a set of determinants of household welfare that comprise of the non-income household factors (for example, the demographic factors, institutional variables, and climate variability indicators – temperature variability ad variability in precipitation). On the other hand, q_i represents the set of consumption goods and services. Additionally, it is assumed that all farming households have the same total utility functions (Lekobane & Seleka, 2017; Skoufias & Vinha, 2013). The study maximises equation (3.1.1) subject to a budget constraint. Solving the maximisation problem yields a utility maximising bundle (equation 3.1.2) at total cost of y_i and price P_i.

$$q_i = q(p_i, y_i, X_i) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (3.1.2)$$

By replacing q_i into equation 3.1.1, we obtain the indirect utility function for the representative farming household given as:

$$V_i = v(p_i, y_i, X_i) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (3.1.3)$$

Equation (3.1.3) gives the maximum welfare (utility) obtained by the household at price p_i, income level y_i and non-income household factors X_i that include the climate variability indicators

(Skoufias et al., 2011). Equation (3.1.3) is a dual to expenditure minimization problem solution, hence inverting equation (3.1.4) yields the farming household expenditure function expressed as:

$$E_i = e(u, p_i, X_i) \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots .. \dots \dots \dots \dots . (3.1.4)$$

Therefore, equation (3.1.4) is defined as the minimum cost of a representative household's welfare outcome or total utility (u) for a representative farming household i attained at prices p_i and other welfare determinants, X_i including variability in climate factors, C_i. Following, Skoufias & Vinha (2013), this study further assumes that prices (p_i) and welfare (u) are fixed implying that in this case, the consumption expenditure function for the farming household, E_i depends on X_i only. X_i comprises all model regressors including household characteristics, institutional factors, and variability in climate factors. Putting this into consideration, equation (3.1.4) is modified as:

$$E_i = e(x_i, C_i) \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots .. \dots \dots \dots \dots \dots . (3.1.5)$$

Hence, equation (3.1.5) provides the theoretical model for analysing the link between variability in climate and welfare outcomes of households in Uganda. The model proposes that the farming households' consumption expenditure is influenced by variables that are household specific and institutional specific, that is, (x_i) and the variability in climate (C_i).

The selection of household consumption expenditure as the measure of welfare outcome for a farming household is based on the argument that compared to other measures, consumption expenditure is more accurate and reliable and helps to capture the long run welfare losses (Meyer et al., 2003; Skoufias & Quisumbing, 2007). In addition, as outlined by Deaton & Zaidi (1999) and Skoufias et al. (2011), the consumption expenditure of a household is a reasonable measure of welfare outcomes in developing countries because consumption expenditure comprises of other aspects of welfare - income, food security, health and education, freedom, and life expectancy (Deaton & Zaidi, 1999; Skoufias et al. 2011).

3.3.2 Empirical model

In line with Skoufias et al. (2011), and the theoretical model resulting from equation (3.1.5) the empirical model can be described as follows:

$$lnE_{it} = \alpha_0 + \theta_i C_{it} + \beta_i x_{it} + \varepsilon_{it} \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots . \dots \dots (3.2.1)$$

Where E_i represents the adult equivalent consumption expenditure for each household i at period t, C_i is a set of variability in climate factors – variability in precipitation denoted as $PrecV$ and variability in temperature variability denoted as $TempV$. In this study, variability in temperature comprises of two components – variability in minimum temperature denoted as $MinTempV$ and variability in maximum temperature denoted as $MaxTempV$. Hence, $C_{it} = (PrecV_{it}, MinTempV_{it}, MaxTempV_{it})$. x_i is a set of other regressors (explanatory variables) in the model. These include household location including the region, value of household assets, age of the household head, level of education and marital status of the household head. The study includes access to credit, market, and extension services as the institutional variables in the model. α_0 , β_i and θ_i are parameters that model estimates. ε_{it} is the stochastic (random) error (disturbance) that is presumed not to be correlated with any of the explanatory variables in the model. The error is also assumed to have a normal probability distribution function.

The assumed non-linearity effect of variability in climate on farm household welfare outcomes is accounted for (measured) in this study by including both the linear and the squared terms of climate variability variables included in the model. The study further assesses whether the access to extension services offsets the impact of variability in precipitation on welfare. This is done by interacting variability in precipitation and access to extension services $(PrecV_{it} * Ext_{it})$. Therefore equation (3.2.1) is now given as:

$$\begin{aligned} lnE_{it} = \alpha_0 + \theta_1 PrecV_{it} + \theta_2 PrecV^2{}_{it} + \theta_3 MinTempV_{it} + \theta_4 MinTempV^2{}_{it} \\ + \theta_5 MaxTempV_{it} + \theta_6 MaxTempV^2{}_{it} + \beta_i x_{it} + \gamma_1 (PrecV_{it} * Ext_{it}) \\ + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .. (3.2.2) \end{aligned}$$

The marginal effects that show the direction and magnitude of variability in climate on welfare (lnE_{it}), captured in this study as household per adult equivalent consumption expenditure, computed at average values are given as:

$$\frac{\partial lnE_{it}}{\partial PrecV_{it}} = \theta_1 + 2\theta_2 Prec + \gamma_1 Ext \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots . \ldots . . \ldots (3.2.3)$$

$$\frac{\partial lnE_{it}}{\partial MinTempV_{it}} = \theta_3 + 2\theta_4 MinTempV \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.2.4)$$

$$\frac{\partial lnE_{it}}{\partial MaxTempV_{it}} = \theta_5 + 2\theta_6 MaxTempV \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots . \ldots\ldots\ldots (3.2.5)$$

Pooled OLS and Random effects models are used to estimate the two models (3.2.1 and 3.2.2). The use of these estimation techniques depends on the nature of the panel (whether balanced or unbalanced) and the assumptions on the unobserved fixed effects and the period covered by the panel (Nkegbe & Kuunibe, 2014; Hill et al., 2012). But, as per Hill et al. (2012) and Baltagi (2013), the Fixed Effects Model (FEM) is not recommended for short period panels as they yield inefficient estimates. Thus, in this study, Average Pooled Ordinary Least Squares estimation technique and Random Effects Model are the only ones used in empirical estimation. These two have an advantage over FEM in that they cater for correlation of household observations over time (Green, 2012). The study uses the Breusch-Pagan Lagrange multiplier test to help us make a choice between the two estimation methods. The test's null hypothesis is that the average pooled OLS is preferred against the alternative hypothesis that the random effect model is the preferred estimation model. If the null hypothesis is rejected, it implies that there are random effects in the model and thus, the random effects model is appropriate (Baltagi, 2013; Green, 2012; Hill et al., 2012).

3.3.3 Definition and measurement of the study variables

Dependent Variable of the study: In this study, the dependent variable is household welfare measured by the per adult equivalent consumption expenditure in the household. Uganda Bureau of Statistics defines household per adult consumption expenditure as the total household consumption expenditure divided by the number of adult equivalents in a household (UBoS, 2018). This enables comparison of expenditures across households.

Independent Variables: In this study, the independent variables are divided into three categories. The first category is made up of the variability in climate (variability in precipitation and variability in temperature - minimum and maximum temperature variability). The second category consists of household characteristics for example gender, age, income level, marital status, household size and education level of the household head as well as the location of the household. The third category is made up of the community and institutional variables such as access to market, availability of credit services and access to extension services.

Table 8: Definition and measurement of the study variables

Variable	Definition and Measurement	Expected Sign	Literature Source
Household welfare	Measured by total consumption spending per adult equivalent in each household. This is done by UBOS.	Dependent variable	Deaton & Zaidi, (1999); UBoS (2018)
Climate variability	Coefficient of variation averaged for over 30 years for both precipitation and temperature (minimum and maximum) observations.	+/-	Wossen et al. (2018)
Household head Gender	Dummy variable (=1 Male, 0 otherwise)	+/-	Hisali et al. (2011)
Household head Age	Number of complete years	+/-	Guloba (2014)
HH head level of education	Number of years spent in a school	+	Hertel et al. (2010)
HH head marital status	Dummy (=1 Married, 0 otherwise)	+/-	Skoufias et al. (2011)
Size of household	How many people are in a household	+	Dzanku (2015)
Size of farm	Acres of land (plot size)	+	Guloba (2014)
Regional dummies	Central Uganda (1 = Yes, 0 otherwise)[14] Eastern Uganda (1=Yes,0 otherwise) Western Uganda (1 = Yes, 0 otherwise) Northern Uganda (1 = Yes, 0 otherwise)	-/+	Asfaw et al. (2016)
Location	Residential status (=1 urban, 0, otherwise	+/-	Skoufias et al. (2011)
Land tenure	Land ownership status (= 1 Formal, 0, otherwise	+	Beliyou et al. (2018)
Assets of the household	Household assets value expressed in Uganda shillings (UGX)	+	Skoufias & Vinha (2013)
Access to credit	Dummy variable (=1 Yes, 0, otherwise)	+	Dzanku (2015)
Access to market	Dummy variable (=1 Yes, 0, otherwise)	+/-	Skoufias et al. (2011)
Extension services Access	Dummy variable (=1 Yes, 0, otherwise)	+	Wossen et al. (2018)

3.3.4 Data Sources and types

In this chapter, two data types are used – historical climate data and household level survey data. The survey data is part of several waves of the Uganda National Panel Survey (UNPS) that is collected by the Uganda Bureau of Statistics (UBoS). UNPS is a nationally representative dataset and is part of the Living Standards Measurement Study (LSMS) of the World Bank. Each wave accounts for a twelve-month period to consider the seasonality associated with Uganda's

[14] Central region is the reference category.

agricultural sector and the various components of annual consumption expenditure. The data is collected in two visits (six months apart) to account for agricultural outcomes attendant to the two farming seasons in the country. This means that every household in the UNPS sample was interviewed twice in a year and hence data collected can help us appreciate the dynamics of welfare at the household level. The study involves six UNPS waves (2009/10, 2010/11, 2011/12, 2013/14, 2015/16 and 2018/19) with each wave covering around 2,500 households with complete requisite data, resulting in around 12,500 total observations. These surveys consist of data on household social economic, community and agricultural variables. The data set is adequate and dependable to warrant credible analysis, and to yield unbiased, efficient, and consistent estimates. In addition, the long-term data on climate was obtained from the United States' National Oceanic and Atmospheric Administration (NOAA).

The NOAA collects daily climatic data for most countries across the globe. However, for this study, the daily climatic data on our selected variables are merged into monthly data and then into annual data before determining the coefficient of variation for each variable averaged for at least 30 years. The reason for doing this is to match it with the annual survey data. The two data sets are then merged by use of GPS information that is contained in the UNPS and which was also used to download the historical climate data.

3.4.0 Empirical Findings of the study

3.4.1 Descriptive Statistics

Poverty Trends and Household Consumption Expenditure in Uganda (2009 – 2019)

Table 9 below shows the summary statistics for the two indicators of household welfare outcomes - per adult equivalent household consumption expenditure and poverty from 2009/10 to 2018/19.

Table 9: Summary Statistics for Household Welfare Outcome Indicators

Welfare Indicator	Mean	Std. Dev.	Min	Max
Per adult equivalent household consumption expenditure (Uganda shillings)	62001.76	98317.4	3380.6	5816762
Status of poverty[15]	0.30	0.46	0	1

Source: Author's calculations based on UNPS data sets (2009/10-2018/19)

[15] Poverty status = 1 if the household is categorised as poor – that is below the poverty line.

Table 9 shows that on average, household monthly consumption expenditure per adult equivalent (welfare) is approximately Uganda shillings 62,001.76 (US$17.7)[16] for the period under study. According to Uganda National Household Survey (UNHS) report for 2016/17, average monthly household expenditure marginally declined from Uganda shillings 328,200 (US$94) in 2012/13 to Uganda shillings 325,800 (US$93) in 2016/17 (UBOS, 2017). A decrease in consumption expenditure is linked to a drop in household welfare. However, only 30% of households were classified as poor since they were below the poverty line.

In table 10 below, the chapter classifies regions by their household poverty status between 2009 and 2019. The statistics in table 8 present substantial changes in the average poverty incidences in the four regions of the country where the Northern region had the greatest portion of households (40.7%) categorised below the poverty line. The Eastern region came second and Western Uganda third with 37.8% and 25.2% of households classified below the poverty line respectively.

Table 10: Average Poverty statistics by region (2009 - 2019)

	Poverty Status		
Region	Non-poor	Poor	**Total**
	2,847	497	3,344
Central	85.14%	14.86%	100%
	2,223	1,352	3,575
Eastern	62.18%	37.82%	100%
	2,278	1,564	3,842
Northern	59.29%	40.71%	100%
	2,751	925	3,676
Western	74.84%	25.16%	100%
	10,099	4,338	14,437
Total	69.95%	30.05%	100%

Source: Author's calculations based on UNPS data sets (2009/10-2018/19)

Table 10 further shows that the central region, which consists of the capital city, Kampala, has the lowest percentage below the poverty line at 14.9%. These results display an unequal income distribution across Uganda. However, the Uganda National Household Survey 2016/17 report shows Eastern Uganda to have the highest poverty rate at 35.7 percent, much higher than the

[16] 1 USD = UGX 3500 (Bank of Uganda, 2020)

national poverty rate of 21.4 percent. In the Eastern region, 38.2 percent of children lived below the national poverty line (UBOS, 2019). Prior to 2016/17, the Northern region of Uganda had suffered protracted civil war courtesy of the Lord's Resistance Army (LRA) and as a result had the highest poverty rate (Asfaw et al., 2016). Rural areas in the country have a higher poverty incidence than urban areas.

Using the 2016/17 Uganda National Household Survey data, UBOS classified Ugandans into three groups – the non-poor, the non-poor but insecure and the poor. The poor are the ones living below the poverty line whereas the non-poor but insecure are those with equivalent consumption expenditure lower than two times the expenditure at the poverty line. Conversely, the non-poor are those with per adult equivalent consumption expenditure that is bigger than two times the expenditure at the poverty line.

Table 11: 2016/17 Poverty Groups based on UBOS Calculated Survey Weights

Poverty Status Group	Population	Frequency	Cum. Frequency
Poor	803,202	21.42	21.42
Non-poor but insecure	15347787	40.93	62.35
Non-poor	14118784	37.65	100.00
Total	**37498773**	**100.00**	

Source: 2016/17 Uganda National Household Survey Report (2018)

Table 11 shows that, out of 37.5 million Ugandans, 21.4 percent were poor by the financial year 2016/17. Further, 40.9 percent of the Ugandan population were non-poor but insecure. Hence, collectively, 62.3 percent of the Ugandan population is susceptible to poverty and so there is a need for policy actions that are evidence-based to be implemented to fight poverty and make progress towards achieving the second goal of the United Nations SDGs. On a positive note, 37.7 percent of the Ugandan population were non-poor and secure during the 2016/17 financial year and had a low probability of sinking back into poverty. Appendix 2 displays a map of the regional distribution of the headcount poverty ratio following the 2016/17 Uganda National Household Survey. The map shows that in comparison to other regions, high poverty rates are still high in the Northern and Eastern regions of the country.

Table 12: Summary statistics of other variables in the analysis

Variable	Mean	Std. Dev.	Min	Max
Variability of precipitation	0.58	0.14	0.04	1.27
Variability of min temperature	0.05	0.02	0.02	0.19
Variability of max temperature	0.08	0.01	0.05	0.16
Gender of HH head (=1 if Male, 0 otherwise)	0.71	0.45	0	1
Age of HH head	48.15	15.28	14	100
Marital status of HH head (=1 if married)	0.71	0.45	0	1
Location (=1 if Urban)	0.11	0.32	0	1
Land tenure system (=1 formal, 0 otherwise	0.52	0.50	0	1
Education (years of schooling)	5.42	3.89	0	17
Household assets (shillings)	48713.68	239222.70	0	1.67E+07
Land size (hectares)	2.70	16.56	0.01	820.6
Regional dummies				
Central	0.23	0.42	0	1
Eastern	0.25	0.43	0	1
Northern	0.27	0.44	0	1
Western	0.25	0.44	0	1
Market access	0.85	0.35	0	1
Credit access	0.75	0.43	0	1
Access to extension services	0.39	0.49	0	1

Source: Author's calculations based on UNPS data sets (2009/10-2018/19)

The summary statistics in table 12 present the average coefficient of variation of precipitation as 0.58 which is greater than that of minimum temperature (0.05) and maximum temperature (0.08), all of which show the presence of climate variability in the country. The outcome agrees with what scholars have found regarding the presence of variability in climate in the country (see for example Egeru, 2012 and Nuwagaba & Namateefu, 2013).

Household heads attained on average a minimum of 5 years of education, equivalent to primary five class and hence could read and write. Out of the households under study, 85 percent had access to markets and 75 percent could access credit services. On the other hand, only 39 percent of households had access to agricultural extension services - which is below the average and thus, all the stakeholders concerned should work to enable a minimum of 50 percent of the farming households in the country to access extension services (Yonas & Jonathan, 2013). According to Asfaw et al. (2016), doing so could serve to stimulate farmers' productivity.

3.4.2 Regression results

This study estimates both the pooled OLS model and the random effects regression model over the entire sample to evaluate the vulnerability levels of household consumption to climate variations. The estimates for these two models are shown in table 12. The robust standard errors in the table are clustered at household level. This provides the correction between the omitted unobserved effects and the disturbance term (unobserved heteroscedasticity) over time for a particular household i.

