Impact of climate smart agriculture on farm productivity under extreme weather events in Malawi

BY

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DEDICATION

To Inka PANGAPANGA, my dearest daughter,
Lucy PANGAPANGA, my one and only youthful wife,
Christopher Abbolf PANGAPANGA, my only brother,
Shawo Aaron MKWALA, I know you are smiling seeing me reach this far.
Jubilant Mirriam Eliness MWENELUPEMBE, my fondly mum,
Yafika Kiliness Nandofi NAKAUNDI, I call her my beloved mother and mbuya, and
Tonnex Whitemore Chiza MWENELUPEMBE, my uncle.

DECLARATION

I, **Innocent PANGAPANGA-PHIRI,** declare that the Thesis, which I hereby submit in partial fulfilment for the requirement of the Degree of the Doctor of Philosophy (PhD) in Environmental Economics, at the University of Pretoria, is my work and has not previously been submitted by me for the award of a degree at this or any other tertiary institution. Noticeably, the second chapter of this Thesis has been formally published in the peer reviewed Elsevier International Journal of Disaster Risk Reduction, (https://doi.org/10.1016/j.ijdrr.2021.102322). Besides, the fourth chapter on the effect of tropical cyclones –related floods on farm productivity is undergoing third peer review with the Taylor and Francis Journal of Climate and Development. I take responsibility of any error of inaccuracies, found in this Thesis.

Innocent PANGAPANGA-PHIRI	....	31.01.2022
Name	**Signature**	**Date**

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IMPACT OF CLIMATE SMART AGRICULTURE ON FARM PRODUCTIVITY UNDER EXTREME WEATHER EVENTS IN MALAWI.

BY

Innocent Pangapanga-Phiri

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Faculty	**:**	**Natural and Agricultural Sciences**
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ABSTRACT

Agricultural productivity in Malawi continues to decline and frustrate the food security agenda despite massive investments, namely, farm input subsidy programs and climate-smart agriculture (CSA) –related practices. Households have further adopted integrated pest management (IPM), and sustainable landscape management (SLM) strategies, which are responsive to extreme weather events, like droughts, fall armyworms (FAW), and tropical cyclones -related floods (TCRFs). High poverty levels, poor agricultural practices, fragmented landholding sizes, missing credit markets, and declining soil fertility are some of the fundamental constraints limiting household agricultural productivity. Additionally, extreme weather events have exasperated the situation, pushing more households into further food insecurity and poverty. In containing the negative effects of different extreme weather events, Government of Malawi and other stakeholders, including households, have adopted various CSA, IPM, and SLM-related practices, such as, organic manure application, intercropping, timely planting, improved crop varieties, mulching, zero tillage, soil and water conservation, liming, and chemical pesticides' application. Though CSA, IPM, and SLM –related practices have presented opportunities to address the adverse effects of the extreme weather events, households fail to derive the maximum potential farm productivity. Furthermore, households engaging in rural – urban migration (RUM), as a climate adaptive strategy, do not yield the intended results due to missing market infrastructures for improved agricultural inputs and outputs.

This thesis, thus, examines the impacts of climate smart agriculture on household farm productivity under varying extreme weather events by posing four empirical questions: (i) Do drought, FAW, and TCRFs significantly affect farm productivity? (ii) Do household and farm-level factors, namely, age, education, total farm size, and soil types drive the adoption of CSA, IPM, and SLM-related practices

under the different extreme weather events? (iii) Do CSA, IPM and SLM-related practices substantially induce farm productivity? Finally, (iv) does RUM, which is an climate adaptive strategy, improve the technical efficiency of maize production in the study area under extreme weather events? This thesis uses data from the Integrated Household Panel Survey, compiled by the National Statistics Office (NSO) and the World Bank, between 2010 and 2020.

In this thesis, Chapter two (2) employs the conditional fixed effect logit model, the panel-based Cobb-Douglas stochastic frontier analysis (SFA) model, and the triple-hurdle panel-based Tobit regression model to investigate the drivers of CSA practices' adoption and their influence on the technical efficiency of maize production under drought episodes. Chapter three (3) adopts the panel-based Endogenous Switching Regression (ESR) to interrogate the effects of FAW and IPM-related practices on farm productivity and food security. Similarly, Chapter four (4) applies the ESR to ascertain the impact of TCRFs and SLM-related practices on the farm productivity. Chapter five (5) uses the two-stage panel based Tobit regression to examine the influence of RUM on the technical efficiency of maize production under extreme weather events.

The results from Chapter two (2) show that households affected by drought are 76 percent more likely to adopt organic manure and 29 percent more probable to invest in soil and water conservation techniques relative to their counterparts. Based on panel-based ESR model, Chapter three (3) demonstrates that FAW significantly reduces farm productivity by 12 percent, on the one hand, but enhanced the likelihood of adopting IPM –related practices by 6 percent, on the other hand. The study reveals that adoption of IPM –related practices improves farm productivity by at least 21 percent. Findings from Chapter four (4) show that TCRF reduces farm productivity by 31 percent while augmenting the likelihood of investing in SLM-related practices, which consequently enhance farm productivity by 27 percent. Moreover, after interacting TCRFs and SLM, chapter (4) reveals that 24 percent improvement in farm productivity. Unless RUM is interacted with the adoption of other CSA –related practices, chapter five (5) reveals that RUM negatively and considerably influences maize farm productivity by 9 percent due to low family labour supply.

The thesis concludes that droughts, FAW, TCRFs, and RUM have negative and significant effects on farm productivity. Households affected by any extreme weather events are distinctly more likely to adopt any of the CSA, IPM, and SLM-related practices, which positively enhance farm productivity and ultimately improve household food security. Consequently, the study recommends an extension delivery mechanism that significantly promotes the adoption of any of the CSA, IPM, and SLM-related practices to improve the household farm productivity, which would eventually boost food security under different extreme weather events. Furthermore, the study proposes creation of accessible credit markets, which should allow households access farm inputs, namely, hired labour, inorganic fertilizer, and improved crop varieties, critical for the sustainable adoption of various CSA, or IPM, or SLM –related practices in the study area.

The study results inform the policy making process in Malawi in four broad-ways. First, it provides evidence regarding the drivers of CSA, IPM, and SLM-related practices' adoption and their effects on farm productivity. These adaptation strategies are appropriate when the climate models project frequent, intense, and severe extreme weather events in Malawi in the coming decades. Second, the study isolates the most efficient adaptation practices, which enhance farm productivity and minimize the dis-adoption decision of the CSA, IPM, and SLM-related practices at the household level. Third, the study enhances climate-resilient farm productivity under different extreme weather events. Additionally, the study findings mainstream indigenous experiences in climate adaptation, ensuring CSA, IPM, and SLM-related practices' suitability, flexibility, and sustainability. Ultimately, the study results are relevant to the current debate on achieving the Sustainable Development Goal (SDGs) on agricultural productivity under different extreme weather events.

Key words: Farm Productivity; Climate-Smart Agriculture; Integrated Pest and Sustainable Land Management; Rural-Urban Migration; Panel-Based Stochastic Frontier Analysis; Panel-Based Endogenous Switching Regression Model; Conditional Fixed Effect Model; Triple Hurdle Tobit Model.

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LIST OF ACRONYMS AND ABBREVIATIONS

AAE	Agricultural and Applied Economics
AER	Annual Economic Report
AGRA	Africa Green Revolution in Agriculture
ATET	Average Treatment Effect on the Treated
ATU	Average Treatment Effect on the Untreated
AU	African Union
BCA	Bunda College of Agriculture
CWV	Climate and Weather Variability
CL	Conditional Logit
CSA	Climate Smart Agriculture
CWA	Climate and Weather Adaptation
CWV	Climate and Weather Variability
DAC	Drought Affected Communities
DEA	Development and Environmental Analysis
DODMA	Department of Disaster Management Affairs
ENRM	Environmental and Natural Resource Management
ESR	Endogenous Switching Regression
FAH	Fall Army Worms Affected Households
FAO	Food and Agricultural Organization
FAOStat	Food and Agricultural Organization Statistics
FAW	Fall Army Worms
FMH	Fall Army Worms Management Adapted Households
GDP	Gross Domestic Product
GoM	Government of Malawi
HA	Hectare
HWM	Household with Migrants
HNM	Household without Migrants
IHPS	Integrated Household Panel Survey
IID	Identically, Independently Distributed
IIA	Irrelevant Independent Alternatives
IMR	Inverse Mills Ratio
IPM	Integrated Pest Management
Kg	Kilogram
LUANAR	Lilongwe University of Agriculture and Natural Resources
LSMS	Living Standard Measurement Study
MAP	Manure Application
MGDS	Malawi Growth and Development Strategies

IMV	Improved Maize Varieties
MLI	Maize Legume Intercropping
MNL	Multinomial Logit
MOAIWD	Ministry of Agriculture, Irrigation and Water Development
NAIP	National Agricultural Investment Plan
NPK	Nitrogen, Potassium and Phosphorus
NSO	National Statistics Office
PDA	Panel Data Analysis
PhD	Doctor of Philosophy
RUFORUM	Regional University Forum for Capacity Building in Agriculture
RUM	Rural-Urban Migration
SDGS	Sustainable Development Goals
SFA	Stochastic Frontier Analysis
SLM	Sustainable Landscape Management
SSA	Sub-Sahara Africa
SWC	Soil and Water Conservation Practices
TAH	Tropical Cyclone Affected Households
TCRFs	Tropical Cyclone –related Floods
UP	University of Pretoria

CHAPTER ONE

GENERAL INTRODUCTION

1. Introduction

In this Chapter one, the study presents the context, regarding agricultural production and productivity in Sub-Sahara Africa (SSA) and Malawi. This Chapter further discusses the effect of extreme weather events on agricultural productivity. It also highlights the influence of weather events on the adoption of various climate-smart agricultural (CSA) –related practices. Finally, this Chapter highlights the rationale of the study, the problem statement, the objectives, research questions; the general methodology, and the organization of the study.

1.1 Study Context

Globally, agricultural production, which is the transformation of various input combinations into desired outputs (Kumbhakar et al., 2015), is increasing with maize almost tripling from 476.8 million tonnes in 1989 to over 1.1 billion tonnes in 2016 (FAO, 2018, see Figure 1. 1). Similarly, in Africa, maize production has doubled from 41.6 million tonnes in 1989 to over 84.2 million tonnes in 2016, and fostering higher agricultural productivity is one of the core Africa strategies for overall development (Deininger and Binswanger, 1995; Binswanger and Townsend 2000, FAO, 2014). The increase in global agricultural production is largely attributed to increased use of inorganic fertilizers, improved crop varieties, and agricultural intensification (Singh et al., 2020; World Bank, 2020). Agriculture constitutes 20 percent of the Africa' s Gross Domestic Product (GDP) and contributes about 60 percent of employment (World Bank, 2014, 2010; Pangapanga and Mungatana, 2021). It forms half of the total export earnings and about 85 percent of the population in rural African countries, like Malawi, Lesotho, Swaziland, and others, depend on agriculture for their livelihood security (World Bank, 2014).

However, Sub Sahara Africa (SSA) has seen a declining trend in agricultural production from 12.8 million metric tonnes in 1989 to 8.0 million metric tonnes in 2016 (Benson et al., 2021). SSA agricultural performance has been falling further behind other developing regions in the world (Benin, 2016, see Figure 1. 1). Low use of fertilizer, traditional crop varieties, small land holding sizes, and marginal land cultivation partly limit agricultural production in SSA (Chauvin et al., 2012). For instance, the average use of fertilizer per hectare in SSA is only 16kg instead of 200kg (African Union [AU], 2020). Furthermore, SSA has not thoroughly mainstreamed the role of indigenous knowledge in formulating effective agricultural-related climate change adaptation strategies (Nyadzi et al., 2021; Makondo and Thomas, 2018). Moreover, SSA agriculture is rain-fed dependent rendering it vulnerable to climate and weather variability (FAO, 2014). Additionally, SSA is facing 20 percent higher extreme heat waves (African Union, 2020) in 2020 than two decades ago, with the undernourished people rising by almost 10 percent between 2014 and 2020 (World Bank, 2020). These realities, including recent high food prices in many SSA countries, have renewed the concern for knowledge gaps, regarding suitable strategies for revamping and maintaining higher agricultural productivity (Benin, 2016).

In response to the declining agricultural production, SSA has aligned its agricultural programmes with the Comprehensive Africa Agricultural Development (CAADP) and the Sustainable Development Goals (SDGs) of the United Nations to enhance resilience of rural agricultural production systems to negative effects of different extreme weather events (Pangapanga and Mungatana, 2021), namely, droughts, floods, dry spells, and pest outbreaks (World Bank, 2020; AU, 2020). SSA countries have further made reference to employing narratives, lessons, and technologies, viz., adoption of high yielding varieties, and modern management practices, achieved under the Green Revolution successes in Asia and India (Benin, 2016). Unfortunately, the SSA suffers from low adoption of improved agricultural practices. For example, only 15 percent of agricultural suitable land has sustainable land management (SLM) –related practices and under 10 percent is irrigated, indicating the need to increase agricultural public expenditure (World Bank, 2020). This financial support should equally enhance access to agricultural inputs, promote technology adoption, and augment investment in resilience building towards different extreme weather events (AU, 2020; MoAIWD, 2018; DoDMA; 2018).

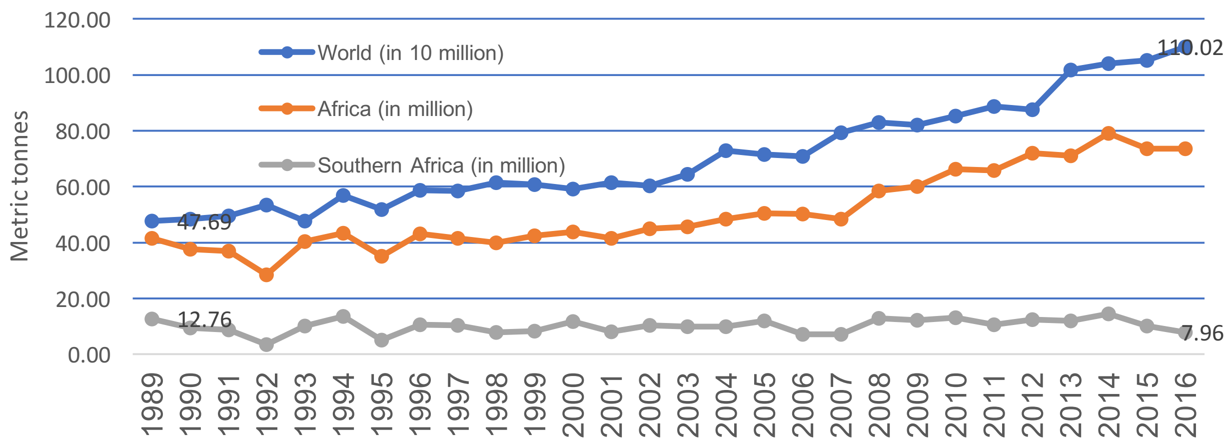

Figure 1. 1. Maize production for the World, Africa and Southern Africa between 1989 and 2016

Source: FAOStat (2020)

1.2 Agricultural production in Malawi

Agriculture in Malawi predominantly drives the economy (World Bank, 2020, 2018, 2016; Mapemba et al., 2020; GoM, 2018), contributing one third of the GDP and 80 percent of the total export earnings (National Statistics Office [NSO], 2020, 2018). About 64 percent of employment emanate from agriculture and women forms over 70 percent of its workforce (AU, 2020; FAO, 2015). Agricultural production is the main source of livelihood for rural households in Malawi (Lipper et al., 2018; GoM, 2017; Amadu et al., 2020). It also defines the pace and direction of the country economic growth (GoM, 2018; Tchale, 2009). For example, the underperformance of the agriculture sector in 2016 and 2018 resulted into a decline in economic growth (see Figure 1.2). Studies by Amare et al (2015), and Ravallion and Datt (1999) demonstrate that improving agricultural production is therefore the main pathway of addressing poverty in most developing countries. In other words, the agricultural production determines Malawian livelihoods, food security, and poverty incidences (NSO, 2020).

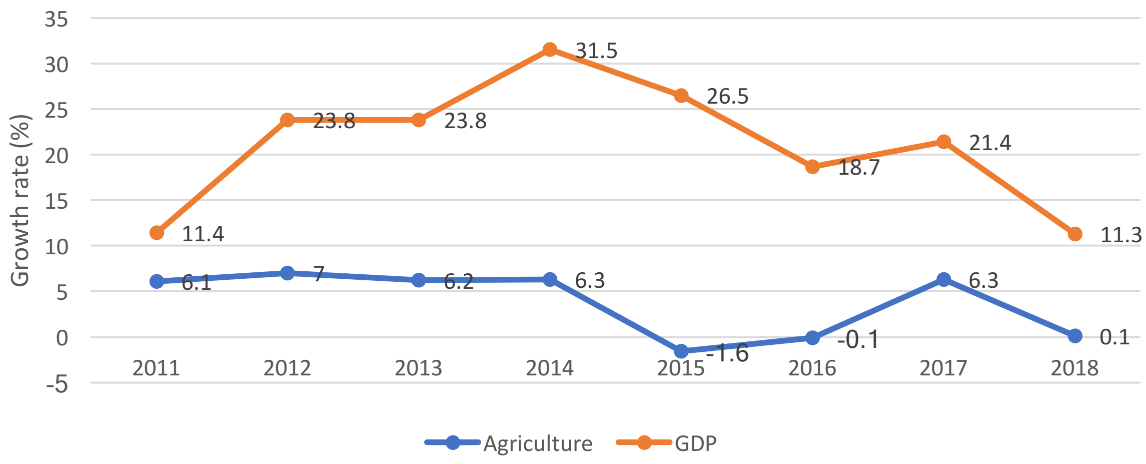

Figure 1. 2. Agricultural and economic (GDP) growth in Malawi between 2011 and 2018

Source: FAOStat (2020)

The country' s agricultural sector is categorized into smallholder and estate sub-sectors (GoM, 2018). The smallholder sub-sector, which cultivates on communal land, makes up 78 percent of agricultural sector while estate, which cultivates on leasehold and freehold land, accounts for 22 percent (Asfaw et al., 2016) of agricultural land. There are about 3.3 million hectares under smallholder agriculture and 1 million hectares under estate sub-sectors (Deininger and Xia, 2017; NSO, 2007). While the estate sub-sector largely cultivates commercial crops, viz., tobacco, sugar, and tea, for exports, smallholders predominantly produce food crops, like maize, rice, cassava, sweet potatoes, and sorghum, for subsistence requirement and surplus for sale (MoAWID, 2018). Smallholder sub-sector dominates the agricultural sector output by 80 percent, and 90 percent of the total value additions in agriculture (GoM, 2021; NSO, 2020). Almost 83 percent of smallholder farmers stay in rural areas and currently farm on land holding size of 0.5 hectare, which has declined from 1.53 hectares in 1970s due to population pressure (NSO, 2020). Half of the farming households cultivate local and recycled maize varieties, which are highly susceptible to weather events, such as fall armyworms, floods, and drought episodes. African Union (2020) states that smallholder subsistent farmers are heavily affected by the effects of extreme weather events. However, the ecosystems which they rely on for food production is increasingly degraded. In addition, most smallholder farmers are poor, cultivates on rain-fed agriculture, and have limited access to improved agricultural inputs, such as, hybrid varieties and inorganic fertilizers (NSO, 2018, 2020). In terms of land user-rights across gender, women cultivate only 0.4 of a hectare while men farm on 0.8 of a hectare (NSO, 2020).

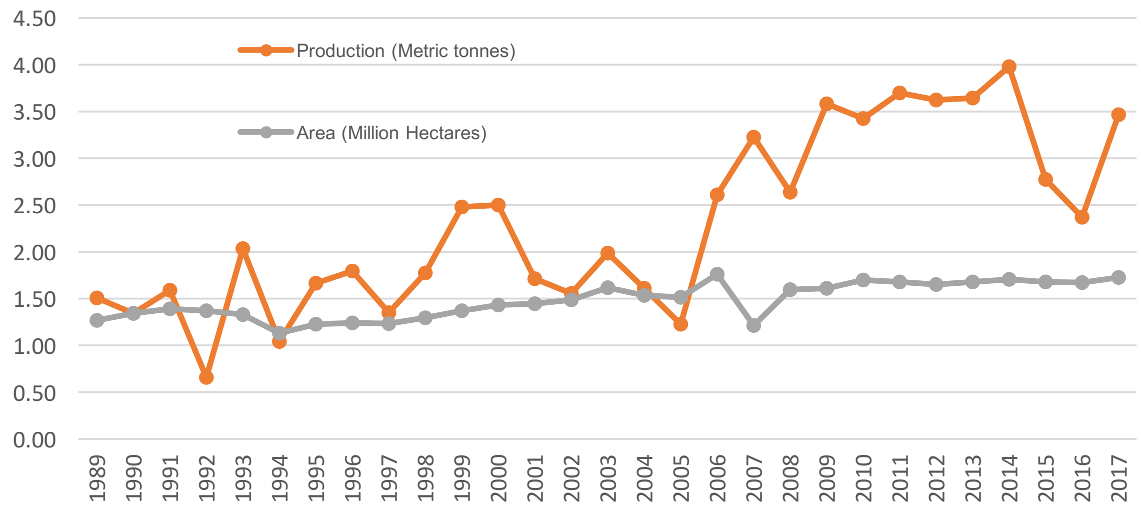

Figure 1. 3. Agricultural production and area expansion in Malawi between 1989 and 2017

Source: FAOStat (2020)

1.3 Agricultural productivity in Malawi

Augmenting higher agricultural productivity, which is measured as a ratio of quantity of produced outputs to a given quantity of inputs (see Muyanga and Jayne, 2019; Aragon et al., 2019; Djougnessi, 2018; Kumbhakar et al., 2015), is one of the collective core economic development and growth strategies in Malawi (MoAIWD, 2018). However, over the past decades, agricultural productivity has been erratic in the country despite massive agricultural investments and displaying an increasing trend (see Figure 1.3). On the one hand, the dwindling agricultural productivity is attributed to declining soil fertility, land fragmentation due to rapid population growth, communal land tenure system, limited improved agricultural technologies, uncoordinated SLM -related practices, unaffordable chemical pesticides, limited agricultural extension services, underdevelopment of markets, and poorly maintained infrastructure (Kilic et al., 2021; Lipper et al., 2018; GoM, 2017; Mapila et al., 2012). Further, the country has the lowest labour productivity in the SSA (FAO, 2017, 2016, 2014, 2013, 2010), with per capita labour productivity (US$ 209.0) being three times below the average SSA' s (US$ 680.0) while land productivity (US$ 155.0/ha) is likewise lower than the average SSA land productivity (US$ 270.0/ha). This has resulted into rural – urban migration, where more than 40 percent of households are reported to have migrated to rural areas between 2010 and 2020 (NSO, 2020). Additionally, Malawi continues to lose soils of about 32 - 40 tonnes per hectare per year of inorganic fertilizer, due to excessive run-off (MoAIWD, 2018; Chirwa, 2003).

Recently, on the other hand, agricultural productivity in the country has been deteriorating due to climate and weather variability (CWV) (McCarthy et al., 2021; Asfaw et al., 2016; Asfaw and Maggio, 2017; Kilic et al., 2015). Archeologically, the country location along the East African Rift Valley and effect of El Nina and LA Nina are among the main factors influencing its vulnerability to extreme climate and weather events (World Bank, 2015, 2016, 2018, 2020). Accordingly, Mwase et al. (2013) argue that the country optimal harvest is associated with favourable climate and weather conditions. Distinctly, the country has experienced higher agricultural production during the years of 2006, 2009, 2011, and 2014 when the country had favourable rainfalls and temperatures (see Figure 1.3). While, it has observed a reduction in maize production in 2015, 2016, and 2018 during the years of floods, droughts, and pest outbreaks, respectively. These extreme weather events have demonstrated varying negative effects on household welfare, especially, food security. In 2015, over 0.24 million households became food insecure due to floods (World Bank, 2015). In 2016, drought pushed over 1.4 million households into food insecurity (World Bank, 2016). In 2018, almost 0.2 million households became food insecure due to fall armyworms (FAW) and having an annual economic loss of US$ 0.23 – 0.56 million

(World Bank, 2020). In 2019, tropical cyclone Idai affected over a million people (World Bank, 2019). Sadly, climate predictive models have repeatedly illustrated increasing frequency, intensity, and prolonging extreme weather events, exerting huge cost to lives, property, and pressure to the country fiscal policy (DoDMA, 2018).

1.4 Climate-Smart Agriculture in Malawi

Climate-Smart Agriculture (CSA) presents an excellent opportunity for improving farm productivity at household level and enhance the role of agricultural production in national development agenda (Martey et al., 2020; Marenya et al., 2020; Phiri, 2020, Tufa et al., 2019; MoAIWD, 2018; Lipper et al., 2014; Vermeulen et al., 2012; Nyadzi et al., 2021; Maganga et al., 2021; Pangapanga and Mungatana, 2021). Lipper et al. (2014), FAO (2010, 2013), and World Bank (2020) define CSA as technique that transforms and reorients agricultural development towards CWV, which (i) principally and sustainably increases agricultural production and productivity; and (ii) adapts and enhances resilience to climate and weather variability. Consequently, stakeholders, including the Government of Malawi, non-government organizations, and households have designed various CSA, including the integrated pest management (IPM), and the sustainable landscape management (SLM) –related practices (McCarthy et al., 2021; Day et al., 2017; Teklewold and Mekonnen, 2017).

The IPM is a CSA –related approach which economically suppress pest population, by using techniques that minimize harm to the environment, including people (Day et al., 2017). In addition, the IPM –related practices are climate and weather events' sensitive, where they are heavily applied during pest infestation, which is induced by climate and weather variability (Day et al.,2017). Similarly, the SLM is the CSA adaptive method that enhances and maintains the quality of soil, water, and air resources through socially and economically acceptable agricultural practices for realising higher agricultural production and productivity (McCarthy et al., 2021). Households have essentially adopted SLM practices through undertaking soil and water conservation structures, agroforestry, manure and lime application, improved crop varieties, cereal legume intercropping, crop rotations, and mulching on the farm (MoAIWD, 2018). Likewise, households have adopted these SLM practices, which are responsive to climate weather variability. Besides, some households have engaged in climate driven rural-urban migration (RUM) to alleviate the adverse effects of extreme weather events (Anglewicz, 2012; Anglewicz et al., 2017; Adams and Cuecuecha, 2013, 2010; Adams and Page, 2005; Chilimampunga, 2006). Households re-invest the remittances from migrants in CSA -related practices (Anglewicz and Myroniuk, 2018).

Furthermore, the country has strongly aligned its national agricultural policies with the CAADP and SDGs of the United Nations (McCarthy et al., 2021), where they have advocated for the adoption of the CSA, IPM, and SLM-related practices to build resilient agricultural production systems at household level (MoAIWD, 2018; Amadu et al., 2020). Moreover, the country has increased the national agricultural budget from six percent in 2005 to at least 10 percent in 2006 onwards (African Union [AU], 2020), where stakeholders have invested over US$ one billion in various CSA, IPM, and SLM-related practices between 2008 and 2020 (World Bank, 2010, 2020; DoDMA, 2018). Additionally, the country' s farm input subsidy programmes have increased the use of fertilizer from 27kg in 2004 to over 50kg per hectare (ha) in 2006 (MoAIWD, 2018, AU, 2020). Recently, the country has further increased access to affordable farm inputs by horizontally expanding the number of beneficiaries (AER, 2021).

Nevertheless, agricultural production and productivity have continued to deteriorate, remained below the potential productivity, and highly correlated with CWV, with total production annually fluctuating between 2.37 and 3.98 million metric tons, thereby failing to meet the household food demand (NSO, 2020; Kilic et al., 2013). The challenge, however, is that households have implemented, translated, and named these CSA, IPM, and SLM -related practices differently (McCarthy et al., 2021; Chinseu et al., 2018; Fisher et al., 2018). Some farmers have even abandoned some already embraced CSA, IPM, and SLM -related practices due to information irregularity, low production, and limited research (Holden et al., 2018; BisYishay and Mobaraka, 2014; Pangapanga and Mungatana, 2021). Moreover, the current CWV discussions have partially mainstreamed indigenous knowledge in formulating the adoption of the CSA-related practices that are locally effective, suitable, and affordable (Nyadzi et al., 2021; Makondo and Thomas, 2018; Belfer et al., 2017; Fairhead et al., 2017). Moreover, households opting for RUM have not realised the benefits from investing the remittances in CSA practices (NSO, 2020; Chilimapunga, 2006; de Fuente, 2010).