Table 13: Regression results (Dependent variable: Household consumption expenditure per adult equivalent)

	Pooled OLS Model			Random Effects Model		
Variables	1	2	3	4	5	6
Precipitation variability	1.345***	1.029***	1.200***	1.227***	1.099***	1.239***
	(0.316)	(0.285)	(0.289)	(0.217)	(0.220)	(0.224)
Precipitation variability squared	-0.752***	-0.575***	-0.575***	-0.717***	-0.635***	-0.628***
	(0.245)	(0.221)	(0.221)	(0.167)	(0.170)	(0.172)
Minimum temperature variability	-5.365***	-4.058***	-4.029***	-4.079***	-3.723***	-3.742***
	(1.730)	(1.358)	(1.364)	(0.994)	(1.006)	(1.011)
Minimum temp variability squared	42.242***	28.555**	28.692**	31.083***	28.371***	28.907***
	(15.868)	(12.130)	(12.197)	(8.813)	(8.941)	(8.996)
Maximum temperature variability	5.602	2.131	2.439	6.894***	5.824**	6.178**
	(3.742)	(3.276)	(3.274)	(2.425)	(2.510)	(2.498)
Maximum temp variability squared	-29.466	-8.656	-10.571	-38.701***	-31.922**	-34.094**
	(22.424)	(19.521)	(19.500)	(14.588)	(15.136)	(15.052)
Household head gender (male)		-0.131***	-0.130***		-0.088**	-0.088**
		(0.032)	(0.032)		(0.037)	(0.037)
Household head age		0.003	0.003		0.008*	0.008*
		(0.004)	(0.004)		(0.005)	(0.005)
Household age squared		0.000	0.000		-0.000	-0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Marital status (married)		-0.060*	-0.059*		-0.041	-0.039
		(0.036)	(0.036)		(0.038)	(0.038)
Value of household assets		0.061***	0.060***		0.018***	0.017***
		(0.007)	(0.007)		(0.005)	(0.005)
HH head Education level (years)		0.062***	0.062***		0.048***	0.048***
		(0.003)	(0.003)		(0.004)	(0.004)
Land size (hectares)		0.012***	0.012***		0.001	0.001
		(0.004)	(0.004)		(0.004)	(0.004)
Land size squared		-0.000***	-0.000***		-0.000	-0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Regional dummies						
Eastern region		-0.306***	-0.306***		-0.382***	-0.382***
		(0.038)	(0.038)		(0.036)	(0.036)
Northern region		-0.379***	-0.378***		-0.485***	-0.484***
		(0.039)	(0.039)		(0.038)	(0.038)
Western region		-0.185***	-0.184***		-0.178***	-0.178***
		(0.031)	(0.031)		(0.031)	(0.031)
Residential location (urban)		0.280***	0.280***		0.233***	0.233***
		(0.039)	(0.039)		(0.037)	(0.037)
Land tenure system (formal ownership)		0.090***	0.090***		0.034	0.033
		(0.029)	(0.029)		(0.029)	(0.029)
Access to extension services		-0.149***	0.076		-0.118***	0.072**
		(0.013)	(0.048)		(0.010)	(0.036)

	(1)	(2)	(3)	(4)	(5)	(6)
Precipitation variability*Extension			-0.401***			-0.341***
			(0.083)			(0.063)
Constant	10.042***	9.465***	9.361***	10.077***	9.742***	9.648***
	(0.174)	(0.199)	(0.200)	(0.116)	(0.175)	(0.175)
Observations	12,601	11,854	11,854	12,601	11,854	11,854
R-squared	0.006	0.240	0.241			
F-statistic	12.55***	56.10**	54.57***			
BPLM Test: Var ($v_i = \mu_i + \varepsilon_{it}$)[17]= 0				10668.4***	7003***	7023.5***

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations based on UNPS (2009-2019) and climate data (1979-2013)

The Breusch-Pagan Lagrange Multiplier test is used to select between the pooled OLS and the random effects model. The random effects (RE) model and not the pooled OLS model is found appropriate or consistent with the study's data set (Baltagi, 2013; Green, 2012). Thus, we only discuss the random effects model estimates (models 4, 5 and 6) and use these to derive policy recommendations.

3.4.3 Discussion of the chapter findings

The findings indicate a significant non-linear impact of variability in climate on per adult equivalent household consumption expenditure, which is the household welfare indicator. This result is presented by the model estimates (coefficients) of both the linear and the squared terms of the variables of variability of temperature and precipitation being statistically significant. The results indicate that - other factors remaining constant - the precipitation variation has a significant hill-shape (concave) effect on household per adult equivalent consumption expenditure. This result means that variability in precipitation only negatively affects welfare if it increases beyond the up to a given level (threshold level). They could be since severe variations in precipitation could force households to reduce their consumption expenditure leading to a decline in welfare. According to Skoufias et al. (2011), Yonas & Jonathan (2013) and Asfaw et al., (2016), reducing consumption expenditure is a way of adapting to climate change and its effects especially on household income levels. This follows the fact that extreme precipitation variability indirectly affects agricultural

[17]The error term has two components (unobserved individual effects μ_i assumed to be randomly distributed and independent of model regressors and the disturbance term ε_{it}). Rejecting the null hypothesis implies that RE is the appropriate model that is consistent with the data set (Hill et al., 2012).

production as established in essay 1 and decreases food items and income forcing households to reduce their consumption expenditures (Skoufias & Vinha, 2013; Hertel et al., 2010; Alem et al., 2010). However, the findings of a study by Asfaw & Maggio (2017) in Malawi differ – they found that variability of precipitation has a non-significant effect on the consumption expenditure of households. Herrera et al. (2018) found a negative linear impact of variability in precipitation on the welfare outcomes of households.

From the findings in table 13, minimum temperature variability has a significant U-shaped (convex) relationship with household per adult equivalent consumption expenditure (household welfare indicator), other factors held constant. This means that per adult household consumption expenditure drops with changes in minimum temperature up to a point where the coefficient of variation (CV) of minimum temperature equals = 3.8. This finding shows that household welfare outcomes as measured by household per adult equivalent consumption expenditure tend to decrease with minor changes in the minimum temperature as compared to extreme changes in minimum temperature variability. This outcome agrees with the predictions of Intergovernmental Panel on Climate Change (IPCC, 2014) that presented that a 2^0C rise in temperature will be linked to about 0.2 – 2.0 percentage decline in the economic activities of households and resulting in welfare loss. Some empirical studies, for example Burke et al. (2015) and Beliyou et al. (2018) attribute this outcome to households' autonomous adaptation practices encouraged by changing temperature conditions.

However, conversely, variability in maximum temperature has a hill shaped relationship with per adult equivalent household consumption expenditure. The result agrees with the findings of a global study carried out by Burke et al. (2015) showing changes in maximum temperature and income have an inverted U-shaped pattern. This study outlines that excessive temperature changes might be linked to the emergence of pests and diseases that were previously not seen. The pests and diseases affect farming households' crop and livestock yields hence affect their income levels and welfare (Hertel et al., 2010; Lazzaroni, 2012).

The results shown in table 12 show that the consumption expenditure of households rises with the number of years of education of the household head. In particular, an extra school year for a given household head raises the household welfare by 0.048 percentage points, ceteris paribus. According to Skoufias et al. (2011), education is a multiplier of human capital and productivity and enhances the chances of earning non-farm income wage or salary, gaining access to job opportunities and could enable households to diversify their income sources. These enable households to shield themselves from adverse effects on their welfare, for example because of dropping agricultural incomes due to climate variability. According to Asfaw et al., (2019), the higher the education level of the household head the easier it is for the household to adapt to the changing climatic conditions. The study findings also show that welfare goes up with the value of assets owned by a given household. A unit growth in household assets value raise per adult equivalent household consumption expenditure by 0.018 percentage points, ceteris paribus. In the literature, the value of assets of a household is an indicator of household wealth status (Dzanku, 2015) and is acceptable as security against credit borrowed from a financial institution (Asfaw et al., 2016). Such credit makes it possible for the households to smoothen their consumption patterns and sometimes use the acquired credit to start up non-farm income generating activities such as businesses (Skoufias & Vinha, 2013).

When we consider the regions, the results show that northern Uganda underwent the greatest loss in welfare, the eastern region was second and the western and central regions came third and fourth respectively. Likewise, households in urban areas have higher per adult equivalent consumption expenditure as compared to households in rural areas. Living in an urban area increases welfare by 0.23 percentage points. This result agrees well with that of Skoufias et al. (2011) who argues that in urban areas there is a myriad of economic activities that are non-agricultural as opposed to rural areas where the major activity is nature-dependent agriculture that is very prone to variability in climate.

Access to extension services improves the welfare of a household by 0.07 percentage points. Extension services provide skills and information that farming households require to increase their productivity as well as income sources (Asfaw et al., 2016). Additionally, extension services empower households to adapt to the changes caused by variability in climate (Ali & Erenstein, 2017). This chapter examines this assertion by interacting precipitation variability and access to extension services with welfare outcomes of households. We find that farmers respond to information on variability in climate provided via extension services by cutting down their expenditure on consumption by 0.34 percentage points. This shows a decrease in household welfare as a response to knowledge acquired from extension workers.

3.5.0 Conclusion and policy implications

3.5.1 Conclusion

This chapter has evaluated the effects of variability in climate on the welfare of households in Uganda using per adult equivalent household consumption expenditure as the indicator for welfare. The findings of the study show that precipitation variability has a hill shaped relationship with household welfare outcomes. This finding implies that adverse changes in precipitation variability affects household welfare negatively, whereas moderate changes in precipitation are linked to rising per adult equivalent household consumption expenditure, and thus a rise in household welfare outcomes. The results show that minor changes in the minimum temperature variability result in a drop in consumption expenditure whereas minimal changes in the maximum temperature variability are linked to a growth in welfare. This follows the argument that slight change in minimum temperature results in major surface temperature change (Asfaw et al., 2019). Existing literature considers a drop in consumption expenditure to adapt to variability in climate (Nkegbe & Kuunibe, 2014). Also, a change in temperature causes decreased agricultural production and fewer opportunities of income, and affects welfare negatively (Skoufias & Vinha, 2013; Dzanku, 2015). Further, adverse climate variability occurrences for instance landslides, prolonged dry seasons and floods could undermine the economic gains resulting from poverty reduction efforts and threaten social economic progress (Mwungu et al., 2019). For instance, prolonged drought, landslides, and floods experienced from 2012 and 2017 increased the household poverty headcount ratio from 19.7 in 2012/13 financial year to 21.4 in the financial year 2016/17 (UBOS, 2019). Other factors that affect the welfare of households in Uganda are the gender of the household head, the value of the household assets, the location of the household (urban versus rural), and access to extension services.

3.5.2 Policy Implications

The government of Uganda and other concerned stakeholders including the farming households should consider putting into place programs that would enhance climate adaptation, for example subsidising the costs of irrigation equipment. Encouraging irrigation could reduce the effect of variability in precipitation on household welfare and stabilise yields as well as incomes from households' agricultural activities. This measure would in turn stabilise household welfare outcomes. In the same way, the government of Uganda and other stake holders could provide and facilitate non-farming employment alternatives to ensure economic diversification in the country, by means of introducing programs to facilitate even distribution of industries and service firms across Uganda. These programs would serve to reduce over-dependence on rain-fed agricultural activities, especially among rural households. At the same time, these policy actions ought to cater for gender balance to make sure both households headed by males and females participate and profit equally.

Furthermore, the government could enhance farmers' accessibility to extension services including timely provision of relevant information and advice, for instance variability in climate information, skills, and methods of adapting to variability in climate.

3.5.3 Areas for Further study

First, this study did not assess the effect of variability in climate on the demand for commodities. An evaluation of the effect of variability in climate on demand would be useful to determine the extent and direction of the effects of variability in climate on demand for commodities such as food stuffs, durables, and non-durable goods in an economy. It could also help obtain elasticity of demand for the main commodities in the economy, with respect to variability in climate.

Secondly, the study has not assessed the effect of adapting to variability in climate on the welfare of the household, and what factors affect the decision of a household to adapt. Such a study would help obtain evidence needed to put in place measures to facilitate adaptation practices amongst farm households and come up with programs and policies that encourage adaptation. The findings of the study indicate the presence of variability in climate. Therefore, adaptation as a response to climate variability in Uganda would improve the welfare of households. However, to arrive at such a conclusion would require scientific evidence, which is to be obtained only through empirical research.

References

Adhikari, U., Nejadhashemi, A. P., & Woznicki, S. A. (2015). *Climate change and eastern Africa: a review of impact on major crops*. https://doi.org/10.1002/fes3.61

Ahmed, S. A., Diffenbaugh, N. S., & Hertel, T. W. (2009). *Climate volatility deepens poverty vulnerability in developing countries*. https://doi.org/10.1088/1748-9326/4/3/034004

Ali, A., & Erenstein, O. (2017). Assessing farmer use of climate change adaptation practices and impacts on food security and poverty in Pakistan. *Climate Risk Management*, *16*. https://doi.org/10.1016/j.crm.2016.12.001

Amare, M., Jensen, N., Shiferaw, B., & Cissé, J. (2018). Rainfall shocks and agricultural productivity: Implications for rural household consumption. *Agricultural Systems*, *166*, 79–89.

Arslan, A., Belotti, F., & Lipper, L. (2017). Smallholder productivity and weather shocks: Adoption and impact of widely promoted agricultural practices in Tanzania. *Food Policy*, *69*, 68–81. https://doi.org/10.1016/j.foodpol.2017.03.005

Asfaw, S., & Maggio, G. (2017). Gender, Weather Shocks and Welfare: Evidence from Malawi Gender, Weather Shocks and Welfare: Evidence from Malawi. *The Journal of Development Studies*, *00*(00), 1–21. https://doi.org/10.1080/00220388.2017.1283016

Asfaw, S., Mortari, A. P., Arslan, A., Karfakis, P., & Lipper, L. (2016). *Welfare impacts of climate shocks: Evidence from Uganda*. *May*. https://doi.org/10.13140/RG.2.1.4581.7200

Asfaw, S., Scognamillo, A., Caprera, G. Di, Sitko, N., & Ignaciuk, A. (2019). Heterogeneous impact of livelihood diversification on household welfare: Cross-country evidence from Sub-Saharan Africa. *World Development*, *117*, 278–295. https://doi.org/10.1016/j.worlddev.2019.01.017

Auffhammer, M., & Schlenker, W. (2014). Empirical studies on agricultural impacts and adaptation. Energy Economics, 46, 555–561. *Energy Economics*, *46*, 555–561. https://doi.org/10.1016/j.eneco.2014.09.010

Azzarri, C., & Signorelli, S. (2020). Climate and poverty in Africa South of the Sahara. *World Development*, *125*, 104691. https://doi.org/10.1016/j.worlddev.2019.104691

Baltagi, H. B. (2013). *Econometric Analysis of Panel Data, 5th edn. UK: John Wiley & Sons*.

Beliyou, H., Signorelli, S., Azzarri, C., & Johnson, T. (2018). *Welfare effects of weather variability: multi-country evidence from Africa south of the Sahara*. 1–23.

Brunnermeier, M. K., & Parker, J. A. (2005). Optimal expectations. *American Economic Review*, *95*(4), 1092–1118. https://doi.org/10.1257/0002828054825493

Burke, M., Hsiang, S., & Miguel, E. (2015). Non-linear Effect of Temperature on Economic Production. *Global Nature*, *527*, 235–239. https://doi.org/https://doi.org/10.1038/nature15725

Call, M., Gray, C., & Jagger, P. (2019). Smallholder responses to climate anomalies in rural

Uganda. *World Development*, *115*, 132–144. https://doi.org/10.1016/j.worlddev.2018.11.009

Coromaldi, M. (2020). The impact of weather fluctuations and climate shocks on farmers' welfare: insights from rural Ethiopia. *International Journal of Environmental Studies*, *77*(4), 619–635. https://doi.org/10.1080/00207233.2019.1695433

Deaton, A., & Zaidi, S. (1999). *Guidelines for Constructing Consumption Aggregates for Welfare Analysis* (No. 127).

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, *4*(3), 66–95. https://doi.org/doi:10.1257/mac.4.3.66

Dzanku, F. M. (2015). Household Welfare Effects of Agricultural Productivity: A Multidimensional Perspective from Ghana. *Journal of Development Studies*, *51*(9), 1139–1154. https://doi.org/10.1080/00220388.2015.1010153

Egeru, A. (2012). *Role of Indigenous Knowledge in Climate Change Adaptation: A case study of the*. *11*(April), 217–224.

Green, H. (2012). Econometric Analysis (7th ed.). Journal of Boston: Pearson Education, 803-806.

Guloba, M. (2014). Analysi*s of Adaptation to Climate Variability and Change in Uganda: A Gender and Household Welfare Perspective*. https://doi.org/10.1016/0375-9601(73)90015-7

Herrera, C., Ruben, R., Dijkstra, G., & Ruben, R. (2018). *Climate variability and vulnerability to poverty in Nicaragua*. *6544*. https://doi.org/10.1080/21606544.2018.1433070

Hertel, T. W., Burke, M. B., & Lobell, D. B. (2010). The poverty implications of climate-induced crop yield changes by 2030. *Global Environmental Change*, *20*(4), 577–585. https://doi.org/10.1016/j.gloenvcha.2010.07.001

Hill, R. C., Griffiths, W. E., & Lim, G. C. (2012). *Principles of Econometrics* (John & I. Wiley and Sons (eds.); Fourth edition).

IPCC. (2012). *Managing the risks of extreme events and disasters to advance climate change adaptation. a special report of working groups i and ii of the ipcc. Technical report.*

IPCC. (2018). *Summary for Policymakers. In: Global warming of 1.5°C. An IPCC Special Report on the impacts of global warming*. https://www.ipcc.ch/

Jha, C. K., Gupta, V., Chattopadhyay, U., & Amarayil Sreeraman, B. (2017). Migration as adaptation strategy to cope with climate change. *International Journal of Climate Change Strategies and Management*. https://doi.org/10.1108/ijccsm-03-2017-0059

Kabubo-Mariara, J. (2009). Global warming and livestock husbandry in Kenya: Impacts and adaptations. *Ecological Economics*, *68*, 1915–1924.

Lazzaroni, S. (2012). Climate Change, Weather Variability and Food Consumption: A Multidisciplinary Study of Rural Uganda. he Hague, The Netherlands.

Lekobane, K. R., & Seleka, T. B. (2017). Determinants of Household Welfare and Poverty in Botswana, 2002/2003 and 2009/2010. Journal of Poverty, 21(1), 42–60.

https://doi.org/10.1080/10875549.2016.1141381

Matovu, J. M., & Buyinza, F. (2010). *"Growth and Household Welfare Effects of Climate Change", Revised report submitted for background papers for the preparation of the Uganda National Human Development Report, 2010.UNDP, Uganda*.

Meyer, B. D., Sullivan, J. X., Meyer, B. D., & Sullivan, J. X. (2003). *Measuring the Well-Being of the Poor Using Income and Consumption Published by: University of Wisconsin Press Measuring the Well-Being of the Poor Using Income and Consumption*. *38*, 1180–1220.

Mubiru, D. N., Radeny, M., Kyazze, F. B., Zziwa, A., Lwasa, J., Kinyangi, J., & Mungai, C. (2018). Climate trends, risks, and coping strategies in smallholder farming systems in Uganda. *Climate Risk Management*, *22*(August), 4–21. https://doi.org/10.1016/j.crm.2018.08.004

Mulwa, C. K., & Visser, M. (2020). Farm diversification as an adaptation strategy to climatic shocks and implications for food security in northern Namibia. *World Development, 129*, 104906. https://doi.org/10.1016/j.worlddev.2020.104906

Mwaura, F. M., & Okoboi, G. (2014). Climate variability and crop production in Uganda. Journal of Sustainable Development, 7(2), 159. https://doi.org/10.5539/jsd.v7n2p159

Mwungu, C. M., Mwongera, C., Shikuku, K. M., Acosta, M., Ampaire, E. L., Winowiecki, L. A., & Läderach, P. (2019). *Household Welfare Effects of Stress- - Tolerant Varieties in Northern Uganda*. https://doi.org/10.1007/978-3-319-92798-5

Nelson, R., Kokic, P., Crimp, S., Martin, P., Meinke, H., Howden, S. M., de Voil, P., & Nidumolu, U. (2010). The vulnerability of Australian rural communities to climate variability and change: Part II-Integrating impacts with adaptive capacity. *Environmental Science and Policy*, *13*(1), 18–27. https://doi.org/10.1016/j.envsci.2009.09.007

Nkegbe, P. K., & Kuunibe, N. (2014). Climate variability and household welfare in northern Ghana (No. 2014/027). WIDER Working Paper.

Nuwagaba, A., & Namateefu, L. K. (2013). Climatic Change, Land Use and Food Security in Uganda: A Survey of Western Uganda. *Journal of Earth Sciences and Geotechnical Engineering*, *3*(2), 61–72.