Following the above frustrations from the implementation of various CSA, IPM, SLM, and RUM, the adoption of these practices has become short-lived (DoDMA, 2018; MoAIWD, 2018; Fisher et al., 2018; Schafsma et al., 2019; World Bank, 2015, 2016, 2018, 2019, 2020). Consequently, households have failed to derive optimal benefits from the adoption of CWA-related practices, which are supposed to enhance farm productivity (Martey et al., 2020; Khataza et al., 2018). Furthermore, the debacles associated with CWV and under-performance of various CSA, IPM, and SLM-related practices have led to selling of household assets; reducing dietary diversity, food consumption, and access to quality food; declining agricultural income, and further creating poverty traps, which have increased food insecurity and long-term malnutrition (World Bank, 2020; 2018; DoDMA, 2018; AU, 2020). Nonetheless, limited research on drivers of CSA, IPM, and SLM-related practices is one of the main facilitators to low acceptance and further abandonment of the already adopted practices (Amadu et al., 2020). Additionally, previous studies on farm productivity have concentrated on one crop, for instance, maize (Katengeza et al., 2018; Khataza et al., 2018; Asfaw et al., 2016; Pangapanga et al., 2012), instead of examining all crops (Muyanga and Jayne, 2019; Aragon et al., 2019). Moreover, households have lacked information on the benefits of these CSA, IPM, SLM, and RUM, especially under different extreme weather events (McCarthy et al., 2021, Kilic et al., 2021; de Fuente, 2010).

It is in the prior context, that this study largely examines the influence of CSA, IPM, SLM, and RUM on farm productivity under different extreme weather events. Specifically, the study disentangles the drivers of the adoption of CSA, IPM, and SLM – allied practices under different extreme weather events. Second, it unpacks the effect of extreme weather events, viz., drought, tropical cyclones induced floods, and fall armyworms on farm productivity. Lastly, the study interrogates the contribution of CSA, IPM, SLM, and RUM on farm productivity. Consequently, the study informs the existing policy making processes in four broad-ways, namely, (i) enhances adoption of CSA, IPM, and SLM-related practices under different extreme weather events, (ii) minimises household abandonment of already adopted strategies, (iii) augments climate resilient farm productivity, and (iv) promotes mainstreaming of field experience in programming and implementation of CSA, IPM, SLM, and RUM. Ultimately, the study findings are appropriate to the realisation of Malawi Vision 2063 and the United Nations' SDGs' 2030 targets on improving agricultural productivity, under different extreme weather events.

1.5 Problem Statement and Rationale

Agricultural productivity in Malawi continues to decline (Kilic, et al., 2013; McCarthy et al., 2021) and frustrate the food security agenda (World Bank, 2020; 2018) despite massive investments including farm input subsidy programmes, CSA-related practices, integrated pest management (IPM), sustainable landscape management (SLM) and rural-urban migration (RUM) (DoDMA, 2018; Truen et al., 2016; Pangapanga and Mungatana, 2021; Chilimapunga, 2006). Over 10 percent of the national domestic resource envelope is appropriated to agriculture programmes, viz., the farm input subsidy (FISP 2004 - 2020), the agricultural sector wide approaches (2011 – 2020), the Greenbelt initiatives (GBI 2004 - 2020), and the affordable input program (AIP 2020 - 2021) (GoM, 2021). Besides, in the recent past, households have adopted various CSA-related practices (Kilic et al., 2021; MoAIWD, 2018, Asfaw et al., 2016) and about 15 percent of agricultural land is under SLM -related practices (African Union, 2020). Only 10 percent of households have adopted various climate-induced agricultural practices (Fisher et al., 2018; Chinseu et al., 2018).

According to the MoAIWD (2018) and World Bank (2020), agricultural productivity is still volatile (AU, 2020). Moreover, farmers still yield one quarter of the potential production (AER, 2018; GAP, 2010) despite increasing the use of chemical fertilizer from 27kg/ha in 2005 to over 50kg/ha in 2018 (MoAIWD, 2018; DoDMA, 2018). The deteriorating agricultural productivity has also been attributed to several constraints, viz., traditional crop varieties; poor agricultural practices; low technological adoption; increasing population pressure on land, and declining soil fertility (MoAIWD, 2018; World Bank, 2019, 2018, 2016, 2015; Phiri et al., 2012). Furthermore, prolong and intensified occurrence of extreme weather events, namely, droughts, tropical cyclone –induced floods, and fall armyworms have further exasperated the declining agricultural productivity (McCarthy et al., 2021; DoDMA, 2018; FAO, 2018; McCarthy et al., 2021). For instance, households have experienced reduced farm productivity, viz., in 2014/2015 and 2015/2016 when different extreme weather events occurred (see Figure 1.4). In 2018, FAW reduced maize production for over 0.2 million households (DoDMA, 2018). On the other hand, during favourable weather events in 2009/2010 and 2012/2013, households have had higher agricultural productivity (MGDS, 2018).

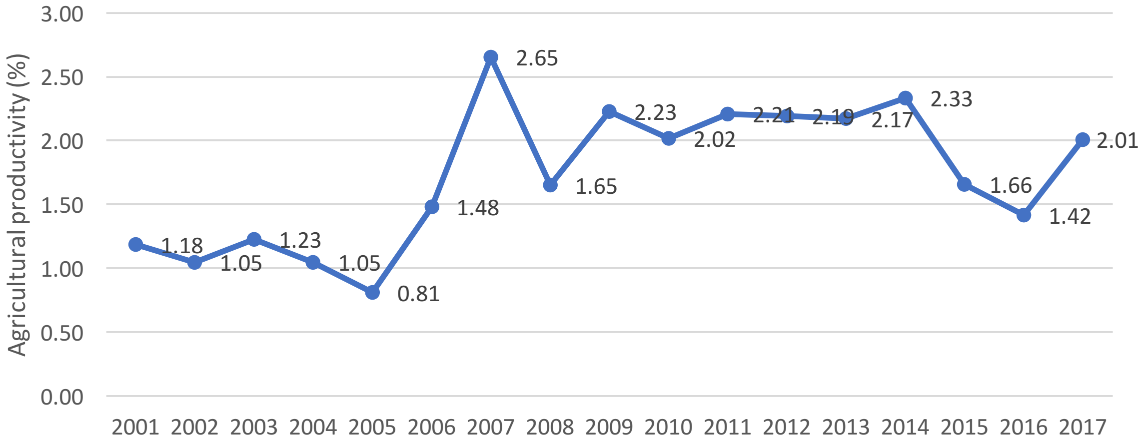

Figure 1. 4. Maize productivity in Malawi between 2001 and 2017

Source: FAOStat (2020)

Additionally, the negative effects of intensifying extreme weather events, namely, droughts, tropical cyclone –related floods, and pest infestation, on agricultural productivity have resulted into chronical food insecurity and malnutrition (McCarthy et al., 2021; MoAIWD, 2018; Asfaw et al., 2016). For instance, in 2015, about 1.1 million people become food insecure, due to floods in 2014/2015 cropping season (World Bank, 2016). In 2016, around 6.5 million people were food insecure and demanded immediate food assistance, following droughts in the 2015/2016 cropping season (DoDMA, 2018). In 2017, about 68% of households had experienced irregular rains, resulting into widespread crop failures (World Bank, 2020). In 2018, approximately 0.8 million people were food insecure due to fall armyworms (FAW) (MoAIWD, 2018). FAW destroyed the crop vegetative and reproductive structures, thereby reducing crop production by 40 percent – translating into an annual economic loss of US$ 0.23 – 0.56 million. Approximately, 0.2 people became food insecure following FAW infestation on the farm (DoDMA, 2018). Similarly, in 2019, tropical cyclone (TC) -related floods pushed over a million people into food insecurity (World Bank, 2019). Empirically, extreme weather events have augmented the number of affected households from 20 percent in 2010 to 60 percent households in 2019 (NSO, 2020).

Unfortunately, smallholder households have relied on rain-fed farm production, and are on the fore-front feeling the impact of climate and weather variability (AU, 2020). Extreme weather events have exerted additional pressure on the household resources forcing them to sell assets, reduce food consumption and dietary diversity, migrate from rural to urban areas, and opt for less preferred food types (AU, 2020; DoDMA, 2018; World Bank, 2020). Accordingly, the majority of rural households have remained poor over the past decades (NSO, 2010, 2014, 2018, 2020), where approximately 50 percent of the population still live below the poverty line, and 37 percent of children are malnourished (NSO, 2020; DNHA, 2020).

The Government and other key stakeholders, including households, have, thus, adopted various CSA, IPM, and SLM-related practices to cushion farm production and productivity from extreme weather events (DoDMA, 2018; McCarthy et al., 2021; Pangapanga and Mungatana, 2021). Some households have further partially migrated from rural to urban areas to fetch for income, which is sent home for adapting to adverse effect of extreme weather events (Chilimapunga, 2006). Households have re-invested these remittances in modern agricultural practices, like CSA, IPM, and SLM – related practices. Unfortunately, the adoption of these CSA, IPM, and SLM-related practices is not consistent with the investments made, where extreme weather events have continued to reduce agricultural productivity by over 10 percent (Katengeza et al., 2018; Thierfelder et al., 2016). Nonetheless, few studies have interrogated the effects of various CSA, IPM, and SLM-related practices on the farm productivity in Malawi. Moreover, the adoption rate of CSA, IPM, and SLM-related practices is still very ten (10) percent (Chinseu et al., 2018; Phiri et al., 2012) and under 20 percent of agricultural land is still unsustainably cultivated (AU, 2020). Awkwardly, some households have started abandoning some already adopted CSA, IPM, and SLM-related practices (Fisher et al., 2018; Day et al., 2017). Furthermore, most studies have only investigated the effect of CSA, IPM, and SLM-related practices, based on one crop approach instead of farm productivity (Khataza et al., 2018, Katengeza et al., 2018; Muyanga and Jayne, 2019; Aragon et al., 2019; Pangapanga and Mungatana, 2021; Kilic et al., 2021)

In this study, pose four (4) empirical questions are posed to addressing the declining farm production and productivity, which are relevant to the policy making processes and sparkling debate in Malawi, namely, (i) Do household (e.g. gender, education, mobile ownership, and credit accessibility) and farm-level (i.e. soil quality, type, and slope), drive the adoption of CSA-related practices? (ii) Do CSA, IPM and SLM-related practices (i.e. organic farming, intercropping, agroforestry, soil and water conservation, pesticides, and improved crop varieties) have any significant influence on the farm productivity? (iii) Do extreme weather events, viz., drought, TC –related floods, and fall armyworms substantially affect farm productivity and the adoption of CSA, IPM, and SLM -related practices? and (iv) Does RUM improve the technical efficiency of maize production in the study area under extreme weather events?

The study uses the four-waves Malawi integrated household panel survey (IHPS) data, compiled by the NSO and the World Bank between 2010 and 2020 (NSO, 2020). The study undertakes rigorous panel-based econometric methods, viz., Conditional Logit, Stochastic Frontier Analysis (SFA), Endogenous Switching Regression (ESR) models, to address the study empirical questions. The study has published the article from Chapter two in the peer-reviewed Elsevier Journal of Disaster Risk Reduction (Pangapanga and Mungatana, 2021). An article from Chapter three on tropical cyclones is also under review and language editions in the Taylor and Francis Journal of Climate and Development. In subsequent sections, this Chapter One presents the main objectives, the research questions, the general methodology adopted in the entire study, and finally, the study outline.

1.6 Objective of the study

The main objective of this study is to examine the effect of CSA, IPM, and SLM -related practices on the farm productivity under different extreme weather events in Malawi. The study has the following specific objectives: -

1. Determining the household and farm characteristics influencing the adoption of CSA, IPM, and SLM -related practices under different extreme weather events.
2. Investigating the contribution of CSA, IPM, and SLM-related practices, as well as RUM on the farm productivity under different extreme weather events.
3. Assessing the effect of droughts, TC-related floods, and FAW on the farm productivity among adopters and non-adopters of CSA, IPM, and SLM -related practices.

1.7 Research Questions of the study

The study highlights a number of questions that contextually provide a direction on achieving the study main objective as follows:

1. Do household (e.g. gender, education, mobile ownership, and credit accessibility) and farm-level (i.e. soil quality, type, and slope), drive the adoption of CSA-related practices?
2. Do CSA, IPM and SLM-related practices (i.e. organic farming, intercropping, agroforestry, soil and water conservation, pesticides, and improved crop varieties) have any significant influence on the farm productivity?
3. Do extreme weather events, viz., drought, TC –related floods, and fall armyworms substantially affect farm productivity and the adoption of CSA, IPM, and SLM -related practices? and
4. Does rural-urban migration improve the technical efficiency of maize production under extreme weather events?

1.8 Conceptual Framework of the study

Different authors have presented the conceptual framework differently (Ravitch and Riggan, 2017; Miles et al., 2016; McCartan and Rossman, 2016). For instance, Ravitch and Riggan (2017) have focused on the conceptual framework as an argumentation for the study. Miles et al. (2014) have presented the conceptual framework in form of presenting explanatory variables. Merriam and Tisdell (2016) have illustrated the conceptual framework as generating elements of the research design and methods. McCartan and Rossman (2016) have presented the conceptual framework as a variable relationship. While, Maxwell (2013) has discussed it in forms of explanation, and justification of the study. This study has adopted the conceptual framework as proposed by Miles et al. (2016) and McCartan and Rossman (2016).

Figure 1.5 presents the conceptual framework of the study. A conceptual framework highlights an argument about why the study and the methods proposed are appropriate and rigorous (Miles et al., 2014). In this study, the CSA, IPM, SLM, and RUM conceptual framework is based on FAO (2010), MaCarthy et al. (2021) and Kilic et al. (2021) where extreme weather events form fundamental elements, influencing household choices and livelihoods. The study understands that several variables affect farm productivity. Extreme weather events, namely, droughts, tropical cyclone related floods (TCRFs), and fall army worms (FAW) may adversely affect farm productivity, thereby negating household income and food security status. However, these extreme weather events may also influence the behaviour of households. Households may start undertaking some adaptive strategies to cushion farm productivity from the negative effects of various extreme weather events. Some of these adaptive strategies include CSA, IPM, and SLM –related practices (McCarthy et al., 2021; Kilic et al., 2021; Pangapanga and Mungatana, 2021). Similarly, some households may opt for RUM, as a climate adaptive strategy, where migrating household members generate income, which is sent back to household members left behind. These household members, left behind, then re-invest the remittances in CSA, IPM, and SLM –related practices.

Nonetheless, the adoption of any of the various CSA, IPM, and SLM –related practices, including RUM is affected by several socioeconomic, institutional, and farm -level production factors (Asfaw et al., 2016). Socioeconomic factors like age, education, literacy, and gender of household head influence the understanding of the fundamental role played by the adopted practices on the farm. For example, some practices demand the household head to be literate to comprehend the instruction manuals. Similarly, institutional factors such as input, output, and credit markets influence household access to agricultural resources, namely, inorganic fertilizer organic manure, and improve crop seed varieties. Likewise, farm –level factors, viz., soil type, quality, and slope determine the type of CSA, IPM, and SLM –related practices to undertake. For instance, households with steep slope are more likely to adopt contour bunds to control excessive soil erosion.

Figure 1.5 further illustrates that the adoption of CSA, IPM, SLM, and rural-urban migration may have effect on farm productivity, which further influences household available income and food security status (McCarthy et al., 2021). Besides, farm -level factors, such as labour in terms of personal days, farm holding size allocated to crops, total available farm holding size, slope, soil type, and quality may likely influence farm productivity (Khataza et al., 2018, Katengeza et al., 2018).

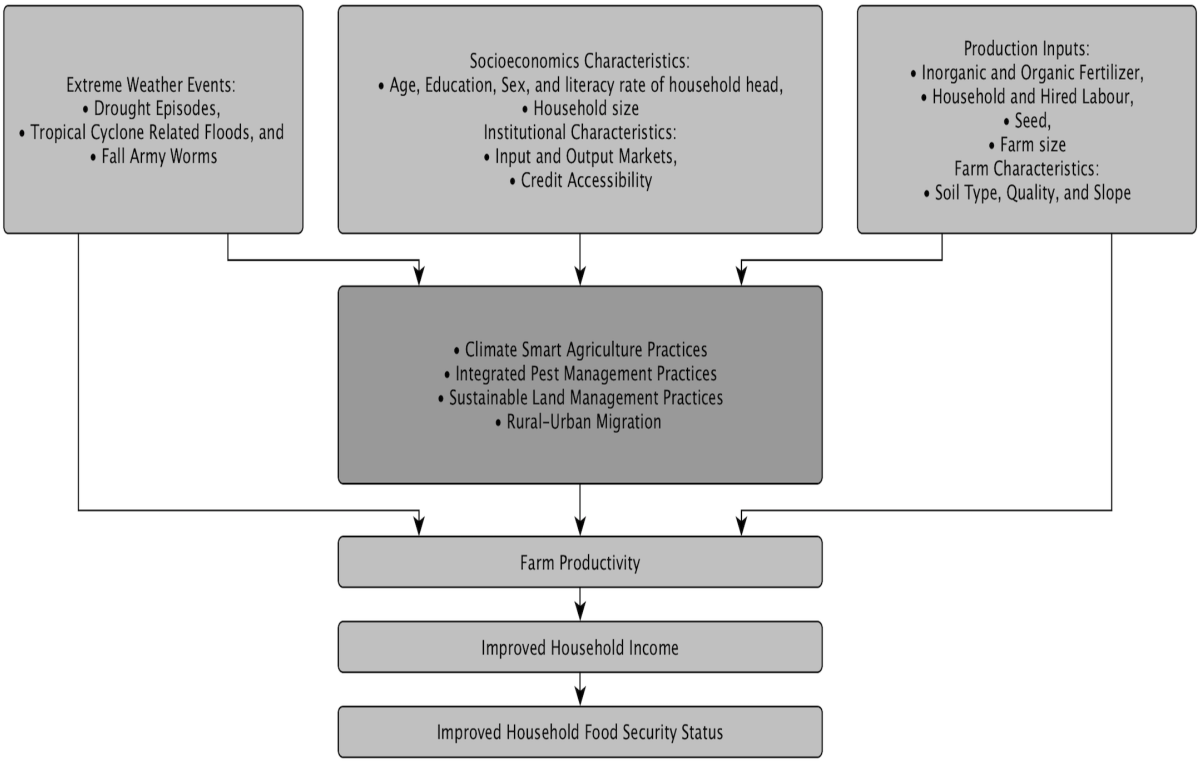

Figure 1. 5 : Conceptual Framework of the Study (FAO, 2010; MaCarthy et al., 2021; Kilic et al., 2021; Pangapanga and Mungatana, 2021).

1.9 Theoretical and Empirical Frameworks

The expected random utility maximization theory informs the study analysis of household decision (McFadden, 1978, 1974). Formally, the study considers an individual household i from a random sample of N households, who has to decide at time t to adopt any of the CSA, IPM, and SLM-related practices j, namely, early maturing varieties, intercropping, agroforestry, conservation farming, chemical pesticides, and soil and water conservation measures. In other words, any households undertaking any CSA, IPM, or SLM practice is defined as an adopter, and otherwise, non-adopter. An individual household attaches a utility value (U_{ijt}) to the adoption decision of CSA, IPM, and SLM-related practices, depending on various attributes associated with the practice (Wooldridge, 2016; 2002). The household is assumed to be rational, functional and efficient and only adopt a practice, which provides optimal utility (Coombs, 1964). However, preference of a utility value (U_{ijt}) depends on household specific characteristics, x_{ijt}, community factors C_{ijt} viz., market access, and climate variables W_{ijt}, namely, temperature, rainfall, droughts, floods and fall armyworms (Kumbhakar and Lovell, 2000). Households are also constrained by time, labour, and availability of CSA, IPM, and SLM-related practices (McCarthy et al., 2016; Pangapanga et al., 2012; Jumbe and Angelsen, 2011; McFadden, 1974).

The study specifies a multiplicative latent utility function $[U_{ijt}(.)]$ of an individual household as in equation (1):

$$U_{ijt} = f(X_{ijt}, C_{ijt}, W_{ijt}, q, \beta, \varphi) + \psi_{ijt}, \quad (1)$$
$$j = 1,2, \ldots \ldots, J; i = 1,2, \ldots, N; t = 1,2,3$$

where $f(.)$ is non-stochastic and reflects the representative taste of the randomly drawn individual households; X_{ijt}, C_{ijt}, and W_{ijt} represent various specific taste characteristics of the household; q, φ, and β are unknown parameters; and ψ_{ijt} is the error term reflecting the idiosyncrasies of the individual taste for the alternatives CSA, IPM, and SLM -related practices with several attributes and has zero mean and constant variance. Households adopt CSA, IPM, and SLM -related practices j that maximises utility (Jumbe and Angelsen, 2011). The study assumes the household adoption decision $[A_{ijt}]$ as a binary choice variable that take the value of one if a household adopts any of the CSA, IPM, and SLM -related practices, j, and otherwise, zero (0), with a certain probability as presented in equation (2):

$$P_{i1t}(A_{i1t} = 1/x_{ijt}) = Pr\ (U_{i1t} > U_{ijt}) \quad (2)$$

where x_{ijt} is the vector of household characteristics, affecting the adoption decision of any of the CSA, IPM, and SLM –related practices. The household adoption decision (A_{ijt}) is displayed as in equation (3).

$$A_{ijt} = \begin{cases} \beta_0 + \beta_j x_{i1t} + \mu = 1 & if\ U_{i1t} > U_{ijt} \\ \beta_0 + \beta_j x_{i1t} + \mu = 0, & \text{otherwise} \end{cases} \tag{3}$$

where β and μ denote unknown parameters and error terms, respectively while U_{i1t} and A_{ijt} as prior defined. In most choice models, random components of the utility expressions determine the functional form of the model (McFadden, 1974). Usually, they demonstrate the independent and identically distribution (IID) properties with type I extreme value distribution, leading into the development of multinomial related models. Fortunately, most multinomial logit models have an elegant closed mathematical structure that is easy to implement and interpret. They also saddle on independence of irrelevant alternative (IIA) properties (McFadden, 1974). This implies that households make adoption decisions of CSA, IPM, and SLM -related practice independent of the other alternatives. However, on the ground, households simultaneously adopt at least one of any of the CSA, IPM, and SLM -related practices in the same farm (McCarthy et al., 2021; MoAIWD, 2018), implying interdependence of the decision, which nullifies the application of the IIA properties in this study.

There are several models, which address the IIA properties' challenge, namely, the Random Parameter, the Conditional Logit Fixed Effect, the Nested Logit, the Multivariate Probit, and Mixed Logit models (Madala, 1983; Baltagi, 2005; Wooldridge, 2002). In subsequent sub-sections, the study briefly discusses the models adopted by this study, namely, conditional logit fixed effect regression and SFA used in Chapter two (2); endogenous switching regression (ESR) model applied in Chapters three (3) and four (4); and panel-based SFA used in Chapter five(5).

1.10 Panel-based Conditional fixed effect logit model

This study examines the influence of household and farm-level characteristics on the adoption of CSA practices using the Conditional logit fixed effect model (Manda et al., 2015). It applies the Conditional logit model because the expected utilities of the choice decision are derived through the characteristics of the alternatives rather than the attributes of the individual household (Lancaster, 1966; Baltagi, 2005; Bun and Sarafidiz, 2013; Hoffman and Duncan, 1988; Hensher and Green, 2002; McFadden, 1974). In contrast, the multinomial logit regression focuses on the household as a unit of analysis and uses the households' characteristics as explanatory variables for the adoption of various CSA practices (Kangogo et al., 2021). Following Hoffman and

Duncan (1988), the study shows the choice probabilities for the Conditional logit fixed effect model as in equation (4):

$$P_{i1t} = \exp(x_{ijt}, Z_{ijt}, \beta) \Big/ \sum_{k=1}^{J} \exp(x_{ijt}, Z_{ijt}, \beta) \tag{4}$$

where x_{ijt} stand for the household characteristics and z_{ijt} for the CSA attributes, with the corresponding parameters vectors denoted by β. The error term in the Conditional logit folds an extreme value distribution and is independent across alternatives (Michael, 2020). The study relaxes the choice probabilities by including the household characteristics that are constant across the adoption of various CSA practices. Accounting for the related choice probabilities, it linearizes the utility $[v(x_{ijt}, Z_{ijt})]$ of an individual household in unknown parameters as in equation (5) (McFadden, 1974):

$$v(x_{ijt}, Z_{ijt}) = \emptyset_1 v^1(x_{ijt}, Z_{ijt}) + \emptyset_2 v^2(x_{ijt}, Z_{ijt}) + \cdots + \emptyset_k v^k(x_{ijt}, Z_{ijt}) \tag{5}$$

where $v^k(.)$ are specified as numerical functions and $\emptyset_k$ denote unknown parameters, while the x_{ijt} and Z_{ijt} as prior defined.

1.11 Panel-Based Endogenous Switching Regression Model

Adoption of CSA, or IPM, or SLM –related practices is an improvements from past experiences of extreme weather events (MoAIWD, 2018; DoDMA, 2018; Auci et al., 2019; Manda et al., 2015) and the decision depends solely on the household ability, motivation, and derived utility values (McFadden, 1974; Powers, 1993; Madala, 1983). However, sample selection is a common problem in empirical work and unobservable heterogeneity makes policy direction challenging (Malikov and Kumbhakar, 2014). Household characteristics are not fully observed, that some of them are endogenous, causing standard ordinary least square (OLS) techniques inefficient. Coincidentally, the use of sample selection models with binary dependent variable are pervasive in econometric literature (Rosenbaum and Rubin, 1983; Wooldridge, 2010; 2016; Madala, 1983).

The effect of sample selection –related adoption decision on household welfare has been studied as binary (Alene and Manyongo, 2007; Kassie et al., 2018), multinomial ESR (MESR) (Kassie et al., 2015, Teklewold et al., 2013; Khonje et al., 2015), and Propensity Score Matching (PSM) (Kassie et al., 2011). Abdulai and Huffman (2014) argue that PSM does correct selection bias from unobservable factors while ESR –related model does control through the use of Inverse Mills Ratios (IMRs)

(Bourguignon et al., 2007). Murtazashvili and Wooldridge (2016) extended the standard ESR approach to panel-data structure to assess the effect of adoption on household outcome indicators. The Chamberlain-Mundlak Approach extends the ESR model through allowing heterogeneity to correlate with time varying explanatory variables (see Mundlak, 1978).

The ESR -related models accounts for potential selection bias and unobserved heterogeneity (Wooldridge, 2010). A standard selection model has a situation where an outcome, q_{ijt} is only observed when the household adopts any of the CSA, or IPM, or SLM –related and is best estimated using the ESR model (Powers, 1993; Lokshin and Sajaia, 2004). Nevertheless, estimation of selection models is complicated since random assignment to different treatment units is hardly possible following ethical reasons (Heckman, 1979). Actually, it requires the exogeneity of the treatment effects from the sample data to address the selection problem or any missing data problem (Dorfman, 1996; Dustmann and Barrachina, 2007). In other words, when all the variables are exogenous, then a standard OLS procedure is employed (Madala, 1983). However, under the inclusion of endogenous variables, the ESR is applied and accounts for selectivity bias by allowing two sources of endogeneity, namely, the selection variable and endogenous explanatory variable (Auci et al., 2019; Heckman, 1978). It is modelled simultaneously in two stages. First, the study estimates the probit corrected selection model to account for unobservable heterogeneity (Murtazashvili and Wooldridge, 2016). The first stage accordingly generates the IMRs (Wooldridge, 2010). Second, the OLS method assesses the effect of adoption, with IMRs as extra variables to address selection bias from the unobservable heterogeneity (Kassie et al., 2018). In other words, the selection bias is addressed through incorporation of generalised residuals.

Following Murtazashvili and Wooldridge (2016), Lokshin and Sajaia (2004) and Wooldridge (2010), the household adoption decision, assuming A_{ijt}, leads to observing two possible outcome regimes as in equations (6) and (7):

$$Regime\ 1 = \ q_{it1} = \propto_1 + \propto_j x_{it1} + \delta A_{it1} + \rho_{i1} + \varepsilon_{it1} \text{ if } A_{ijt} = 1 \qquad (6)$$
$$Regime\ 2 = \ q_{it2} = \propto_2 + \propto_j x_{it2} + \delta A_{it2} + \rho_{i2} + \varepsilon_{it2} \text{ if } A_{ijt} = 0 \qquad (7)$$

where q_{it1} and q_{it2} denote the outcome indicators in the two regimes for i-th household in year t. The outcome indicator (q_{ijt}) represents farm productivity, which is measured as total farm value in Malawi Kwacha divided by cultivated area (Muyanga and Jayne, 2019; Aragon et al., 2019). While x_{it} represents household characteristics and A_{it} denotes the adoption decision of various CSA, IPM, or SLM -related practices. An adopter in this study is any household practising one or more of the any CSA, IPM, or SLM related practices. δ is the treatment effect of the adoption decision. The ρ_i is the individual effect and ε_{it} is the idiosyncratic error term, which is assumed independent of the exogenous explanatory variables (Wooldridge, 2010).

According to Murtazashvili and Wooldridge (2016), the two panel-based ESR regimes in equation (6) and (7) can be linearly combined as in equation (8):

$$q_{it1} = \propto_j x_{it1} + \tau_j x_{it1} q_{it3} + \delta A_{it1} + \delta(A_{it1} - A_{it2}) q_{it3} + \rho_{i1} + q_{it3}(\rho_{i1} - \rho_{i2}) + q_{it3}(\varepsilon_{it1} - \varepsilon_{it1}) + \varepsilon_{it1} \quad (8)$$

where τ_j is equal to $\propto_1 - \propto_2$ and takes the differences of the coefficients of explanatory variables in the two regimes. The q_{it3} is the endogenous switching variable at the basis of the sample selection interacting with both time constant and time varying variables. Other parameters are as prior defined. The equation (8) becomes consistent after including the mean values of all time varying variables, as additional covariates, following the Mundlak device (see Mundlak, 1978). After applying the Mundlak device, the equation (8) can be re-presented as in equation (9):

$$q_{it1} = \propto_0 x_{it1} + \tau_1 x_{it1} q_{it3} + \delta A_{it1} + \delta(\overline{\mathrm{G}}) q_{it3} + \rho_o + q_{it3}(\overline{\mathrm{G}})\rho_1 + \varepsilon_{it0} + q_{it3}\varepsilon_{it1} \quad (9)$$

where $\overline{\mathrm{G}}$ is the Mundlak device, which is the mean of the exogenous variables, while ε_{ijt} is a vector of idiosyncratic errors of the Mundlak relationship, and ρ_j assumes unknown parameters to be estimated by the model (Wooldridge, 2010).

In this study, the standard errors in equations (6) and (9) are bootstrapped to control for heteroscedasticity arising from the IMRs (Murtazashvili and Wooldridge, 2016). The treatment effect, δ, reduces to the difference in intercepts between the two regimes if the adoption decision is a random practice (Lokshin and Sajaia, 2004; Khonje et al., 2015). After incorporating the Chamberlain-Mundlak technique, the study derives the treatment effect, which is the expected value from a panel based binary response correction selection model (Vela, 1998) can be written as generalised residual function $h(.)$ as in equation (10):

$$\mathrm{E}\left(q_{ijt} \middle| q_{it3}, x_{ijt}\right) = h(\propto_0 x_{it1} + \tau_1 x_{it1} q_{it3} + \delta(\overline{\mathrm{G}}) q_{it3} + \rho_o + q_{it3}(\overline{\mathrm{G}})\rho_1 + \varepsilon_{it0} + q_{it3}\varepsilon_{it1}) = q_{it3}\lambda(\propto_0 x_{it1} + \tau_1 x_{it1} + \delta(\overline{\mathrm{G}}) + \rho_o + (\overline{\mathrm{G}})\rho_1 + \varepsilon_{it0} + \varepsilon_{it1}) - (1 - q_{it3})\lambda(\propto_0 x_{it1} + \tau_1 x_{it1} + \delta(\overline{\mathrm{G}}) + \rho_o + (\overline{\mathrm{G}})\rho_1 + \varepsilon_{it0} + \varepsilon_{it1}) \quad (10)$$

where $\lambda(.)$ is the IMR function while other variables are as prior defined. The IMR function term is characterised with zero mean and no correlation with the explanatory variables of the binary regression model. The study conditionally estimates the impact of household adoption decision on farm productivity as illustrated in equation (11) and (12).

$$\mathrm{E}\left(q_{ij1}\middle|q_{it3}, x_{ijt} = 1\right) = \propto_{10} x_{it1} + (\overline{\mathrm{G}})\rho_{10} + \Gamma_{10}\hat{h}_{it3} \qquad (11)$$
$$\mathrm{E}\left(q_{ij1}\middle|q_{it3}, x_{ijt} = 0\right) = \propto_{01} x_{it1} + (\overline{\mathrm{G}})\rho_{01} + \Gamma_{01}\hat{h}_{it3} \qquad (12)$$

Where $\hat{h}_{it3}$ is the generalised residuals which controls for the endogeneity of the selection variable, while x_{it1} represents explanatory variables, The $\propto, \rho$, and Γ are vectors of unknown parameters to be estimated by the model, after bootstrapping the standard errors to control for inclusion of the generalised residuals. Following Wooldridge (2010), the study derives the average treatment effect on the treated (ATET) households and on the untreated (ATU) (Maketa et al., 2019) from equations (11) and (12).

Usually, households mutually adopt at least two of the various CSA, IPM, or SLM-related practices in the same farm, which can be modelled through a multivariate binary or multinomial choice regression (Wooldridge, 2010). According to Midingoyi et al. (2019), a multinomial treatment variables orderly arises from adoption of any CSA, IPM, and SLM –related practices $[j = 1,2,3, \ldots\ldots, J]$ that yields the highest utility. Similarly, the adoption of CSA, IPM, and SLM –related practices involved more than one practice to manage the adverse effects of extreme weather events (Wollni et al., 2010; Teklewold et al., 2013). A Poisson regression model is often applied where the treatment is count data (Wooldridge, 2010; Midingoyi et al., 2019). Nonetheless, it is only appropriate when the occurrence of each CSA or IPM or SLM -related practices does not alter the likelihood of an alternative practice (Plan, 2014; Midingoyi et al., 2019). The Poisson assumption does not hold when the probability of choosing the first practice highly correlate with the likelihood of selecting the second or third practice (Teklewold et al., 2013; Wollni et al. 2010), which is the case in this study. Binary ESR models have also studied the effect of adoption decision on household outcome indicator (Wooldridge, 2010, Kassie et al., 2015).

Following Madala (1983), Khanal et al. (2018), Hermans et al. (2020), Asres et al.(2013), and Midingoyi et al. (2019), the study uses government extension services as an excludability restriction variable. Government extension services in Malawi provides information on the merits and demerits of various CSA, or IPM or SLM –related practices to various households (Pangapanga and Mungatana, 2021; MoAIWD, 2018; Hermans et al., 2020). In accordance with literature (Teklewold et al., 2013; Khonje et al., 2015; Kassie et al., 2018), this study empirically employs factors of production (such as land, fertilizer, labour, seeds), farm characteristics (i.e. soil quality, type, and slope), and extreme weather events as explanatory variables in the outcome equation, where farm productivity is the dependent variable. In addition, age, education, gender, and household size are included as some of the variables in the selection equation. Furthermore, the study uses either binary or multiple adoption decision of CSA, or IPM, or SLM –related practices as dependent variable in the selection model.

1.12 Panel-based Stochastic Frontier Analysis

In this study, the Stochastic Frontier Analysis (SFA) assesses the effect of extreme weather events on farm productivity, under varying extreme weather events. The SFA includes the maximum output, which can be generated given a set of inputs and available technologies (Assefa et al., 2019; Kumbhakar and Lovell, 2000). By definition, production process is a black box, which mathematically accounts for a transformation of inputs into outputs, and has the "frontier of possible production bundles" (Battese, 1992). A production function is in itself devoid of any economic intuition (Pangapanga and Mungatana, 2021; Kumbhakar et al., 2015). However, it can model optimization problems, after attaching the structural properties such as weak monotonicity, quasi-concavity, and essentiality (Knowles, 2015).

The econometric modelling of production functions was first developed by Farrell (1957) to estimate the production efficiency. Later, Meeusen and van den Broeck (1977) and Aigner et al (1977) individually extended and proposed the SFA. Mathematically, the basic panel data production function is expressed as in equation 10, where y_{ikt} denote output of plot (k) of the household (i) and at time (t). In other words, y_{ikt} is the farm productivity (Muyanga and Jayne, 2019; Aragon et al., 2019). While x_{jkt} represents production inputs (j) used by the household (i) such as land holding size, labour, seed, and inorganic fertilizers. The study measures land holding size as the available total land in hectare, seed and inorganic fertilizer are captured in kilogrammes, while labour is measured as adult equivalent of personal-days including both family and hired labour. The β denotes unknown parameters to be estimated by the model as in equation (13).

$$y_{ikt} = f\left(x_{jkt}, \beta\right) \equiv f(x)\,, \qquad (13)$$

The interest of this study is to understand the effect of CSA, or IPM, or SLM - related practices on farm productivity (Battese, 1992; Fuss et al., 1978; Pangapanga and Mungatana, 2021). Technical inefficiency is referred as the failure to derive crop production along the possibility frontier, which could either be through input combination or output. Households may operate away from the production possibility frontier (PPF) due to several factors, including the extreme weather events and the management style (Mango et al., 2015; Kumbhakar et al., 2015; Battese and Coelli, 1995; Hurlin, 2010). The study captures the output and input-oriented technical inefficiency of maize production as specified in equation (14) and (15), respectively:

$$y_{ikt} = f(x_{jkt}).\exp(-u)\,, u \geq 0, \tag{14}$$

$$y_{ikt} = f(x_{jkt}.\exp(-\theta))\,, \theta \geq 0, \tag{15}$$

where u and θ measure output and input oriented technical inefficiencies, respectively. The study derives economic effects from the production function (Varian, 2016; Fuss et al., 1978). First, it examines the homogeneity and return to scales of output over increasing level of inputs. It assumes that a production function is homogeneous if it satisfies the monotonicity assumption and mathematically specify as in equation (17), where (λ) represents a scalar factor is (x_{jkt}) denotes various input combinations and (y_{ikt}) is the output as in equation (16).

$$\lambda^{\gamma} y_{ikt} = f(\lambda x_{1kt}, \dots, \lambda x_{nkt}), \tag{16}$$

If all inputs increase by a factor of (λ) as in equation 13, then output increases by a factor of (λ^{γ}) and the production function is homogenous of degree γ in x (Mezgebo et al., 2021; Kumbhakar et al, 2015). If $\gamma = 1$, then households operate at constant returns to scale. If If $\gamma > 1$, then households operate at increasing returns to scale and lastly If $\gamma < 1$, then function observes decreasing returns to scale (Martey et al., 2020; Jerepo et al., 2020). Returns to scale (RTS) only depends on x_{jkt} if the production function is not homogenous. This study does not derive RTS as it is affected by output oriented technical inefficiency. Second, Following Kumbhakar et al. (2015), there are only two inputs and σ_{12}, with a marginal rate of technical substitution of $\left({}^{f_1}/{}_{f_2}\right)$and σ_{ij} is specified as in equation (17) and (18):

$$\sigma_{12} = \frac{dln\left({}^{x_{2kt}}/{}_{x_{1kt}}\right)}{dln(MRTS)} = \frac{-f_1 f_2(x_{1kt}f_1 + x_{2kt}f_2)}{x_{1kt}x_{2kt}(f_{11}f_2^2 = 2f_{12}f_1f_2 + f_{22}f_1^2)} \tag{17}$$

$$\sigma_{ij} = \sigma_{ji} = \frac{\sum_i x_{1kt}f_i}{x_{1kt}x_{2kt}} * \frac{F_{ji}}{F}, \tag{18}$$

In general, the value of σ_{ij} lies between zero and infinity for convex isoquants. The study observes the perfect substitution of two inputs when σ_{ij} infinity is, complementary substitution is depicted when σ_{ij} is negative and always positive when inputs are just substitutes. The study presents σ_{ij} related variance-covariance matrix as in expression (19):

$$\Omega = \begin{bmatrix} 0 & f_1 & f_2 & \cdots & f_J \\ f_1 & f_{11} & f_{12} & \cdots & f_{1J} \\ f_2 & f_{12} & f_{22} & \cdots & f_{2J} \\ f_3 & f_{13} & f_{23} & \cdots & f_{3J} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ f_J & f_{1J} & f_{2J} & \cdots & f_{JJ} \end{bmatrix}, \quad (19)$$

A production function exhibits some technical change due to adoption of various agricultural technologies, including the CSA practices. Furthermore, climate risks or shocks negatively affected farm production (MoAIWD, 2018; Pangapanga and Mungatana, 2012), thereby creating incentivises for households to adopt CSA practices to cushion output from the adverse effects of extreme climate and weather events (Pangapanga and Mungatana, 2021). The adoption of CSA practice is assumed to indicate any household implementing any of the various CSA practices for maize production. On the one hand, technical change does not depend on any input, unless otherwise (Simwaka et al., 2013; Tchale, 2009). On the other hand, a production function is affected by both inputs (x) of production, CSA practices and lessons learnt over time (t) , i.e. $y = f(x, t)$. Mathematically, technical change (Kumbhakar et al., 2015) is illustrated as in equation (20):

$$TC(x_{jkt}, t) = \frac{dlnf(x_{jkt}, t)}{dt}, \quad (20)$$

The commonly adopted production functions include the Cobb-Douglas (CD), the Generalised Production Function (GPF), the Transcendental, and the Translog Production Functions. This study adopts the CD production form because it is flexible, simple, interpretable, and executable (Kumbhakar, et al., 2015; Simwaka et al, 2013; Tchale, 2009; Chirwa, 2007). Moreover, Kumbhakar et al. (2015) states that once the technology is known, the same scores of technical efficiencies can be derived through any of the SFA production specification. The CD can therefore be linearly specified as in equation (21):

$$lny_{ikt} = \beta_o + \sum_{j=1}^{J} \beta_j lnx_{jkt} + \beta_j t, \quad (21)$$

where $\beta_o = lnA$, x_{jkt} is the inputs of production and β_j are variables to be estimated by the model. The CD satisfy strictly concavity assumption when the $0 < \beta_j < 1$ for all $j: 1, \ldots., J$; $0 < \sum_{j=1}^{J} \beta_j < 1$; and $A > 0$ and quasi concavity when the unknown parameters meet the non-negativity property for all $j: 1, \ldots \ldots., J$. the CD function is homogenous of degree $r = \sum \beta_j$ as illustrated in equation (22).

$$f(x_{jkt}, \lambda) = \lambda^{\sum \beta_j} f(x_{jkt}) = \lambda^r f(x_{jkt}), \qquad (22)$$

Accordingly, the study generates the elasticity of output, returns to scale, and technical change as shown in expression (23), (24), and (25), respectively.

$$\varepsilon_j = \frac{\partial ln y_{ikt}}{\partial ln x_{jkt}} = \beta_j, \qquad (23)$$

$$RTS = \sum_{j=1}^{J} \varepsilon_j = \sum_{j=1}^{J} \beta_j = r, \qquad (24)$$

$$TC = \frac{\partial \ln y_{ikt}}{\partial t} = \beta_j, \qquad (25)$$

There are several ways through which technical inefficiency can enter a CD function (Kumbhakar et al., 2015), namely, through input combinations or output. In this study, the technical inefficiency ($-u$) linearly enters the CD function as an additive factor as presented in equation (26).

$$\ln y_{ikt} = \beta_o + \sum_{j=1}^{J} \beta_j ln x_{jkt} + \beta_j t - u, \qquad (26)$$

The study adopts the panel data methods for a number of reasons. First, the panel data methods thoroughly correct for the true state dependence, the endogeneity, and the unobserved heterogeneity (see Kumbhakar et al., 2015). Panel approach satisfies this heterogeneity condition by adopting time invariant individual (unobservable) effect α_i and individual specific factors that do not interacted with other variables. Furthermore, the cross-sectional approaches pose measurement challenges, regarding capturing the technical efficiency in three-folds (Kumbhakar et al., 2015). First, they assume the technical inefficiency to be independent of the regressors, which is unlikely to be true. Second, the Jondrow, Lovell, Materov and Schmidt (JLMS)(1982) estimator as in equation (27):

$$E[u_{it}|\varepsilon_{it}] = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\emptyset(a_{it})}{1-\emptyset(a_{it})} - a_{it}\right], \qquad (27)$$

is not consistent as it hypothesizes that production output never approaches inefficiency as the number of individual households' approaches infinity.

1.13 Study area, sample size, and sampling strategy

This study is conducted in Malawi. Malawi shares the borders with Zambia in the North-West, Tanzania to the North-East, Mozambique to the East, South and West (GoM, 2017; NSO, 2020, 2014, 2012; Pangapanga and Mungatana, 2021). The country has three administrative regions, namely, the Northern, the Central and the Southern regions. The country is further sub-divided into a total of twenty-eight districts, namely, Chitipa, Karonga, Rumphi, Nkhatabay, Mzimba, and Mzuzu City in the Northern region; NKhotakota, Kasungu, Ntchisi, Dowa, Lilongwe, Salima, Mchinji, Dedza, and Ntcheu in the Central region; and Mangochi, Machinga, Zomba, Phalombe, Blantyre, Chiradzulu, Mulanje, Thyolo, Chikwawa, Nsanje, Mwanza, Balaka, and Neno (see Figure 1.5, NSO, 2020). Each district is divided into a Traditional Authority, which is further demarcated into Enumeration Areas, used for surveys and censuses (NSO, 2014).

The country is slightly over 11,800 square kilometers in size, with a population of barely above 18 million (NSO, 2008). Lake Malawi covers one-third of the total country size. The country has altitudes, which vary from 500 to 1500, temperature ranging from below 20 to 40 degrees Celsius, and precipitation averaging from 725 mm to 2500 mm across the country. Almost 90 of the population lives in rural areas and depend on agriculture for livelihood security (NSO, 2020). Over 80% of the foreign earnings come from agriculture and maize is one of the most important staple food crops (MoAIWD, 2018). Over 50% of the population report having low agricultural production, which is due to increasing extreme weather events in the country (NSO, 2018, 2020).

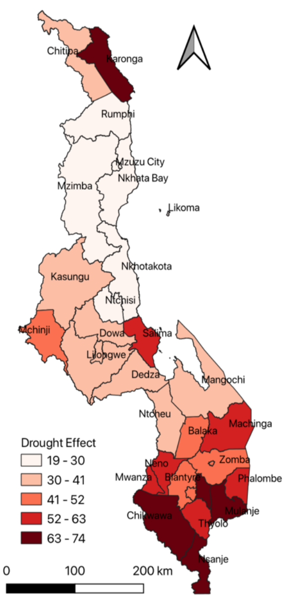

Figure 1. 6 : The Map of Malawi

Originally, the NSO and the World Bank visited 3246 households in 2010/2011 as a panel, which were later visited in 2013, 2016/2017, and 2019/2020. The 3246-panel based sample of 2010/2011 grew to 4000 in 2013 following splitting and new formed households, where the original panel was 3000. In 2016/2017, the NSO and the World Bank refreshed the sample to recruit new households together with the original sample of 1900. The study successfully matched 1300 households across the four waves that is 2010/2011, 2013, 2016/2017, and 2019/2020.

This study follows the multi-stage sampling strategy of the Integrated Household Panel Survey (IHPS), conducted by the NSO and the World Bank between 2010 and 2020. The NSO is the powerhouse of nationally and official representative household and agricultural data (NSO, 2013). Within the sampling procedure, the districts formed the first stage of the multi-sampling procedure. Traditional Areas constituted the second stage, while the Enumeration Areas formed the third stage of the multistage sampling procedure and were the primary sampling units. Households were randomly selected from the sampled Enumeration Areas. The survey asked each household whether they have ever experienced any extreme weather events, viz., droughts, tropical cyclone Idai-induced floods, and fall armyworms (Kilic et al., 2021; McCarthy et al. 2021).

1.14 Data source, acquisition, definitions, and measurements

The study uses a four-wave integrated household panel survey (IHPS) datasets, collected by the NSO and the World Bank between April 2010 and March 2020 (NSO, 2020). The original raw data can be found through https://microdata.worldbank.org/index.php/catalog/3819/get-microdata (World Bank, 2022). The IHPS administered a multi-topic questionnaire to randomly sampled households (Kilic et al., 2021). It captured demographic factors, education, health, labour and time use, housing, non-farm enterprises, food security, food and non-food expenditures, anthropometrics, income sources and social safety nets, migration, durable goods and agricultural assets ownerships (NSO, 2012; 2014; 2018; 2020). Additionally, the IHPS collected data on agriculture, including farm sizes, coupon use, seeds and other inputs, crop production, marketing and storage, plot-level characteristics, namely, farm size, slope, soil quality and type, climate related variables such as rainfall, temperature, and CSA, IPM or SLM -related practices, viz, manure application, cereal legume intercropping, soil and water conservation, inorganic fertilizer, improved crop varieties, agroforestry, and conservation agriculture (Kilic et al., 2021; Pangapanga and Mungatana, 2021). Furthermore, the survey captured data on extreme weather events, namely, droughts, Tropical Cyclone related floods (TCRFs), fall armyworms (FAW).

Based on empirical studies,

Table 1. 1 highlights various variables selected for analytical use in this study (Kilic et al., 2021; McCarthy et al., 2021; Asfaw, et al., 2016; Khonje et al., 2015; Khataza et al., 2019; Katengeza et al., 2018; Kassie et al., 2015; Kansanga et al., 2020). Household characteristics, namely, sex, education, labour, wage, farm size, age, remittance and migration may influence the decision to adopt any of the CSA, IPM, and SLM –related practices. The influence of household socioeconomic factors on the adoption of CSA, IPM, and SLM –related practices, may be either positive or negative. Besides, the study assumes that communal or weather-related characteristics, viz., markets, drought, tropical cyclone Idai, fall armyworms, rainfall, temperature, credit, and access to extension services may affect the decision of the household to undertake any of the CSA, IPM, and SLM –related practices. Furthermore, the adoption or non-adoption of the CSA, IPM, and SLM –related practices may likely influence farm productivity. In this study, an adopter is defined as any household that undertook any of the CSA, IPM, or SLM –related practices and vice versa. Moreover, the study assumed adoption as random, where a household may adopt any of the CSA, IPM, or SLM -related practices in one wave of the panel and dis-adopt in the other wave of the panel. In other words, this means any household may decide to adopt or dis-adopt any of CSA, IPM or SLM-related practices. Data analytically, several panel data models have the capacity to handle such randomness sceneries of the CSA, or IPM or SLM adoption and dis-adoption (Woodridge, 2016; Kumbhakar et al. 2015). In this study, an adopter of CSA, or IPM, or SLM –related practices is therefore any household that has undertaken any of the CSA, or IPM, or SLM –related practice in their farm-it may mean just one or combination of several CSA, or IPM, or SLM –related practices.

Table 1. 1: **Definitions and measurements of variables used in this study**

CLUSTERS	VARIABLES	MEASUREMENTS	EXPECTED SIGNS	REFERENCES
Household Characteristics	Gender (Sex)	1=Male; 0=Female	+	NSO (2012, 2020); Kilic et al. (2021); McCarthy et al. (2021); Asfaw, et al. (2016); FAO (2010); Khonje et al. (2015); Khataza et al. (2019); Katengeza et al. (2018); Kassie et al. (2015); Kansanga et al. (2020); Muyanga and Jayne (2019); Oregano et al. (2019).
	Education	Years of schooling	+	
	Household size	Counts (Number)	+	
	Labour	Personal day in adult equivalents	+	
	Wage	Malawi Kwacha	+	
	Farm size	Hectare	+	
	Income (Remittance)	Malawi Kwacha	+	
	Age	Years	+/-	
	Marital status	1=Married; 0=Not in marriage	+/-	
	Migration	1= Yes; 0=No	+/-	
	Literacy	1=Literate; 0=Illiterate	+	
Farm characteristics	Soil quality (Good)	1= Yes; 0=No	+	
	Soil quality (Fair)	1= Yes; 0=No	+/-	
	Soil quality (Poor)	1= Yes; 0=No	+/-	
	Soil type (Clay)	1= Yes; 0=No	+/-	
	Soil type (Loamy)	1= Yes; 0=No	+	
	Soil type (Sandy)	1= Yes; 0=No	+/-	
	Slope (Flat)	1= Yes; 0=No	+	
	Slope (Gentle)	1= Yes; 0=No	+/-	
	Slope (Steep)	1= Yes; 0=No	+/-	
Communal variables	Input markets	1=Access; 0=No access	+	
	Output markets	1=Access; 0=No access	+	
	Access to credit	1=Access; 0=No access	+	
	Extension	1=Access; 0=No access	+	
	Rainfall	Average Millimeters	+/-	
	Temperature	Average Degree Celsius	+/-	
	Fall Army Warms (FAW)	1= Yes; 0=No	-	

CLUSTERS	VARIABLES	MEASUREMENTS	EXPECTED SIGNS	REFERENCES
Extreme weather events	Drought episodes	1= Yes; 0=No	-	
	Tropical Cyclone related Floods	1= Yes; 0=No	-	
CSA, IPM, and SLM-related practices	Intercropping	1=Yes; 0=No	+	
	Farrow cultivation	1= Yes; 0=No	+	
	Crop rotation	1= Yes; 0=No	+	
	Mulching	1= Yes; 0=No	+	
	Cover cropping	1= Yes; 0=No	+	
	Manure application	Kg/Hectare	+	
	Inorganic fertilizer	Kg/Hectare	+	
	Chemical pesticides	Kg/Hectare	+	
	Irrigation farming	1= Yes; 0=No	+	
	Zero tillage	1=Yes; 0=No	+	
	Minimum cultivation	1=Yes; 0=No	+	
	Planting dates	1= Yes; 0=No	+	
	Quantity of improved seeds	Kg/Hectare	+	
	Quantity of local seeds	Kg/Hectare	+	
	Crop diversification	1= Yes; 0=No	+	
	Planting of agroforestry trees	1= Yes; 0=No	+	
	Intercropping	1= Yes; 0=No	+	
	Early planting	1= Yes; 0=No	+	
	High yielding varieties	1= Yes; 0=No	+	
	Rural-urban migration	1=Migrated; 0=Did not migrate	+/-	
	Seed	kg	+	
Outcome indicators	Yield	Kg/Hectare	+/-	
	Food Security	Calories/Person/Year	+/-	
	Farm Productivity	Malawi kwacha/Hectare	+/-	

1.15 Research Strength, Limitation, Assumption and Ethics

The strength of this study first relies on its rigorous methodology, examining the drivers of CSA, IPM, and SLM-related practices' adoption using the Conditional Fixed Effect Model. Second the study unpacks the influence of various CSA, IPM, and SLM –related practices on farm productivity under different extreme weather events using the triple hurdle panel-based Tobit regression. Third, the study isolates the endogenous treatment effects of extreme weather events on farm productivity using both multinomial and panel-based probit ESR models. Four, the study interrogates the contribution of RUM on the farm productivity under changing extreme weather events through application of panel-based SFA models. The study uses the IHPS data compiled by the NSO and the World Bank, which has strong multi-topical components on socioeconomic and agriculture, critical for rural economy and is internationally comparable (McCarthy, et al., 2020; Asfaw, et al., 2016).

Furthermore, the study strongly assumes that data collectors were thoroughly trained by the NSO and the World Bank (NSO, 2012, 2014, 2018, 2020). In addition, the survey got the consent from participating households to truthfully provide information about their household economic activities, CSA, or IPM or SLM -related practices' adoptions and experience of extreme weather events (NSO, 2020). Ethically, the study ensured confidentiality of the households, which participated in the survey per the Malawi Statistics Act (GoM, 2013), which empowers the NSO to collect household and agricultural data for statistical and research purposes in Malawi. In addition, the study adhered to the ethical procedures of the University of Pretoria and best international practices, throughout the data compilation, processing, report writing, publication, and result dissemination stages.

Although this study combines various methodologies to understand the impact of CSA adoption on farm production under different extreme weather events in Malawi, the study hardly tested some hypotheses due to use of secondary data. The IHPS was executed for a different objective other than for this study i.e. for welfare profiling in Malawi. The secondary data lacked some disaggregated data for specific CSA practice' techniques. Thus, this study did not address the following research questions: (i) what is the effect of specific contour bunds, drainage ditches, terrenes and actual rate of soil erosion on farm productivity, and (ii) what concurrent application of organic and inorganic fertilizer was optimal to enhance farm productivity? Moreover, the study uses a short panel data with utmost four waves, where in some instances, some households could only appear in at least two waves (NSO, 2020), making the study fail to isolate the persistent and transient technical efficiencies of the farm. In addition, the study does not present the long-term effect of Covid-19 pandemic on farm productivity and food security because of the absence of longitudinal household data on the pandemic.

Further, land is, was and will remain very critical in transforming agriculture in the country (MoAIWD, 2018), hence, a study, which would assess the effects of these specific SWC or IMV or MLI with varying land tenure systems, would become informative to customary land regularization policies in the country. Therefore, the study suggested that future research should include such researchable hypotheses to thoroughly inform CSA implementation under both extreme drought episodes and varying land tenure systems. In terms of fall army worms, the study does not use the damage of FAW on farm production as the secondary data does not collect such data. Future studies should accordingly attempt to assess the impact of actual FAW damages on farm productivity, while using then level of damage as the variable of interest instead of the experience of FAW. Similarly, for food security, the panel IHPS instrument presents different questions to the FANTA approach by FAO as well as the 16 different food groups as prescribed by World Health Organization, hence the study could not use the actual nutrient values to estimate food security (NSO, 2020). Hence, future studies should assess the effect of extreme weather events, namely, drought, floods, and FAW on food security, while adopting the FANTA approach by FAO or the nutrient value approach by WHO.