Oort, P. A. J. Van, & Zwart, S. J. (2018). *Impacts of climate change on rice production in Africa and causes of simulated yield changes*. *July 2017*, 1029–1045. https://doi.org/10.1111/gcb.13967

Sam, A. G., Abidoye, B. O., & Mashaba, S. (2021). Climate change and household welfare in sub-Saharan Africa: empirical evidence from Swaziland. *Food Security*, *13*(2), 439–455. https://doi.org/10.1007/s12571-020-01113-z

Skoufias, E., Rabassa, M., & Olivieri, S. (2011). *The poverty impacts of climate change: A review of the evidence*. *April*. https://doi.org/10.1596/1813-9450-5622

Skoufias, E., & Vinha, K. (2013). *The impacts of climate variability on household welfare in rural Mexico*. 370–399. https://doi.org/10.1007/s11111-012-0167-3

Slesnick, D. T. (1998). Empirical Approaches to the Measurement of Welfare. *Journal of Economic Literature*, *36*(4), 2108–2165.

Srinivasan, J. T., Sekhara, C., & Nuthalapati, R. (2019). *Groundwater Extraction, Agriculture and Poverty in Godavari River Basin*. *2*(July), 45–74.

Ssewanyana, S. N., & Kasirye, I. (2014). *Uganda's progress towards poverty reduction during the last decade 2002/3- 2012/13: is the gap between leading and lagging areas widening or narrowing? 118*, 1–40.

Tesfaye, W., & Tirivayi, N. (2020). Crop diversity, household welfare and consumption smoothing under risk: Evidence from rural Uganda. *World Development*, *125*, 104686. https://doi.org/10.1016/j.worlddev.2019.104686

UBOS. (2019). Statistical Abstract, 2018, Uganda Bureau of Statistics (UBOS), Kampala, Uganda.

UBOS. (2018). Statistical Abstract, 2017. Uganda Bureau of Statistics (UBOS), Kampala, Uganda

UBOS. (2012). Agricultural Sector Statistics Profile. Uganda Bureau of Statistics (UBOS), Kampala, Uganda

Urgessa, T. (2015). The Determinants of Agricultural Productivity and Rural Household Income in Ethiopia. *Ethiopian Journal of Economics*, *24*(2). https://www.ajol.info/index.php/eje/article/viewFile/146625/136151

Vu, L., & Glewwe, P. (2011). Impacts of Rising Food Prices on Poverty and Welfare in Vietnam Poverty of Rising Food Prices on and Welfare in Vietnam. *Journal of Agricultural and Resource Economics*, *36*(1), 14–27.

Wossen, T., & Berger, T. (2014). Climate variability, food security and poverty: Agent-based assessment of policy options for farm households in Northern Ghana. *Environmental Science and Policy*, *47*: 95–107. https://doi.org/10.1016/j.envsci.2014.11.009

Wossen, T., Berger, T., Haile, M. G., & Troost, C. (2018). Impacts of climate variability and food price volatility on household income and food security of farm households in East and West Africa. *Agricultural Systems*, *163*, 7–15. https://doi.org/10.1016/j.agsy.2017.02.006

Yayeh, D., & Leal, W. (2017). Farmers' perceptions of climate variability and its adverse impacts on crop and livestock production in Ethiopia. *Journal of Arid Environments*, *140*, 20–28. https://doi.org/10.1016/j.jaridenv.2017.01.007

Yonas, A., & Jonathan, C. (2013). *Optimal Expectations and the Welfare Cost of Climate Variability: A Subjective Well-Being Approach Yonas Alem and Jonathan Colmer Centre for Climate Change Economics and Policy*. *138*.

CHAPTER FOUR

ADAPTATION TO CLIMATE VARIABILITY AND HOUSEHOLD WELFARE OUTCOMES IN UGANDA

4.1.0 Introduction

4.1.1 Background to the study

The present and future effects of climate variability are of great concern globally and Uganda given that about 68 percent of households rely on rain-fed subsistence agriculture for their survival and livelihood (Mwungu et al., 2019; UBOS, 2019). About 50,000 people are affected and about $60 million dollars in GDP is lost annually due to changes in Uganda's climate (World Bank, 2019). Adverse climatic events including floods, prolonged drought, and rising temperatures could severely affect agricultural production and thus cause uncertainty in farming household incomes (IPCC, 2014; Mubiru et al., 2018). The reduction in agricultural output creates scarcity of food items in the markets leading to a rise in price and reduced income levels for farmers (Tesfaye & Tirivayi, 2020). This shows that climate change poses a risk to household food security, incomes and all programs aimed at uplifting households from extreme poverty and hunger (Issahaku & Abdulai, 2019; Roco et al., 2017). The magnitude of vulnerability is higher among the rural small-scale farmers and dwellers due to limited non-agricultural livelihood alternatives and employment options (Asfaw et al., 2019; Kom, 2020).

Uganda's weather statistics indicate that all the four regions of Uganda are experiencing forms of variability in climate such as floods, hailstorms, altered rainfall patterns, landslides, heat waves and rising temperatures (Call et al., 2019; Mwaura & Okoboi, 2014). This is further confirmed by Uganda National Panel Survey (UNPS) results that indicate that most Ugandan households largely experience climate related shocks in comparison to other shocks (Table 14). These shocks affect agricultural activities, incomes, and welfare outcomes of those engaged in agriculture, given that the majority of Ugandan farmers depend on rain fed agricultural activities (UBOS, 2019).

Table 14: Categories of shocks experienced by Ugandan households between 2008 and 2020 (%)

Shock Category	Uganda National Panel Survey waves					
	2009/10 N= 2400	2010/11 N= 2300	2011/12 N=2300	2013/14 N=2200	2015/16 =2200	2018/19 N=1500
Climate related shocks	76.4	69.5	70.5	76.0	69.4	57.6
Crop pests and animal diseases	11.6	4.9	7.4	6.6	5.4	9.8
Price	6.3	4.4	4.8	4.1	1.3	7.2
Income	21.9	26.9	17.4	12.0	14.1	18.5
Death	5.6	7.0	6.1	7.7	8.1	7.0
Other shocks	27.5	13.8	13.8	13.3	11.6	13.9

Source: UBOS UNPS data sets (2009/10, 10/11, 11/12, 13/14, 15/16 and 18/19)

Climate related shocks occurring in Uganda are largely because of variability in climate caused by global climate change (Nuwagaba & Namateefu, 2013; Shivakumar et al., 2019). Variabilities in climate are further influencing the occurrence of other shocks such as crop pests and diseases which never used to be experienced in the country further affecting incomes and livelihoods of households that rely directly or indirectly on agriculture and nature (Kom, 2020; Mubiru et al., 2018). Therefore, adaptation[18] to climate variability can be thought of as one of the viable, effective and appropriate ways to ameliorate the impact of climate variability and change (Abid et al., 2016; IPCC, 2014, 2018). Adaptation processes can be initiated by the households themselves taking up measures aimed at coping up with the changing climatic conditions in their area (Dhakal et al., 2016; Ojo & Baiyegunhi, 2018). They could also be initiated by the government directly financing adaptation interventions or coming up with policy measures or incentives aimed at encouraging adaptation efforts in the country (Opare, 2018; Kom, 2020).

The commonly used adaptation strategies in Uganda include diversification of crop varieties planted by farmers, change of the timing of farming operations, planting improved varieties of crops that can do well in adverse climatic conditions, and to a small extent use of irrigation on farms (UBoS, 2018; Hisali et al., 2011; Shisanya & Mafongoya, 2016). In some areas, adaptation options include behavioural adjustments by the farming households such as taking up alternative employment in sectors other than the agricultural sector for example the industrial and the service

[18] Adaptation refers to a response to direct and indirect impacts of variability or change in climate for the purpose of reducing or overcoming negative effects of changes in climate (IPCC, 2014).

sectors (Call et al., 2019; Gorst et al., 2018). It is further argued that adaptation mechanisms in form of strengthened institutional capacities, such as having developed meteorological forecasting capabilities and improved access to climate forecast information by farmers across the country play a big role in alleviating impacts of climate variability and could have welfare implications as well (Di Falco & Veronesi, 2013; Vachani et al., 2014). The availability of timely information on climate and weather forecasts enables farmers to plan accordingly on how to mitigate the likely impact on their activities (Di Falco, 2014; IPCC, 2014).

Therefore, adaptation practices are projected to expand household's productive capacity leading to increased agricultural yields and thus increased incomes and food security especially among the adapting households (Ssewanyana & Kasirye, 2014; Kabubo-Mariara & Mulwa, 2019). In addition, as a climatic and livelihood risk hedging option, adaptation to climate variability can further promote household resilience[19], lessen the risk of crop failures and thus prevent yield and income variability among farmers (Beliyou et al., 2018). This is also important in mitigating the price risks for the poor and marginal farming households that rely mainly on rain-fed agricultural activities for income and survival (Gorst et al., 2018; Mulwa & Visser, 2020).

4.1.2 Problem statement

Existing studies that have examined adaptation as a key solution to variability in climate and its effects have largely been conducted in developed and emerging countries for example see Debaeke et al., 2017 in Europe, Kibue et al. (2016) and Zhang et al. (2017) in China, Gbetibouo et al. (2010) in South Africa. The few ones in the developing countries include Di Falco (2014) in Sub-Saharan Africa, Kabubo-Mariara & Mulwa (2019) and Bozzola & Smale (2020) in Kenya among others. Coming to Uganda, a few studies that have examined the factors that influence adaptation decision include Guloba (2014), Hisali et al. (2011), Nabikolo et al. (2012) and Shikuku et al. (2017). However, none of the Ugandan studies, to the best of our knowledge has analysed the welfare implications of adaptation to variability in climate. The welfare implications of variability in climate have largely been either ignored or given limited attention in empirical research. In addition, as argued by Mendelsohn (2012) and Onzima et al. (2019), the drivers and benefits of

[19] Resilience is defined by the IPCC (2014) as the ability to cope with extreme events or a trend or disturbances such as extreme climatic events – drought, altered rainfall patterns or changing temperatures.

the adaptation process will vary by country and time, thus necessitating the need for a country specific study. This study uses six waves of Uganda National Panel Survey (UNPS)[20] collected from 2009 to 2019 to determine the impact of adaptation to climate variability on household welfare outcomes as measured by the household consumption expenditure.

4.1.3 Objectives of the study

The major objective of this chapter is to investigate the determinants of adaptation to climate variability and its associated impact on household welfare outcomes in Uganda. The specific objectives include:

(i) To investigate factors affecting the choice of adaptation to variability in climate in Uganda.

(ii) To analyse the effect of adaptation on household welfare outcomes in Uganda.

(iii) To assess the difference in welfare outcomes between adapters and non-adapters to climate variability in Uganda.

4.1.4 Justification of the study

This chapter makes significant contributions to the literature by generating empirical evidence on the household welfare implications of adaptation to climate variability. It differs from existing empirical studies in many aspects. First, most of the existing related studies were carried out using cross-sectional data only. Such studies are likely to suffer from the econometric problem of endogeneity due to the failure to capture welfare dynamics over time leading to measurement errors. This chapter utilises a rich panel survey dataset, which makes it possible to capture the dynamics in the adaptation process and its consequences on household welfare outcomes. Second, to solve the econometric problem of endogeneity and reverse causality, and hence yield reliable estimates of the impacts of adaptation on welfare, the chapter employs the switching regression model. This model is estimated by use of the Full Information Maximum Likelihood (FIML) estimator that produces consistent and efficient estimates. Third, the evidence generated by this paper will support the design of effective and appropriate policies to further adaptation and welfare

[20] UNPS is an agricultural and a living measurement integrated survey covering many areas including household factors, agriculture, and welfare.

improvement efforts in Uganda. Overall, the results present valuable evidence to guide policy making process on adaptation to variability in climate as one of the ways of improving household welfare outcomes in Uganda.

4.1.5 Structure of the chapter

Section 2 presents a review of the relevant literature, while section 3 covers the methods that the chapter employs to achieve its objectives. Section 4 presents findings, while section 5 concludes.

4.2.0 Literature review

4.2.1 Theoretical Literature

Adaptation to climate variability is a measure taken by farming households to avoid losses that may result from climate variability and its effects (Shahzad & Abdulai, 2020; Adade et al., 2019). Therefore, a farming household is referred to as an adapter if it practices some climate variability coping mechanisms and non-adapter if it does not (Silvestri et al., 2012; Kabubo-Mariara & Mulwa, 2019). Existing literature demonstrates a direct relationship between adaptation to variability in climate and household welfare outcomes mainly for those engaged in the agricultural sector (Eisenack & Stecker, 2010; Abid et al., 2015). Smit & Skinner (2002) and Seo & Mendelsohn (2008) argued that adaptation to climate variability plays a key role in safeguarding economic downturn of farming households especially small-scale farmers in rural areas in tropical countries that have agriculture as the major source of livelihood (Altieri and Nicholls, 2017).

Adaptation to variability in climate mainly relies on the adaptive ability and the socio-economic characteristics of households in question (Debaeke et al., 2017; Makondo & Thomas, 2018). The theory of efficient adaptation to variability in climate, farming households should adapt if and only if climate variability affects their decisions, welfare, and utility (Mendelsohn, 2012). Similarly, a particular household will adapt only if expected returns exceed the costs associated with the adaptation strategies (Smit & Pilifosova, 2001; Abid et al., 2015). Hence, the decision to adapt to climate variability follows the theory of random utility maximisation where a representative household decides to adopt a given adaptation mechanism due to its expected net benefits (Adiku et al., 2015; Tesfaye & Tirivayi, 2020). These net benefits can be in the form of improved welfare outcomes such as increased consumption levels, reduced poverty levels, increased productivity, and income among households (Kom, 2020; Shahzad & Abdulai, 2020).

Literature shows that farming households tend to adopt a mixture of different adaptation mechanisms such as planting varieties of crops that are tolerant to variations in climate, changing planting dates, use of crop insurance mechanisms, changing occupations to less affected sectors, irrigation and practising water and soil preservation methods (Di Falco et al., 2011; Wossen & Berger, 2014). However, there are indications of adaptation deficits among some farming households especially in developing countries like Uganda (Nabikolo et al., 2012; Nelson et al., 2010). The interest of this chapter is to largely explore what determines the choice of adaptation against climate variability and how adaptation affects the welfare of the farming households.

4.2.2 Empirical literature

Existing empirical studies on the determinants and the effect of adaptation to variability in climate on the outcomes of household welfare have mixed findings. For instance, Shahzad & Abdulai (2020) analysed the heterogeneity effects of adopting climate-smart agricultural (CSA) practices as one of the adaptation strategies on three welfare outcomes – food security, nutrition security and poverty reduction in Pakistan. Using the Marginal Treatment Effects (MTE) and Policy-Relevant Treatment Effects (PRTE) approaches, their study established that adaptation significantly enhances food security and alleviates poverty among the adapting households. Still in Pakistan, Ali & Erenstein (2017) while investigating the utilisation of climate change adaptation practices and their effect on poverty and food security among Pakistan farmers, found out that the more educated farmers had more chances of adapting to changes in climate as compared to uneducated farmers. In addition, farmers who were adopting more than one adaptation option had higher levels of food security and reduced poverty levels than those who were using only one option. Ali & Erenstein's study further established that the choice to adapt to climate change is positively related to household level of wealth, household head's gender (male), farmer's land size, household size, availability and access to extension and credit services.

In Uganda, Guloba (2014) used two rounds of UNPS (2005/06 and 2009/10) data to analyse the impact of adaptation to climate change on households' welfare in Uganda. She used IV-2SLS technique to address the endogeneity problem in the choice of household adaptation mechanisms.

Her study used as the welfare indicator the household per adult equivalent consumption expenditure and established that some of the adaptation mechanisms practised impacted positively on welfare while others had a negative welfare impact instead. For example, her findings showed that the coping mechanisms adopted in times of prolonged dry seasons affected household welfare negatively while those adopted in times of livestock epidemics impacted household welfare positively. Earlier, still in Uganda, Nabikolo et al. (2012) empirically analysed the factors affecting adaptation to climate variability among men and women led farming households. The study was conducted in eastern Uganda because according to the authors the region is synonymous with the occurrences of floods, mudslides, landslides, and prolonged dry spells. Using a sample size of only 136 households, Nabikolo et al.'s study found out that the determinants of female-headed households to adapt vary from those of male-headed households. However, this study ignored differences in household welfare outcomes between the adapting and non-adapting farming households.

Hisali et al. (2011) using data from the 2005/06 Uganda National Household Survey (UNHS) evaluated the factors influencing the choice of adaptation strategies in agricultural production. The study identified access to credit, age of the household head, access to extension facilities and security of land tenure as the key factors that determine the decision to adapt among farmers. Hisali et al. (2011)'s work however, ignored the welfare impacts of adaptation. On the other hand, Bagamba et al. (2012) used the trade - off analysis model to investigate the effect of climate change on peoples' livelihoods and likely adaptation mechanisms to enhance the resilience and sustainability of the agricultural sector in central and southwestern Uganda. Their results show that 70-97 percent of the surveyed households were negatively impacted by variability in climate and that southwestern Uganda in comparison to central Uganda was more affected due to dependency on small sized farms (subsistence agriculture) and limited livelihood alternatives. The authors further argued that there would be no positive gains from swamp encroachment as a way of adapting to variability in climate and its related stress by farmers. Instead, the study recommended the need to enhance productivity returns from main crops – banana in Southwestern Uganda, sweet potatoes and banana in Central Uganda, and adoption of high milk yielding cattle breeds as better adaptation mechanisms to deal with climate variability and its effects in these two regions of Uganda.

In Ethiopia’s Nile Basin, Di Falco et al. (2011) using data from a survey of 1000 households investigated the effect of adaptation to changes in climate on household’s food security. They controlled the possibility of endogeneity in the choice of adaptation strategies by adopting a simultaneous equations regression model, which was estimated by Full Information Maximum Likelihood (FIML) estimator. Interestingly, their findings found out that food productivity had increased among the adapting households. Their study also established credit access, existence of climate data, and use of modern farming methods as the leading determinants of adaptation among households. However, Di Falco et al.’s study made no effort to estimate welfare implications of adaptation to climate variability. Similarly, Issahaku & Abdulai (2019) examined the effect of adaptation to changes in climate on food and nutrition security in the Northern part of Ghana using an endogenous switching regression model. Their study findings demonstrate that adaptation to changes in climate positively affects both food and nutrition security and that this impact is strongly felt by the low-income groups. These results agree with those a panel study in Kenya by Kabubo-Mariara & Mulwa (2019) estimated using the same methodological approach of the endogenous switching regression model.

Bryan et al. (2013) examined farmers' perceptions on changes in climate, the adaptation measures being carried out, and factors affecting their decisions to adapt in Kenya. The study findings indicate that households suffer substantial obstacles while adapting to changes in climate. In addition, many of the farmers make slight changes in their farming approaches as a way of responding to the changing climatic conditions such as adjustment in the planting time. Only a few farmers in Kenya can use irrigation or engage in agroforestry to adapt to variability in climate. The study thus emphasised the need to invest more in interventions targeted at developing agriculture especially in rural areas such as irrigation to help households to make adaptation decisions that are strategic and long-term and the need to increase access to climate information by households. The study further identified access to climate information, extension, and credit services as factors that aid adaptation and increase resilience to changes in climate. The study however makes no effort to evaluate the welfare implications of adaptation to climate variability.

Lastly, Regmi, Dhakal & Ghimire (2017) investigated the factors influencing the choice of adaptation options to changes in climate using farm level data collected randomly from 100 households in Syangja district of Nepal. Applying a logit regression model, their findings show that farmer's level of training, livestock holding, and family type have a positive and significant effect on adaptation while the farm size and being economically active reduces the probability of households to adapt.

4.2.3 Summary of the literature and gaps

Existing empirical evidence indicates that adaptation is taking place as a reaction to variability in climate (Kabubo-Mariara & Mulwa, 2019; Adiku et al., 2015; Bryan et al., 2013). However, studies carried out in developing countries such as Uganda show that few farmers have embraced adaptation and this has left many farmers exposed to changes in climate and its likely adverse effects (Guloba, 2014; Opare, 2018; Bozzola & Smale, 2020). In terms of findings, some studies are non-conclusive (see for example Guloba 2014) while others have ignored the welfare implications of adaptation to climate variability (see for example Issahaku & Abdulai (2019) and Bryan et al. (2013)). In addition, some study findings such as those of Nabikolo et al. (2012) were based on the consideration of only one climatic shock and one region or district yet there many other components of climatic shocks and regions and thus findings from such studies may not be generalizable to all shocks and across the country.

Therefore, different from the other existing studies, this study adds to the body of literature by giving fresh empirical evidence on what determines the decision to adapt and how it affects household welfare of both the adapting and non-adapting households. This does not only provide a deep understanding of the benefits associated with the adaptation to climate variability but also provides evidence to support Uganda's National Adaptation Plan making process. The use of a ten-year panel data enables this study to capture dynamics of welfare implications among households. In addition, the study addresses the likely econometric challenges of endogeneity and reverse causality by estimating an endogenous switching regression model.

4.3.0 Methodology

4.3.1 Theoretical model

Following Abid et al. (2016), a random utility theory is used to model the relationship between adaptation to variability in climate and household welfare outcomes in Uganda. The i^{th} farming household decides to adapt to climate variability if its anticipated net benefits because of adaptation are positive (Belay et al., 2017; Bryan et al., 2013; Kom, 2020). In this case, the considered benefit is the improvement in welfare outcomes (household consumption per adult equivalent expenditure) of the farming households. The difference in adaptation benefits (welfare) is expressed using an unobservable latent variable. Let Y^* be defined as the latent variable for the anticipated net benefits from adaptation to climate variability against non-adaptation by a representative household. Y_i denotes the decision to adapt by household i. We consider a latent variable (Y_{it}^*) which equals the expected net returns from adopting a given adaptation mechanism by household i in period t:

$$Y_{it}^* = x_{it}\alpha + u_{it} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (1)$$

Where vector x_{it} includes variables that influence the decision to adapt by household i in period t (Di Falco et al., 2011; Mubiru et al., 2018). These factors can be classified into various categories: farm characteristics (such as location - a farm located in an area with fertile soils may take time to adapt as compared to the one located in an area with less fertile soils); variables of climate (such as precipitation and temperature) and household specific attributes (for example the education level of the household head - Ali & Erenstein, 2017; Shahzad & Abdulai, 2020). Others include access to credit services, timely climate information and access to extension services (Alemayehu & Bewket, 2017; Kom, 2020). α is a vector for model parameters to be estimated.

However, the latent variable (Y_{it}^*) as defined in equation (1) is not observable directly; it is the decision to adapt (Y_{it}) which is directly observable as follows:

$Y_{it} = \{1 \quad if\ Y_{it}^* >$
$0\ 0 \quad otherwise \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (2)$

Where Y_{it} is an observed variable which means that household i decides to adapt to climate variability ($Y_{it} = 1$) if the anticipated net earnings from the adaptation are positive ($Y_{it}^* > 0$).

4.3.2 The empirical model

The empirical model has 2 stages. The first stage involves specifying the selection model for adaptation to variability in climate. This is followed by modelling the effect of adaptation to variability in climate on household welfare outcomes, as proxied by adult equivalent consumption expenditure of the household. The choice to adapt may be centred on the individual household self-selection such that households that adapt display different but unobservable features from their non-adapting counterparts. Not accounting for such unobservable features could result in estimates of the effect of adaptation on household welfare that are inconsistent (Di Falco et al., 2011; Lokshin & Zurab, 2004). This shortcoming is solved in this chapter by estimating a simultaneous equation (endogenous switching regression) model of adaptation to variability in climate and household welfare using the Full Information Maximum Likelihood (FIML) estimator (Menike & Arachchi, 2016; Wossen et al., 2018). In this case, a representative farming household faces two regimes defined as follows:

Regime 1: $E_{1i} = x_{1i}\alpha_1 + u_{1i}\ if\ Y_{it} = 1 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. (3a)$

Regime 2: $E_{2i} = x_{2i}\alpha_2 + u_{2i}\ if\ Y_{it} = 0 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. (3b)$

Where E_i is the household welfare (household consumption expenditure per adult equivalent) for both the adapting and non-adapting farming households; x_i is a vector of regressors such as climate variability factors, household factors, institutional factors, location factors and other social economic factors. The error terms for both equations (3a) and (3b) are assumed to be normally distributed and not correlated since both the adapting and non-adapting farm households cannot be observed at the same time.

4.3.2 Estimation procedure

Before estimating the endogenous switching regression model, the chapter starts by exploring appropriate instruments to use to describe the relationship between adaptation and household welfare outcomes. In the estimation, there is need for instrumental variable(s) that is (are) correlated with an endogenous variable – adaptation choice - but not correlated with the disturbance term. The instruments should not impact on the outcome variable of interest (per household adult consumption expenditure), conditional on the included regressors (x). With this in mind, this chapter selects two instruments – availability of extension services and availability of credit services. These two instruments were tested for validity assumption by regressing each of them on adaptation. To qualify as a valid instrument, each of them should have a statistically significant relationship with adaptation to variability in climate. The switching regression model is applied mainly to distinguish between the expected welfare outcomes of the farming households that practise some adaptation mechanism (4a) and those who do not (4b). Secondly, to explore the anticipated welfare change in hypothetical counterfactual cases (4c) that the adapting farming household did not adapt, and (4d) that the non-adapting farming household adapted. Mathematically, these are expressed as:

$$E(y_i = 1) = X_{1i}\beta_1 + \sigma_{1\gamma}\mu_{1i} \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots .. (4a)$$

$$E(y_i = 0) = X_{2i}\beta_2 + \sigma_{2\gamma}\mu_{2i} \dots \dots \dots \dots \dots . \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (4b)$$

$$E(y_i = 1) = X_{1i}\beta_2 + \sigma_{2\gamma}\mu_{1i} \dots \dots \dots \dots \dots . \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots . (4c)$$

$$E(y_i = 0) = X_{2i}\beta_1 + \sigma_{1\gamma}\mu_{2i} \dots \dots \dots \dots \dots . \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots . (4d)$$

The effect of the treatment variable (adaptation) on the treated sample (TT- adapting households) is obtained by taking the difference between the expected household welfare outcomes from adapting to variability in climate (4a) and expected household welfare outcomes if the adapting household did not adapt (4c):

$$TT = E(y_i = 1) - E(y_i = 1) \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (5)$$

Equation (5) shows the effect of adaptation to variability in climate on the welfare outcomes of the adapting farming households. In the same way, the effect of adapting to climate changes on the welfare of the non-adapting households (untreated sample - TU) is obtained as the difference between the expected welfare if the non-adapting household adapted (4d) and the expected household welfare if the non-adapting household did not adapt (4b).

$$TU = E(y_i = 0) - E(y_i = 0) \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots . (6)$$

Lastly, the study examines the Heterogeneity Transitional Effects (HTE) of adaptation to climate variability on welfare – that is, did adapting to climate variability benefit the adapting households or not? This is obtained by subtracting equation (6) from equation (5) as follows:

$$HTE = TT - TU \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (7)$$

4.3.3 Study Variables

Dependent Variables

The dependent variable of this chapter is the household per adult equivalent consumption expenditure, a household welfare indicator. It is expressed in Uganda shillings (USh) using constant base prices as generated by Uganda Bureau of Statistics (UBOS) for Uganda's case. In the literature, consumption is considered as the preferred welfare measure over income, given that the latter is smoother than the former and hence, the risk-averse individuals choose consumption over income since consumption is less variable (Dercon & Christiaensen, 2011; Dercon, 2004). In Uganda, consumption expenditure is calculated as the summation of the value of food and non-food items consumed whether obtained from own production, from the market, gift or in-kind in the last thirty (30) days. The resulting household total consumption value is scaled to adult equivalent bases to cater for intra-household disparities and needs (UBOS, 2019).

Independent Variables

The choice of the independent variables was derived from economic theory and related existing empirical studies (for example see Di Falco et al., 2011; Kabubo-Mariara & Mulwa, 2019; Mendelsohn, 2012). The independent variables are categorised into three groups: the first group consists of factors of variability in climate, and these include precipitation and temperature variability. These are important given that Ugandan farmers are largely involved in rainfed agricultural practices (UBOS, 2019). The second category consists of the household factors which include: the age, gender, education level, marital status of the household head, household size, farm size, occupation, income level, location of the household and household assets (Di Falco, 2014; Mabe et al., 2014). These factors are unique to a given household and thus may be vital in influencing adaptation to climate variability. For instance, household properties (assets) such as equipment measure the level of a household's level of wealth and sometimes may act as source of capital required to facilitate the adaptation process (Kabubo-Mariara & Mulwa, 2019). The last category consists of the institutional variables such as availability of extension and credit services which are also anticipated to affect the decision by households to adopt a specific strategy and, hence, lead to improvement in welfare (Coromaldi, 2020). For instance, availability of extension services is expected to influence farmers' perceptions about variability in climate and possibly affect the adoption of a certain adaptation mechanism for example early planting or irrigation (Wossen et al., 2018). Table 15 presents the definitions, measurement and literature sources of the variables used in the study.

Table 15: Definition and Measurement of independent variables used in the study.

Variable	Definition and Measurement	Literature Source
Precipitation Variability	Coefficient of variation of precipitation averaged for at least 30 years.	Arshad et al. (2017)
Minimum temperature variability	Coefficient of variation of minimum temperature averaged for 30 years.	Coromaldi (2020)
Maximum temperature variability	Coefficient of variation of maximum temperature averaged for 30 years.	Wossen et al. (2018)
Age	Age of household head in complete years.	Di Falco (2014)
Gender	Gender of household head (1=male)	Mabe et al. (2014)
Education	Years of education	Di Falco et al. (2011)
Marital status	=1 if the household head is married	Adade et al. (2019)
Household size	Number of members in the household	Kabubo-Mariara & Mulwa (2019)
Land size	Plot size in hectares	
Farm assets	Value of farm assets in Uganda shillings	Wossen et al., (2018)
Agro ecology	Regional dummies	Mabe et al. (2014)
Location	Household residential area (1 = Urban)	Adiku et al. (2015)
Land tenure	Land ownership (1= Formal)	Shahzad & Abdulai (2020)
Occupation	Main occupation (1= Agriculture)	Arshad et al. (2017)
Income	Household income level in Uganda shillings	Limantol et al., (2016)
Access to credit	=1 if household received credit	Kabubo-Mariara & Mulwa (2019)
Extension services	=1 if household received extension services	

4.3.4 Data Type and Sources

This chapter uses six waves of Uganda National Panel Surveys that span over a period of 10 years from 2009 to 2019 and a large historical climate dataset (1979 -2013) sourced from world climate data, made available by the U.S. National Oceanic and Atmospheric Administration (NOAA).

These household datasets are nationally representative collected by UBOS in collaboration with the World Bank's LSMS-ISA program. Each wave covers on average around 2,500 households giving a total of about 12,500 observations. The UNPS survey datasets contain rich data on household specific characteristics, household income sources, household assets, data on household consumption expenditure patterns, shocks, and adaptation strategies by households, agricultural, livestock and community information. The data set is rich, large enough and reliable to ensure valid analysis and good precision of the model estimates.

Table 16 presents descriptive statistics (mean and standard deviation) of the variables that have been used in the empirical analysis of this chapter. The statistics are presented for all households, then for the adapting and non-adapting households separately and the differences between the groups is tested using the T-test.

Table 16: Descriptive statistics of all study variables

Variable Name	All households (N=12,900)		Adapters (n = 4,139)		Non-Adapters (n = 8,761)		Diff
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
Dependent Variables							
Adapt (1=yes)	0.32	0.47	1.00	0.00	0.00	0.00	
Per adult Cons Expenditure	57001.11	71742.19	54396.18	70406.15	58231.77	72336.16	-3835.59***
Climate variability							
Precipitation variability	0.56	0.14	0.55	0.13	0.57	0.14	-0.02***
Min temperature variability	0.04	0.02	0.04	0.02	0.04	0.02	0.00
Max temperature variability	0.08	0.01	0.07	0.01	0.08	0.01	0.00
Household characteristics							
Age (years)	48.41	15.01	47.55	14.71	47.42	15.13	-1.28***
Gender (1= male)	0.70	0.46	0.71	0.45	0.69	0.46	0.02**
Education (years)	5.34	3.81	5.31	3.90	5.35	3.78	-0.04
Marital status (1= married)	0.74	0.44	0.76	0.43	0.74	0.44	0.02**
Household size	11.09	13.02	11.26	12.97	11.02	13.04	0.24
Farm size	2.67	10.37	3.06	1.96	2.49	12.50	0.57***
Farm assets (UGX[21])	48039.78	252531.40	35391.94	77816.64	54015.06	301549.30	-18623.12***
Region							
Central	0.25	0.44	0.14	0.35	0.31	0.46	-0.17***
Eastern	0.24	0.43	0.29	0.46	0.22	0.41	0.08***
Northern	0.26	0.44	0.28	0.45	0.24	0.43	0.03***
Western	0.25	0.43	0.29	0.45	0.23	0.42	0.06***
Location (1 =urban)	0.12	0.33	0.11	0.31	0.14	0.34	-0.02***
Land ownership (1=formal)	0.52	0.50	0.48	0.50	0.54	0.50	-0.06***
Occupation (Agriculture)	0.37	0.48	0.45	0.49	0.33	0.47	0.12***

[21] 1 UGX (Uganda shillings) is approximately equal to 0.000286 United States Dollars (BoU, 2020).

Income level (UGX)	228174.00	273667.30	218374.20	224643.60	232803.70	293896.60	-14429.53***
Institutional Variables							
Availability of credit	0.81	0.40	0.81	0.39	0.80	0.40	0.01
Availability of extension services	0.44	0.50	0.36	0.48	0.47	0.50	-0.11***

Note: **, ** and *** indicate statistical significance at the $p < 0.1$, $p < 0.05$, and $p < 0.01$ levels*

Source: Author's calculations based on UNPS (2009-2019) and climate data (1979-2013)

The descriptive statistics in table 16 indicate that 32 percent of the households were practicing at least one form of adaptation option to react to climate shocks. The mechanisms included both autonomous adaptation strategies including planting of new crop varieties, crop diversification, changing cropping practices, migrating to other areas, altering the timing of planting, use of water harvesting technologies, resorting to animal rearing, and taking on non-agricultural jobs among others. Households using one (1) or more of the above strategies were adapters and assigned a value of 1. This follows the assumption that an adapting household consciously uses these mentioned strategies strictly for purposes of adapting to climate variability and not for other purposes such as the need to increase productivity. On the other hand, a household is considered as a non-adapter if it was not practicing any form of adapting to variability in climate and allocated a value of 0. In total, there were 4,139 adapters and 8761 non-adapters. This tends to suggest that the number of adapting households is smaller than that of the non-adapters and hence more efforts are needed to encourage adaptation among the farming households.

Table 16 further shows substantial differences between adapting and non-adapting households. For instance, the average household per adult equivalent consumption expenditure is Uganda shillings 54,396.18 for adapting households and 58,231.77 for non-adapting households. This implies that household consumption expenditure per adult equivalent is slightly higher among the non-adapting households. Similarly, non-adapting households were older in terms of age and had more income compared to the adapting households. The summary statistics also show that adaptation was more common among households having agriculture as their main form of employment. Surprisingly, non-adapting households accessed extension services more than the adapting ones. This could imply that either the extension workers do not encourage farmers to adapt, or the farmers are comfortable with their current situation. However, the results in table 15 show that adaptors were less affected by precipitation variability although they were equally affected by minimum and maximum temperature variability occurring in the country between 2008 and 2020.

4.4.0 Empirical Findings

4.4.1 Estimates from the Endogenous Switching Regression Model (ESR)

Table 17 presents model estimates from the ESR that were estimated using the full information maximum likelihood procedures. The results of the outcome equation that investigates the adaptation impact on welfare are presented in columns 3 for adapting households and 4 for non-adapting households. In column 2, estimates from the selection equation showing the factors that determine the decision to adapt to climate variability by households are presented.

Table 17: Model estimates from the Endogenous Switching Regression Model

Model	**Selection Equation**	**Adaptors**	**Non-Adaptors**
Dependent Variable	**Adapted (1/0)**	**Welfare**	**Welfare**
Precipitation variability	-1.9642***	-0.1046	1.2370***
	(0.5502)	(0.4748)	(0.2722)
Precipitation variability squared	1.2689***	0.0662	-0.8355***
	(0.4308)	(0.3397)	(0.2069)
Minimum temperature variability	1.6331**	-0.0884	-0.9430***
	(0.6590)	(0.4729)	(0.3073)
Maximum temperature variability	-2.2371**	0.1812	0.9343**
	(0.8834)	(0.6441)	(0.4144)
Age	-0.0064***	-0.0000	0.0026***
	(0.0017)	(0.0013)	(0.0007)
Gender	-0.0252	-0.1012***	-0.0450
	(0.0622)	(0.0377)	(0.0321)
Household size	0.0038***	-0.0078***	-0.0077***
	(0.0014)	(0.0006)	(0.0005)
Farm size (hectares)	0.0030	-0.0139**	-0.0012
	(0.0021)	(0.0056)	(0.0010)
Value of farm assets	-0.0998***	-0.0262	0.0144
	(0.0145)	(0.0184)	(0.0094)
Years of education	-0.0003	0.0203***	0.0172***
	(0.0056)	(0.0032)	(0.0028)
Land ownership	0.1422***	0.0311	0.0065
	(0.0550)	(0.0400)	(0.0265)
Occupation	0.2457***	-0.0328	-0.1052***
	(0.0337)	(0.0494)	(0.0220)

Region[22]			
Central Uganda	-0.6850***	0.0034	0.1685***
	(0.0984)	(0.1304)	(0.0552)
Eastern Uganda	0.0886*	-0.0605*	-0.0641**
	(0.0476)	(0.0312)	(0.0269)
Western Uganda	-0.0867	-0.0228	0.0576*
	(0.0688)	(0.0418)	(0.0341)
Income	0.0551**	0.6972***	0.6728***
	(0.0278)	(0.0205)	(0.0145)
Marital status (married)	0.0416	-0.1806***	-0.1914***
	(0.0752)	(0.0426)	(0.0366)
Location (Urban)	-0.0527	-0.0412	-0.0170
	(0.0555)	(0.0416)	(0.0291)
Availability of extension services	-0.1352***		
	(0.0429)		
Availability of credit services	0.0187		
	(0.0254)		
Constant	0.9008**	2.7590***	1.7746***
	(0.3918)	(0.2308)	(0.2259)
Observations	12,885	12,885	12,885
Wald Chi-Square		2866.50***	
Test of Independent of Equations		331.21***	
Rho-0		0.0782	
Rho-1		1.4021***	

Robust standard errors in parentheses

Note: **, ** and *** indicate statistical significance at the p < 0.1, p < 0.05, and p < 0.01 levels*

The OLS model results are not reported because they combine both the adaptors and non-adaptors into one set and estimate the factors determining household welfare as measured by per adult equivalent household consumption expenditure. Such findings are likely to suffer from the econometric problem of endogeneity resulting from the sample selection bias (Coromaldi et al., 2015; Kabubo-Mariara & Mulwa, 2019). This is confirmed by the test of independent equations, which shows that the equations are related; hence, the OLS results are inconsistent and inefficient.