1.16 Organization of the study

This study is outlined in six (6) chapters. The first Chapter highlights the study context, the problem statement and the rationale, the objectives, the research questions, and the general methodology adopted in the entire study. Chapter two (2) determines the drivers of the adoption of CSA –related practices and their influence on the technical efficiency of maize production under different drought episodes using the Conditional logit and panel-based SFA models, respectively. Chapter three (3) and four (4) investigate the effect of fall armyworms (FAW) and the tropical cyclone Idai (TCI) on farm productivity, respectively, using the multinomial endogenous switching regression model. Chapter five (5) unravels the effect of rural-urban migration on farm productivity using the time varying and time-invariant panel-based SFA regressions. Finally, Chapter six (6) provides the summary, the conclusions and the policy recommendations of the thesis.

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CHAPTER TWO

Adoption of CSA practices and their influence on the technical efficiency of maize production under drought episodes

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Abstract

Malawi experiences frequent, intense and prolong extreme weather events that affect rain-fed maize production. Thus, households have adopted various climate-smart agriculture (CSA)-related practices to cushion maize production from the adverse effects of extreme weather events, particularly drought episodes. This study, therefore, examines the drivers of CSA practices' adoption and their influence on the technical efficiency of maize production under different drought episodes. The study finds drought episodes substantively enhancing the adoption of organic manure by 76 percent and soil and water conservation by 29 percent, while holding other factors constant. The study findings reveal that households are 63 percent efficient, implying that they can increase current maize production by 37 percent. Based on a triple hurdle panel-based model, simultaneous adoption of organic manure and inorganic fertilizers on the same farm substantively improves technical efficiency by 18 percent and is more noticeable among drought-affected households. Accordingly, simultaneous adoption of organic and inorganic fertilizers in the same farm would enhance the effect of CSA-related practices on the technical efficiency of maize production under different drought episodes.

Key Words: Drought episodes, Climate-Smart Agriculture; Conditional Logit model; Cobb-Douglas SFA; Triple Hurdle Tobit Model; Technical Efficiency.

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2. Introduction

In this Chapter two, the study presents the context, regarding adoption of various climate-smart agriculture (CSA) –related practices and allied effects on the technical efficiency of maize production under different drought episodes; the problem statement and rationale of the study; the objectives, and the research questions of this study. The chapter also thoroughly discusses the study specific theoretical and empirical strategies, namely, the conditional logit fixed effect model, the panel based Cobb-Douglas, and the triple hurdle Tobit regression. In this chapter, the study further deliberates the results and discussion, the conclusion, and the policy recommendations. Finally, this chapter follows this thesis publication in the peer reviewed Elsevier's International Journal of Disaster Risk Reduction (Pangapanga and Mungatana, 2021).

2.1 Study Context

Agriculture remains the cornerstone of Sub-Sahara Africa's (SSA) economic transformation and achievement of Sustainable Development Goals (SDGs) (Schaafsma et al., 2019; Pangapanga and Mungatana, 2021). Several SSA countries, including Malawi, have adopted agriculture as their pathway out of poverty (MoAIWD, 2018). It is the primary source of livelihood, accounting for 60 percent of the regions labor force and 40 percent of Gross Domestic Product (GDP) (Bjornlund et al., 2020). By 2050, SSA's population is expected to double to 2.1 billion, with a 60 percent increase in food demand (Ittersum et al., 2016). Over the past decades, food production in SSA has been volatile and failed to meet the population demand due to high dependence on rain-fed agriculture, poor agricultural practices, and extreme weather events such as droughts, dry spells and floods (Food and Agricultural Organization [FAO], 2019). El Nino Southern Oscillation events have amplified drought and flood episodes in the region, and temperatures have continuously increased by 1.6°C to 2°C, while precipitation declined by 4% between 1990 and 2018 (World Bank, 2018). In the region, temperature is predicted to increase by 1.0 – 3.0 °C by 2060. Furthermore, high poverty levels and limited credit markets have exacerbated SSA's vulnerability to extreme weather events (McCarthy et al., 2021). These factors have contributed to SSA's weak agricultural adaptive capacity to extreme weather events (Kansanga et al., 2020).

In Malawi, agriculture accounts for 28 percent of GDP, 80 percent of export earnings, 64 percent of the workforce, and 85 percent of household livelihoods (MoAWID, 2018). The sector is dualistic, comprising smallholder (70%) and estate (30%) sub-sectors. Smallholder farmers' landholding sizes have diminished from 1.53

hectares (ha) in 1968 to 0.4 ha in 2020 following rapid population growth (National Statistics Office [NSO], 2020; Asfaw et al., 2016). The crop sub-sector accounts for over 80 percent of the agricultural sector and 17 percent of GDP. As a staple food, maize dominates the crop sub-sector and is cultivated by over 92 percent of households (NSO, 2012, 2014, 2018, 2020). Women contributes 70 percent of the total labour-force in the crop sub-sector (Kilic et al., 2015), nevertheless, they have limited access and use of agricultural input, insecure land tenure systems and informal institutions governing farm management (Palacios-Lopez and Lopez, 2015). Despite maize production determining national and household food security, its impact is limited by rain-fed dependence, small landholding sizes, low soil fertility, and poor agricultural practices (Fisher et al., 2018; Kilic et al., 2015, Kilic et al., 2021). With overwhelming evidence of extreme weather events by 2040 (DoDMA, 2018; MoAWID, 2018) and without adaptation, maize production stands to be adversely affected (McCarthy et al., 2021; NSO, 2020; IPCC, 2018).

In the recent past, Malawi has experienced increasing dry days by almost 27 percent and late on-set of rainfall during main cropping seasons, resulting in crop failures and over 6.5 million people being food insecure (World Bank, 2016; McCarthy et al., 2021). Seven major drought episodes have occurred between 1990s and 2020, reducing maize production by 48 percent, affecting over 32 million people, and downscaling GDP by 21.5 percent (DoDMA, 2018). These realities, compounded by rapid population growth and high poverty levels, have negatively affected the technical efficiency of maize production and the food security status of the country (MoAWID, 2018; NSO, 2018).

Following the adverse effects of drought episodes on maize production, the Government of Malawi (GoM) and several other stakeholders, including households, have championed various climate change adaptation strategies (Ngwira et al., 2014). The Government has promoted Climate-Smart Agriculture (CSA), which integrates climate responsiveness in agriculture at the household level (Asfaw et al., 2016; FAO, 2016). CSA concepts include conservation agriculture, sustainable land management, and agroforestry practices (Lipper et al., 2014). The main objectives of CSA are to enhancing agricultural productivity, adaptation, and mitigation to the adverse effects of climate and weather variability (FAO, 2010). For instance, conservation agriculture practices which are some of the CSA practices has double benefits, where it induces agricultural productivity and adapt to climate and weather variability. While sustainable land management practices have triple gains: augmenting agricultural production, adaptation, and mitigation against the negative effects of climate and weather events. While the CSA concept is new and still evolving, many of its practices have existed before (Lampach et al., 2021; Wagura et al., 2014; Chinseu et al., 2018; Thierfelder et al., 2016). Besides externally inspired CSA, households have adopted locally enthused CSA practices (MoAWID, 2018). Nonetheless, the rate of adopting these CSA practices is still not consistent with investment, and extreme weather events are predicted to indisputably reduce maize production by 10 percent by 2040 (Katengeza et al., 2018; World Bank, 2018).

CSA practices present an opportunity to address the effects of extreme drought episodes and enhance the sustainability of maize production in Malawi (World Bank, 2018). The challenge, however, is that in Malawi, households have operationalized CSA practices differently, with various local translations and nomenclatures across several communities (Chinseu et al., 2018). Some households have even abandoned already adopted CSA practices due to information asymmetry on the ground (Holden et al., 2018; BenYishay and Mobaraka, 2014). Contrary to recommendations of adopting CSA as a package (Vermeulen et al., 2012), most households have undertaken only two of the five CSA practices, and allied implementation has often been short-lived (Fisher et al., 2018). Consequently, farmers have failed to derive the full potential benefits of CSA on enhancing maize production, thereby increasing poverty incidences and food insecurity at the household level (Fisher et al., 2018; Khataza et al., 2018). Additionally, limited research on the drivers and the climate resilience of CSA has facilitated low adoption at the household level (Amadu et al., 2020; Kilic et al., 2015). For instance, only 10 percent of households have adopted some of the CSA –related practices (Chinseu et al., 2018). Moreover, most households lack information on the technically efficient CSA practices that induce maize productivity under extreme weather conditions (McCarthy et al., 2021; Katengeza et al., 2018). Thus, additional studies on the drivers and the technical efficiency of CSA practices are assertive to cope with extreme weather events in Malawi (Kansanga et al., 2020; Kassam et al., 2014).

Therefore, this paper examines drivers of CSA practices' adoption and their influence on the technical efficiency of maize production under extreme drought episodes (Pangapanga and Mungatana, 2021). It uses a panel dataset representing farming households in Malawi for 2010/2011 to 2016/2017. While using a conditional logit model (CL), the study assesses drivers of adopting various CSA practices. It also evaluates CSA practices' influence on the technical efficiency of maize production through the application of a triple hurdle Tobit regression. This study's contribution to the existing literature on extreme drought episodes is four-fold. First, it provides evidence regarding the drivers and the effects of CSA practices on maize production in Malawi. Second, it minimises CSA dis-adoption through isolating efficient CSA practices at household level. Third, the study enhances the adoption of climate resilient CSA practices that have substantial effects on the technical efficiency of maize production. Finally, it ensures suitability, flexibility and sustainability of CSA practices by mainstreaming indigenous knowledge in climate adaptation programming. Overall, the study adds to the existing SDGs' literature on improving agricultural productivity under intensifying weather events.

2.2 Research Methodology

2.2.1 Study Area

The study has used data from the Integrated Household Panel Survey conducted in rural farming communities in Malawi by the NSO and the World Bank(see Figure 1.5), capturing information for households affected by extreme drought episodes. Malawi is a land-locked country and relies on rain-fed maize production for national food security. District altitudes vary from below 500 to 1500 m above sea level. Malawi has one annual rainy season from November to April, with average precipitation varying from 725 mm to 2,500 mm. It has experienced drought episodes since 1980s, with extreme drought events, becoming more pronounced in the recent past, with Chikwawa, Chiradzulu, Karonga, Mulanje, Nsanje and Phalombe being the most affected districts. Several models have predicted increasing vulnerability, intensity, magnitude and frequency of extreme drought events (DoDMA, 2018; IPCC, 2018). Apart from the high poverty levels and limited adaptive capacity (Amadu et al., 2020), El Niño and La Niña phenomena have further intensified the country's climate vulnerability (World Bank, 2018).

2.2.2 Panel-based Conditional fixed effect logit model

This study derives the analytical framework of examining household adoption decisions over various CSA –related practices, based on the random utility theory (McFadden, 1974) and is described in two-fold. First, the objects of various CSA practices over which farmers have preferences, namely, organic manure (MAP), soil and water conservation (SWC), improved maize varieties (IMV) and legume intercropping (MLI), cushion maize production from the adverse effects of extreme drought episodes. Second, household attributes such as age, education, gender and other socioeconomic factors determine household choices over CSA practices.

The independence of irrelevant alternatives (IIA) assumption of the multinomial logit (MNL) model assumes that the choice of one CSA practice does not influence the choice of another (Baltagi, 2005; Wooldridge, 2002; Hensher and Greene, 2002). On the contrary, households in the study area combine CSA practices in the same plot, thus ruling out use of the MNL (McCarthy et al., 2021; Chinseu et al., 2018). Several models that allow for correlation across various CSA practices, however, exist, viz., the multinomial probit (MNP) and the conditional logit (CL) (Kassie et al., 2015). The study adopts the CL due to its flexibility to estimate either a standard, uniform, or log-normal choice distribution (McFadden and Train, 2000; Geweke et al., 1994). Following Hoffman and Duncan (1988) and Heckman (1981), the study also considers the CL appropriate because household choices of various CSA –related practices are a function of socioeconomic characteristics. The study thus specifies the panel-based CL model as in equation (1).

$$CSA_{ijt} = \begin{cases} 1 \ if \ CSA^*_{ijt} = \sum_{j=0}^{J} \beta_j M_{ijt} + \omega_i R_{ijt} + \alpha_i + \varepsilon_{ijt} > 0 \\ 0 \ if \ CSA^*_{ijt} = \sum_{j=0}^{J} \beta_j M_{ijt} + \omega_i R_{ijt} + \alpha_i + \varepsilon_{ijt} \leq 0 \end{cases} \quad (1)$$

where CSA_{ijt} takes a value of 1 if a household adopts any of the various CSA practices including MAP, SWC, IMV, MLI and otherwise, zero. The M_{ijt} is a vector of age, education, farm size, literacy, cell-phone ownership, household size, distance to district headquarters, slope, soil quality and soil type. R_{ijt} represents dummies for drought experience, access to credit, and extension services. The β and ω_i are unknown parameters to be estimated by the model. The α_i is treated as a random component, while the ε_{ijt} is the error term, with zero mean and constant variance.

2.2.3 Panel-based Cobb-Douglas Stochastic Frontier Analysis (SFA)

Technical efficiency is defined as the plot manager' s ability to generate maximum maize output from a given technology and inputs' combination. It further assumes that drought episodes partially widen the gap between the observed and frontier outputs, which correspondingly determine household technical inefficiency, ceteris paribus. However, a production function is devoid of any economic intuition unless it has some specified structural properties such as utility maximization (Mango et al., 2015; Kumbhakar et al., 2015; Sihlongonyane et al., 2014).

Technical efficiency has been examined using either a parametric or a non-parametric approach (Kumbhakar et al., 2015; Mango et al., 2015). The parametric approach uses stochastic frontier analysis (SFA), while the non-parametric uses data envelopment analysis (DEA). A key advantage of the SFA over DEA is its ability to split the random error term' s impact from the inefficiency effect (Imad et al., 2019; Kumbhakar et al., 2015). Inadequate record keeping and high illiteracy rates among smallholder farmers popularly favour the SFA use (Mango et al., 2015). Farrell (1957) developed the SFA, which Aigner et al. (1977) as well as Meeusen and van den Broeck (1977) extended to evaluate technical efficiency across various fields. In this study, following limitations on price data for rural farming households, the analysis is restricted to technical efficiency instead of profit efficiency.

The SFA has been used to investigate technical efficiencies of crop production. Musaba and Bwacha (2014) and Mango et al. (2015) adopted the SFA to study the technical efficiency of smallholder farmers' maize production in Zambia and Zimbabwe, respectively. Mehmood et al. (2017) employed the SFA to assess the influence of liquidity constraints on wheat producers' technical efficiency in Pakistan. Some studies have used the SFA to examine the technical efficiency of maize production in Malawi, using cross-section data and with bias on demographic factors (Chirwa, 2008; Tchale, 2009). In this study, we use panel data to investigate the influence of CSA practices on the technical efficiency of maize production in Malawi, thereby contributing to the existing literature on improving agricultural productivity (Amadu et al., 2020). We adopt the Cobb-Douglas (CD) specification because of its flexibility, excitability and interpretability (Imad et al., 2019). Based on previous studies, a CD model is preferred due to the study preference of only assessing physical factors which enter into the production system (Tchale, 2009; Chirwa 2008). The panel-based maximum likelihood Cobb-Douglass SFA model is expressed as in equation (2).

$$lny_{ijt} = \sum_{j=0}^{J} \beta_j lnx_{ijt} + \sum_{m=1}^{M} \lambda_m D_{ijt} + \alpha_i + v_{ijt} + u_{ijt} \tag{2}$$

where lny_{ijt} is the log of yield in kg/ha for plot-manager at time point. lnx_{ijt} is a vector of various inputs, namely, farm size, fertilizer, seed, labor and organic fertilizer. In terms of farm size, the study uses total available land holding size to avoid collinearity problem between the left-hand side variable (lny_{ijt}) and the farm size. The D_{ijt} denotes dummies for soil quality, slope and drought experience. The λ_m and β_j are unknown parameters, while α_i is the individual fixed effect. The u_{ijt} is the technical inefficiency which is derived through its exponential while the v_{ijt} is the random error, with zero mean and constant variance.

2.2.4 Triple hurdle panel-based censored Tobit regression

This study further adopts a triple hurdle panel-based censored Tobit model to analyse the influence of CSA on the technical efficiency of maize production under extreme drought episodes. In the first hurdle, the study employs a binary panel-based Probit model to predict the CSA practices farmers adopt, while accounting for possible endogeneity (Amadu et al., 2020). The study presents a panel based Probit model as in equation (3):

$$A_{ijt} = \sum_{j=0}^{J} \omega_j H_{ijt} + \alpha_i + \kappa_{ijt} \tag{3}$$

where A_{ijt} takes a value of 1 if the household adopts any CSA practice as mentioned above, and zero otherwise. The H_{ijt} is a vector of education, age, gender, farm size, household size, mobile phone, access to extension services and credit. The ω_j stands for the unknown parameters to be estimated. The κ_{ijt} is the white noise, with zero mean and constant variance, while the α_i is as presented previously.

In the second hurdle, the study uses the panel-based Cobb Douglass SFA to predict the technical efficiency scores which form part of the dependent variable in the Tobit model. In the third hurdle, the study employs a panel-based Tobit model to interrogate socioeconomic and institutional factors affecting maize productivity as specified in equation (4):

$$\hat{u}_{ijt} = \omega_0 + \sum_{j=1}^{J} \omega_j \hat{Z}_{ijt} + \gamma_j K_{ijt} + \alpha_i + \epsilon_{ijt} \tag{4}$$

where $\hat{u}_{ijt}$ is the technical efficiency score predicted from equation (2). $\hat{Z}_{ijt}$ is a vector of CSA practices values estimated from equation 3 such as $\widehat{MAP}$, $\widehat{SWC}$, $\widehat{MIV}$and $\widehat{MLI}$, and K_{ijt} is a vector that includes variables like access to subsidy and credit, land productivity, livestock ownership, gender, literacy, household size and marital status. The ω_j and γ_j are the unknown parameters to be estimated by the model. The ϵ_{ijt} is the error term with zero mean and constant variance, while the α_i is as prior-defined.

2.2.5 Sampling and Data Acquisition

The study uses the Integrated Household Panel Surveys (IHPS) dataset, compiled by the NSO and the World Bank between 2010 and 2017. Accordingly, the study adopts the IHPS multi-stage sampling procedure, covering 208 enumeration areas, and representative at the national, urban/rural, regional, and district levels (NSO, 2020). The IHPS instruments include households, agriculture, fishery, and community questionnaires. Between 2010/2011 and 2016/2017, the IHPS asked all sampled households to state whether they experienced any drought episodes. Consequently, the study refers households reporting experience of any drought episodes as drought-affected community (DAC) households, otherwise non-drought-affected community (NDAC) households. The IHPS captures data on household socioeconomic characteristics (such as age, marital status, education, household size, mobile phone ownership, credit accessibility, and extension services), extreme weather events (drought and dry spell) and plot characteristics (like plot area, slope, soil quality and type) (NSO, 2018, 2020). It also captured farm level data like labor, farm holding size, seed, inorganic fertilizers, CSA practices (such as organic fertilizer, soil and water conservation, improved maize varieties, intercropping), crops cultivated and harvest. The study presents and defines the variables of interest as in Table 1.1.

After matching panel households, this study uses household sample sizes of 1329 for 2010, 1311 for 2013, and 1193 for 2016/2017. The IHPS data shows several households experiencing extreme drought episodes, with half of households reporting the effect of extreme drought in 2010/2011, 34 percent in 2013 and 46 percent in 2016/2017 cropping seasons. In this study, drought episodes negatively affect the technical efficiency of maize production, and adoption of CSA practices strengthens the climate resilience of maize production at the household level. Finally, this study complements household interviews with IHPS community (qualitative) focus group interviews.

2.3 Results and Discussions

2.3.1 Summary statistics of household characteristics

Table 2.1 presents summary statistics for drought-affected (DAC) and non-drought-affected (NDAC) communities. The study shows that males (75%) headed most households in DAC and NDAC communities. The mean household head age is 44 years, with a mean household size of 5 persons. Two-thirds of household heads have ever attended school, with the majority having attained senior primary education, that is from grade 5 to 8. Furthermore, the study finds that household location in relation to agricultural markets have a bearing on input accessibility. Almost half of households own a working mobile phone. The qualitative data shows that the mobile phones are used for accessing agricultural information from relatives, fellow farmers, and extension workers. These results are in line with NSO (2020).

The study further indicates that households cultivate maize on an average farm size of 0.48 ha, with female farmers farming on 0.41 ha. Half of the cultivated farms have loamy soils, with substantial differences between DAC (63%) and NDAC (56%) households. About 62 percent of the households have good soil quality and flat farm. Female farmers produce 370 kg/ha less than their male counterparts. The study findings reveal significant differences of DAC maize yield between 2010 and 2017, with no substantial disparity among NDAC over the same period.

Error! Reference source not found. shows the distribution of households adopting various CSA –related practices. The study finds that most households (65%) implement two to three of the five CSA practices. Furthermore, about 76 percent of households apply NPK fertilizers, increasing from 37.5 kg per acre (2010) to 54 kg per acre (2017). More male farmers (78%) apply NPK fertilizers relative to their female counterparts (72%), thus explaining the depth of resource constraints among female farmers.

The study also finds that 21 percent of households use organic fertilizer, applying on average about 178 kg per acre (see Table 2.1). The study further notes a considerable increase in organic fertilizer application, viz., composite, green, and animal manure, between 2010 (126.5 kg) and 2017 (321.6 kg). Through the existing agricultural policy (NAP, 2016), Government has been promoting the use of organic manure in agricultural production, given the high cost and unaffordability of inorganic fertilizers for most smallholder farmers. Besides, more than half of the households invest in SWC techniques such as terraces (5%), erosion control bunds (26%), sandbags (1%), vetiver grass (8%), water harvest bunds (1%) and ditches (4%). Smallholder farmers have increasingly undertaken SWC because of higher water stressing environment that before, forcing farmers to practices SWC which conserve water during drought times. Additionally, adoption of IMV rose from 46 percent in 2010 to 56 percent in 2017. The increase in adoption of various CSA –related practices is attributed to the experience of previous adverse effects of drought episodes on maize productivity.

Table 2. 1: Summary statistics of household socioeconomic characteristics in Malawi

		2010			2013			2016			POOLED 2010-2016					DIFF_TEST	
	UNIT_M	TOTAL	DAC	NDAC	TOTAL	DAC	NDAC	TOTAL	DAC	NDAC	TOTAL	DAC	NDAC	MHHD	FHHD	DAC/NDAC	M/FHHD
Matched sample	%	35%	51%	49%	34%	37%	63%	31%	46%	54%		44%	56%	75%	25%		
Gender	Male=1	0.76	0.73	0.79	0.76	0.76	0.75	0.73	0.76	0.70	0.30	0.50	0.10	0.30	0.20	***	
Married	Yes=1	0.79	0.76	0.81	0.78	0.80	0.77	0.77	0.79	0.75	0.75	0.75	0.75	0.75	0.25		
HH size	Number	5.04	4.86	5.22	5.55	5.75	5.44	5.47	5.58	5.37	0.78	0.78	0.78	0.97	0.20		***
Age	Years	43.47	43.45	43.49	46.47	45.97	46.76	48.42	48.66	48.21	46.02	45.84	46.17	44.64	50.15		***
Literacy	Yes=1	0.62	0.62	0.63	0.67	0.65	0.63	0.63	0.66	0.61	0.57	0.53	0.61	0.66	1.32		***
Class reached	Years	6.22	5.71	6.70	6.20	5.99	6.32	5.68	5.52	5.82	5.35	5.35	5.35	5.65	0.31		***
Mobile phone ownership	Yes=1	0.46	0.39	0.53	0.55	0.48	0.60	0.72	0.75	0.70	6.04	5.72	6.29	6.38	4.76	***	***
Distance to main road	Km	1.05	1.13	0.98	1.07	1.19	1.00	1.02	1.07	0.98	1.19	1.19	1.19	1.15	4.46	***	***
Distance to ADMARC	Km	7.61	8.07	7.14	7.90	8.40	7.61	7.78	7.50	8.03	1.05	1.13	0.99	1.05	1.03	***	
Distance to HQ	Km	51.14	44.50	57.93	25.24	23.18	26.42	27.30	29.62	25.29	7.76	7.98	7.59	7.48	8.60	**	***
Sandy soils	Yes=1	0.22	0.23	0.22	0.19	0.25	0.16	0.27	0.31	0.25	0.23	0.26	0.21	0.22	0.26	***	**
Loamy soils	Yes=1	0.53	0.57	0.48	0.54	0.47	0.58	0.59	0.63	0.56	0.55	0.56	0.54	0.56	0.52		**
Clay soils	Yes=1	0.22	0.18	0.25	0.26	0.27	0.25	0.35	0.31	0.39	0.27	0.25	0.29	0.28	0.26	***	
Good soils	Yes=1	0.48	0.50	0.45	0.42	0.44	0.41	0.62	0.64	0.60	0.50	0.53	0.48	0.51	0.47	***	**
Fair soils	Yes=1	0.40	0.35	0.44	0.42	0.38	0.45	0.45	0.45	0.44	0.42	0.39	0.45	0.42	0.43	***	
Poor soils	Yes=1	0.13	0.15	0.11	0.15	0.18	0.14	0.15	0.17	0.14	0.14	0.17	0.13	0.14	0.17	***	**
Flat slope	Yes=1	0.56	0.55	0.57	0.57	0.57	0.57	0.61	0.63	0.58	0.58	0.58	0.57	0.59	0.55		**
Slight steep	Yes=1	0.33	0.32	0.35	0.31	0.28	0.32	0.49	0.47	0.51	0.37	0.36	0.39	0.37	0.39	*	
Moderate slope	Yes=1	0.08	0.10	0.06	0.09	0.12	0.08	0.15	0.16	0.15	0.11	0.12	0.09	0.11	0.10	***	
Hilly	Yes=1	0.03	0.03	0.02	0.03	0.03	0.03	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03		
Seed	Kg	13.08	13.00	13.17	14.22	14.82	13.88	20.49	21.30	19.78	15.78	16.21	15.43	16.13	14.74		**
Labor	Hours	55.90	55.39	56.42	32.33	34.54	31.05	23.42	25.01	22.04	37.73	39.66	36.18	39.62	32.07	***	***
Farm size	Acre	1.00	0.97	1.03	0.95	0.90	0.98	1.59	1.63	1.56	1.17	1.16	1.17	1.22	1.00		***
Inorganic fertilizer	Kg	37.46	37.09	37.85	32.22	29.94	33.54	53.72	53.16	54.20	40.73	40.30	41.07	43.90	31.25		***
Organic fertilizer	Kg	126.55	51.91	202.90	99.68	92.92	103.57	321.63	338.44	307.05	178.08	156.53	195.34	196.47	123.12		
Manure Application	Yes=1	0.14	0.13	0.15	0.19	0.20	0.18	0.31	0.33	0.29	0.21	0.22	0.20	0.21	0.22		
NPK Fertilizer Application	Yes=1	0.81	0.78	0.84	0.74	0.71	0.76	0.74	0.75	0.72	0.76	0.75	0.77	0.78	0.72	*	***
SWC	Yes=1	0.57	0.54	0.59	0.50	0.45	0.54	0.65	0.64	0.67	0.57	0.55	0.59	0.56	0.60	***	**
Extension Services	Yes=1	0.41	0.46	0.37	0.73	0.69	0.75	0.91	0.92	0.91	0.67	0.66	0.67	0.68	0.62		***
Access to subsidy	Yes=1	1.00	1.00	1.00	0.53	0.55	0.52	0.42	0.42	0.41	0.61	0.64	0.59	0.61	0.61	***	
Credit Accessibility	Yes=1	0.11	0.09	0.13	0.22	0.24	0.21	0.24	0.27	0.22	0.19	0.19	0.19	0.20	0.16		**
Improved varieties	Yes=1	0.46	0.43	0.50	0.48	0.50	0.47	0.57	0.59	0.56	0.50	0.50	0.51	0.53	0.42		***
Intercropping	Yes=1	0.44	0.55	0.33	0.57	0.63	0.53	0.66	0.63	0.69	0.45	0.51	0.40	0.42	0.53	***	***
Drought	Yes=1	0.51	1.00	-	0.37	1.00	-	0.46	1.00	-	0.44	1.00	-	0.44	0.45		
Pest infestation	Yes=1	0.09	0.12	0.06	0.23	0.29	0.19	0.13	0.24	0.04	0.15	0.21	0.10	0.16	0.11	***	***
Yield	Kg/Acre	552.06	439.01	667.69	607.87	483.17	679.66	736.13	818.88	664.39	628.44	574.85	671.38	698.34	419.54		***

Note: * $p<0.10$, ** $p<0.05$, and *** $p<0.01$

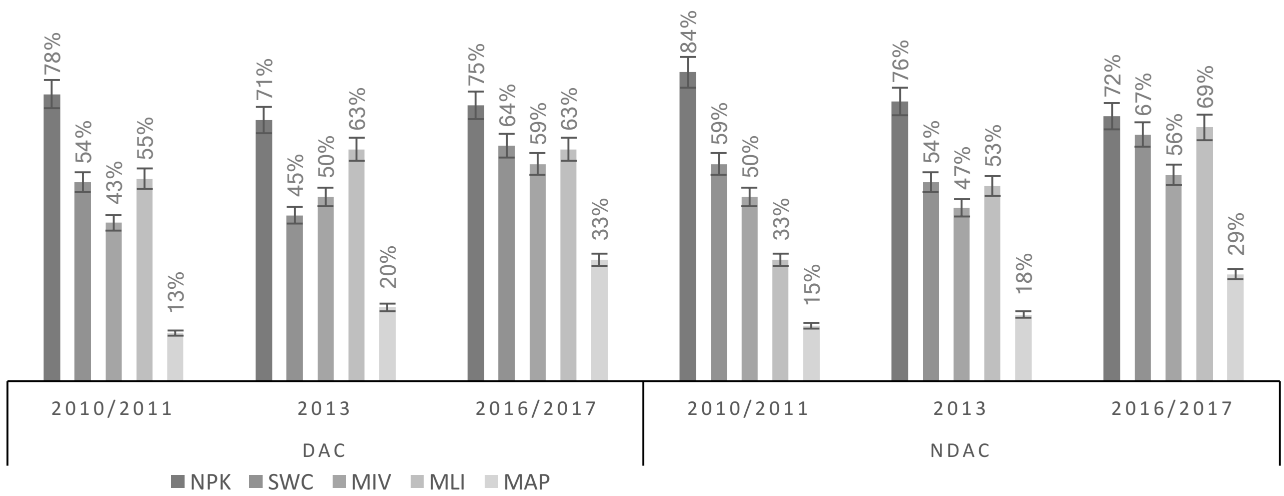

Figure 2. 1: Distribution of DAC and NDAC households adopting various CSA practices between 2010/2011 and 2016/2017]

2.3.2 What factors affect the adoption of Climate Smart Agricultural Practices?

Factors such as household head's education, distance to district headquarters, slope and soil quality significantly influence households' decision to adopt SWC – related techniques (see Table 2.2). Furthermore, households with steep slopes, poor soil quality and drought experience had higher probabilities of adopting the various SWC techniques (see Table 2.2). Nevertheless, the study finds no significant differences in terms of drivers affecting SWC adoption between DAC and NDAC households. These results in Table 2.2 are in line with Nguyen et al. (2020), Darkhwh et al. (2019) and Teshome et al. (2016).