The two institutional variables in the selection equation – availability of extension services and availability of credit services were used for model identification. The relevancy test for the two instrumental variables showed a significant statistical relationship between adaptation to

[22] Northern Uganda is a reference region.

variability in climate and availability of extension services, and hence considered as a strong instrument. However, the relationship between adaptation to variability in climate and availability of credit services was not statistically significant, and thus considered as a weak instrument. Columns 3 and 4 present the factors that determine household welfare outcomes for farm households that did adapt (Eq. 4a) and those households that failed to adapt (Eq. 4b) to variability in climate respectively. The model diagnostic tests are conducted on (Rho-0) and (rho-1) to determine the association between the disturbance (error) term of the selection equation and the error term of the outcome equations (4a) and (4b). The findings indicate that rho-0 is not statistically significant (not different from zero), implying that the selection and non-adaptation equations are not correlated. However, the results show that the correlation coefficient for adapters (Rho-1) is statistically significant and positive. The positive sign implies that households who adapt are likely to have better welfare outcomes than any other random household in the whole sample, while those who prefer not to adapt are likely to have the same household welfare outcomes as any other random household in the sample under consideration.

The selection equation results presented in column 2 of table 17 indicate that extreme cases of variability in precipitation, variability in minimum temperature, the household size, having agriculture as the main occupation, and the household's level of income have a significant and positive impact on the household's decision to adapt to variability in climate. The age of the household head, value of household assets and access to extension services have a negative and significant impact on the adaptation to variability in climate decisions by the households.

Factors affecting household per adult equivalent consumption expenditure varied between the houses that adapted and households that did not adapt, as shown in columns 3 and 4 (Table 17) of the estimated ESR model results. The findings indicate that household per adult equivalent increase in expenditure on consumption with the years of education and income level of both the adapting and non-adapting household heads. As expected, variability in climate does not have a significant impact on adapting household welfare but significantly impacts on the non-adapting households' welfare. This corroborates the theoretical propositions and other findings of the previous studies that adaptation is one of the leading measures against climate variability (Bozzola & Smale, 2020; Di Falco, 2014).

The findings further show that adapting households with male-heads are associated with decreasing per adult equivalent consumption expenditure. Per adult equivalent consumption expenditure rises with the age of the household head for the non-adapting households. This outcome can be explained by the fact that as the farm household head gets older, the more rigid and resilient he or she becomes due to accumulated farming experience (Bedeke et al., 2019; Hisali et al., 2011). In this case, age and thus the experience in farming is in itself an adaptation mechanism (Guodaar et al., 2019). As a result, older farmers tend to resist adaptation as one of the ways of improving their welfare outcomes. This is further confirmed by the negative significant relationship between household head's age and adaptation to climate variability as presented in columns 2 of table 17. Furthermore, household consumption expenditure (welfare) declines with the household size for both adapting and non-adapting households. Non-adapting households largely engaged in agriculture as the main occupation and thus their main source of income experienced a welfare decline caused by variability in climate. Both the adapting and non-adapting households in Eastern Uganda also experienced a decline in welfare. High-income levels increase welfare of both the adapting and non-adapting households. This follows the fact that a rise in income implies increased disposable income to households to finance consumption, and thus increased purchasing power.

4.4.2 Conditional Expectations, Treatment and Heterogeneity Effects

Table 18 below illustrates the expected household consumption expenditure for the adapting and non- adapting households under the treatment (actual) and counterfactual subsamples of the study. Cells (a) and (b) of table 18 represent the expected household per adult equivalent consumption expenditure as observed in the actual sub-sample.

Table 18: Expected per adult Household Consumption Expenditure outcomes.

	Decision		
Sub-samples	Adapt	No adapt	Treatment effects
Adaptors	40,945.6 (a)	40538.2	4,053.9***
Non-adaptors	18,769.7	43477.6 (b)	-24,707.9***
Heterogeneity effects	22,175.9	-2,939.4	28,761.8***

Note: **, ** and *** indicate statistical significance at the p < 0.1, p < 0.05, and p < 0.01 levels*
Source: Author's computations based ESR model results

The findings show that farm households which adapted to climate variability had an average expected household per adult equivalent consumption expenditure of Uganda shillings 40,945.6 (USD 11.7) as compared to Uganda shillings 43,477.6 (USD 12.4) for non-adapting households. The difference between the two groups was Uganda shillings 2532 (USD 0.72) per month. This indicates that non-adapting households were spending 5.8% more on consumption than the adapting farm households. This is obtained by subtracting (b) from (a) divided by (b) multiplied by 100 ($\frac{40945.6-43477.6}{43477.6}x100=-5.8\%$). The negative sign implies that the non-adapting households were spending 5.8% more than the adapting households on consumption. However, the results in table 5 further show that it pays the adapters to adopt otherwise they would lose as much as 4,054 Uganda shillings (USD 12) per month due to climate variability and its effects. Further, it pays the non-adapters not to adopt, as they are likely to lose 24,708 Uganda shillings if they ever adapted as indicated by the negative sign on this amount in table 18. Overall, the results in table 18 suggest that adaptation to climate variability is a better option judging from the positive impact result of the heterogeneity effect (TH). In the existing literature, a decline in consumption expenditure among the farming households practising at least one of the adaptation mechanisms has been largely attributed to the need to raise adequate resources to cover the costs associated with the adaptation process (Gorst et al., 2018; Limantol et al., 2016; Kom, 2020). In addition, studies such as Guloba (2014) and Bedeke et al. (2019) noted that not all adaptation mechanisms are welfare improving and that during the early periods of adaptation, farmers largely incur losses due to the high initial costs involved in the process of adaptation. However, with time, the adapting farmers recover their initial costs and thus start to gain from their adaptation efforts (Karki et al., 2020; Yamba et al., 2019).

4.4.3 Discussion of the findings

The estimated heterogeneous treatment effects show that it is beneficial for adapting households to continue adapting. Adaptation is perceived as one of the ways of improving household welfare among the farming households (Bozzola & Smale, 2020; Kilimani et al., 2020; Tesfaye & Tirivayi, 2020). Our findings, however, tend to establish otherwise, although this could be explained by the high costs incurred in the adaptation process and the fact that agricultural products continue to attract low prices in Uganda (Guloba, 2014; UBOS, 2019). In addition, previous works such as Yamba et al., (2019), Bedeke et al. (2019) and Karki et al. (2020) concluded that not all adaptation measures are welfare improving and that their efficiency could vary from one region or country to another. In some cases, the results are sensitive to the welfare measure, for example Shahzad & Abdulai (2020) using poverty as a welfare measure, established a positive relationship between poverty reduction and adaptation in Pakistan, although their study only considered one form of adaptation – use of climate smart agriculture.

The study results further show that precipitation variability has a concave significant impact on per adult consumption expenditure of the non-adapting households. This implies that variations in precipitation variability are associated with increasing welfare up to a point where variability in precipitation equals 0.74. Beyond this point, any extra increase in variability of precipitation leads to a reduction in welfare of the non-adaptors. This result agrees with that outlined by Asfaw et al. (2019) in Malawi but differs from that of Kahsay & Hansen (2016) who established a non-significant impact of precipitation variability on welfare. However, when it came to adapting farm households, the impact of precipitation variability on adapting welfare was statistically non-significant. This therefore could support the notion that adaptation might be an appropriate mechanism to alleviate negative effects of variability in climate (Asfaw et al., 2019; Kilimani et al., 2020). For example, Asfaw et al. (2019) after establishing a negative effect of variability in climate on outcomes of household welfare in Malawi, recommended adaptation as a successful potential remedy to the negative effects of variability in climate. He argued that even though adaptation could be costly and thus non-profitable to farmers in the short run, in the long term the adaptors benefit extensively in terms of improved productivity and returns, hence leading to improved welfare.

Similarly, variability in temperature also has a significant impact on non-adapting household's welfare, but no significant impact of adapting households' welfare. The results show that variability in minimum temperature reduces non-adapting household welfare by 0.94 percentage points. According to Kotir (2011), when the minimum temperature changes, the overall surface temperature also changes and it will likely affect agricultural returns negatively, causing deterioration in incomes and thus welfare. However, the findings further reveal that variability in maximum temperature is linked to an increase in per adult equivalent expenditure on consumption of the non-adapting households by 0.93 percentage points. This could be because of the high costs that are incurred as a result of high temperatures such as increased water bills due to water scarcity and buying temperature regulating gadgets among others (Arshad et al., 2017; Ndamani & Watanabe, 2015). This could also explain why variability in temperature does not affect consumption expenditures of the adapting households.

Welfare increases with the household head's age among the non-adapting households but does not affect the welfare of adapting households significantly. It is argued that household heads that are older become resilient through experience and hence can safeguard themselves against deterioration in their welfare despite the occurrences of adverse weather events because of variability in climate (Belay et al., 2017; Hisali et al., 2011). Results also indicate that with every extra year the household head spends in school, the welfare for both the adapting and non-adapting households increase. It should be noted that education is an empowerment tool that increases an individual's productivity and employability (Adade et al., 2019). Secondly, education increases the probability and ability of a farm household head to find a job in non-agricultural sectors such as the industrial and service sectors (Abdul-Razak & Kruse, 2017; Skoufias et al., 2011).

On the determinants of adaptation to climate variability, the estimates from the selection equation shows that variability in precipitation plays a big role in encouraging households to adapt. The same applies to variability in minimum temperature. Mild variability in precipitation is associated with a decline in the likelihood of adaptation among households up to a point when variability in precipitation equals 0.78. Beyond this point, any extra increase in precipitation increases the likelihood of adaptation to variability in climate. Bryan et al. (2013) argues that increased variability in precipitation is associated with increased unreliability in rainfall, which forces farming households to embrace some adaptation methods such as water harvesting and early planting. On the other hand, variability in maximum temperature has a significant negative effect on the adaptation to variability in climate. It reduces the likelihood of households adapting to climate variability by 2.19 percentage points. This finding can be explained by the lack of significant impact of variation in maximum temperature on livelihood sources such as agriculture as compared to variability in precipitation and minimum temperature (Kahsay & Hansen, 2016; Bedeke et al., 2019).

Although all regions in Uganda are related to an increase in probability of adapting to climate variability, households in eastern Uganda have the highest likelihood of adapting to variability in climate in comparison to those in other regions. This could be due to the fact that in comparison to other regions, eastern Uganda is the region most affected by the occurrence of adverse climatic conditions for instance floods, prolonged drought, and landslides (UBOS, 2019; Kilimani et al., 2020). Formal land ownership is associated with a higher probability of farming households adapting to climate variability. Formal land ownership can act as collateral security to obtain financing from commercial banks and other financial institutions to facilitate the adaptation process or programs such as buying drought resistant crop varieties, irrigation gadgets among others (Asfaw et al., 2019). The findings however indicate a negative significant relationship between adaptation to variability in climate and availability of extension services. This contradicts the conclusion by Bryan et al. (2013) who established a positive relationship between availability of extension services and the choice to adapt to climate variability. Extension services are expected to encourage households to adapt by availing to them the required information and what it takes to adapt to variability in climate including assisting them to adapt (Kom, 2020; Tessema et al., 2013).

Finally, adaptation to variability in climate declines with the age of the household head. This implies that the likelihood to adapt reduces with a rise in the household head's age. Specifically, an additional one year in the age of the household head, reduces the likelihood of a household to adapt to climate variability by 0.002 percentage points, other factors remaining constant. In other words, older, more experienced farmers are less likely to adapt to variability in climate as opposed to their counterparts. The reason could be described by learning-by-doing theory where farmers learn over time through various experiences making older farmers better in using local technologies in their farming activities (Hisali et al., 2011; Kabubo-Mariara & Mulwa, 2019). Although owning farm assets by households was projected to have a positive effect on the decision to adapt, in this study, it was found to have a negative impact on the probability that the household will adapt. Owning assets is seen as a measure of a household's wealth status. Wealthier households are assumed to be able to afford various adaptation mechanisms such as smart agricultural technologies, irrigation use, improved crop varieties that are drought tolerant among others (Karki et al., 2020; Nabikolo et al., 2012). However, this finding could be due to the fact that farm assets are part of 'sunk' costs and are thus not representative of the liquidity status of the household hence the negative impact.

4.5.0 Conclusions and policy implications

4.5.1 Conclusions

This study investigated the factors affecting adaptation to variability in climate and how adaptation influences household welfare outcomes in Uganda. The essay utilised a large dataset consisting of six waves of a nationally representative Uganda National Panel Survey collected by Uganda Bureau of Statistics from 2009 to 2019 and historical climate data (1979-2013) obtained from the U.S. National Oceanic and Atmospheric Administration (NOAA). For empirical analysis, an endogenous switching regression model was estimated. Its findings identified variables such as variability in precipitation in minimum temperature; household specific characteristics such as age, location, years of education, occupation, and wealth status (among others) and institutional variables – availability of extension services, as significant determinants of the choice to adapt to variability in climate among farm households. These findings provide the required insights and evidence to design measures and mechanisms aimed at encouraging adaptation among the farm household in the country. The study uncovers a convex relationship between precipitation variability and the likelihood of farming households adapting. These results suggest that farming households are more likely to adapt to variability in climate under extreme cases of precipitation variability. This is true given that the majority of Ugandans rely on rain for their agricultural activities and the fact that mild variability in precipitation might have negligible impact on their output and hence the less likelihood to adapt (Kom, 2020; Yamba et al., 2019).

While extreme variability in precipitation could lead to disruptions in planting seasons, changes in temperature influences occurrence of new pests and diseases and thus affect the quantity and quality of harvests leading to variability in household income levels (Kabubo-Mariara & Mulwa, 2019; Mabe et al., 2014). This in turn influences farming households to adopt some measures such as irrigation and planting of climate variability resistant crop varieties (Kilimani et al., 2020; Shikuku et al., 2017). The chapter further uncovers a surprising negative impact of availability of extension services on the adaptation decision in Uganda. Yet, theoretically, extension services are expected to equip farmers with necessary skills to improve their productivity including timely information on variability in climate and how to handle changes in climate (Mendelsohn, 2012). Therefore, this finding could be due to inefficiency, incompetence and inaccessibility of the extension workers and general extension services across the country (Kilimani et al., 2020; Nabikolo et al., 2012). Hence, there is need to streamline and make extension services more available and affordable to all farmers irrespective of their location in the country.

Comparisons of welfare outcomes between the adapting and non-adapting households show that per adult equivalent consumption expenditure among adapting households declines by 5.8% relative to that of the non-adapting households. This is quite surprising given the theoretical predictions that adaptation would enhance welfare of the farming households through improved returns from the agricultural activities (Asmare et al., 2019; Karki et al., 2020). However, this finding simply communicates the need for Uganda to do more to make adaptation process beneficial and welfare improving to Ugandan farm households. The high costs and relatively low prices of agricultural products could be responsible for the welfare decline among the adapting households (Guloba, 2014; Kilimani et al., 2020). This is because the results obtained show that the difference in welfare outcomes between adopters and non-adapters is positive which implies that adaptation to variability in climate could positively influence the welfare of the farmers. Therefore, this finding provides an avenue or a baseline to improve adaptation process in Uganda if farmers' welfare is to be improved.

4.5.2 Policy implications

Based on the study findings, there is a need for measures aimed at encouraging adaptation among farming households as a way of safeguarding themselves from welfare loss as shown by the findings. This can be done by sensitising farmers on associated short run and long run benefits of adaptation. This effort can be followed up with pinpointing appropriate technologies that the household could employ as per their socio-economic status, income level and regional or residential conditions. It is critical to identify specific and appropriate adaptation techniques for each region given that the magnitude of climate variability is not uniform across all the regions. From the findings, we note the need to subsidise the available adaptation measures such as irrigation to make adaptation as cheap and beneficial as possible.

In addition, there is a need to strengthen and improve the provision, availability, efficiency, competence and quality of extension workers and services across the country. This is because, through extension services, farming households can be trained on the timely management of the farming operations in response to changes in climate such as planting period, crop type to plant, weeding and harvesting which acts as adaptation measures to make sure they are carried out when they will have the best results. This will not only encourage adaptation in the country but also make it profitable and thus welfare improving. Finally, sensitization on the benefits of adaptation should focus on all farmers but with more emphasis on farmers who have been in traditional farming for a relatively long time as they tend to be rigid to adapt to new methods of farming and adaptation measures. These prefer to maintain their old ways of doing things at the expense of adopting modern adaptation measures, which might in the long run compromise their welfare outcomes.

4.5.3 Areas for further research

This study has analysed the determinants and the effect of adaptation to variability in climate on household welfare. However, the study could not analyse the effect of each adaptation mechanism on welfare due to data limitations. There is a need to analyse the impact of different adaptation mechanisms such as use of irrigation, smart agriculture, conservation agriculture and crop diversification on agricultural productivity; and then how individually each can influence the welfare outcomes of both the adapting and non-adapting households (if they adapted). This would help identify the most welfare improving adaptation option for Ugandan farmers given their income levels and guide targeting of policy measures.