Literacy and extension services substantially affect the IMV adoption. For instance, most literate households cultivate IMV due to the extension messages on the demerits and merits of improved varieties under different drought episodes. The study qualitative data confirmed that farmers have information on the merits and demerits of various maize varieties, which presents the freedom of choice among households. Interestingly, the study demonstrates that extension services and drought episodes are the only factors essentially influencing IMV adoption among DAC. These findings conform to Amondo et.(2019), Katengeza et al. (2019), and Ayedun (2019) results.

This study further observes that gender and drought episodes significantly affect maize-legume intercropping decision. The study notes that several male farmers intercropped maize with leguminous crops relative to female farmers, where drought episodes significantly enhance the intercropping of maize with leguminous crops. Besides, the study qualitative data explains that intercropping maize with leguminous crops, namely, beans, Mucuna, lablab, Sesbania sesbans, chick peas, pigeon peas, and cow peas, reduces run-off water and enhances nitrogen fixation. Conversely, the study finds slightly above half of the households (56%) still practicing maize mono-cropping despite increasing drought episodes. These results are similar to those of Bouwman et al. (2021), Timothy et al. (2017) and Simtowe et al. (2016).

Further, the study results reveal that credit accessibility, age and drought experience substantively influence household adoption of organic fertilizer. The qualitative data demonstrates that households access credit to hire labor for composite manure production, which is labour intensive. Similarly, the study notes elder people engaging in organic fertilizer manufacturing while household with larger farms practise fallow cultivation as an adaptation strategy to the adverse effect of drought. The qualitative data indicates that households are interested in cultivating a farm that has higher soil fertility for improved crop production.

Table 2. 2: **Results of Conditional Logit Regression: What factors drive the adoption of CSA practices in Malawi**

	NDAC				DAC				POOLED			
	SWC	**IMV**	**MLI**	**OMA**	**SWC**	**IMV**	**MLI**	**OMA**	**SWC**	**IMV**	**MLI**	**OMA**
GENDER (MALE=1)	0.038	-0.490***	0.304*	-0.189	0.113	-0.126	0.415*	-0.220	0.046	-0.334**	0.363***	-0.205
	(0.220)	(-3.32)	(2.200)	(-0.89)	(0.550)	(-0.65)	(2.270)	(-0.69)	(0.350)	(-2.87)	(3.320)	(-1.18)
CREDIT (ACCESS=1)	0.027	-0.121	0.014	0.438*	0.366	-0.108	0.035	0.505	0.142	-0.114	0.011	0.423*
	(0.160)	(-0.85)	(0.100)	(2.140)	(1.670)	(-0.53)	(0.180)	(1.670)	(1.080)	(-0.98)	(0.090)	(2.520)
CELLPHONE(OWN=1)	0.010	-0.108	0.074	-0.166	-0.022	-0.117	0.056	-0.095	0.002	-0.112*	0.062	-0.147
	(0.130)	(-1.73)	(1.230)	(-1.70)	(-0.18)	(-1.09)	(0.550)	(-0.62)	(0.030)	(-2.08)	(1.200)	(-1.82)
AGE (YEARS)	-0.001	0.0120**	0.007	0.011	0.005	0.009	0.005	0.007	0.001	0.0118***	0.00613*	0.00948*
	(-0.11)	(3.110)	(1.870)	(1.880)	(0.870)	(1.640)	(1.080)	(0.810)	(0.200)	(3.820)	(2.130)	(1.970)
LITERATE (YES=1)	0.321*	-0.359**	0.147	0.131	0.057	-0.241	0.326*	-0.610*	0.197	-0.285**	0.226*	-0.122
	(2.050)	(-2.69)	(1.140)	(0.640)	(0.310)	(-1.41)	(2.020)	(-2.14)	(1.670)	(-2.73)	(2.260)	(-0.74)
HHSIZE (NUMBER)	0.035	-0.007	0.030	0.025	0.023	-0.070	0.043	-0.022	0.032	-0.027	0.036	0.012
	(1.170)	(-0.26)	(1.190)	(0.620)	(0.580)	(-1.94)	(1.290)	(-0.37)	(1.350)	(-1.30)	(1.810)	(0.350)
DISTANCE TO HQ	-0.470*	-0.226	-0.784***	-0.142	-0.939*	-0.162	-0.594	0.053	-0.542**	-0.235	-0.739***	-0.080
	(-2.01)	(-1.10)	(-4.18)	(-0.48)	(-2.29)	(-0.47)	(-1.79)	(0.120)	(-2.69)	(-1.35)	(-4.54)	(-0.33)
SLOPE (FLAT=1)	-0.213***	-0.115	0.230*	-0.098	-0.182***	-0.085	0.219	0.519	-0.007***	-0.096	0.236**	0.102
	(-15.89)	(-0.98)	(2.030)	(-0.55)	(-11.09)	(-0.55)	(1.470)	(1.950)	(-19.48)	(-1.02)	(2.630)	(0.700)
SOIL QUALITY(GOOD=1)	-0.280*	0.071	0.162	-0.244	-0.532**	0.086	0.145	0.086	-0.363***	0.071	0.144	-0.126
	(-2.09)	(0.620)	(1.450)	(-1.39)	(-3.23)	(0.570)	(1.000)	(0.350)	(-3.51)	(0.780)	(1.640)	(-0.89)
SOIL TYPE(CLAY=1)	0.069	0.257	0.135	0.441*	0.050	0.282	0.001	-0.265	0.070	0.260*	0.076	0.195
	(0.410)	(1.780)	(0.960)	(2.020)	(0.270)	(1.640)	(0.010)	(-0.92)	(0.560)	(2.360)	(0.720)	(1.130)
EXTENSION(ACCESS=1)	-0.061	0.237*	0.078	0.314	-0.123	0.370*	-0.289*	-0.094	-0.081	0.276**	-0.061	0.157
	(-0.45)	(2.060)	(0.700)	(1.690)	(-0.73)	(2.390)	-(1.99)	(-0.35)	(-0.78)	(3.030)	(-0.70)	(1.040)
LAND AREA(HA)	-0.004	-0.005	-0.007	-0.098	-0.208**	0.111	0.005	-0.093	-0.051	0.001	0.001	-0.093
	(-0.30)	(-0.96)	(-0.61)	(-1.54)	(-2.78)	(1.750)	(0.320)	(-1.36)	(-1.29)	(0.300)	(0.290)	(-1.94)
DROUGHT(YES=1)									0.292**	0.231*	-0.463***	0.759***
									(2.770)	(2.460)	(-5.15)	(5.150)
CONSTANT	0.066	0.465	-0.830**	-0.794**	0.600	0.541	-0.493***	0.123	0.160	0.368	-0.857***	-0.98**
	(0.210)	(1.640)	(-3.05)	(-2.87)	(1.500)	(1.460)	(-3.62)	(0.190)	(0.640)	(1.620)	(-3.93)	(-2.87)
LR(χ^2)	92.22***	67.85***	35.81***	13.97***	23.22***	24.89***	21.58***	24.36***	37.17***	74.84***	104.65***	136.53***
N	2705	2705	2705	2705	1785	1785	1785	1785	4491	4491	4491	4491

Note: t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$

2.3.3 Panel-based Cobb Douglas Stochastic Frontier Analysis

Table 2.3 highlights the maximum likelihood estimated results of a Cobb-Douglas Stochastic Frontier Analysis (SFA) between DAC and NDAC households. The study notes that slopes, soil quality, labor, inorganic fertilizer, seed, farm size, and drought experience significantly affect maize productivity. Households that applied chemical (NPK) fertilizer enhance maize productivity by at least 3 kg, ceteris paribus. Similarly, labor improves maize yield by 26 kg in NDAC and 35 kg in DAC households, while holding all other factors constant. The study findings also reveal that farm size yields higher returns than any factor of production, ceteris paribus. In this study, farm size refers to total available land in hectare for any potential household agricultural activities. Likewise, organic fertilizer improves maize production by 15 kg in NDAC and 8 kg in DAC households, ceteris paribus. The study finds farms with steep slopes having lower maize yield of 4 kg in DAC and 8 kg in NDAC relative to farms with flat slope, while holding all other factors constant. The study qualitative data clarifies that farms with steep slopes experience excessive soil erosions, while farms with loamy soils have better soil structure and water filtration. Drought episodes reduce maize yield by 20 percent, ceteris paribus, and these results are in line with McCarthy et al. (2021) and Asfaw et al. (2016).

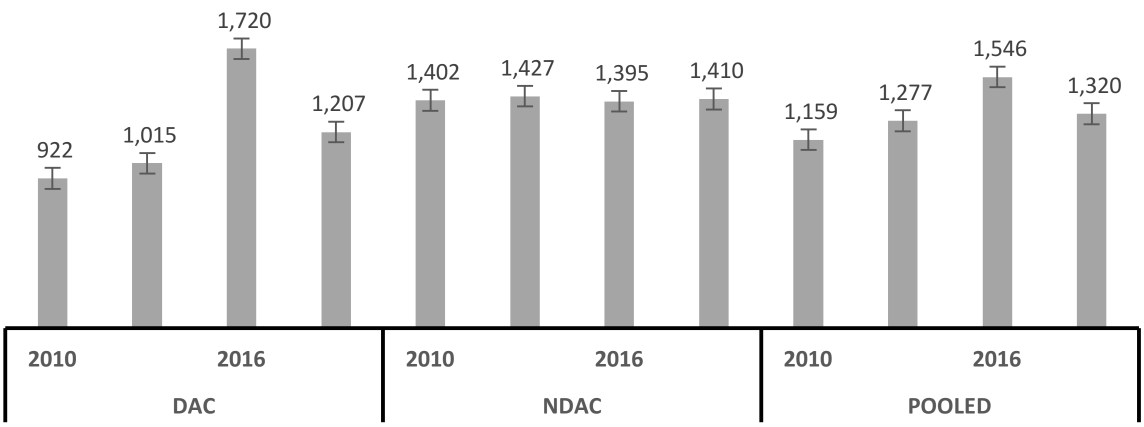

Figure 2. 2: Average maize yield (kg ha^{-1}) among households affected and not affected by drought [2010 – 2016/2017]

Figure 2. 2 shows the average maize yield per hectare among households affected and not affected by droughts between 2010 and 2016/2017. Despite the negative effect of drought on maize productivity, the study observes DAC households descriptively report higher yield per ha than NDAC counterparts. Accordingly, the chi-square test shows a significant correlation between yield and drought episode

experience, and there is a considerable difference between maize yield by DAC and NDAC. Among DAC households, maize yield has significantly increased from 922 kg/ha in 2010 to 1720 kg/ha in 2016. Focus group discussions show that the increase in yield is more auspicious among households, which adopted various CSA –related practices. In other words, descriptively, the study can speculate that the adoption of any of the CSA –related practices ably cushions household maize production from drought episodes.

Table 2. 3: **Results of a Cobb Douglas Stochastic Frontier: the effects of drought episodes on farm productivity in Malawi**

LN_YIELD (KG/ACRE)		**COBB-DOUGLAS SFA**				
	UNIT	**NDAC**	**DAC**	**MALE**	**FEMALE**	**POOLED**
LNFERTILIZER	KILOGRAM	0.0306*	0.0498**	0.087***	0.096**	0.0348**
		(2.16)	(2.67)	(4.23)	(3.17)	(3.05)
LNFARMSIZE	ACRE	0.485***	0.512***	0.611***	0.560***	0.493***
		(19.10)	(16.90)	(21.89)	(11.51)	(24.99)
LNLABOR	HOURS	0.263***	0.352***	0.0102	0.094***	0.295***
		(8.66)	(9.03)	(0.96)	(3.60)	(12.08)
LNSEED	KILOGRAM	0.0124*	0.00859	0.130***	0.142*	0.0114**
		(2.15)	(1.31)	(4.34)	(2.55)	(2.62)
LNMANURE	KILOGRAM	0.150***	0.0823*	-0.0329	-0.142	0.115***
		(5.34)	(2.48)	(-0.73)	(-1.78)	(5.31)
STEEP SLOPE	YES=1	-0.055	-0.0443	0.0715	0.128	-0.0371
		(-1.37)	(-0.92)	(1.59)	(1.64)	(-1.20)
SANDY SOIL	YES=1	-0.123*	-0.0578	-0.107*	0.0216	-0.0843*
		(-2.46)	(-1.07)	(-2.04)	(0.25)	(-2.29)
GOOD QUALITY	YES=1	0.0820*	0.132**	0.217***	0.313***	0.101**
		(2.06)	(2.76)	(4.95)	(3.99)	(3.29)
DROUGHT	YES=1			-0.514***	-0.0514	-0.203***
				(-5.63)	(-0.30)	(-6.63)
CONSTANT		0.883***	0.647***	0.641	1.079	0.806***
		(16.04)	(10.27)	(0.02)	(0.03)	(19.68)
USIGMA (CONS)		4.826**	15.05*	0.683***	0.722***	7.406**
		(2.61)	(2.25)	(21.45)	(10.88)	(3.27)
VSIGMA (CONS)		0.641***	0.715***	0.0871***	0.0965**	0.717***
		(22.07)	(20.66)			(35.17)
LR(χ^2)		627.04***	409.48***	843.61***	202.32***	1090.31***
N		2127	1705	3361	1130	4491

Note: t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$

2.3.4 What is the influence of CSA adoption on the technical efficiency of maize production?

Technical efficiency determines the potential households have to achieve maximum production. In this study, technical efficiency is assessed to check how far below are households from the potential production possibility frontier. Figure 2. 3, therefore, illustrates the distributions of technical efficiency for DAC and NDAC households. The study observes that households are 63 percent technically efficient, implying that households can reduce current input use by 37 percent to achieve the same production level. In other words, households can probably increase production by 37 percent given the same input combination. The student' s t-test reveals a substantial difference between the technical efficiency of DAC (62%) and NDAC (64%) households. About 74% of both DAC and NDAC households have a technical efficiency score above 50%. Almost 22% of DAC versus 18 percent of NDAC households have technical efficiency below 50%, implying more maize production loss for DAC than NDAC households.

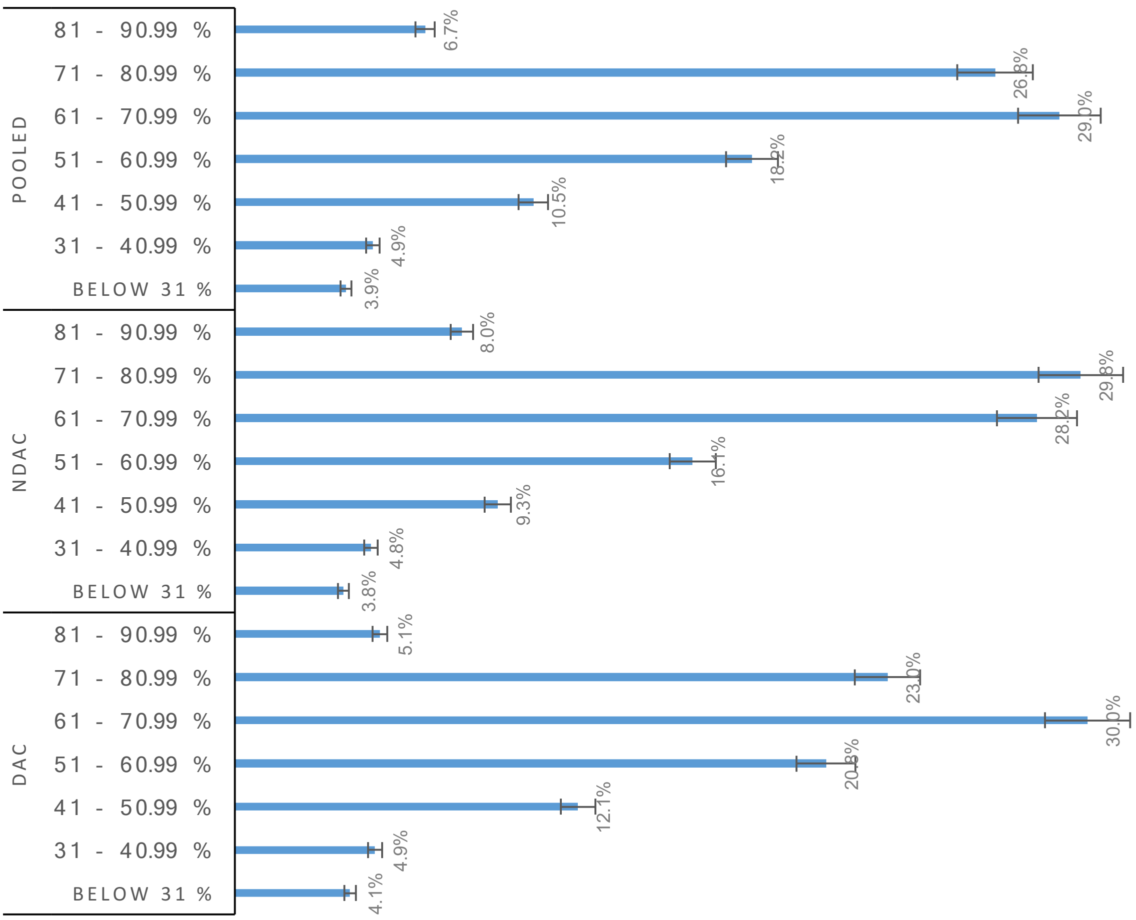

Figure 2. 3: Distribution of the technical efficiency score between DAC and NDAC households [2010 – 2016/2017]

Table 2. 4: presents results from a triple hurdle panel-based censored Tobit model, which assesses the CSA –related practices' influence on the technical efficiency of maize production. The Chi-square test shows that the model if good enough to examine the effect of CSA –related practices on the technical efficiency of maize production. In the first step, the study estimates the technical efficiency of maize productivity. In the second, the study accounts for the potential endogeneity of CSA choices through the use of CSA-related predicted values. In the third step, the study evaluates the effect of CSA practices on the technical efficiency of maize production. The study notes that SWC adoption significantly improves the technical efficiency of maize production for both DAC and NDAC households by two (2) percent and one (1) percent, respectively. The study qualitative data reveals that contour-farming and erosion control bunds conserve soil moisture and increase water infiltration rate. These findings are consistent with Kumawat et al. (2020)

Similarly, the study finds cultivation of improved maize varieties other than local maize varieties enhancing the technical efficiency of maize production by three (3) percent for DAC and two (2) percent for NDAC households. The data shows that farmers cultivate early maturing and drought-tolerant improved maize varieties. Furthermore, households that intercrop maize with leguminous crops like soybeans, pigeon peas, Sesbania sesbans, cow peas, and common beans enhance the technical efficiency by two (2) percent for both DAC and NDAC. Nonetheless, the study finds more DAC (51%) than NDAC households (40%) intercropping maize with beans, pigeon peas and groundnuts. Intercropping generally enhances soil fertility through soil moisture retention and nitrogen fixation (Burker et al., 2019).

Additionally, the study records that concurrently adopting organic fertilizer and inorganic fertilizer strongly increase the technical efficiency of maize production by 18 percent. Furthermore, simultaneously applying organic manure and inorganic fertilizer is more effective and evident for DAC than NDAC households, implying the efficacy of the combination in managing the negative effects of droughts in the study area. This study also observes that land productivity positively influences the technical efficiency of maize production. Nevertheless, the study notices negative relationship between livestock ownership and credit accessibility, on the one hand, and the technical efficiency of maize production, on the other hand. In other words, there is limited complementarity between livestock, credit, and maize production (Mehmood et al., 2017). Household heads' gender, literacy, marital status, and family size substantively affect the technical efficiency of maize production. The study also finds female farmers less technically efficient than male farmers due to limited access to improved maize varieties, hired labour, and credits for procuring inorganic fertilizers.

Table 2. 4: **Results of a Triple hurdle Tobit model: the influence of CSA adoption on the technical efficiency of maize production in Malawi**

DEP_VARIABLE: EFFICIENCY		POOLED	DAC	NDAC	MALE	FEMALE
SWC	YES=1	0.102**	0.176	0.108*	-0.0596	0.217
		(2.63)	(1.87)	(2.02)	(-1.03)	-1.82
IMV	YES=1	0.180***	0.277***	0.160**	-0.0093	0.0873
		(4.57)	(4.15)	(2.64)	(-0.18)	-0.77
MLI	YES=1	0.0468	0.0411	0.0175**	-0.0894	-0.15
		(1.21)	(0.05)	(3.10)	(-1.54)	(-1.29)
NPK*MAP	YES=1	0.184**	0.350**	0.154	0.132	-2.176
		(3.16)	(2.86)	(1.79)	(0.22)	(-0.74)
NPK	YES=1	0.0504***	0.0414*	0.0674***	0.01	0.041
		(5.16)	(2.03)	(4.45)	(0.85)	(0.78)
MAP	YES=1	0.0313	0.0445	0.0807	-0.0658	-0.375*
		(1.24)	(0.86)	(1.31)	(-0.86)	(-2.23)
ACCESS TO SUBSIDY	YES=1	0.011***	0.047***	0.066*	0.018***	0.068***
		(4.32)	(7.33)	(2.08)	(6.83)	(5.34)
LAND PRODUCTIVITY	YES=1	0.048	0.064***	0.042	0.0216	0.0375
		(0.65)	(3.49)	(0.45)	(0.32)	(0.67)
LIVESTOCK	YES=1	-0.099***	-0.013	-0.086***	-0.018***	-0.011*
		(-6.50)	(-0.48)	(-3.57)	(-9.50)	(-2.27)
CREDIT	YES=1	-0.0293	0.0382	-0.0455	-0.0183	0.0283
		(-2.33)	(0.18)	(-2.34)	(-1.11)	(0.70)
MALE	Male=1	0.279***	0.266***	0.280***		
		(50.93)	(30.26)	(36.14)		
LITERACY	YES=1	0.0416***	0.0457***	0.0465***	-0.101	-0.131
		(8.63)	(5.50)	(6.63)	(-1.50)	(-1.04)
HH SIZE	NUMBER	0.00854***	0.00459*	0.00651***	-0.0559***	-0.0492
		(7.19)	(2.54)	(3.87)	(-3.91)	(-1.52)
MARRIED	YES=1	0.300***	0.301***	0.319***	0.783**	0.158
		(45.76)	(29.12)	(35.06)	(2.65)	(0.91)
LR(χ^2)		19268***	85.72***	134.65**	167.93***	46.70***
N		2127	1705	4491	3361	1130

Note: t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$

2.4 Conclusion and Key Policy Recommendations

Drought episodes negatively affect maize production. Hence, households undertake various CSA –related practices to cushion maize production from the adverse influence of drought episodes. This study, thus, examines the drivers of CSA practices' adoption and their influence on the technical efficiency of maize production under extreme weather events, especially drought episodes. The study uses a three-wave panel dataset (2010/2011, 2013, and 2016/2017) containing 3,800 randomly sampled households. To address the research objectives, the study adopts the Conditional Logit (CL) model to assess drivers of CSA practices' adoption and the triple hurdle Tobit regression to evaluate CSA –related practices' influence on the technical efficiency of maize production in the study area.

Based on the CL model, the study notes that farm size, mobile phones, extension, slope, soil quality, and drought significantly influence the adoption of soil and water conservation, organic fertilizer, improved varieties and legume intercropping. Furthermore, drought episodes considerably enhance the adoption of soil and water conservation (29%), improved maize varieties (23%), and organic fertilizer application (76%). The study observes a strong bias of maize mono-cropping in the study area, especially among households with large farms. Nonetheless, the study findings reveals that more households intercrop maize with leguminous crops in DAC than in NDA communities. Besides, the study results indicates an inverse relationship between distance to the district office and the likelihood of adopting CSA –related practices due to reduced extension service visits. Additionally, the study depicts a negative relationship between credit accessibility and the technical efficiency of maize production due to limited complementarity between off and on-farm household activities.

Furthermore, a Cobb-Douglass Stochastic Frontier Analysis (SFA) illustrates that inorganic fertilizer, farm size, labor, seed and organic manure remarkably influence maize productivity. Contrarily, drought episodes negatively affect maize productivity by around 20 percent, ceteris paribus. The study finds households being 63 percent technically efficient with varying scores between DAC and NDAC households, implying that the current technical efficiency can, on average, be improved by 37 percent. In terms of gender, female farmers are 5 percent less technically efficient than male farmers because female farmers have limited access to agricultural inputs. A triple hurdle panel-based censored Tobit model reveals substantive influence of adopting CSA –related practices on the technical efficiency of maize production. Remarkably, SWC and IMV enhance the technical efficiency of maize production by 9 and 15 percent, respectively. Furthermore, the concurrent adoption of organic fertilizer and inorganic fertilizer in the same farm improves the technical efficiency of production by

18 percent and the effect is heavily observed among DAC households. The study also finds that household head' s literacy and marital status are critical in determining the technical efficiency of maize production. Additionally, DAC households (1720 kg per ha) have higher yields that NDAC households (1400 kg per ha) and this is attributed to the adoption of various CSA –related practices.

In general, the study recommends simultaneous adoption of organic and inorganic fertilizer at farm-level to enhance the technical efficiency of maize production. Besides, the study proposes gender targeting extension services in promoting various CSA –related practices since women have limited access to agricultural inputs, insecure land tenure systems, and informal institutions governing farm management. Besides, the study suggests future studies to assess the effect of specific techniques of SWC, namely, terraces, contour bunds, vetiver grass and others on the technical efficiency of maize production under different drought episodes and land tenure security systems.

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CHAPTER THREE

Understanding the effect of fall armyworm and integrated pest management practices on the farm productivity and food security in Malawi

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Abstract

Fall armyworm (FAW) (*Spodoptera frugiperda*), an invasive lepidopteran pest, has caused substantial yield loss since its first detection in September 2016, thereby threatening the farm productivity, food security and poverty reduction initiatives in Malawi. Several stakeholders, including households have adopted chemical pesticides to control FAW, without accounting its costs on welfare, health and the environment. Thus, this study has used panel data endogenous switching regression model to investigate the impact of FAW and the integrated pest management (IPM) –related practices on farm productivity and food security. The study finds that FAW substantively reduces farm productivity by seven (7) percent and influenced the adoption of IPM –related practices, namely, intercropping, mulching, and agroforestry, by 6 percent, ceteris paribus. Interestingly, multiple adoption of the IPM -related practices noticeably increases farm productivity by 21 percent. After accounting for potential endogeneity through the endogenous switching regression model, the IPM practices further demonstrates tenfold more improvement on food security, implying the role of the IPM –related practices in containing the effect of FAW at household level.