References

Abdul-Razak, M., & Kruse, S. (2017). The adaptive capacity of smallholder farmers to climate change in the Northern Region of Ghana. *Climate Risk Management*, *17*, 104–122. https://doi.org/10.1016/j.crm.2017.06.001

Abid, M, Scheffran, J., Schneider, U. A., & Ashfaq, M. (2015). *Farmers' perceptions of and adaptation strategies to climate change and their determinants: the case of Punjab province, Pakistan*. 225–243. https://doi.org/10.5194/esd-6-225-2015

Abid, Muhammad, Schneider, U. A., & Scheffran, J. (2016). Adaptation to climate change and its impacts on food productivity and crop income: Perspectives of farmers in rural Pakistan. *Journal of Rural Studies*, *47*, 254–266. https://doi.org/10.1016/j.jrurstud.2016.08.005

Adade, P., Crespo, O., & Abu, M. (2019). Climate Risk Management Adapting to changing climate through improving adaptive capacity at the local level – The case of smallholder horticultural producers in Ghana. *Climate Risk Management*, *23*(September 2018), 124–135. https://doi.org/10.1016/j.crm.2018.12.004

Adiku, S. G. K., MacCarthy, D. S., Hathie, I., Diancoumba, M., Freduah, B. S., Amikuzuno, J., Traore, P. C. S., Traore, S., Koomson, E., Agali, A., Lizaso, J. I., Fatondji, D., Adams, M., Tigana, L., Diarra, D. Z., N'diaye, O., & Valdivia, R. O. (2015). *Climate Change Impacts on West African Agriculture: An Integrated Regional Assessment (CIWARA)*. 25–73. https://doi.org/10.1142/9781783265640_0014

Alemayehu, A., & Bewket, W. (2017). Determinants of smallholder farmers' choice of coping and adaptation strategies to climate change and variability in the central highlands of Ethiopia. *Environmental Development*, *24*, 77–85. https://doi.org/10.1016/j.envdev.2017.06.006

Ali, A., & Erenstein, O. (2017). Assessing farmer use of climate change adaptation practices and impacts on food security and poverty in Pakistan. *Climate Risk Management*, *16*. https://doi.org/10.1016/j.crm.2016.12.001

Altieri, M. A., & Nicholls, C. I. (2017). The adaptation and mitigation potential of traditional agriculture in a changing climate. *Climatic Change*, *140*(1), 33–45. https://doi.org/10.1007/s10584-013-0909-y

Arshad, M., Kächele, H., Krupnik, T. J., Amjath-Babu, T. S., Aravindakshan, S., Abbas, A., Mehmood, Y., & Müller, K. (2017). Climate variability, farmland value, and farmers' perceptions of climate change: implications for adaptation in rural Pakistan. *International Journal of Sustainable Development and World Ecology*, *24*(6), 532–544. https://doi.org/10.1080/13504509.2016.1254689

Asfaw, S., Scognamillo, A., Caprera, G. Di, Sitko, N., & Ignaciuk, A. (2019). Heterogeneous impact of livelihood diversification on household welfare: Cross-country evidence from Sub-Saharan Africa. *World Development*, *117*, 278–295. https://doi.org/10.1016/j.worlddev.2019.01.017

Asmare, F., Teklewold, H., & Mekonnen, A. (2019). The effect of climate change adaptation strategy on farm households' welfare in the Nile basin of Ethiopia: Is there synergy or trade-offs? *International Journal of Climate Change Strategies and Management*, *11*(4), 518–535.

https://doi.org/10.1108/IJCCSM-10-2017-0192

Bedeke, S., Vanhove, W., Gezahegn, M., Natarajan, K., & Van Damme, P. (2019). Adoption of climate change adaptation strategies by maize-dependent smallholders in Ethiopia. *NJAS - Wageningen Journal of Life Sciences*, *88*, 96–104. https://doi.org/10.1016/j.njas.2018.09.001

Belay, A., Recha, J. W., Woldeamanuel, T., & Morton, J. F. (2017). Smallholder farmers' adaptation to climate change and determinants of their adaptation decisions in the Central Rift Valley of Ethiopia. *Agriculture and Food Security*, *6*(1), 1–13. https://doi.org/10.1186/s40066-017-0100-1

Beliyou, H., Signorelli, S., Azzarri, C., & Johnson, T. (2018). *Welfare effects of weather variability: multi-country evidence from Africa south of the Sahara*. 1–23.

Bozzola, M., & Smale, M. (2020). The welfare effects of crop biodiversity as an adaptation to climate shocks in Kenya. *World Development*, *135*, 105065. https://doi.org/10.1016/j.worlddev.2020.105065

Bryan, E., Deressa, T. T., Gbetibouo, G. A., & Ringler, C. (2009). Adaptation to climate change in Ethiopia and South Africa: options and constraints. *Environmental Science and Policy*, *12*(4), 413–426. https://doi.org/10.1016/j.envsci.2008.11.002

Bryan, E., Ringler, C., Okoba, B., Roncoli, C., Silvestri, S., & Herrero, M. (2013). Adapting agriculture to climate change in Kenya: household strategies and determinants. *Journal of Environmental Management*, *114*, 26–35. https://doi.org/10.1016/j.jenvman.2012.10.036

Call, M., Gray, C., & Jagger, P. (2019). Smallholder responses to climate anomalies in rural Uganda. *World Development*, *115*, 132–144. https://doi.org/10.1016/j.worlddev.2018.11.009

Coromaldi, M. (2020). The impact of weather fluctuations and climate shocks on farmers' welfare: insights from rural Ethiopia. *International Journal of Environmental Studies*, *77*(4), 619–635. https://doi.org/10.1080/00207233.2019.1695433

Coromaldi, M., Pallante, G., & Savastano, S. (2015). Adoption of modern varieties, farmers' welfare, and crop biodiversity: Evidence from Uganda. *Ecological Economics*, *119*, 346–358. https://doi.org/10.1016/j.ecolecon.2015.09.004

Debaeke, P., Casadebaig, P., Flenet, F., & Langlade, N. (2017). Sunflower crop and climate change: vulnerability, adaptation, and mitigation potential from case-studies in Europe. *Ocl*, *24*(1), D102. https://doi.org/10.1051/ocl/2016052

Dercon, S., & Christiaensen, L. (2011). Consumption Risk, Technology Adoption and Poverty tarps: Evidence from Ethiopia. *Journal of Development Economics*, *96*(2), 159–173.

Dercon, Stefan. (2004). Growth and shocks: Evidence from rural Ethiopia. *Journal of Development Economics*, *74*(2), 309–329. https://doi.org/10.1016/j.jdeveco.2004.01.001

Dhakal, S., Sedhain, G., & Dhakal, S. (2016). Climate Change Impact and Adaptation Practices in Agriculture: A Case Study of Rautahat District, Nepal. *Climate*, *4*(4), 63. https://doi.org/10.3390/cli4040063

Di Falco, S., & Veronesi, M. (2013). How can African agriculture adapt to climate change? A counterfactual analysis from Ethiopia. *Land Economics*, *89*(4), 743–766.

Di Falco, S. (2014). Adaptation to climate change in Sub-Saharan agriculture: Assessing the evidence and rethinking the drivers. *European Review of Agricultural Economics*, *41*(3), 405–430. https://doi.org/10.1093/erae/jbu014

Di Falco, S, Veronesi, M., & Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, *93*(3), 825–842. https://doi.org/10.1093/ajae/aar006

Eisenack, K., & Stecker, R. (2010). An action theory of adaptation to climate change. *Conference on the Human Dimensions on Global Environmental Change*, 13. http://www.diss.fu-berlin.de/docs/receive/FUDOCS_document_000000006991

Gbetibouo, G. A., Hassan, R. M., & Ringler, C. (2010). Modelling farmers' adaptation strategies for climate change and variability: the case of the Limpopo basin, South Africa. *Agrekon*, *49*(2), 217–234.

Gorst, A., Dehlavi, A., & Groom, B. (2018). Crop productivity and adaptation to climate change in Pakistan. *Environment and Development Economics*, *23*(06), 679–701. https://doi.org/10.1017/s1355770x18000232

Guloba, M. (2014). *Analysis of Adaptation to Climate Variability and Change in Uganda: A Gender and Household Welfare Perspective*. https://doi.org/10.1016/0375-9601(73)90015-7

Guodaar, L., Asante, F., Eshun, G., Abass, K., Afriyie, K., Appiah, D. O., Gyasi, R., Atampugre, G., Addai, P., & Kpenekuu, F. (2019). How do climate change adaptation strategies result in unintended maladaptive outcomes? Perspectives of tomato farmers. *International Journal of Vegetable Science*, *00*(00), 1–17. https://doi.org/10.1080/19315260.2019.1573393

Hassan M, R. (2011). Implications of Climate Change for Agricultural Sector Performance in Africa: Policy Challenges and Research\nAgenda. *Journal of African Economies*, *19*, 29. https://doi.org/10.1093/jae/ejp026

Hisali, E., Birungi, P., & Buyinza, F. (2011). Adaptation to climate change in Uganda: Evidence from micro level data. *Global Environmental Change*, *21*(4), 1245–1261. https://doi.org/10.1016/j.gloenvcha.2011.07.005

IPCC. (2018). *Summary for Policymakers. In: Global warming of 1.5°C. An IPCC Special Report on the impacts of global warming*. https://www.ipcc.ch/

Issahaku, G., & Abdulai, A. (2019). Can Farm Households Improve Food and Nutrition Security through Adoption of Climate-smart Practices? Empirical Evidence from Northern Ghana. *Applied Economic Perspectives and Policy*, *0*(0), 1–22. https://doi.org/10.1093/aepp/ppz002

Kabubo-Mariara. J; Di Falco, S. & Mulwa, R. (2016). The impact of climate change on food calorie production and nutritional poverty: evidence from Kenya. *Environment for Development Discussion Paper - Resources for the Future (RFF), March*, 35 pp.

Kabubo-Mariara, J., & Mulwa, R. (2019). Adaptation to climate change and climate variability and its implications for household food security in Kenya. *International Society for Plant Pathology and Springer Nature B.V. 2019*. https://doi.org/10.1007/s12571-019-00965-4

Kahsay, G. A., & Hansen, L. G. (2016). The effect of climate change and adaptation policy on agricultural production in Eastern Africa. *Ecological Economics*, *121*, 54–64. https://doi.org/10.1016/j.ecolecon.2015.11.016

Karki, S., Burton, P., & Mackey, B. (2020). Climate change adaptation by subsistence and smallholder farmers: Insights from three agro-ecological regions of Nepal. *Cogent Social Sciences*, *6*(1). https://doi.org/10.1080/23311886.2020.1720555

Kibue, G. W., Liu, X., Zheng, J., Zhang, X., Pan, G., Li, L., & Han, X. (2016). Farmers' perceptions of climate variability and factors influencing adaptation: Evidence from Anhui and Jiangsu, china. *Environ. Manage.*, *57*(5), 976–986.

Kilimani, N., Nnyanzi, J. B., Okumu, I. M., & Bbaale, E. (2020). Agricultural Productivity and Household Welfare in Uganda: Examining the Relevance of Agricultural Improvement Interventions. In O. E.S. (Ed.), *The Palgrave Handbook of Agricultural and Rural Development in Africa*. https://doi.org/https://doi.org/10.1007/978-3-030-41513-6_8

Kom, Z. (2020). Determinants of small-scale farmers' choice and adaptive strategies in response to climatic shocks in Vhembe District, South Africa. *GeoJournal*, *7*. https://doi.org/10.1007/s10708-020-10272-7

Kontgis, C., Schneider, A., Ozdogan, M., Kucharik, C., Tri, V. P. D., Duc, N. H., & Schatz, J. (2019). Climate change impacts on rice productivity in the Mekong River Delta. *Applied Geography*, *102*(December 2018), 71–83. https://doi.org/10.1016/j.apgeog.2018.12.004

Kotir, J. H. (2011). Climate change and variability in Sub-Saharan Africa: A review of current and future trends and impacts on agriculture and food security. *Environment, Development and Sustainability*, *13*(3), 587–605. https://doi.org/10.1007/s10668-010-9278-0

Limantol, A. M., Keith, B. E., Azabre, B. A., & Lennartz, B. (2016). Farmers' perception and adaptation practice to climate variability and change: a case study of the Vea catchment in Ghana. In *SpringerPlus* (Vol. 5, Issue 1). Springer International Publishing. https://doi.org/10.1186/s40064-016-2433-9

Lokshin, M., & Zurab Sajaia. (2004). Maximum likelihood estimation of endogenous switching regression models. *The Stata Journal*, *4*(3), 282–289. http://www.stata.com/bookstore/sj.html

Mabe, F. N., Sienso, G., & Donkoh, S. A. (2014). Determinants of Choice of Climate Change Adaptation Strategies in Northern Ghana. *Research in Applied Economics*, *6*(4), 75. https://doi.org/10.5296/rae.v6i4.6121

Makondo, C. C., & Thomas, D. S. G. (2018). Climate change adaptation: Linking indigenous knowledge with western science for effective adaptation. *Environmental Science and Policy*, *88*(January), 83–91. https://doi.org/10.1016/j.envsci.2018.06.014

Mendelsohn, R. (2008). The impact of climate change on agriculture in developing countries. *Journal of Natural Resources Policy Research*, *1*(1), 5–19. https://doi.org/10.1080/19390450802495882

Mendelsohn, R. (2012). The Economics of Adaptation To Climate Change in Developing Countries. *Climate Change Economics*, *03*(02), 1250006.

https://doi.org/10.1142/S2010007812500066

Mubiru, D. N., Radeny, M., Kyazze, F. B., Zziwa, A., Lwasa, J., Kinyangi, J., & Mungai, C. (2018). Climate trends, risks and coping strategies in smallholder farming systems in Uganda. *Climate Risk Management*, *22*(August), 4–21. https://doi.org/10.1016/j.crm.2018.08.004

Mulwa, C. K., & Visser, M. (2020). Farm diversification as an adaptation strategy to climatic shocks and implications for food security in northern Namibia. *World Development*, *129*, 104906. https://doi.org/10.1016/j.worlddev.2020.104906

Mwaura, F. M., & Okoboi, G. (2014). *Climate Variability and Crop Production in Uganda*. *7*(2), 159–172. https://doi.org/10.5539/jsd.v7n2p159

Mwungu, C. M., Mwongera, C., Shikuku, K. M., Acosta, M., Ampaire, E. L., Winowiecki, L. A., & Läderach, P. (2019). *Household Welfare Effects of Stress- - Tolerant Varieties in Northern Uganda*. https://doi.org/10.1007/978-3-319-92798-5

Nabikolo, D., Bashaasha, B., Mangheni, M., & Majaliwa, J. (2012). Determinants of climate change adaptation among male and female headed farm households in eastern Uganda. *African Crop Science Journal*, *20*(2), 203–212.

Ndamani, F., & Watanabe, T. (2015). *Farmers' Perceptions about Adaptation Practices to Climate Change and Barriers to Adaptation: A Micro-Level Study in Ghana*. 4593–4604. https://doi.org/10.3390/w7094593

Nelson, R., Kokic, P., Crimp, S., Martin, P., Meinke, H., Howden, S. M., de Voil, P., & Nidumolu, U. (2010). The vulnerability of Australian rural communities to climate variability and change: Part II-Integrating impacts with adaptive capacity. *Environmental Science and Policy*, *13*(1), 18–27. https://doi.org/10.1016/j.envsci.2009.09.007

Ojo, T., & Baiyegunhi, L. (2018). *Determinants of Adaptation Strategies to Climate Change among Rice Farmers in Southwestern Nigeria: A Multivariate Probit Approach*.

Onzima, B., Katungi, E., & Bonabana-Wabbi, J. (2019). The effect of climate change adaptation strategies on bean yield in central and Northern Uganda. *African Journal of Agricultural and Resource Economics*, *14*(4), 279–291.

Opare, S. (2018). Adaptation to climate change impacts: coping strategies of an indigenous community in Ghana to declining water supply. *Climate and Development*, *10*(1), 73–83. https://doi.org/10.1080/17565529.2016.1184610

Schapendonk, A. H. C. M., Dijkstra, P., Jansen, M. J. H., Pot, C. S., Van De Geijn, S. C., Visser, A., & Rozema, J. (1995). Climate change and agricultural productivity. *Studies in Environmental Science*, *65*(PART B), 709–713. https://doi.org/10.1016/S0166-1116(06)80095-6

Seo, S. N., & Mendelsohn, R. (2008). A structural Ricardian analysis of climate change impacts and adaptations in African agriculture. *Agricultural Economics*, *38*(2), 151–165.

Shahzad, M. F., & Abdulai, A. (2020). The heterogeneous effects of adoption of climate- smart agriculture on household welfare in Pakistan. *Applied Economics*, *00*(00), 1–26. https://doi.org/10.1080/00036846.2020.1820445

Shikuku, K. M., Winowiecki, L., Twyman, J., Eitzinger, A., Perez, J. G., Mwongera, C., & Läderach, P. (2017). Smallholder farmers' attitudes and determinants of adaptation to climate risks in East Africa. *Climate Risk Management*, *16*, 234–245. https://doi.org/10.1016/j.crm.2017.03.001

Silvestri, S., Bryan, E., Ringler, C., Herrero, M., & Okoba, B. (2012). Climate change perception and adaptation of agro-pastoral communities in Kenya. *Regional Environmental Change*, *12*(4), 791–802. https://doi.org/10.1007/s10113-012-0293-6

Skoufias, E., Rabassa, M., & Olivieri, S. (2011). *The poverty impacts of climate change: A review of the evidence*. *April*. https://doi.org/10.1596/1813-9450-5622

Ssewanyana, S. N., & Kasirye, I. (2014). *Uganda's progress towards poverty reduction during the last decade 2002/3- 2012/13: is the gap between leading and lagging areas widening or narrowing? 118,* 1–40.

Tesfaye, K., Gbegbelegbe, S., Cairns, J. E., Shiferaw, B., Prasanna, B. M., Sonder, K., Boote, K., Makumbi, D., & Robertson, R. (2015). International Journal of Climate Change Strategies and Management Article information: *International Journal of Climate Change Strategies and Management*, *7*(3), 247–271. https://doi.org/doi.org/10.1108/17568691211277755

Tesfaye, W., & Tirivayi, N. (2020). Crop diversity, household welfare and consumption smoothing under risk: Evidence from rural Uganda. *World Development*, *125*, 104686. https://doi.org/10.1016/j.worlddev.2019.104686

Tessema, Y. A., Aweke, C. S., & Endris, G. S. (2013). *Understanding the process of adaptation to climate change by small-holder farmers: the case of east Hararghe Zone, Ethiopia*. 1–17.

UBOS. (2019). *Uganda bureau of statistics 2019 statistical abstract*. Uganda Bureu of Statistics (UBOS), Kampala, Uganda

Vachani, S., Usmani, J., & Lewis, J. I. (2014). Assessing climate change impacts and adaptation strategies in China. *Adaptation to Climate Change in Asia*, *January 2012*, 93–116. https://doi.org/10.4337/9781781954737.00010

Wossen, T., & Berger, T. (2014). ScienceDirect Climate variability, food security and poverty : Agent-based assessment of policy options for farm households in Northern Ghana. *Environmental Science and Policy*, *47*, 95–107. https://doi.org/10.1016/j.envsci.2014.11.009

Wossen, T., Berger, T., Haile, M. G., & Troost, C. (2018). Impacts of climate variability and food price volatility on household income and food security of farm households in East and West Africa. *Agricultural Systems*, *163*, 7–15. https://doi.org/10.1016/j.agsy.2017.02.006

Yamba, S., Appiah, D. O., & Siaw, L. P. (2019). Smallholder farmers' perceptions and adaptive response to climate variability and climate change in southern rural Ghana. *Cogent Social Sciences*, *5*(1). https://doi.org/10.1080/23311886.2019.1646626

Zhang, P., Zhang, J., & Chen, M. (2017). Economic impacts of climate change on agriculture: The importance of additional climatic variables other than temperature and precipitation. *Journal of Environmental Economics and Management*, *83*. https://doi.org/10.1016/j.jeem.2016.12.001

CHAPTER FIVE

SUMMARY, CONCLUSION AND POLICY RECOMMENDATIONS

5.1 Introduction

This section summarises the main findings, main conclusions and policy implications derived from the findings of this study. This chapter is presented in four sections with section 5.2 covering the summary of the main study findings, section 5.3, 5.4 and 5.5 presents conclusion, policy recommendations and areas of further research respectively.