Key words: Hunger; Invasive Fall Army Worms; Integrated Pest Management Practices; Chemical Pesticides; Farm Productivity; and Food Security

3. Introduction

In this Chapter three, the study highlights the context, regarding adoption of various integrated pest management (IPM) –related practices and their effects on farm productivity under adverse effects of fall army worms (FAW). It also focuses on country FAW response plan; the objectives; the research motivation; and questions guiding the chapter. Furthermore, the chapter discusses the theoretical and empirical framework, which is the multinomial endogenous switching regression model. Lastly, the study presents the results and discussion, the conclusion, and the key policy recommendations.

3.1 Study Context

Fall armyworms (FAW) (*Spodoptera frugiperda*), an invasive lepidopteran pest, with its origins in the Americas, is one of the most damaging pests in Sub-Sahara Africa (SSA) and attacks over 80 different plant species (Tambo et al., 2020; William et al., 2019; Cock et al., 2017; Day et al., 2017; Sparks, 1979; Yang, 2021). The FAW can feed on more than 353 plant species, including staple cereals, leading to crop failures and low food shortages and the most preferred host of FAW is maize (Sun-xiao et al., 2021). The FAW has quickly spread across SSA, following its natural migration capacity, international trade, and eased transportation (FAO, 2019; Early et al., 2018). It is also affected by climate and weather variability factors, widening its geographical area, growth rate, abundance, survival, development, and mortality (Ramirez-Cabral et al., 2017). In 2016, the FAW was discovered in the Central and Western Africa, and spreading to most SSA countries (Tambo et al., 2021; Day et al., 2017; Goergen et al., 2016; Yang, 2021). It has annually travelled at least 1600 – 2000 km (Rose et al., 1975). In SSA countries, warmer climates have intensified the FAW outbreak, survival, and growth (Baudron et al., 2019), thereby threatening the SSA food security and pushing more households into poverty trap (Diaz-Alvares et al., 2020; IPCC, 2018). Coupled with other climate and weather variabilities challenges, the rapid spread of FAW poses economic threats developing countries, in particular, SSA (Midingoyi et al., 2018; Day et al., 2017; Yunhe et al., 2021). Recently, the FAW infestation has been escalated by climate and weather variability (World Bank, 2018; DoDMA, 2018; MoAWID, 2018).

An excessive FAW attack on crops have resulted into national and household economic yield losses in SSA, registering the crop loss of between fifteen and seventy-three percent. In Kenya, Ghana, and Ethiopia, the FAW have reduced yield by twenty-seven – forty-seven percent (Kumela et al., 2019; Rwomushana et al., 2018). In Zimbabwe, households have experienced about fifty-eight percent yield losses (Chimweta et al., 2019). In Zambia alone, FAW have attacked thirty-five percent of cultivated crop (Granger et al., 2020). Climate models projects the FAW to intensify in magnitude, frequency and reduce the present yield by forty percent. Moreover, climate and weather variability have worsened the prevalence and adverse effect of FAW on household food security and wealth creation (World Bank, 2018; DoDMA, 2018; MoAWID, 2018; IPCC, 2018). Ultimately, without understanding climate-induced FAW development, survival and spread to inform its controlling strategies, most Sustainable Development Goals (SDGs) of ending chronic hunger by 2030 may probably become a mere dream for SSA countries, including Malawi. Moreover, un-managed FAW outbreak may influence negatively the agricultural productivity. Meanwhile, the FAW has resulted into an annual economic loss of US$ 2.5 to US$ 6.3 million (Abrahams et al., 2017).

In Malawi, over ninety percent of the population depend on subsistent crop production as the main source of livelihood (MoAIWD, 2018). In September 2016, the country established the first FAW outbreak, which destroyed the crop vegetative and reproductive structures (MoAIWD, 2018; World Bank, 2018; Goergen et al., 2016). It reduced crop production by forty-two percent, translating into economic loss of US$ 0.23 – 0.56 million. Consequently, approximately 6.5 million people became food insecure. Low adoption of FAW control practices, poor agricultural practices, and warmer climates have exaggerated the spread and substantial damage of FAW in Malawi (FAO, 2018). Temperatures, which have ranged between 20 and 35 degree Celsius, have influenced the FAW development, survival and rapid spread (Diaz-Alvares et al., 2020). In other words, FAW infestation in the country is induced by climate and weather variability (DoDMA, 2018). Without controlling the FAW at development stage, it will adversely affect the household farm production and food security (Kansiime et al., 2019).

Various strategies have been recommended for managing climate induced FAW, including cultural, biochemical, and agronomic controls, namely, sanding, ashing, soup, killing, mulching, and synthetic pesticides (Danso-Abbeam and Baiyegunhi, 2018; Food and Agricultural Organization [FAO], 2019). For instance, in 2016/2017, the Government of Malawi developed a national response plan towards managing the FAW outbreak, where chemical pesticides, namely, pyrethroids, organophosphates, chlorpyrifos, and cypermethrin were procured and distributed to households. These strategies are also climate-smart due to unpredictability of FAW infestation following changes in climate and weather variability (World Bank, 2018). However, these management strategies are effective only when households are efficiently trained and timely employed (FAO, 2018). Moreover, some chemical controls have environmental and human health risks. Furthermore, some FAW are resistant to over 30 active insecticides (Zhao et al., 2017). Sadly, most chemical controls have limited information regarding its health effects and usage, locally inaccessible, and not affordable to rural households (Murray and Jepson, 2019; Midega et al., 2018).

Climate induced agronomic and cultural control strategies, comprising the integrated pest management (IPM) practices, present an opportunity to households in Malawi (Blake et al., 2007; Pretty and Bharucha, 2015; Ekezi et al., 2011; Muriithi et al., 2016; MoAIWD, 2018; Bateman et al., 2018; Bezu et al., 2014). They are affordable, accessible, and have lower risks to the environment (Baudron et al., 2019; Thierfelder et al., 2018; Thomson et al., 2007). The IPM principle is not new and includes a combination of several practices, viz., mulching, handpicking, dusting, intercropping, timely planting, and improved varieties, which suppress pest outbreaks and attach, with minimal harm to the environment and human life (FAO, 2018).

However, the challenges are, recommendations on most of the climate induced IPM-related choices in Malawi are imported and sometimes very anecdotal, making it difficult to domesticate their use (Tambo et al., 2019; Day et al., 2017). (Pretty and Bharucha, 2015; Gautam et al., 2017; Tambo et al., 2019; Day et al., 2017). Moreover, the FAW strain in Malawi is new and available empirical data is limited to guide recommendations for the effectiveness of the IPM (Chimweta et al., 2019; McGrath et al., 2018). Furthermore, few studies have provided households' indigenous knowledge of FAW and IPM practices in Malawi (NPC, 2020; MoAIWD, 2018). Besides, Malawi staple food is maize, which is the most favorable condition for FAW survival and widespread outbreak (DiTomaso et al., 2017). Additionally, flights into Malawi from Kenya, Ethiopia, and South Africa, where FAW is rampant, could become a pathway for its further spread if climate induced IPM practices are not mainstreamed at the farm (Day et al., 2017).

This study informs policy making processes on FAW in three-folds. First, the study assesses the effect of FAW and climate induced IPM practices on the household farm productivity through the endogenous switching regression (ESR) model. Second, the study interrogates combinations of factors which affect the adoption of IPM – related practices, including chemical pesticides at household level. Third, while accounting for potential endogeneity of the IPM adoption, the study examines the effect of various IPM practices on household food security. The IPM –related practices, which are sustainable production intensification approach, notably promote less use of insecticides in agricultural production. Accordingly, households enhance farm productivity and food security without increasing use of insecticides, thereby reducing its negative impact on the environment.

The study results are also relevant to achieving the SDGs and Malawi Vision 2063 on ending hunger and application of environmental friendly practices (Midingoyi et al., 2018; NPC, 2020; Zhao et al., 2017). The study findings further complement previous studies by adopting the farm productivity as the dependent variable measure of interest, where the study goes beyond "the usual exploring factors affecting the IPM adoption" by estimating the effect of multiple adoption of the IPM –related practices on the farm productivity and food security. Previously, studies have focused on one crop, such as, maize, to assess the damage of FAW (Tambo et al., 2020; Kumela et al., 2019; McGrath et al., 2018). Moreover, previous studies have concentrated on interrogating the harmful effect of the applied synthetic pesticides on the environment, without linking it to farm (Liu et al., 1995; Okello and Swinton, 2010; Skevas et al., 2013; Sanglestsawai et al., 2015; Kibira et al., 2015; Isoto et al., 2008). This study uses data from the integrated household panel survey, which is compiled by the NSO and the World Bank between 2016 and 2020.

3.2 Research Methodology

3.2.1 Study Area, Sampling Strategy, and Data Acquisition

This study is conducted in rural farming communities of Malawi (see Figure 1.5), who rely on crop production for household livelihoods, food security, and eventual poverty reduction (Kilic et al., 2021; Tambo et al., 2020; NSO, 2012, 2014, 2018, 2020). Malawi is 118,480 km square in size, with Lake Malawi covering one-third of its size. The country is subdivided into districts; with altitudes varying from below 500 to 1500 meter above sea level. Malawi has one annual rainy season from November to April, with average precipitation varying from 725 mm to 2,500 mm. Households experience FAW, with Chikwawa, Chiradzulu, Karonga, Mulanje, Nsanje, Lilongwe, Mzimba and Phalombe being the most affected districts (Pangapanga and Mungatana, 2021). In 2018, over 21% of households' crop production was affected by FAW. Several models have predicted increasing vulnerability, intensity, magnitude and frequency of extreme weather events, namely, pest and outbreaks (Pangapanga and Mungatana, 2021; DoDMA, 2018; IPCC, 2018). Apart from the high poverty levels and limited adaptive capacity (Pangapanga and Mungatana, 2021; Amadu et al., 2020), El Niño and La Niña phenomena have further intensified the country's vulnerability to climate variables, viz, FAW outbreaks, in particular (Pangapanga and Mungatana, 2021; World Bank, 2018).

The study uses the panel data compiled by the NSO and the World Bank between 2016 and 2020 using the Integrated Household Survey (IHPS) (Kilic et al., 2021), which has a matched household sample size of 1289 for 2016/2017 and 1236 for 2019/2020. The IHPS follows a multi-stage sampling procedure and has a strong component on agriculture. It captures data on demographic factors such as gender, age, education, income, and agriculture variables such as inputs of production, namely, farm size, seeds, fertilizer use, pesticides, organic manure and improved varieties. It also administers a shock related module to the households, where each household is asked whether they experience any FAW in farms. In this study, households, which experience any FAW, are termed FAW affected households (FAH), and otherwise, non FAW affected households (NFAH). Similarly, households, which adopt any IPM –related practices, are identified as FAW IPM adopting households (FMH), and otherwise, non FAW IPM adapted households (NFMH). In other words, any household practicing any of the climate induced IPM –related practices is regarded as an adopter. For instance, a household is referred an adopter if the household apply only lime or ashes or a combination of any of the various climate induced IPM practices. The study presents variables definition, measurements, and expected signs for this Chapter in Table 1.1.

3.2.2 Theoretical and Empirical Framework

This study evaluates the effect of FAW and IPM -related practices on farm productivity and food security based on the rational choice theory. Technically, the theory assumes that a household only adopts an IPM –related practice which provides higher utility than the alternatives (McFadden, 1974). Thus, we compare the effect of FAW and related adoption on farm productivity and food security. Following Tambo et al. (2021), and Ragasa and Mazunda (2018), the study defines FAW adoption as the implementation of any IPM practices, viz. mulching, intercropping, improved crop varieties, chemical pesticides, landscape management strategies, and agroforestry. Primarily, the study measures farm productivity through converting yield per ha into a common monetary value for each crop, following methodologies advocated by Muyanga and Jayne (2019) and Aragon et al. (2019). The farm productivity procedure allows the aggregation of the farm-level output value divided by amount of cultivatable farm-size. Households in Malawi rely on farm production for livelihoods and food security (MoAIWD, 2018; NPC, 2020; Pangapanga and Mungatana, 2021). Hence the output value obtained from the farm determines household food consumption (Bezu et al., 2014; Shiferaw et al., 2011), which can be translated into food security (MoAIWD, 2018). In Malawi, any household member who consume about 270 kg of maize per year is food secure (NSO, 2020; MoAIWD, 2018; NPC, 2020).

Adoption of various climate induced IPM -related practices potentially suffers from endogeneity problems due to non-randomness of the household decision, where some households self-select whether to adopt or not to adopt (Danso-Abbeam and Baiyengunhi, 2018). This implies that there are some other household factors, which may have a combined effect on the adoption decision and the farm productivity, but are unobservable, namely, household management ability and risk aversion. Application of ordinary techniques, which does not account for such unobservable factors may yield misleading estimates. The study, therefore, employs the endogenous switching regression (ESR) and extended regression models with endogenous treatment assignment -related model to account for both observable and unobservable factors effect on the FAW management adoption decision, farm productivity, and food security (Andresen, 2018; Gould, 2018; Mundlak, 1978).

Following Adela and Wooldridge (2010) and Kassie et al. (2018), lets U_{it}^{*} denotes the latent utility between IPM –related practices' adoption and non-adoption. A_{it}^{*} is the adoption status of any IPM –related practices, which is made in related to the adverse effect of FAW on farm productivity or food security and can be written as in equation (1):

$$A_{it} = \begin{cases} 1 & if\ \emptyset_1 W_{1it} + \mu_{1i} + \epsilon_{1it} > 0 \\ 0 & if\ \emptyset_2 W_{1it} + \mu_{2i} + \epsilon_{2it} < 0 \end{cases} \quad (1)$$

where A_{it} denotes one if an individual household adopts any of IPM –related practices, and otherwise, zero. Households may further adopt various IPM –related practices in an orderly form, depending on the derived utilities. In this study, household is named an adopter if it undertakes at least one of the IPM –related practices. The W_{it} is a vector of socioeconomic characteristics which determine household adoption status. The $\emptyset_i$ is the vector of unknown parameters to be estimated, the μ_i is the panel-level random effect for the adoption decision, and ϵ_{it} is the error term, and they $(\mu_{ji}, \epsilon_{jit})$ are bivariate normally related (see Wooldridge, 2010; Madala, 1983; Heckman, 1976).

Following Lokshin and Sajaia (2004), the adoption of IPM –related practices (A_i) enhances farm productivity, thus improving household food security. It is assumed the adoption decision of IPM –related practices result into two outcome regimes of farm productivity $(\hat{y}_{jit})$ and can be specified as in equation (2):

$$y_{jit} = \begin{cases} y_{1it} = \emptyset_1 x_{1it} + \varphi_1 \hat{h}_{it3} + v_{1i} + \varepsilon_{1it} & if\ A_{it} = 1 \\ y_{2it} = \emptyset_2 x_{2it} + \varphi_2 \hat{h}_{it3} + v_{2i} + \varepsilon_{2it} & if\ A_{it} = 0 \end{cases} \quad (2)$$

where y_{jit} is the household farm productivity for time t and is a continuous variable. For farm productivity, the study multiplied price of each crop against its production quantity, this allowed the conversion of other crops to maize equivalents, following Muyanga and Jayne (2019) and Oregano et al. (2019). In terms of food security, the study generated the kilocalories from the food consumed at household, as defined by the Government of Malawi, where every person requires a minimum of 2200 calories per day to be food secure (NSO, 2012, 2020; Aberman et al., 2018). Accordingly, the study divided the total kilocalories by the number of household members. The x_{jit} represents household and farm -level factors such as age, education, slope, soil type and quality, access to extension services, credit, farm size, and others.

The $\hat{h}_{it3}$ is a vector of generalized residuals, which is computed through the first stage of the ESR model, that captures the IPM adoption status (Mundlak, 1978; Murtazashvili and Wooldridge, 2016). The $\emptyset_j$ and φ_j are the vector of the unknown parameters to be estimated as prior defined. The v_{ji} is the panel level random effect, while the ε_{jit} is the observation-level error term, and are bivariate normal (see Wooldridge, 2010). It further allows correlation between the panel level random effect with strictly exogenous variables through the Mundlak (1978) device (Murtazashvili and Wooldridge, 2016). Contrarily, the ε_{jit} and ϵ_{it} have a trivariate normal distribution (Khonje et al., 2015; Lokshin and Sajaia, 2004), with mean vector zero and the covariance matrix (Ω) as in equation (3):

$$\Omega = \text{covariance}\,(\epsilon, \varepsilon_{1t}, \varepsilon_{2t}) = \begin{bmatrix} \sigma_{\epsilon}^2 & \sigma_{\epsilon 1} & \sigma_{\epsilon 2} \\ \sigma_{\epsilon 1} & \sigma_1^2 & . \\ \sigma_{2\epsilon} & . & \sigma_2^2 \end{bmatrix} \tag{3}$$

where σ_{ϵ}^2 = variance (ϵ), σ_1^2 = var (ε_{1t}), σ_2^2= variance (ε_{2t}), $\sigma_{\epsilon 1}$ = covariance (ϵ, ε_{1t}), and $\sigma_{\epsilon 2}$ = covariance (ϵ, ε_{2t}). It accepts that σ_{ϵ}^2 equal to 1 and is estimable only up to a scalar factor (Wooldridge, 2010; Midingoyi et al., 2018). Since y_{1it} and y_{2it} are never observed simultaneously, the covariance between ε_{1it} and ε_{2it} is not defined (Khonje et al., 2018), never observed simultaneously and have non-zero error terms' outcome, resulting in inefficient estimates when using estimated through any ordinary least square procedure (Rabe-Hesketh et al., 2002). In accordance with Mundlak (1978), the standard ESR model can be extended to a panel model and can be used to examine the effect of IPM practices on farm productivity and food security through estimating the average treatment effect on the treated (ATET) and average treatment effect on the untreated (ATEU). The ATET measures the difference in farm productivity between IPM adopters and non-adopters.

Commonly, Propensity Score Matching (PSM) has been applied to study the effect of adoption decision between adopters and non-adopters (Kassie et al., 2018). However, PSM techniques have ignored the probable effect from unobservable characteristics on the household adoption, farm productivity, and eventually food security (Tecklewold et al., 2013; Asfaw et al., 2012). Moreover, they only use a sub-sample, which has attained the balancing property rule. The study simultaneously estimates the ESR model in two stage (Heckman, 1978). In the first step, the model generates the Inverse Mills Ratios (IMRs) (Madala, 1983) through a probit regression, which capture the unobservable heterogeneity between IPM adopters and non-adopters. Second, it incorporates the IMRs as addition variables to control for any potential selection bias (Kassie et al., 2018; Wooldridge, 2010) and estimates the effect of IPM related practices on farm productivity and food security (Ragasa and Mazunga, 2018). Through these two steps, the ESR model captures both unobservable and observable characteristics (Lokshin and Sajaia, 2004).

According to Murtazashvili and Wooldridge (2016), the study combined the two panel-based ESR regimes as in equation (4):

$$y_{it1} = \emptyset_j x_{it1} + (\emptyset_1 - \emptyset_2)\, x_{it1} y_{it3} + \varphi_{1_j} \hat{h}_{it3} + (\varphi_{1_1} - \varphi_1) \hat{h}_{it3} y_{it3} + v_{i1} + y_{it3}(v_{i1} - v_{i2}) + y_{it3}(\varepsilon_{it1} - \varepsilon_{it1}) + \varepsilon_{it1} \qquad (4)$$

where y_{it3} is the endogenous switching variable at the basis of the sample selection. It is interacted with both time constant and time varying variables. While $y_{ijt}, \emptyset_j, \varphi_{1_j}, v_j, and\ x_{ijt}$ are as formerly described and the whole model becomes consistent only after including the time varying variables' mean values (Mundlak, 1978; Murtazashvili and Wooldridge, 2016), as additional covariates. Following Murtazashvili and Wooldridge (2016), equation (4) can be estimated as presented in equation (5).

$$y_{ijt} = \emptyset_j x_{it1} + l_j x_{it1} y_{it3} + \varphi_{1_j} \hat{h}_{it3} + \forall_j \hat{h}_{it3} y_{it3} + \overline{\mathrm{G}} v_{i1} + y_{it3}(\overline{\mathrm{G}}) v_1 + \varepsilon_{it1} y_{it3} \hat{h}_{it3} + \varepsilon_{it2} \hat{h}_{it3} + y_{it3}(\overline{\mathrm{G}}) \varepsilon_{it1} + \varepsilon_{ijt} \qquad (5)$$

where $\hat{h}_{it3}$, $y_{it3}\hat{h}_{it3}$, $\overline{\mathrm{G}}$, and $y_{it3}(\overline{\mathrm{G}})v_1$ are used as instruments in the second step of the ESR panel model (Mundlak, 1978). The l_j is vector of the differences $(\emptyset_1 - \emptyset_2)$ of the coefficients of household and farm-level explanatory variables (Murtazashvili and Wooldridge, 2016). The $\forall$ is the difference between $\varphi_1\ and \varphi_2$ of the generalized residuals. The $(\overline{\mathrm{G}})$ is the Mundlak device, which is the mean value of the explanatory variables, while ε_{ijt} is a vector of idiosyncratic errors of the Mundlak relationship (Mundlak, 1978). Other parameters and variables in equation (4) are as prior discussed. The treatment effect, γ_j is the difference $(\varphi_{1_1} - \varphi_{1_2})$ in intercepts between the two regimes if the IPM adoption is a random practice (Lokshin and Sajaia, 2004). After incorporating the Chamberlain-Mundlak technique, the study derives the treatment effect, which is the expected value from a panel based ESR correction model (Murtazashvili and Wooldridge, 2016) as in equation (6):

$$\mathrm{E}(y_{ijt} | y_{it3}, x_{ijt}) = h(\emptyset_j x_{it1} + l_j x_{it1} y_{it3} + \varphi_1 \hat{h}_{it3} + \forall_j \hat{h}_{it3} y_{it3} + \overline{\mathrm{G}} v_{i1} + y_{it3}(\overline{\mathrm{G}}) v_1 + \varepsilon_{it1} y_{it3} \hat{h}_{it3} + \varepsilon_{it2} \hat{h}_{it3} + y_{it3}(\overline{\mathrm{G}}) \varepsilon_{it1} + \varepsilon_{ijt})$$

$$
\begin{aligned}
= y_{it3}\lambda\big[&\emptyset_1 x_{it1} + l_1 x_{it1} y_{it3} + \varphi_1 \hat{h}_{it3} + \forall_1 \hat{h}_{it3} y_{it3} + \overline{\mathrm{G}} v_{i1} + y_{it3}(\overline{\mathrm{G}}) v_1 + \varepsilon_{it1} y_{it3} \hat{h}_{it3} \\
&+ \varepsilon_{it1} \hat{h}_{it3} + y_{it3}(\overline{\mathrm{G}}) \varepsilon_{it1} + \varepsilon_{it1}\big] \\
&- \big[(1 - y_{it3})\lambda\big(\emptyset_2 x_{it2} + l_2 x_{it2} y_{it3} + \varphi_2 \hat{h}_{it3} + \forall_2 \hat{h}_{it3} y_{it3} + \overline{\mathrm{G}} v_{i2} + y_{it3}(\overline{\mathrm{G}}) v_2 \\
&+ \varepsilon_{it2} y_{it3} \hat{h}_{it3} + \varepsilon_{it2} \hat{h}_{it3} + y_{it3}(\overline{\mathrm{G}}) \varepsilon_{it2} + \varepsilon_{it2}\big)\big]
\end{aligned} \tag{6}
$$

where $h(.)$ is the generalized residual function exploiting the probit function in the first step (Murtazashvili and Wooldridge, 2016), $\lambda(.)$ is the IMR function while other parameters and variables are as previously defined. The IMR term is characterized with zero mean and no correlation with the explanatory variables of the binary regression model. The study further estimates the influence of IPM adoption as specified in equations (7) and (8) (Midingoyi et al., 2018).

$$
\begin{aligned}
\mathrm{E}\big(y_{it1} \big| y_{it3}, x_{ijt} = 1\big) &= \sigma_{\mu 1} \frac{\mathbb{M}(\emptyset_1 x_{it1} + l_1 x_{it1} y_{it3} \dots)}{\mathbb{Z}(\emptyset_1 x_{it1} + l_1 x_{it1} y_{it3} \dots)} \\
&\equiv \emptyset_1 x_{it1} + (\overline{\mathrm{G}}) v_1 + \mathfrak{y}_1 \hat{h}_{it3} && (7) \\
\mathrm{E}\big(y_{it2} \big| y_{it3}, x_{ijt} = 0\big) &= \sigma_{\mu 2} \frac{\mathbb{M}(\emptyset_2 x_{it2} + l_2 x_{it2} y_{it3} \dots)}{(1 - \mathbb{Z})(\emptyset_2 x_{it2} + l_2 x_{it2} y_{it3} \dots)} \\
&\equiv \emptyset_2 x_{it2} + (\overline{\mathrm{G}}) v_2 + \mathfrak{y}_2 \hat{h}_{it3} && (8)
\end{aligned}
$$

Equations (7) and (8) represent the ESR model' s expected actual and counterfactual derived effects of adopting any IPM –related practices, respectively (Wooldridge, 2010). $\mathbb{M}(.)$ is the standard normal probability density function, $\mathbb{Z}(.)$ the standard normal cumulative density function (Wooldridge, 2010). Where $\hat{h}_{it3}$ is the generalised residuals which account for the endogeneity of the selection variable (Murtazashvili and Wooldridge, 2016), while $x_{it1}\ or\ x_{it2}$ represents household and farm -level explanatory variables. The $\emptyset_j, v_j$, and $\mathfrak{y}_j$ are vectors of unknown parameters to be estimated by the model, that is after bootstrapping the standard errors to control for inclusion of $h(.)$ (Murtazashvili and Wooldridge, 2016). Other parameters and variables are as previously defined.

In addition, the study attempts to understand the effect of FAW and IPM adoption on farm productivity and ultimately food security, through estimating the average treatment effect on the treated (ATET) and the average treatment effect on the untreated (ATU) (Tambo et al., 2019; Midongoyi et al., 2019; Murtazashvili and Wooldridge, 2016) as written in equations (10) and (11):

$$
\mathrm{ATET} = \mathrm{E}\big(y_{ij1} \big| y_{it3}, x_{ijt} = 1\big) - \mathrm{E}\big(y_{ij1} \big| y_{it3}, x_{ijt} = 0\big) \tag{10}
$$

$$
\mathrm{ATU} = \mathrm{E}\big(y_{ij2} \big| y_{it3}, x_{ijt} = 1\big) - \mathrm{E}\big(y_{ij2} \big| y_{it3}, x_{ijt} = 0\big) \tag{11}
$$

Furthermore, literature shows that households adopt at least one of the IPM - related practices in the same farm, which arises to a multivariate binary or multinomial choice regression (Kassie et al., 2018; Khonje et al., 2018; Teklewold et al., 2013). Any Poisson model is suitable when the treatment or the dependent variable is a count data (Wooldridge, 2010). However, it is only appropriate when the adoption of one IPM practice does not alter the adoption likelihood of an alternative practice (Plan, 2014; Wollni et al., 2010). In this study, the adoption of one or several IPM –related practices may likely alter the likelihood of adopting any alternative. Hence, this study employ the panel-based ESR model to capture the effect of climate induced FAW and IPM adoption on farm productivity and food security (Kassie et al., 2018; Murtazashvili and Wooldridge, 2016).

The ESR model can be fit through either a two-step least square, control function, or the full information maximum likelihood method. However, the first two estimation methods result in heteroskedastic residuals, requiring cumbersome adjustments to derive consistent standard errors (Wooldridge, 2010; Madala, 1983; Heckman, 1976; Kassie et al., 2015; Lokshin and Sajaia, 2004). This study, therefore, employs the full-information maximum likelihood, which uses the joint normality of the error terms, to simultaneously estimate the binary and continuous parts of the model in order to derive consistent standard errors. The signs and significance levels of the correlation coefficients of the outcome equations determine the presence of the endogenous switching (Lokshin and Sajaia, 2004).

For the ESR model to be well identified, the selection equation should exclude at least one variable in the outcome equations in addition to those generated through various model parameters (Blundell and Powell, 2004; Chamberlain, 1980). Moreover, the estimation of the impact of various climate induced IPM –related practices on farm productivity or food security can be modelled through either an endogenous multinomial, or a multivariate, or a binary framework (Midingoyi et al., 2018; Kassie et al., 2018; Sharma and Peshin, 2016; Isoto et al., 2008; Wollni et al., 2010; Teklewold et al., 2013; Wooldridge, 2010). On one hand, following Midingoyi et al. (2018), the study can equally estimate the impact of FWA and IPM using a multinomial but ordered probit treatment effect framework. On the other hand, the study can evaluate the role of FAW and IPM –related practices on farm productivity or household food security using the binary treatment variables as purported by Sanglestsawai et al. (2015), Sharma and Peshin (2016), and Kibira et al. (2015).