5.2 Summary

Climate variability is a public good problem which has generated adverse effects that are already being experienced and have been projected to deepen as time goes on, especially if nothing is done to mitigate its effects (IPCC, 2014, 2018). According to the Intergovernmental Panel on Climate Change (IPCC), "Impacts from the recent climate-related extremes, such as heatwaves, droughts, floods, cyclones, and wildfires, reveal significant vulnerability and exposure of some ecosystems and many human systems to current climate variability" (Barbier & Hochard, 2018). The degree of vulnerability and exposure is projected to be worse in low-income countries which have a substantial share of the population which live in rural areas, involved in nature dependent rain fed agricultural activities, and have agriculture as their main economic activity due to limited non-farm opportunities (Adhikari et al., 2015; Coromaldi, 2020). For example, 80 percent of Ugandans stay in rural areas and about 78% of them practise subsistence agriculture (UBOS, 2018, 2019).

It is thus important to apprehend how the varying climate is affecting Uganda's agricultural productivity and household welfare outcomes, and how best Ugandan farming households can cope with the varying climatic conditions in the country. This is important to provide the required evidence for designing optimal, effective, and appropriate policy measures aimed at combating variability in climate and its effects but also enhancing agricultural productivity and welfare among farming households. Against this background, this study investigates the effect of variability in climate on productivity of agriculture and household welfare in Uganda. The study also assessed the decision to adapt to variability in climate among households and further investigated the welfare differences between the adapting and non-adapting farm households in the country. The study used six waves of the Uganda National Panel Survey (UNPS - 2009/10, 2011/12, 2012/13, 2013/14, 2015/16 and 2018/19) collected by the Uganda National Bureau of Statistics (UBOS) from 2009 to 2019 and the long-term daily historical climate data (1979 – 2013) gotten from the United States National Oceanic and Atmospheric Administration (NOAA). Both the survey and the climate datasets were interpolated at the household level and matched using GPS information contained in UNPS data.

In the first essay, the thesis analyses the effect of variability in climate on Uganda's productivity in agriculture using the total factor productivity approach. The estimated results at the national level showed a significant U-shaped effect of precipitation variability on agricultural productivity while the regional analysis indicates that relative to other regions of the country, Eastern Uganda is the most affected and vulnerable region. The crop-specific results, on the other hand, showed that beans and bananas are more sensitive and vulnerable to variability in climate in comparison to other crops in the analysis - maize and cassava. Access to extension services, size of the household, the household head's education level, and the value of farm equipment (a proxy for household level of capital) were found to affect agricultural productivity positively.

In the second essay, pooled average OLS and random fixed effects models were used to assess the household welfare implications of climate variability. The study findings indicate a non-linear effect of variability in climate on Ugandan households' welfare outcomes. Specifically, the essay 2 findings show that variability in minimum temperature and precipitation results in a household welfare decline while variability in maximum temperature leads to an increase in welfare. The findings further show that households' improved access to extension services and the household head's education level offset the negative effect of variability in climate on household welfare outcomes.

To investigate the determinants of the decision to adapt and welfare differences between households that adapted to variability in climate and those that did not adapt; the thesis used an endogenous switching regression (ESR) model - also known as the simultaneous equation approach - that accounts for the selection bias caused by observable and unobservable factors and captures the differential welfare impacts of adaptation on adaptors and non-adaptors. The findings indicate that adapting to climate variability is beneficial to adaptors as it safeguards welfare deterioration. Climate variability factors - variability in precipitation and minimum temperature;

household specific characteristics including the household head's years of education, age, location, occupation, wealth status as well as access to extension services were identified as significant determinants of the decision to adapt to variability in climate among Ugandan households.

5.3 Conclusion

This study unearths a number of interesting conclusions. In essay one, the study established a significant U-shaped relationship between variability in precipitation and Uganda's agricultural productivity. This finding implies that, as variability in precipitation persists, farming households automatically adapt to the changing precipitation levels and conditions, thereby offsetting the earlier negative impact associated with precipitation variability. Farming households, either on their own or with the help of their fellow farmers, extension workers, non-governmental organisations or government agencies such as National Agricultural Advisory Services (NAADS), Operation Wealth Creation (OWC) and National Agricultural Research Organization (NARO) among others devise ways of dealing with the varying climatic conditions and their effects on their farming activities (Codjoe et al., 2011). The spontaneous and autonomous adaptation to climate variability practices by the farming households may thus result in increased agricultural productivity returns, and this explains the U-shaped relationship between variability in precipitation and agricultural productivity among farmers (Kabubo-Mariara, 2012; Arshad et al., 2018). In other words, through experience, farming households learn how to offset the negative impact on their farms by the variability in precipitation.

The results from essay one further showed that Eastern Uganda is the most affected and vulnerable region to the extreme consequences of variability in climate as opposed to other regions – northern, Western, and Central Uganda. This communicates the urgency to prepare farmers from Eastern Uganda on how to hedge themselves against climate variability and its effects especially on agriculture, which is their main economic activity. Otherwise, this might affect their earnings and thus increase the intensity of food insecurity and poverty in the region. In terms of crops, the findings in essay one show that climate variability largely influences beans and banana yields when compared to maize and cassava crops. From the existing literature, it is shown that bananas and beans require a reliable and steady supply of water as compared to maize and cassava crops. The recommended solution in the literature is irrigation but as shown by the summary statistics, the majority of Ugandan farmers (68% of them) depend on nature (rainfall) with few of them (32%)

depending on irrigation. Therefore, given the fact that these are crops that are grown by the majority of Ugandans and depend on them for both food and income, any factor that negatively affects production of these crops should be dealt with accordingly to protect people's livelihoods and other welfare outcomes including poverty and food security.

Essay one also identified availability and access to extension services by the farmers as a key factor in increasing crop yields as well as overall agricultural productivity in Uganda. Through extension services, farmers can get information on high quality seeds, better farming methods, weather, and climate forecast information among others, from technical agricultural officers (Mendelsohn, 2014). Extension workers can encourage farmers to use better drought tolerant crop varieties to hedge against climate variability and form groups to benefit from one another through exchange of information and other ideas on farming, including on how to adapt to climate changes. In this case, farmers can devise ways of improving their productivity and resilience against climate variability and its effects. Furthermore, in essay one, it was shown that the level of capital invested by farming households is positively related to crop productivity. This result could be ascribed to the fact that higher levels of capital enable the farming household to purchase high yielding seeds, use of machines, improved inputs and hire of more and higher-quality labour force (Sheng & Xu, 2019).

Similarly, in essay one, the educational level of the household head was found to be associated with an increase in agricultural productivity among farm households. Reed et al. (2013, 2017) argued that education plays a crucial part in improving productivity of farmers. In addition, education enables farmers to adapt to climate changes through adopting improved methods of farming such as planting improved seeds, irrigation use and fertiliser use. These practices lead to improved productivity returns among farmers as compared to uneducated farmers. Farmers who stay near urban or peri-urban areas are associated with less agricultural productivity as opposed to farmers in rural areas. This is quite surprising, as one would expect farmers near urban areas to be more productive than their counterparts in rural areas given the limited size of their land, their level of exposure to modern farming methods and accessibility to market and extension services. However, this could be due to the differing objectives of farmers in urban areas relative to those in rural areas. Secondly, the government of Uganda has implemented many agricultural interventions targeting largely the rural population such as improved seed and fertiliser provision at free cost and placing tractors in rural areas aimed at improving both output and productivity (UBOS, 2012). Thus, the higher productivity of rural farming households as compared to those in urban areas could be a result of these interventions.

Essay 2 (chapter three) analysed the effects that variability in climate has on household welfare in Uganda and used as the welfare indicator the per adult equivalent household consumption expenditure. The findings show that precipitation variability has an inverted U-shaped relationship with outcomes of household welfare, which suggests that continued variability in precipitation negatively affects welfare outcomes of the farm households. This is in line with the argument that moderate or non-persistent precipitation variability can enhance agricultural yields as opposed to the adverse cases such as heavy hailstorms, prolonged drought, floods, and landslides that negatively affect crops and livestock and result in losses of income and reduced welfare (Beliyou et al., 2018; Skoufias et al., 2011). The two components of variability in climate (minimum and maximum variability) have differing effects on household consumption expenditure. The results show that a small increase in variability in minimum temperature causes a drop in consumption while slight increases in maximum temperature variability are linked to increased household welfare outcomes. Existing literature argues that a minor rise in minimum temperature makes the overall surface temperature rise (Asfaw et al., 2019). One way for a household to adapt to changes in climate is to reduce consumption expenditure (Nkegbe & Kuunibe, 2014; Skoufias & Vinha, 2013; Dzanku, 2015). Adverse climate variability events for instance landslides, floods and prolonged droughts could erode economic gains achieved over the years and therefore they are a threat to socio-economic progress (Mwungu et al., 2019; UBOS, 2019).

Still in essay two, in terms of regional welfare implications of climate variability, the results indicate that northern Uganda is the region that is most vulnerable followed by eastern Uganda. The two regions are known to experience frequent adverse climatic events (such as hailstorms, floods, landslides, and prolonged dry seasons) as compared to central and western regions of Uganda (UBOS, 2017; Mwungu et al., 2019). This partly explains the difference in vulnerability. For instance, according to the 2016/17 Uganda National Household Survey, northern and eastern Uganda reported a decline in the average household expenditure, while that of central and western Uganda remained constant (UBOS, 2019). However, this does not imply that the two regions central and western Uganda are insulated from experiencing welfare loss due to climate variability as the results project a decline in household welfare outcomes across all regions due to climate variability. The results further indicated that households living near urban areas had higher per adult consumption expenditure as opposed to those in rural areas. Urban areas, unlike rural areas, have alternative non-farm employment opportunities that are less affected by climate variability, where urban farmers can supplement their incomes. However, the welfare of rural dwellers largely depends on rain fed agriculture or nature-based activities that are prone to variability in climate (Arslan et al., 2017).

Comparisons of welfare outcomes between the adapting and non-adapting households in essay three show that adapting to climate variability is beneficial to the adapting households as it safeguards their welfare deterioration. The results also show that adapting to climate variability reduces per adult equivalent household consumption expenditure among the adapting households by 5.8% more than that of the non-adapting households. This is quite surprising given that adaptation is expected to enhance welfare of the farming households largely through improved returns from the agricultural or nature-based activities that increase household income levels (Asmare et al., 2019; Karki et al., 2020). However, this finding seems to communicate the need for the government of Uganda and other stakeholders involved in Uganda's agriculture sector to do more to make adaptation process affordable, beneficial and welfare improving to all farmers across the country. The high initial costs associated with the adaptation process and relatively low prices of agricultural products coupled with shortage of ready markets for agricultural products could be responsible for the welfare decline among the adapting households as shown by the decline in the household consumption expenditure (Guloba, 2014; Kilimani et al., 2020).

Therefore, this thesis adds to the body of literature on climate variability impact on agricultural productivity and household welfare outcomes by combining both survey and long-term historical climate data. This is important in accounting for agricultural complexities and solves model selection bias that may lead to inconsistent and inefficient estimates. In addition, identifying the effect of variability in climate on the welfare of households provides insights into the role of climate in welfare and evidence required to improve the wellbeing of people despite the presence of climate variability events such as prolonged drought. Unlike previous studies such as Matovu & Buyinza (2010) who used poverty status to evaluate the household welfare outcomes, this study makes use of per adult equivalent household consumption expenditure. This is regarded in the literature as the most appropriate and effective indicator of household welfare outcomes since it is more reliable than income or household poverty status and caters for the other dimensions of welfare such as income, wealth, poverty, and health status (Meyer et al., 2003; Skoufias & Vinha, 2013). The thesis further uses a random effects model in estimation and this controls for latent heterogeneity over time for each household (Green, 2012). This thus solves the problem of endogeneity and yields model estimates that are robust, consistent, efficient, and reliable for policy recommendations.

Lastly, this thesis investigates the differences in household welfare outcomes in terms of household consumption expenditures between the adapting and non-adapting farming households in essay three. This does not only provide a deep understanding of the benefits associated with the adaptation to climate variability to farming households but also provides evidence to support Uganda's National Adaptation Plan making process. In addition, the thesis provides insights into the factors that determine the decision to adapt to variability in climate among households engaged in farming in Uganda, which are important in guiding policy makers and implementers.

5.4 Policy implications

A number of policy lessons can be derived from the findings of this thesis. The results support the presence of variability in climate in Uganda and show how it affects agricultural productivity and welfare outcomes. Therefore, the government of Uganda should design policies aimed at combating climate variability and its effects across the country. Similarly, the government of Uganda and all stakeholders including development partners should invest in sensitising farming households on climate variability and how it affects agriculture and welfare to enable them plan accordingly on how to alleviate and cope up with the changing climate patterns in the country. In addition, the government and partners should provide timely information on climate variability and weather forecasts to enable farmers to prepare on time, plan and adjust their farming practices, including the type of crops grown, where and which farming methods to apply.

The impact of variability in precipitation can be minimised through construction of water dams that provide affordable water for irrigation (Nagasha et al., 2019). Nagasha et al. (2019) established a positive link between irrigation and crop yields, suggesting that irrigation could offset the negative effects that variability in climate has on agricultural yields. More so, farmers can also resort to early planting of varieties of crops that are resilient to climate variability. Climate variability effects can also be solved through availing and making extension services more accessible to the farmers across the county (Guloba, 2014; UBOS 2019; Kilimani et al., 2020). This is because extension services are important sources of learning, information dissemination and skills to households. To boost access to extension services by the farmers, the government can set up demonstration farms and farmer training centres or extension centres at the local or regional levels across the country. These should be equipped with hands-on agronomic and technical training services at free or affordable cost to all farmers across the country.

The thesis findings show that agricultural productivity and welfare increase with the household head's level of education despite the presence of climate variability. Therefore, the government of Uganda and partners could design education programs targeting farmers to provide them with skills and knowledge to build resilience and adaptation to climate changes. The programs could take forms of workshops, fairs and exhibitions or short courses organised for farmers across the country with an aim of providing knowledge and new skills required to not only aid household's cope with the changing climate but also aid them reduce over dependence on rain-fed agricultural activities and nature that is prone to variability in climate.

5.5 Areas for further Research

This study has made an important input to literature on the effect of variability in climate on the productivity of agriculture and household welfare outcomes. The study however did not incorporate the effect of soil related factors due to data limitations, yet soil related factors are predicted to play a big role in land/agricultural productivity. Further research should analyse the effect of soil-related factors such as soil type, soil fertility, and PH level on agricultural productivity in the face of climate variability in Uganda.

Although the study found a statistically significant effect of variability in climate on household welfare outcomes in Uganda, it did not examine the effect of variability in climate on the demand for commodities, as this was outside the scope of the study. An evaluation of the effect of variability in climate on demand is important to determine the extent and direction of the impact of variability in climate on demand for commodities in an economy, for example food stuffs, durables, and non-durable goods. It could also help obtain elasticity of demand for the main commodities in the economy, with respect to variability in climate. Therefore, future studies could examine the demand implications of changes in variability in climate to close the gaps in the existing literature.

References

Adhikari, U., Nejadhashemi, A. P., & Woznicki, S. A. (2015). Climate change and eastern Africa: a review of impact on major crops. Food and Energy Security, 4(2): 110-132. https://doi.org/10.1002/fes3.61.

Arshad, M., Amjath-Babu, T. S., Aravindakshan, S., Krupnik, T. J., Toussaint, V., Kächele, H., & Müller, K. (2018). Climatic variability and thermal stress in Pakistan's rice and wheat systems: A stochastic frontier and quantile regression analysis of economic efficiency. *Ecological Indicators*, *89*: 496–506. https://doi.org/10.1016/j.ecolind.2017.12.014

Arslan, A., Belotti, F., & Lipper, L. (2017). Smallholder productivity and weather shocks: Adoption and impact of widely promoted agricultural practices in Tanzania. *Food Policy*, *69*: 68–81. https://doi.org/10.1016/j.foodpol.2017.03.005

Asfaw, S., Scognamillo, A., Caprera, G. Di, Sitko, N., & Ignaciuk, A. (2019). Heterogeneous impact of livelihood diversification on household welfare: Cross-country evidence from Sub-Saharan Africa. *World Development*, *117*: 278–295. https://doi.org/10.1016/j.worlddev.2019.01.017

Barbier, E. B., & Hochard, J. P. (2018). The Impacts of Climate Change on the Poor in Disadvantaged Regions. *Review of Environmental Economics and Policy*, *12*(1): 26–47.

Barnwal, P., & Kotani, K. (2013). Climatic Impacts Distributions: Across Agricultural Crop Yield Rice, An Application of Quantile Regression on Crops in Andhra Pradesh, India. *Ecological Economics*, *87*: 95–109.

Coromaldi, M. (2020). The impact of weather fluctuations and climate shocks on farmers' welfare: insights from rural Ethiopia. *International Journal of Environmental Studies*, *77*(4): 619–635. https://doi.org/10.1080/00207233.2019.1695433

Green, H. (2012). Econometric Analysis (7th ed.). Journal of Boston: Pearson Education, 803-806.

Haile, B., Signorelli, S., Azzarri, C., & Johnson, T. (2018). Welfare effects of weather variability: multi-country evidence from Africa south of the Sahara. PloS one, 13(11), e0206415.

IPCC. (2014). Climate change 2014: Synthesis report. In Contribution of working groups - I, II and III to the fifth assessment report of the intergovernmental panel on climate change (pp. 151). https://www.ipcc.ch/

Kabubo-Mariara, J. (2012). Institutional Isolation, Soil Conservation and Crop Productivity: Evidence from Machakos and Mbeere Districts in Kenya. *African Journal of Social Sciences*, *2*(3): 1–26.

Luis, M. G., Orlando, R., & Alatorre, J. E. (2015). Climate change, irrigation, and agricultural activities in Mexico: A Ricardian analysis with panel data. *Journal of Development and Agricultural Economics*, *7*(7): 261–272. https://doi.org/10.5897/jdae2015.0650

Mendelsohn, R. (2014). The impact of climate change on agriculture in Asia. *Journal of Integrative Agriculture*, *13*(4): 660–665. https://doi.org/10.1016/S2095-3119(13)60701-7

Meyer, Bruce D and James X. Sullivan. (2003). Measuring The Well-Being of The Poor Using Income and Consumption. Journal of Human Resources, 38: 1180-1220.

Mwungu, C. M., Mwongera, C., Shikuku, K. M., Acosta, M., Ampaire, E. L., Winowiecki, L. A., & Läderach, P. (2019). Household welfare effects of stress-tolerant varieties in northern uganda. In The Climate-Smart Agriculture Papers (pp. 175-186). Springer, Cham. https://doi.org/10.1007/978-3-319-92798-5

Nagasha, J. I., Ocaido, M., & Kaase-bwanga, E. (2019). *Theoretical and conceptual framework for gender analysis of attitudes and adaptation mechanisms to climate change for sustainable livelihoods in Uganda*. *11*(June): 51–57. https://doi.org/10.5897/JASD2019.0532

Nii, S., Codjoe, A., & Owusu, G. (2011). *Climate change / variability and food systems: evidence from the Afram Plains, Ghana*. 753–765. https://doi.org/10.1007/s10113-011-0211-3

Nkegbe, P. K., & Kuunibe, N. (2014). *WIDER Working Paper 2014/027 Climate variability and household welfare in northern Ghana*.

Reed, M. S., Podesta, G., Fazey, I., Geeson, N., Hessel, R., Hubacek, K., Letson, D., Nainggolan, D., Prell, C., Rickenbach, M. G., Ritsema, C., Schwilch, G., Stringer, L. C., & Thomas, A. D. (2013). Combining analytical frameworks to assess livelihood vulnerability to climate change and analyse adaptation options. *Ecological Economics*, *94*, 66–77. https://doi.org/10.1016/j.ecolecon.2013.07.007

Sheng, Y., & Xu, X. (2019). The productivity impact of climate change: Evidence from Australia's Millennium drought. *Economic Modelling*, *76*(July): 182–191. https://doi.org/10.1016/j.econmod.2018.07.031

Skoufias, E., Rabassa, M., & Olivieri, S. (2011). The poverty impacts of climate change: a review of the evidence. World Bank Policy Research Working Paper, (5622). https://doi.org/10.1596/1813-9450-5622

Skoufias, E., & Vinha, K. (2013). The impacts of climate variability on household welfare in rural Mexico. Population and Environment, 34(3): 370-399. https://doi.org/10.1007/s11111-012-0167-3

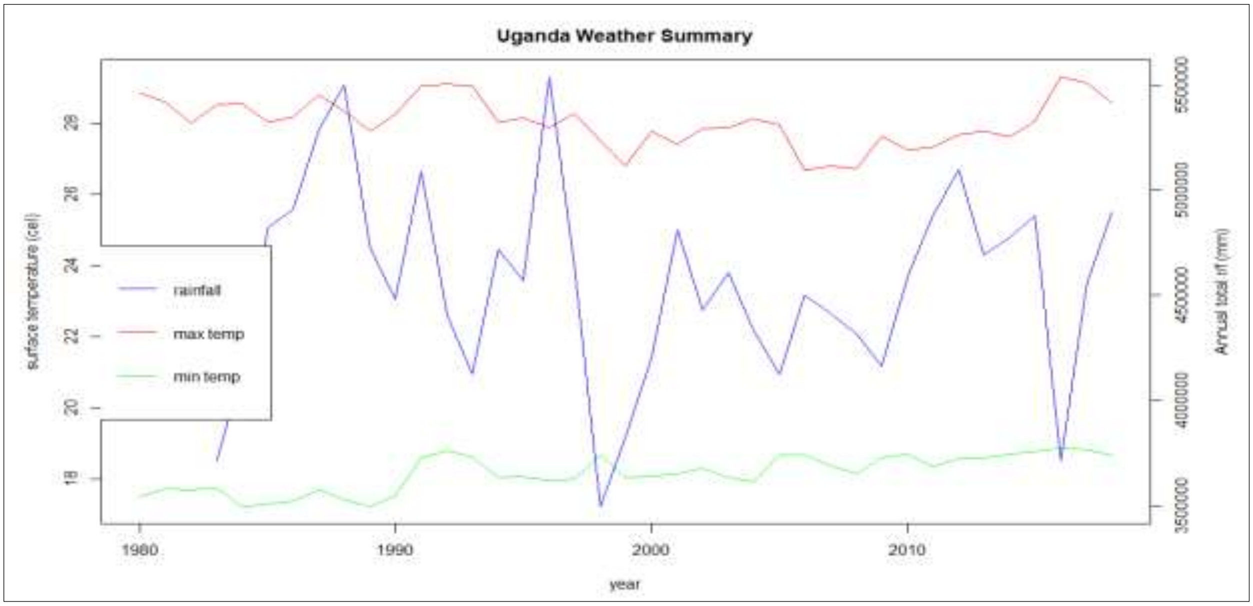
UBOS. (2012). *Agricultural Sector Statistics Profile* 2012. Uganda Bureau of Statistics (UBOS), Kampala, Uganda

UBOS. (2017). *Uganda National Household Survey (UNHS) Report - 2016/17*. Uganda Bureau of Statistics (UBOS), Kampala, Uganda

UBOS. (2019). Uganda bureau of statistics 2019 statistical abstract. Uganda Bureau of Statistics (UBOS), Kampala, Uganda

Appendices

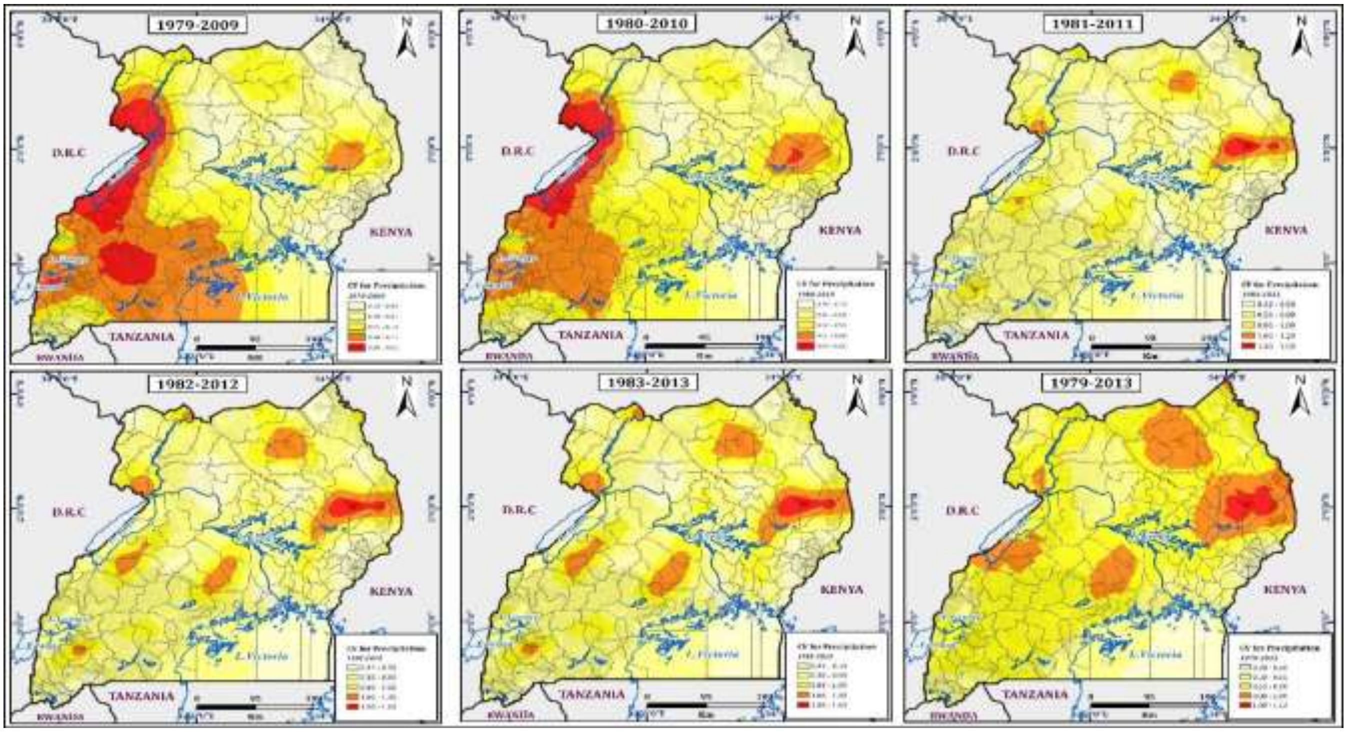
Appendix 1: Figure 4: Uganda's summary annual weather statistics 1980 - 2018



Source: Author's calculations based on climate data obtained from the National Oceanic and Atmospheric Administration (NOAA) website https://www.cpc.ncep.noaa.gov/ *(2019)*

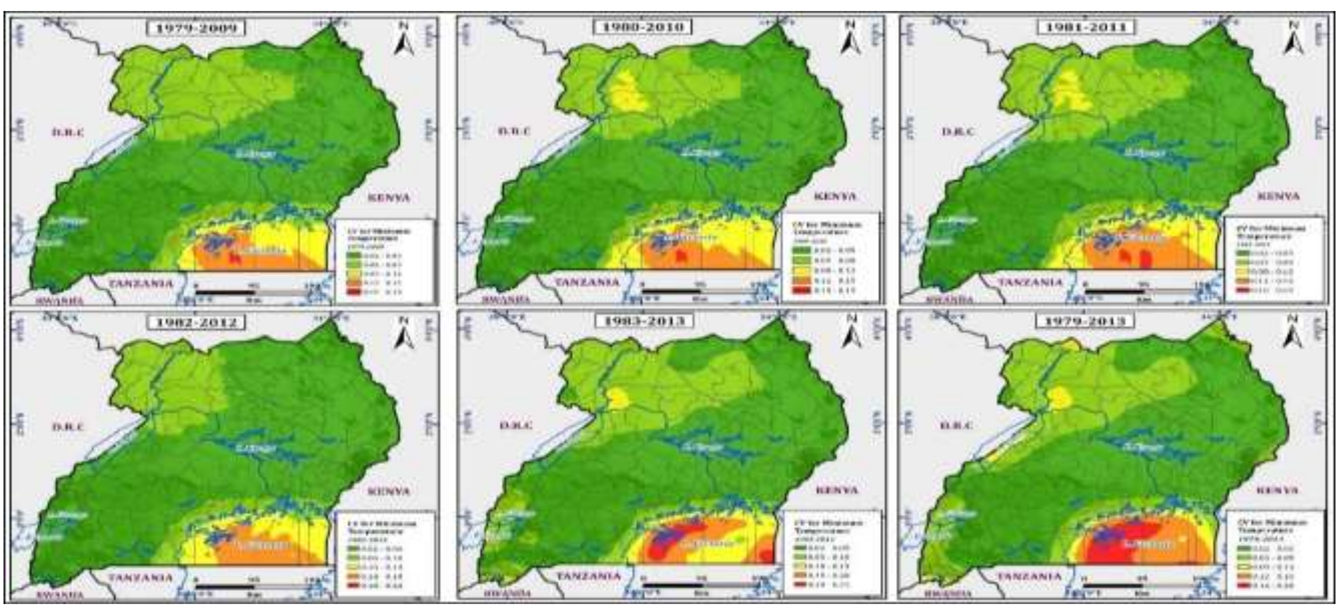
Appendix 2: Maps showing trends of climate variability across various regions of Uganda.

Figure A1: Precipitation variability in Uganda, 1979 - 2013



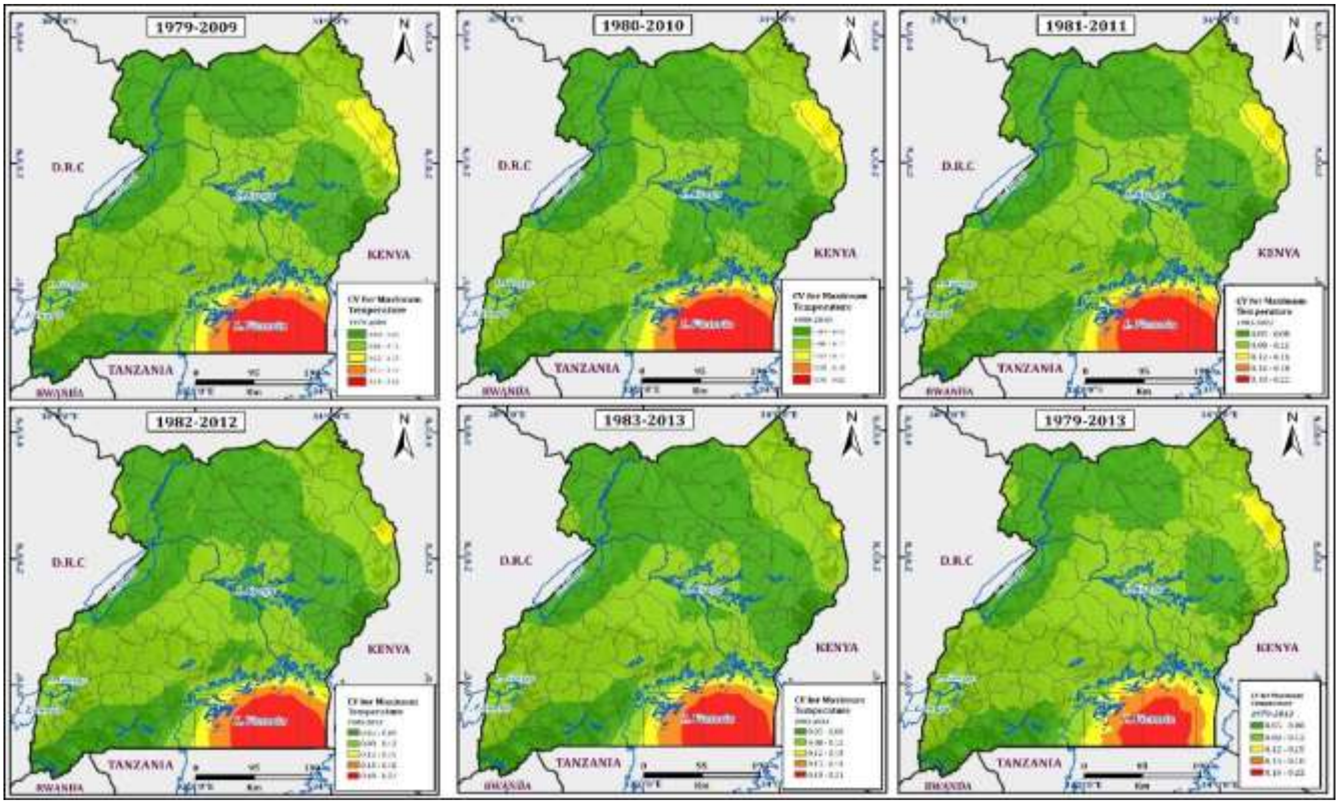
Source: National Oceanic and Atmospheric Administration (NOAA) reanalysis data (2019)

Figure A2: Minimum temperature variability *in Uganda,* 1979 - 2013



Source: National Oceanic and Atmospheric Administration (NOAA) reanalysis data (2019)

Figure A3: Maximum temperature variability in Uganda, 1979 - 2013



Source: National Oceanic and Atmospheric Administration (NOAA) reanalysis data (2019)

Appendix 3: Correlation matrix Results

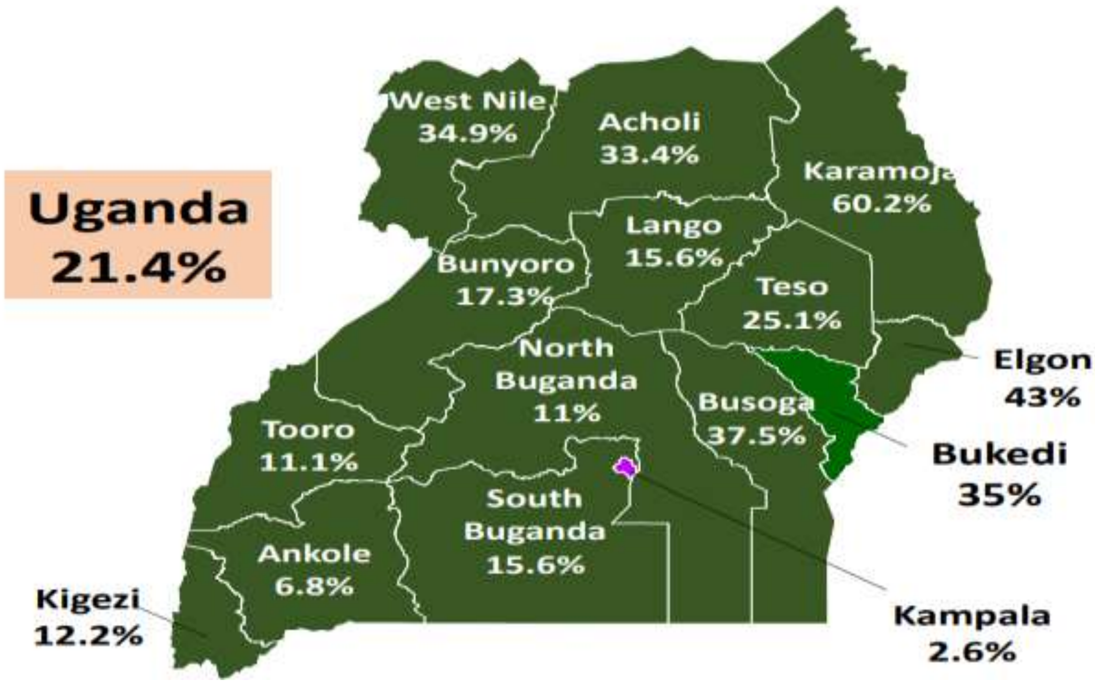
	TFP	ppt_va~y	PPTVar~d	mintem~y	MinVar~d	maxtem~y	MaxVar~d	hhage
TFP	1							
ppt_variab~y	-0.027	1						
PPTVariab_~d	-0.0252	0.9887	1					
mintemp_va~y	0.0158	0.0605	0.0362	1				
MinVariab_~d	0.013	0.0311	0.012	0.9682	1			
maxtemp_va~y	-0.0018	-0.0266	-0.0362	0.0649	0.0897	1		
MaxVariab_~d	-0.0006	-0.0268	-0.0356	0.0706	0.1084	0.989	1	
hhage	-0.0226	0.0237	0.0217	-0.0141	-0.0136	0.0043	0.0057	1
hhagsqd	-0.0277	0.0191	0.0173	-0.0151	-0.0144	0.0051	0.0067	0.9858
hhsex	0.0665	-0.0247	-0.0229	0.0126	0.015	0.0112	0.012	-0.1721
urban	-0.0821	0.0526	0.0507	0.0151	0.0122	0.0131	0.0113	0.0259
Marital_st~s	0.0769	-0.0322	-0.0308	0.0073	0.0057	0.0123	0.0126	-0.2696
hhedyrs	0.0776	0.0041	0.0052	0.0143	0.0176	0.0069	0.006	-0.2261
Extension_~s	0.0577	-0.0496	-0.0477	0.0131	0.0111	-0.0108	-0.0085	-0.0027
mkt_access	0.0017	0.0056	0.0047	-0.0215	-0.0227	-0.0147	-0.0149	0.0051
PPT_Ext	0.0541	0.1476	0.1471	0.0308	0.0226	-0.0175	-0.0158	-0.0008

	hhagsqd	hhsex	urban	Marita~s	hhedyrs	Extens~s	mkt_ac~s	PPT_Ext
hhagsqd	1							
hhsex	-0.1581	1						
urban	0.0137	-0.112	1					
Marital_st~s	-0.2622	0.6853	-0.134	1				
hhedyrs	-0.2341	0.3331	0.144	0.2586	1			
Extension_~s	-0.0031	-0.0081	-0.0124	0.0076	-0.0109	1		
mkt_access	0.003	0.001	0.0228	0.0091	0.0002	-0.0067	1	
PPT_Ext	0.0018	0.0078	0.007	0.0064	-0.0109	0.9531	-0.006	1

Source: *Author's calculations based on UNPS data sets (2009-2019) and World Climate data*

Appendix 4: Uganda Poverty Map

Figure 5: Household poverty distribution in Uganda 2016/17.



Source: Uganda Bureau of Statistics, 2020