Empirically, the review of similar but previous studies has informed the specification and variables of interest for the study model (see McCarthy et al., 2021; Tambo et al., 2020; Bidzakin et al., 2019; Khonje et al., 2015; Teklewold et al., 2013; Kassie et al., 2015; Teklewold et al., 2013; Kassie et al., 2018; Gould, 2018; Pangapanga et al., 2012; Pangapanga and Mungatana, 2021). Accordingly, several factors affect the climate induced IPM adoption, thus, influencing the household farm productivity and food security (Tecklewold et al., 2013; Amadu et a., 2020). This study, therefore, includes farm characteristics (soil type, quality and slope), self-reported rainfall shocks, farm size, inorganic fertilizers, labor, and access to credit; other household characteristics (family size, education, gender, and age); and geographic location, to assess the effect of IPM –related practices on farm productivity, which is defined and measured as in Table 1.1.

Besides, the study adopts an exclusion restriction, which thoroughly identifies the ESR models (see Di Falco et al., 2011; Shiferaw et al., 2014; Jerop et al., 2020; 2018; Tesfaye and Tirivayi, 2016; and Khanal et al., 2018). In this study, access to extension services is used as an exclusion restriction since it is the primary source of information in rural Malawi, either through farmer to farmer, lead farmer, government extension workers (MoAIWD, 2018). For robustness of the results, the study estimates fixed and random effect models (see Baltagi, 2005; Wooldridge, 2010), panel-based Cobb-Douglas SFA models (see Kumbhakar et al., 2015), and annualized ESR models (see Andresen, 2018; Gould, 2018) for 2016/2017 and 2019/2020.

3.3 Results and Discussions

3.3.1 Household characteristics

Table 3.1 shows a summary statistics of characteristics between households affected (FAH) and not affected (NFAH) by FAW in Malawi between 2016/2017 and 2019/2020 cropping seasons. Similarly, Table 3.1 highlights summary statistics for households, adopting and not adopting any FAW-related practices. The study finds most households (74%) are headed by males. They are, on average, aged 43 years, implying that they are still in their productive age. The study observes no difference in age and gender of the household headed, who are affected and not affected by FAW. Eight in ten (10) FAH and NFAH household heads have attended formal education, where only six in ten household heads are literate in local language, indicating that they can easily read and understand extension messages in written forms. Almost 85 percent of household heads have a cell phone, which speculatively help them access climate-related information, namely, merits and demerits of IPM -related practices. Similarly, about 64 percent of FAH and 58 percent of NFAH household heads have accessed FAW-related extension services, allow households to differentiate the cons and pros of adopting different IPM-related practices, namely, pesticides, herbicides, agroforestry species, and improved crop varieties.

This study notes that the average household size is 5 members. Since most households are resource constrained, family labour strongly determines the adoption of various IPM –related practices (MoAIWD, 2018). Households cultivate on a farm size of 0.5 ha, which is in line with the NSO (2018, 2020). The study also finds that households derive about 171800 Malawi Kwacha (MWK) per hectare (ha), where by households, which are affected and not affected by FAW, obtain about 147000 MWK /ha and 160000 MWK /ha, respectively, implying FAW substantively reduced household agricultural income. Households, which adopt and do not adopt any IPM -related practices got an output value of 166000 MWK/ha and 90000MWK/ha, respectively, indicating that the adoption of various IPM –related practices improves household agricultural income. On average, households plant ten (10) kg/acre of seeds, apply at least one bag of 50kg of chemical fertilizer, and cultivate on total farm size of 0.8 of ha. Households cultivate various crops, namely, maize, millet, sorghum, potatoes, and leguminous crops. Maize is cultivated by over 90 percent of the population in the rural areas of Malawi, where the majority mix it with leguminous crops. Likewise, these results are in line with the findings from the NSO (2018; 2020).

Table 3. 1 : Summary of socioeconomic characteristics between FAH and NFHA as well as FMH and NFMH in Malawi

		FAW EXPERIENCE		IPM ADOPTION		POOLED			
		NFAH	FAH	NON-ADAPTOR	ADAPTOR	MEAN	STD. DEV	Diff_FAW EXPERIENCE	Diff_FAW ADOPTION
GENDER	Male=1	0.760	0.727	0.714	0.757	0.738	0.440		**
AGE	Years	43.09	42.20	42.59	42.39	42.484	16.947		***
EDUCATION CLASS	Years	5.825	5.896	5.695	6.022	5.873	4.598		***
MOBILE PHONE	Yes=1	0.853	0.851	0.801	0.895	0.852	1.109		-0.02
CREDIT ACCESS	Yes=1	0.164	0.144	0.135	0.163	0.150	0.357	***	***
ACCESS EXTENSION	Yes=1	0.640	0.576	0.522	0.659	0.597	0.491	*	***
HOUSEHOLD SIZE	Count	5.024	4.939	4.820	5.090	4.967	2.262		***
OWN LAND	Yes=1	0.591	0.695	0.643	0.677	0.662	0.473		
LITERACY	Yes=1	0.716	0.688	0.665	0.724	0.697	0.459		
ATTENDED SCHOOL	Yes=1	0.832	0.820	0.787	0.854	0.824	0.381	**	*
MULTIPLE ADAPTATION	Count	4.983	4.274	3.662	5.207	4.503	2.216	***	
OUTPUT VALUE	Mwk/ha	160000	147063.8	90638.3	166723.4	132,061.447	59,954.900		
YIELD	Kg/ha	1880	1728	1065	1959	1,551.722	6,579.336		
SEED QUANTITY	Kg	9.313	9.405	9.458	9.306	9.375	4.049		
CHEMICAL (NPK) FERTILIZER	Kg	69.24	61.32	46.02	78.81	63.872	230.502		
FARM SIZE IN HA	Ha	0.52	0.483	0.437	0.544	0.495	0.381		

Note: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$

Figure 3.1 highlights summary statistics of farm-level characteristics, namely, slope, soil quality, and soil type in the study area. In terms of slope, approximately 55 percent of households in the study area cultivate on crop-farms, which have flat slope, followed by the gentle (36%), and steep (12%) slope. In terms of soil type, the study notes that 54 percent of the households have farms, which are characterized by loam soil type, followed by sandy (26%), and clay (21%) soil types. Slightly above half of the households in the study areas report having good soil quality, where 37 and 14 percent have farms with fair and poor soil quality, respectively. Households affected and not affected by FAW cultivate on farm which have flat slopes by 54 and 57 percent, respectively. Due to adoption of various IPM –related practices, the study reveals that adopters have better soil quality than non-adopters. Accordingly, the qualitative data attributes the difference to the adoption of various IPM –related practices, namely, organic farming, soil and water conservation measures, agroforestry, crop residues incorporation, and intercropping, implemented by households in various crop farms.

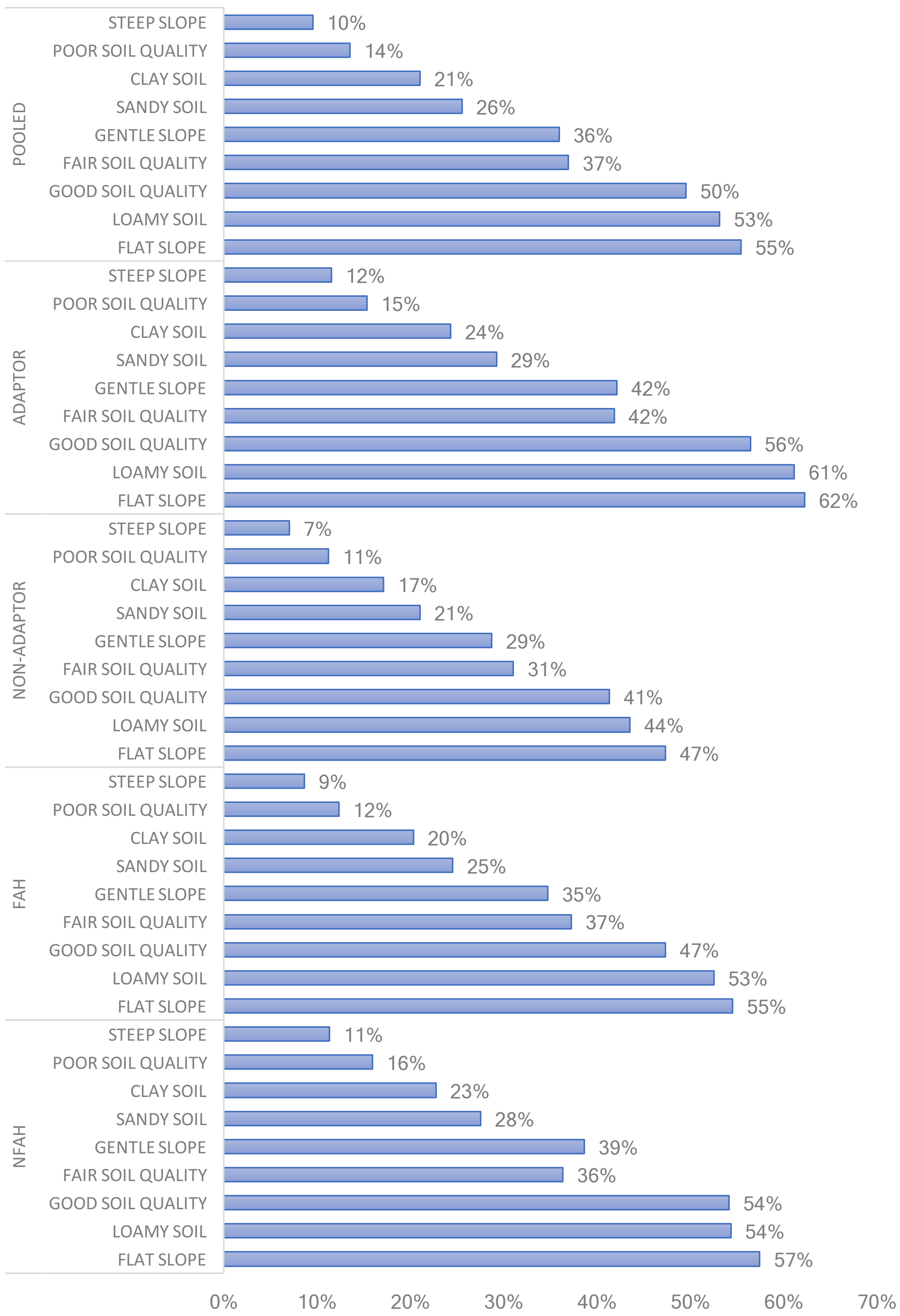

Figure 3. 1 : Summary statistics for farm-level characteristics between FAH and NFAH as well as FMH and NFMH.

Figure 3. 2 presents percentage of households, undertaking various IPM -related practices in the study area during 2016 - 2020. The study finds that almost 40 percent of households in the study area undertake SWC –related measures, intercropping, and timely planted their crops, followed by improved varieties (36%), agroforestry (25%), organic fertilizer (24%), cover cropping (22%), crop residuals (18%), and cultivation in marginal land (16%). Unsurprisingly, the study observes that only two (2) percent of households reported controlling FAW using chemical pesticides and this is due to its associated prohibitive costs.

The study also notes that half of the FAH intercrop various crops with leguminous crops, followed by timely planting (40%), SWC (40%), improved crop varieties (33%), agroforestry (20%), and lastly marginal land cultivation (14%) (see Figure 3. 2). Similarly, the study notes that household-not affected by FAW (NFAH) have also adopted various IPM -related practices (see Figure 3. 2). Fifty-four (54) percent of NFAH timely plant their crops to control for any related pest infestation, followed by intercropping (47%), SWC (49%), improved varieties (28%), and finally, pesticides (7%). This implies that households still undertake some of the IPM –related practices despite of being not affected by any pest. This shows that IPM –related practices further play other roles other than pest controlling.

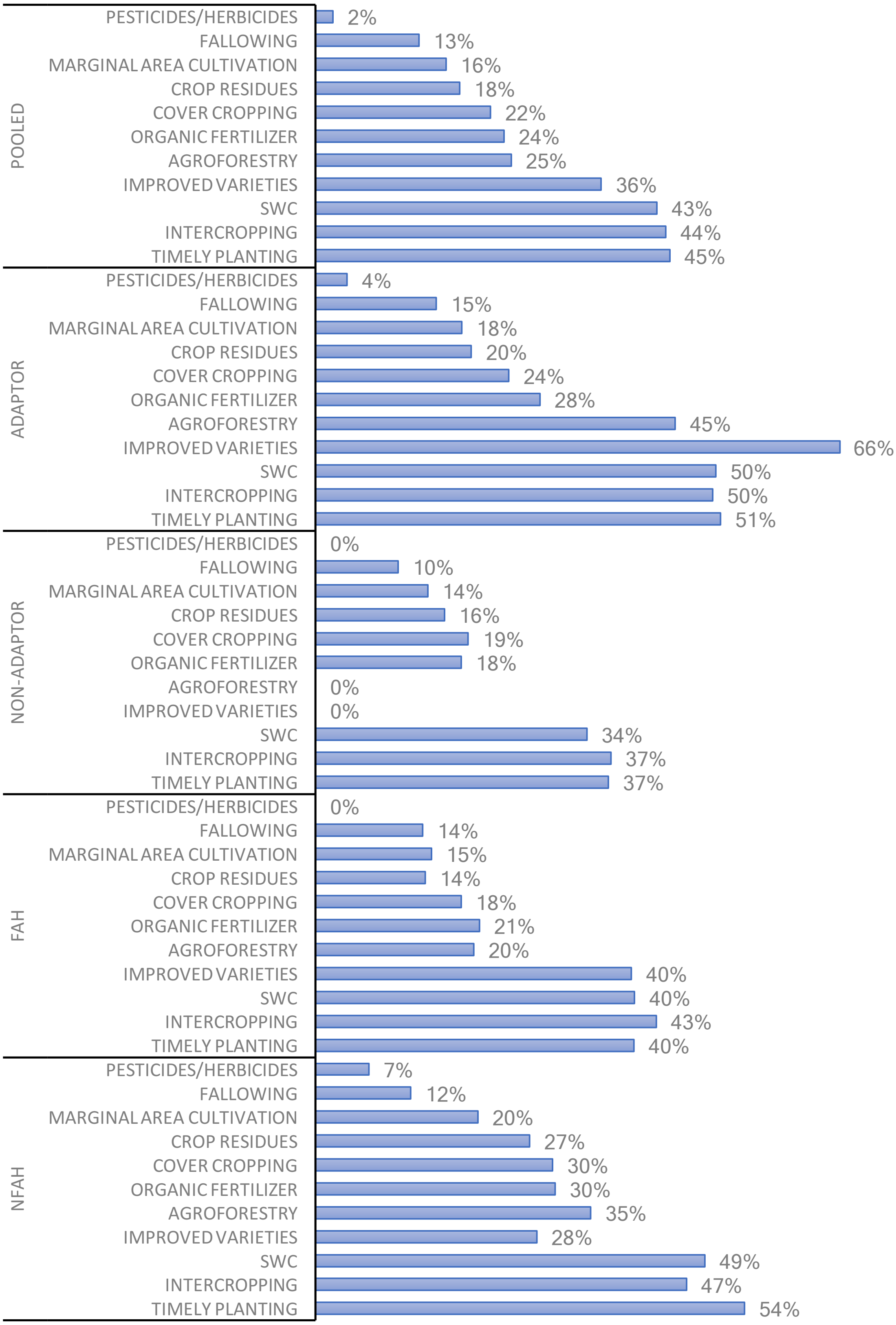

Figure 3. 2 : Percentage distribution of households affected by FAW and adapting IPM –related practices to control the FAW effect on farm productivity: 2016 - 2020.

3.3.2 What factors influence the adoption of the IPM practices, 2016 – 2020?

Adoption of any IPM –related practices does not happen automatically. There are several factors which affect their adoption like age, gender, education, and literacy of the household head. Table 3. 2 shows results from the first stage of the ESR, highlighting factors affecting the adoption of IPM –related practices in the study area. Columns (1-3) report results from the ESR model, based on a maximum likelihood estimation (MLE), two step, and control function, respectively. Columns (4), (5), and (6) indicate ESR econometric output from the binary ESR model, purported by Lokshin and Sajaia (2004), multinomial ordered probit, and panel based ESR model, respectively. Columns (7), (8), (9), and (10) present estimates from the binary and multinomial ESR models for 2016 and 2020, respectively. All variables across all the models indicate the same expected signs, with some slight magnitude of influence on the adoption of various IPM –related practices. The interpretations of the results is based on Columns (4), (5), and (6), while the rest of the Columns are used for checking the robustness of the results.

Based on the estimates results from Column (5), the study finds that FAW enhanced the likelihood of adopting IPM –related practices by 15 percent. Equally important, the Column (6) estimates revealed that FAW significantly improved adoption of IPM –related practices by 6 percent, ceteris paribus. These results are in line with aspirations stipulated by DoDMA (2018) and World Bank (2020). Furthermore, column (6) shows that chemical fertilizer and farm holding size substantively enhance farm productivity by 7 percent, while labour days significantly increase farm productivity by 23 percent, holding all other factors constant. However, improved crop varieties reduce the adoption of IPM –related practices by 37 percent, ceteris paribus, implying the unlikely vulnerability of improved crop varieties to FAW. Likewise, the study observes the same results in Column (5). Speculatively, households find traditional varieties less likely to stand the adverse effects of FAW. These results are in line with Kassie et al. (2020), Baudron et al. (2019), and Midega et al. (2018).

In terms of farm-level characteristics, the study results reveal that households, with loamy and sandy soils, are more likely to adopt IPM practices by 19 percent than households with clay soils (see Column 6). Likewise, households with fair and poor soil quality are more likely to adopt IPM practices by 8 and 13 percent, respectively. Moreover, the study findings shows that household having farms with steep and gentle slope are more likely to adopt any of the IPM –related practices by 20 and 14 percent, correspondingly. This implies that IPM –related practices may ably control the FAW infestation under farms, which are steep in the study area. The PESR model results are in line with MESR model estimates as shown in Column (5). These results are further in accordance with Tambo et al. (2019), Day et al. (2017), Pangapanga and Mungatana (2021), and McNamara et al. (1991).

Furthermore, the study finds socioeconomic characteristics influencing household adoption decision of IPM –related practices (see Column 4). Column (4) reveals that female farmers are 10 percent less likely to adopt IPM -related practices. This is because female farmers are resource constraint (Pangapanga and Mungatana, 2021), suggesting the need of a deliberate IPM -related approach that targets female farmers, in particular. Age significantly improves household adoption decision, where an elder person was more likely to adopt IPM -related practices, holding all other factors constant (Column 4). Likewise, the study notes than households with mobile phone are more likely to adopt IPM –related practices than household without a mobile phone, ceteris paribus. This is explained along the available electronic based extension services in the study areas. Interestedly, the study notes that households with large household size have positive influence on adopting any of the IPM –related practices. These study findings are in line with Kansiime et al. (2019) and Foster and Rosenzweig (2010).

Table 3. 2 : **Results of the ESR models: Factors affecting the IPM adoption in Malawi**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ESR-MLE	**ESR-2SLS**	**ESR-CONT**	**ESR-FMLE**	**MESR**	**PESR**	**ESR 2016/2017**	**ESR 2019/2020**	**MESR 2016/2017**	**MESR 2019/2020**
LOG(FARMSIZE)	0.0676*	0.0751**	0.0751**		0.069**	0.0680**	-0.0606***	-0.0282**	0.167***	0.199***
	(2.38)	(2.64)	(2.62)		(2.94)	(3.09)	(-6.48)	(-2.93)	(4.74)	(5.35)
LOG(LABORDAYS)	0.0528	0.0583	0.0583		0.069**	0.235***	0.0352	0.0640	0.166***	0.066*
	(1.74)	(1.90)	(1.86)		(2.76)	(21.06)	(0.77)	(1.26)	(4.81)	(2.12)
LOG(FERTILIZER)	0.119***	0.123***	0.123***		0.100***	0.0685***	0.0283***	0.0437***	0.0279	0.0128
	(16.28)	(17.04)	(17.06)		(16.01)	(7.67)	(7.03)	(10.59)	(0.21)	(0.87)
LOG(SEED)	-0.18***	-0.18***	-0.181***		-0.102***	-0.373***	0.138***	0.0652***	0.0234	0.0372
	(-5.03)	(-5.07)	(-5.01)		(-3.46)	(-21.20)	(15.55)	(8.73)	(0.59)	(1.00)
LOAMY SOIL	0.417***	0.417***	0.417***	0.916***	0.502***	0.189***	0.150***	0.221***	0.236***	0.219**
	(11.95)	(11.91)	(11.90)	(14.34)	(17.01)	(4.40)	(8.42)	(10.81)	(3.95)	(3.01)
SANDY SOIL	0.350***	0.350***	0.350***	0.929***	0.451***	0.133**	0.155***	0.164***	0.199**	0.0402
	(8.92)	(8.89)	(8.72)	(6.74)	(13.86)	(2.80)	(8.15)	(7.25)	(3.14)	(0.52)
FAIR SOIL	0.155***	0.151***	0.151***	0.395***	0.126***	0.0787*	0.0448**	0.0802***	-0.0117	-0.166**
	(4.74)	(4.62)	(4.55)	(3.97)	(4.62)	(2.01)	(2.71)	(4.09)	(-0.22)	(-2.63)
POOR SOIL	0.215***	0.204***	0.204***	0.345***	0.174***	0.128*	0.0967***	0.111***	0.0140	0.196*
	(4.68)	(4.43)	(4.26)	(5.27)	(4.57)	(2.37)	(4.20)	(4.12)	(0.19)	(2.28)
GENTLE SLOPE	0.162***	0.162***	0.162***	0.343***	0.200***	0.138***	0.0275	0.0234	0.0359	0.0881
	(4.92)	(4.89)	(4.78)	(6.57)	(7.27)	(3.50)	(1.63)	(1.19)	(0.67)	(1.40)
STEEP SLOPE	0.196***	0.195***	0.195***	0.652***	0.194***	0.200**	0.00191	-0.00916	0.0232	0.170
	(3.66)	(3.61)	(3.50)	(6.88)	(4.44)	(3.22)	(0.08)	(-0.30)	(0.30)	(1.65)
MALE=1	0.0805*	0.0588	0.0588	0.0979***	0.0434		-0.0204	-0.0895	-0.122**	-0.0616
	(2.26)	(1.62)	(1.60)	(4.90)	(1.46)		(-1.32)	(-0.43)	(-2.80)	(-1.36)
AGE	0.0259**	0.0307**	0.0307**	0.0478***	-0.001		-0.0184	-0.0279	-0.000649	0.00101
	(2.76)	(3.22)	(3.20)	(8.59)	(-1.28)		(-0.48)	(-0.47)	(-0.60)	(0.81)
AGE_SQUARE	-0.013***	-0.013***	-0.013***	-0.019						
	(-3.75)	(-2.74)	(-2.67)	(-0.57)						
EDUCATION	0.00337	0.00160	0.00160	0.0190***	-0.004		0.0564	-0.0530*	0.0105*	0.0119*
	(0.86)	(0.40)	(0.40)	(8.21)	(-1.32)		(0.31)	(-2.38)	(2.04)	(2.23)
OWN CELLPHONE	0.0511**	0.0216	0.0216	0.0887***	0.050***		0.0225**	0.0324***	0.111***	0.0897***
	(2.92)	(1.32)	(1.37)	(5.35)	(3.61)		(2.67)	(3.54)	(5.79)	(3.75)
CREDIT ACCESS					0.020		0.0106	0.0190	-0.0154	-0.0683
					(0.58)		(0.07)	(0.96)	(-0.31)	(-1.15)
HH SIZE	0.0183*	0.0171*	0.0171*	0.161***	0.014*		0.0137	0.0182	0.0185	0.0615
	(2.57)	(2.33)	(2.35)	(6.69)	(2.35)		(1.40)	(1.64)	(1.94)	(0.60)
FAW	0.106**	0.108***	0.108**	0.119**	0.149***	0.057*	0.0242	0.0488**	0.265***	0.207***
	(3.26)	(3.31)	(3.29)	(2.71)	(4.61)	(2.43)	(-1.27)	(2.75)	(4.40)	(3.37)
LR(χ^2)	2218.79***	3384.91***	16.58***	1493.74***	***	***	2803.66***	5012.04***	***	***
N	2525	2525	2525	2525	2525	2525	1289	1236	1289	1236

Note: t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$

3.3.3 What is the effect of FAW and IPM practices on farm productivity?

In any farming system, household adoption of IPM –related practices is motivated by the utility gained on the farm productivity. Accordingly, this study examines the effect of IPM practices on farm productivity. Table 3.3, thus, presents results of the ESR model, which measures the effect of FAW and IPM -related practices on farm productivity in the study area. Columns (1-3) report results from the ESR model, based on a maximum likelihood estimation (MLE), two step, and control function, respectively. Columns (4- 5) indicate ESR econometric output from the ESR for adopters and non-adopters, respectively, as proposed by Lokshin and Sajaia (2004). Columns (6 - 7) show results for MESR and PESR models, correspondingly. Columns (8 – 9) results are based on the fixed and random effect panel models. Column (10) presents estimates from the panel based SFA. Columns (11 – 14) present estimates from the binary and multinomial ESR models for 2016 and 2020, respectively. All the models indicate variables with the same expected signs, but demonstrating some slight difference in magnitude of influence on farm productivity across factors of interest, namely, FAW. The interpretation of the results is based on Columns (4), (5), (6), and (7) and the rest are used a robustness check.

Based on the estimated results in Column (4) and (5), the FAW has an expected sign and significantly reduce farm productivity by 7 and 15 percent between adopters and non-adaptors, ceteris paribus, respectively. These results are also the same as when the study estimates them through the PESR in Column (7), where FAW reduces farm productivity by 12 percent among households affected by FAW, holding all other factors constant. The FAW feed on vegetative and reproductive structures of the crops, resulting into excessive crop damage (MoAIWD, 2018). These results are in accordance with Abraham et al. (2017), Day et al. (2017) and Tambo et al. (2021).

Besides, the study observes a positive effect of IPM –related practices on farm productivity. Adoption of various IPM –related practices enhance farm productivity by 21 percent, ceteris paribus (see Column 7). Correspondingly, Column (6) estimates revealed that multiple adoption of IPM practices increases the probability of improving farm productivity from 34 percent to over 160 percent, holding all other factors constant. Similarly, Columns (3) and (4) depicted that farm-size, chemical fertilizer, and improved crop varieties substantially increase farm productivity in the study area. An increase in farm-size by one acre enhance farm productivity by 24 and 5 percent for adaptors and non-adopters, ceteris paribus, respectively. Chemical fertilizer improves farm productivity by 10 percent for adopters and 5 percent for non-adopters. Equally important, Column (7) shows that improved crop varieties and chemical fertilizer augment farm productivity by 31 and 17 percent, ceteris paribus, individually. These results are in line with Romeris (2019) who reports improved crop varieties acting as FAW biological control measures.

Furthermore, farm-level characteristics play varying contributions to towards farm productivity at household level (see Column 7). The study notes that poor soil qualities are less likely to improve farm productivity than good soil quality and this is heavily felt for non-adopters of IPM –related practices. These results are in accordance with Fisher et al. (2018), who indicate that households with poor soils do not have any IPM –related practices in their farms. However, Day et al. (2017) suggest that households with poor soils should attempt adopting the IPM –related practices to improve soil structure, texture, and fertility.

Table 3. 3 : **Results of the ESR models: The effect of the FAW and IPM adoption on farm productivity in Malawi**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	ESR MLE	**ESR 2SLS**	**ESR CONT**	**ESR NADAPT**	**ESR ADAPT**	**MESR**	**PESR**	**FE**	**RE**	**SFA BC-95**	**ESR 2016/2017**	**ESR 2019/2020**	**MESR 2016/2017**	**MESR 2019/2020**
LOG(FARMSIZE)	0.238***	0.222***	0.222***	0.0540	0.244***	0.221***	0.300***	0.113*	0.173***	0.467***	0.0127	0.268***	0.127*	0.128*
	(16.25)	(12.12)	(11.63)	(0.54)	(12.86)	(14.58)	(11.37)	(2.28)	(4.65)	(18.73)	(0.12)	(5.67)	(2.48)	(2.36)
LOG(LABORDAYS)	0.147***	0.131***	0.131***	0.819**	0.0701**	0.144***	0.068***	0.156	0.153*	0.0462	0.0600	0.239**	0.150**	0.132**
	(9.39)	(6.81)	(6.75)	(2.85)	(3.20)	(9.10)	(3.69)	(1.84)	(2.36)	(0.97)	(0.54)	(2.78)	(3.15)	(3.25)
LOG(FERTILIZER)	0.0619***	0.0315*	0.0315*	0.0496***	0.101***	0.057***	0.167***	0.240***	0.253***	0.216***	0.0788	0.0519	0.112***	0.160***
	(10.89)	(2.47)	(2.34)	(4.31)	(13.56)	(9.65)	(14.84)	(11.47)	(15.89)	(20.09)	(1.69)	(1.43)	(6.18)	(8.56)
LOG(SEED)	0.0557**	0.0969***	0.0969**	0.387*	0.00279	0.0561**	0.313***	0.763***	0.798***	0.177***	0.932***	2.377***	0.344***	0.427***
	(2.86)	(3.55)	(3.21)	(2.47)	(0.11)	(2.90)	(9.11)	(25.77)	(34.87)	(12.87)	(4.23)	(35.44)	(6.27)	(8.77)
LOAMY SOIL	-0.070**	-0.165***	-0.16***	-2.407***	-0.0126	-0.092**	-0.0568	0.751***	0.634***	0.498***	-0.307	-0.196	-0.102	-0.247*
	(-3.13)	(-3.84)	(-3.68)	(-4.00)	(0.06)	(-3.21)	(-1.15)	(7.35)	(8.23)	(9.08)	(-1.20)	(-0.94)	(-1.16)	(-2.50)
SANDY SOIL	-0.0412	-0.118**	-0.118**	-3.238**	-0.0238	-0.0642*	-0.0228	0.612***	0.470***	0.466***	-0.748**	-0.159	-0.239**	-0.0229
	(-1.79)	(-3.05)	(-2.96)	(-2.80)	(0.13)	(-2.25)	(-0.45)	(5.37)	(5.55)	(7.54)	(-2.79)	(-0.92)	(-2.61)	(-0.23)
FAIR SOIL	-0.113***	-0.146***	-0.14***	-2.091*	-0.139	-0.11***	-0.16***	0.473***	0.399***	0.0494	-0.112	-0.142	-0.0914	-0.287***
	(-6.41)	(-6.09)	(-5.84)	(-2.42)	(-1.90)	(-6.29)	(-3.69)	(5.12)	(5.70)	(1.00)	(-0.88)	(-1.25)	(-1.25)	(-3.38)
POOR SOIL	-0.171***	-0.215***	-0.21***	-0.742***	-0.120*	-0.16***	-0.177**	-0.56***	-0.42***	-0.046	-0.247	-0.196	-0.141	-0.218
	(-6.92)	(-6.48)	(-6.24)	(-4.04)	(-2.04)	(-6.52)	(-3.05)	(-4.27)	(-4.29)	(-0.66)	(-1.18)	(-1.22)	(-1.38)	(-1.90)
GENTLE SLOPE	-0.0723	-0.0284	-0.0284	-0.867***	-0.0154	-0.0084	-0.125**	0.218*	0.148*	0.0555	0.0744	0.0767	0.0805	-0.0997
	(0.40)	(-1.14)	(-1.08)	(-4.37)	(-0.02)	(-0.43)	(-2.87)	(2.34)	(2.07)	(1.11)	(0.64)	(0.81)	(1.09)	(-1.20)
STEEP SLOPE	-0.0738	-0.0398	-0.0398	-0.168***	-0.0733	-0.0161	-0.0834	-0.098	-0.065	-0.055	-0.0538	-0.188	0.0859	-0.180
	(0.03)	(-1.09)	(-1.05)	(-3.55)	(0.73)	(-0.55)	(-0.13)	(-0.66)	(-0.59)	(-0.68)	(-0.34)	(-1.31)	(0.80)	(-1.32)
FAW	-0.06***	-0.085***	-0.08***	-0.148	-0.0647*	-0.14***	-0.122**	-0.78***	-0.85***	-0.43***	-0.0631	-0.031	-0.314***	-0.317***
	(-3.52)	(-3.84)	(-3.84)	(-1.03)	(-2.14)	(-6.61)	(-2.78)	(-8.01)	(-11.8)	(-8.33)	(-0.49)	(-0.34)	(-3.46)	(-3.73)
FAW*IPM	0.061***	0.056***	0.056***					0.036	0.071***	0.064***				
	(2.97)	(2.27)	(2.75)					(1.38)	(3.50)	(3.30)				
IPM ADAPTATION														
ONE PRACTICE	0.201*	0.850***	0.850**			0.0650	0.210*	0.316***	0.445***	0.535***	0.591***	0.102	1.289***	1.234***
	(2.20)	(3.32)	(3.13)			(0.93)	(2.13)	(10.56)	(15.18)	(7.98)	(3.75)	(0.13)	(7.70)	(6.53)
TWO PRACTICES						0.341**							2.342***	2.330***
						(2.71)							(8.69)	(7.05)
THREE PRACTICES						0.756***							3.455***	3.479***
						(4.02)							(8.93)	(7.18)
FOUR PRACTICES						1.604***							4.735***	4.793***
						(4.63)							(9.02)	(6.64)
LR(χ^2)	2218.79***	3384.91***	16.58***	1493.74***	1493.74***	***	***	122.11***	2841.66***	2652.03***	2803.66***	5012.04***	***	***
N	2525	2525	2525	2525	2525	2525	2525	2525	2525	2525	1289	1235	1289	1235

Note: t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.3.4 What is the impact of IPM –related practices on food security?

In rural areas, the main source of livelihood is crop production (MoWAID, 2018, NPC, 2021). Accordingly, the study investigates the impact IPM –related practices on the household food security using the maximum likelihood ESR treatment effect. Table 3. 4 shows the effect of various IPM –related practices between adaptors and non-adaptors. In general, the multiple adoption of various IPM –related practices significantly improve household food security by four times and there was substantial difference between the adopters and non-adopters. This is in line with findings by Tambo et al. (2021) and Shiferaw et al. (2014).

Table 3. 4 : The effect of various IPM practices on household food security

	NON-ADAPTORS	ADOPTORS	DIFFERENCE	%TAGE CHANGE
SWC	1.04	6.54	***	496.2%
MULTIPLE ADOPTION	1.32	7.85	***	456.1%
INTERCROPPING	1.92	8.37	***	298.4%
COVER CROPPING	3.73	7.29	**	101.1%
AGROFORESTRY	0.04	5.62	***	99.3%
CROP RESIDUES	4.21	6.02		43.9%
TIMELY PLANTING	3.93	5.27		36.4%
IMPROVED VARIETIES	4.29	5.56		11.7%
MARGINAL LAND	5.86	1.58	***	-71.3%
FALLOWING	4.94	1.88	***	-62.6%
PESTICIDES	4.54	2.66	*	-37.2%

Note: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$

In particular, the study finds that each IPM practice significantly improves the household food security. For example, the soil and water practices, such as vetiver glasses and lime, enhance household food security by almost five times. Intercropping also noticeably increase household food security by approximately three times. In addition, mulching, agroforestry, crop residues, timely planting, and improved crop varieties augment household food security by 101, 99, 44, 36, and 12 percent, respectively. Controversy, marginal land cultivation (71%), fallowing (63%), and chemical pesticides (37%) reduce household food security and these findings are in line with Tambo et al. (2019) and Day et al. (2017).

3.4 Conclusions and Key Policy Recommendations

This study investigates the effect of FAW and IPM -related practices on farm productivity. The study uses data from an integrated household panel survey, gathered by the NSO and the World Bank between 2010 and 2020. In dealing with the potential endogeneity, the study adopts the ESR model to estimate the actual effect of FAW and IPM –related practices on farm productivity, and eventually household food security. The study results reveal that 51 percent of households in 2010 - 2020 experience FAW. Accordingly, households undertake various IPM –related practices to control the effect of FAW, namely, sustainable land management, intercropping, and timely planting. IPM –related practices such as marginal cultivation harboured FAW, resulting into reduced farm productivity and household food security.

Results from an ESR model show that FAW have significant and negative influence on farm productivity, thereby food security. On the one hand, the panel-based ESR model results reveal that FAW reduce the farm productivity by 12 percent, ceteris paribus. On the other hand, households undertaking IPM -related practices enhance farm productivity by 21 percent, while holding all other factors constant. Multiple adoption of IPM –related practices augments farm productivity by 160 percent based a multinomial ESR model, ceteris paribus. Furthermore, the study finds that characteristics such as farm size, improved crop varieties, loamy and sandy soil types, gentle, credit accessibility, and experience of FAW enhance the probability of adopting the IPM related practices. This study also notes that access to extension services considerably enhance household adoption of IPM –related practices by 14 percent, while credit access improved the likelihood of adopting IPM –related practices by 26 percent, ceteris paribus. The study also finds improved crop variety augmenting the adoption of IPM –related practices.

These results are relevant to the SSA and Malawi smallholder agriculture, where FAW have recently invaded substantial number of crop-farms, resulting in low farm productivity. If no policy is actioned to manage the FAW, the pest infestation would further push households into chronic poverty and hunger. Moreover, the study observes the use of IPM practices as ideal as most rural households do not have formal education and have limited access to extension services. Otherwise, rural households may abuse the use of chemical pesticides, which is harmful to human health and the environment. Hence, this study recommends the promotion of the IPM-led approach, which may likely minimise the unsustainable procurement and use of chemical pesticides. Additionally, the study suggests the introduction and adoption of the FAW resistant varieties, which have already worked elsewhere in SSA, but are not currently available in the country. Furthermore, the extension services should educate farmers on the risky healthy effect of pesticides in controlling the outbreak and spread of FAW.

Moreover, the study finds most households having cell phones, which could be used as means for reaching out with consistent FAW and IPM –related practices' extension services. For future research, it is proposed that in-depth understanding of the health and environment effect of FAW in the study area.

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CHAPTER FOUR

Examining the impact of tropical cyclones –related floods and sustainable landscape management practices on farm productivity

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Abstract

Tropical Cyclones–related floods (TCRFs) in Malawi have devastating effects on smallholder agriculture, thereby threatening household food security agenda, which is already constrained by poor agricultural practices, low use of improved varieties, unaffordable inorganic fertilizers, and fragmenting landholding sizes. Accordingly, households have engineered and indigenously implemented Sustainable Landscape Management (SLM) practices to contain the adverse effects of TCRFs on farm productivity. Hence, this study interrogates the effect of SLM adoption on farm productivity, while controlling for the potential selection bias through application of the Endogenous Switching Regression Model. Substantively, TCRFs reduce farm productivity by 31 percent, on the one hand, and influence the adoption of SLM practices by 27 percent, on the other hand. After interacting SLM with TCRFs, the study observes SLM adoption augmenting farm productivity by 24 percent, ceteris paribus. These study results demonstrate that SLM adoption is appropriate in enhancing farm productivity under intensifying TCRFs in Malawi.

Key words: Tropical Cyclones –related Floods; Sustainable Landscape Management Practices; Farm Productivity; Endogeneity; Endogenous Switching Regression Model.

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4. Introduction

In Chapter four, the study lays-out the context, regarding the understanding the impact of tropical cyclone related floods on farm productivity in Malawi. It also presents the chapter research motivation; the objectives, and questions guiding the chapter. The chapter further highlights the specific theoretical and empirical framework, namely, the endogenous switching regression model. Lastly, this chapter discusses the results and present the conclusion and the key policy recommendations of the study.

4.1 Study Context

Tropical cyclones (TCs) have devastating economic consequences and are the most destructive natural hazards, globally (Knutson et al., 2020; Zhang et al., 2016). From 1980 to 2018, the TCs have been responsible for nearly half of natural disaster loss worldwide, with damage amounting to USD 2.1 trillion (Munich, 2018; Peduzzi et al., 2012). Over 4300 TCs-related floods (TCRFs) have occurred during the last four decades (IPCC, 2021), presenting both positive and negative effects on the economy (Klomp and Valck, 2014). On the one hand, TCRFs have brought water, improved soil fertility, and increased labour productivity, following the post-disaster' s reconstruction or restoration works (Department of Disaster Management Affairs [DoDMA], 2018; Kunze, 2021). On the other hand, they have eroded soil nutrients and microbial activities, delayed planting time, led to crop failure, and directly destroyed productive infrastructure, thereby negatively generating adverse income shock to the economy (Mohan et al., 2019; Kousky, 2014; Noy, 2009). Globally, adaptation costs towards TCRFs have increased from US$ 7 billion in 1980s to US$ 24 billion in 2000s, and is projected to around US$ 330 billion in 2050 (Thomas et al., 2018; Hirabayash et al., 2010; Charlotte and Clay, 2004).

Household vulnerabilities to TCRFs have become a new normal and been increasing since 1970s (Guha-Sapir and Cred, 2020; Tariq et al., 2020), threatening individual life and livelihoods' assets (Hallegatte and Przyluski, 2010). Scholars have attributed poor site selection, traditional agricultural practices, ever fragmenting landholding sizes, low use of improved varieties, and rapid population growth to amplified household vulnerability (Wu et al., 2012). Furthermore, climate and weather variability is another most influencing factor, in the past, present, and future decades (World Bank, 2020, 2010; DoDMA, 2018). Additionally, long-lasting precipitation and warmer air temperature have augmented the frequency and severity of the TCRFs (Dentener et al., 2006). In SSA, temperatures have increased, leading to high probabilities of TCRFs in the region for the next decades (McCarthy et al., 2021; IPCC, 2018).

Historically, over twenty TCRFs have occurred in Malawi since 1980s (World Bank, 2020). A number of geo-climatic factors are ascribed to causing TCRFs in the country, namely, (i) the influence of the El Niño and La Niña phenomena, (ii) the variability in the water levels of the country's three major lakes, and (iii) the broader hydrological network, have intensified the country's high-level vulnerability to TCs (DoDMA, 2018; World Bank, 2020). In addition, the country's location along the African Rift Valley, rapid population growth, climate and weather variability, and highly dependence on rain-fed agriculture have intensified the country's vulnerability to the TCRFs (World Bank, 2019). The climates in the country are driven primary by annual changes in precipitation association with the movement of the inter-tropical convergence zone (DoDMA, 2018). Not only have the TCRFs destroyed households' assets but have also negatively affected agricultural production and food security (Eckstein et al., 2021). Recently, the country has been ranked among the first-five most affected developing countries by TCRFs in 2010, 2015, and 2019 (Margolies et al., 2019).

In 2010, the country experienced localized flooding damages, caused by tropical cyclone Funso, affected 61,085 people, displaced 24,790 people, killed 14 people, and damaged 3,813 hectares of crop land in the Northern region (DoDMA, 2015). In 2015, the country received the highest records of rainfall, causing flooding, predominately in the Southern region (Giertz et al., 2015). It affected over 1.1 million people, displaced about 0.23 million people, killed about 106 people, while 172 people went reported missing (World Bank, 2021). Economically, the floods led to a total disaster effect of US$ 335 million (DoDMA, 2018). In 2017, tropical cyclone Dineo caused flooding in Malawi and damaged crop land, largely in the Southern region. In 2019, the country suffered heavily from the tropical cyclone Idai and Kenneth (TCIK) - related floods, affecting over 0.9 million people, displaced 0.1 million people, killed 60 people, and injured about 672 people (World Bank, 2020). TCIK also washed away over 100,000 hectare (ha) of cropland, submerged already mature crops, prolonged water lodging, facilitated cobs' maturity, and wilted plants beyond regeneration (World Bank, 2019). It further damaged most crops, viz., maize, sorghum, rice, and cassava (Eckstein et al., 2021), ultimately, reducing agricultural production by 20% and leading to over 4.8 million people food insecure (World Bank, 2020).

The prevailing above realities together with high poverty levels have led to engineering of TCRFs adaptation frameworks in the country (World Bank, 2018; MoAIWD, 2018). After each devastating TCRFs, the State President of the republic of Malawi has declared the country disaster prone and developed national response plans to recover from the disaster effects (World Bank, 2020). The Government, through DoDMA, has developed various disaster risk management (DRM) frameworks, namely, the National Resilience Strategy 2018 -2030 (DoDMA, 2018). The country has also reviewed the disaster preparedness and relief Act to include the DRM actions (World Bank, 2018). Since early 2000s, the country has further financed recovery strategies, costing over US$ 1.0 billion, where the 2019 recovery initiatives demanded about US$ 371 million (World Bank, 2020).

Additionally, the country has adopted and institutionalized the building back better concept, which spearhead climate resilient investments in various sectors, including agriculture such as Sustainable Landscape Management (SLM) –related practices (World Bank, 2020, MoAWID, 2018). Furthermore, several stakeholders, including households, have indigenously engineered and adapted various SLM practices, including flood protection infrastructure, conservation agriculture, and agroforestry measures (McCarthy et al., 2021; Nyadzi et al., 2021). The SLM is defined as the usage of soil and water resources to meet changing population needs and values, while ensuring long-term land –related socioeconomic and ecological services (Smyth and Dumanski, 1993). Practically, the SLM approach combines agricultural practices and policies, aiming at integrating socioeconomic and environmental principles, which simultaneously: (i) maintain and enhance productivity; (ii) reduce crop production risks; (iii) enhance soil capacity to buffer against adverse effects of TCRFs, and eventually, augment food security at household level (FAO, 2021, 2016).

However, the efficacy of these SLM practices has remained doubtful, as TCRFs continue to negatively affect household livelihood assets (World Bank, 2019; World Bank; 2020; MoAIWD, 2018; Chinseu et al., 2018; Cole et al., 2019). Moreover, the adoption rate of the SLM practices still remains very low despite their potential maximum benefits (Fisher et al., 2018). Unfortunately, literature is scanty on the microeconomic impact of TCRFs and SLM adoption (Kunze, 2021; McCarthy et al., 2021). Households implement these SLM practices differently due to asymmetric information and variant socioeconomic profiles (Chinseu et al., 2018). TCRFs have recently become common in Malawi, compromising agricultural productivity, food security, and poverty reduction initiatives (MoAWID, 2018; DoDMA, 2018; Pangapanga and Mungatana, 2021). Nonetheless, fewer studies have evaluated the TCRFs impacts on the farm productivity (World Bank, 2020). Moreover, most studies have only examined socioeconomic characterization of household vulnerability to TCRFs, without further understanding drivers of SLM adoption (McCarthy et al., 2021; Botzen et al., 2019; Cole et al., 2019). Likewise, these studies have partially interrogated the effect of TCRFs at household level (Khataza et al., 2018; Katengeza et al., 2018). Otherwise, they have assessed the effect of TCRFs on single crop, namely, maize, instead of the entire farm productivity (Pangapanga and Mungatana, 2021), which may not thoroughly capture the effect of TCRFs on the farm. Aragon et al. (2019) and Muyanga and Jayne

(2019) have discussed how to capture farm productivity, which accounts for all crops cultivated on the farm.

This study results are therefore relevant to the existing policy making process in three-fold. First, the study highlights the impact of TCRFs on farm productivity, thereby providing a thorough impact of the weather event on farm productivity. Second, the study interrogates factors driving the adoption of SLM -related practices, resulting into DRM programming which mainstreams indigenous knowledge and feedback. Lastly, the study examines the role of SLM –related practices on farm productivity under different episodes of TCRFs. This study differs from the previous assessments by adopting the farm productivity concept to holistically capture the impact of TCRFs on farm productivity. In addition, methodologically, the study adopts the ESR model, which controls for both observable and unobservable heterogeneity associated with the adoption of SLM practices. Furthermore, for robustness checks, the study executes the panel based fixed, random effect, and Cob-Douglas (CD) production models. The study uses the household data, compiled by the National Statistics Office (NSO) and the World Bank between 2010 and 2020. Ultimately, the study results inform the existing Sustainable Development Goals (SDGs) and Malawi Vision 2063 farm productivity initiatives under changing TCRFs episodes in Malawi.

4.2 Research Methodology

4.2.1 Study area, Sampling Strategy, and Data Acquisition

The study is conducted in Malawi, which is located in SSA and shares boundary with Mozambique to the East and South West, Tanzania to the North, and Zambia to the West (McCarthy et al., 2021; Kilic et al., 2021). Figure 1.5 presents the map of Malawi, having three regions and 28 administrative districts (NPC, 2021). Accordingly, districts are subdivided into traditional land administrative authorities, which are further demarcated into enumeration areas, for statistical purposes (NSO, 2020). The country has a sub-tropical climate, which is relatively dry and strongly seasonal, influenced by the inter-tropical convergence zone (Pangapanga and Mungatana, 2021). It has one rainy season, which stretches from November to April. The annual average precipitation varies from 725 mm to 2,500mm. Low-lying areas such as the lower Shire valley and along the lakeshore suffers from tropical cyclone -related floods (TCRFs), almost annually. A winter season is evident from May to August, with mean temperature circulating from 4 to 20 degrees Celsius. A dry season lasts only for two months, namely September and October, where mean temperature varies between 25 and 37 degree Celsius (MoAIWD, 2018).

This study uses household data from the integrated household panel survey (IHPS), compiled by the NSO and the World Bank between 2010 and 2020. The survey is representative and adequate to explain variations at the national, regional, urban-rural, and district levels (NSO, 2012). The dataset includes randomly sampled farm households, who received both the household and the agricultural questionnaires (Kilic et al., 2015). Households operate at least one farm land and cultivate crops, viz., maize, sorghum, millet, potatoes, cassava, tobacco, and leguminous crops (NSO, 2012, 2014, 2018, 2020). Farm productivity is thoroughly measured when all cultivated crop on the farm are captured (Aragon et al., 2019). Thus, following Muyanga and Jayne, 2019 and Aragon et al. (2019), the study derives farm productivity by dividing the value of the agricultural output of all crops by the area of land cultivated. Additionally, the IHPS captures data on seeds, organic manure, inorganic fertilizer, and labor in personal days, pesticides, and soil characteristics. The IHPS also collects socioeconomic information, namely, age, education, mobile-phone, credit, and access to extension services, and SLM –related practices (namely, zero disturbance tillage, organic manure, soil and water conservation structures, agroforestry, inorganic fertilizers, and improved crop varieties) (Kilic et al., 2012; McCarthy et al., 2021). Besides, the IHPS asks each household to self-report whether they have experienced any TCRFs or not. Accordingly, in this study, any household, affected by TCRFs is denoted as TCRFs affected households (TAH), and otherwise, non TAH (NTAH). Any household undertaking either one or more SLM –related practices in their farm is referred as an adopter in this study. Similarly, Table 1.1 provides a list of definitions, measurements and expected signs of various variables used in this study. The definitions and measurements of the variables are in accordance with the NSO (2020), Midingoyi et al. (2019), Katengeza et al. (2018), Khataza et al. (2018), and Teklewold et al. (2013).

4.2.2 Theoretical and Empirical Framework

Adoption of Sustainable Landscape Management (SLM) –related practices is a household response from past experiences of TCRFs (DoDMA, 2018; Di Falco et al., 2014). The adoption decision depends on the household ability, motivation, and derived utility values (Powers, 1993; Madala, 1983, Blundell and Powell, 2004; Chamberlain, 1980). The expected utility theory informs the modelling of the effect of the SLM –related practices on farm productivity (McFadden, 1974). The SLM practices include minimum tillage, fallowing, box ridges, contour riding, mulching, intercropping, cover crops, and crop residuals. Household choice of these practices is dependent on several factors, including household characteristics, namely, age, education, gender, access to credit, extension services, farm attributes, and tropical cyclone related floods. Theoretically, the expected utility of adopting SLM related practices is latent (McFadden, 1974) and can be observed through farm productivity.

Following Lokshin and Sajaia (2004) and Wooldridge (2010), the study lets $U_{it}^{*}(.)$ denotes the latent utility obtained from SLM adoption (A_{ijt}). While A_{ijt} can be specified as in equation (1):

$$A_{ijt} = \begin{cases} 1 & if\ \vartheta_1 x_{1it} + v_{1i} + \mu_{1it} > 0 \\ 0 & if\ \vartheta_2 x_{2it} + v_{2i} + \mu_{2it} < 0 \end{cases} \qquad [1]$$

where A_{ijt} is the SLM adoption status of household i across SLM practices j in time t and denotes one if an individual household can apply any of the SLM –related practices in their farm as prior-displayed, and otherwise, zero, in which $i\ represents\ 1, 2, 3, \dots, N$ households, while $j\ is\ indexed\ as\ 1,2,3 \dots, J$ choices. In this study, a household adopting at least one of the SLM –related practices is called an adopter. The x_{ijt} is a vector of observable characteristics which determine SLM adoption status, viz. gender, age, education, and literacy level of the household, soil characteristics (soil type, quality, and slope), and experience of TCRFs. The ϑ_j is the vector of unknown parameters to be estimated by the model, the v_{ij} is the panel-level random effect for adoption decision and μ_{ijt} is the observation-level adoption error term (Wooldridge, 2010). The SLM adoption (A_{ijt}) enhances farm productivity, thus improving agricultural income and food security (McCarthy et al., 2021). Following Murtazashvili and Wooldridge (2016), the SLM adoption decision leads to two farm productivity (k_{jit}) outcomes as in equation (2). Farm productivity is derived through combining all crop value in the farm to maize equivalent, following Muyanga and Jayne (2019) and Oregano et al. (2019). Crop value is generated through multiplying each crop produce in kg with its unit price in Malawi Kwacha, except for maize. Thereafter, this crop value of the other crops is converted to maize equivalent in terms of physical production qualities.

$$k_{jit} = \begin{cases} k_{1it} = \vartheta_1 x_{1it} + \omega_1 \hat{A}_{1it} + r_{1i} + \varepsilon_{1it} & if \ A_{1it} = 1 \\ k_{2it} = \vartheta_2 x_{2it} + \omega_2 \hat{A}_{2it} + r_{2i} + \varepsilon_{2it} & if \ A_{2it} = 0 \end{cases} \quad [2]$$

where $k_{jit}, x_{jit}, \hat{A}_{ijt}$, and ϑ_j are as previously defined. The $\hat{A}_{ijt}$ is the estimated generalized residuals from equation (1) (Blundell and Powell, 2004). The r_{2i} is the panel-based random effect for the adoption decision and the ε_{jit} is the observation-level error term, and are bivariate norm. The ε_{jit} and μ_{it} have a trivariate normal distribution, with mean vector zero and the covariance matrix (Ω) (see Powers, 1983) as in equation (3):

$$\Omega = \text{covariance}\ (\mu, \varepsilon_{1it}, \varepsilon_{2it}) = \begin{bmatrix} \sigma_\mu^2 & \sigma_{\mu 1} & \sigma_{\mu 2} \\ \sigma_{\mu 1} & \sigma_1^2 & . \\ \sigma_{2\mu} & . & \sigma_2^2 \end{bmatrix} \quad [3]$$

where σ_μ^2 = variance (μ), σ_1^2 = var (ε_{1it}), σ_2^2= variance (ε_{2it}), $\sigma_{\mu 1}$ = covariance (μ, ε_{1it}), and $\sigma_{\mu 2}$ = covariance (μ, ε_{2it}). It is assumed that σ_μ^2 equal to 1 and is estimable only up to a scalar factor (Khonje et al., 2015, 2018; Wooldridge, 2010). Since k_{1it} and k_{2it} are never observed simultaneously, the covariance between ε_1 and ε_2 is not defined (Lokshin and Sajaia, 2004; Maddalla, 1983). The covariance between ε_{jit} and μ_i is not defined as k_{1it} and k_{2it} are never observed simultaneously (Lee, 1982). Thus, the error terms of ε_{1it} and ε_{2it} of the outcome equation conditioned on the SLM adoption equation are non-zero (Lokshin and Sajaia, 2004), resulting in inefficient estimates when using any ordinary least square (OLS) estimation.

Most studies have assessed the effect of household adoption decision using the PSM (Teklewold et al., 2013; Asfaw et al., 2016, 2012; Kassie et al., 2018; Khonje et al., 2015). However, the PSM keeps households which have a common support between the SLM adopters and non-adopters (Rosenbaum et al., 1983), thus failing to capture unobservable characteristics. While the ESR model controls for the potential observable and unobserved heterogeneity through incorporation of the Inverse Mills Ratios (IMRs) (Madala, 1983). Through the Mundlak Approach, the standard ESR approach can be extended to a panel-data structure (Mundlak, 1978).

The ESR model is estimated simultaneously in two stages (Heckman, 1978). First, it generates the SLM adoption' s IMRs through estimation of the probit model, which account for unobservable heterogeneity (Wooldridge, 2010). Second, the OLS method assesses the effect of SLM adoption, with IMRs or generalized residuals as additional variables to control for any potential selection bias (Kassie et al., 2018). The study, thereafter, bootstraps the standard errors to control for heteroscedasticity arising from incorporation of the IMRs, (Murtazashvili and Wooldridge, 2016). In other words, households first adopt the SLM practice. Second, households derive improved farm productivity due to investments in the SLM practices. However, the adoption of SLM practices is influenced by several households and farm-level characteristics.

According to Murtazashvili and Wooldridge (2016), the two panel-based ESR regimes in equation (2) can be combined as in equation (4):

$$k_{it1} = \vartheta_j x_{it1} + (\vartheta_1 - \vartheta_2)\, x_{it1}k_{it3} + \omega_j \hat{A}_{it1} + (\omega_1 - \omega_2)\hat{A}_{it1}k_{it3} + r_{i1} + k_{it3}(r_{i1} - r_{i2}) + k_{it3}(\varepsilon_{it1} - \varepsilon_{it1}) + \varepsilon_{it1} \qquad [4]$$

where k_{it3} is the endogenous switching variable at the basis of the sample selection interacting with both time constant and time varying variables. While $k_{ijt}, \vartheta_j, \tau_j, \omega_j, r_j, x_{ijt}\ and\ \hat{A}_{it1}$ are as formerly described and the whole model becomes consistent only after including the time varying variables' mean values (Mundlak, 1978), as additional covariates as in equation (5):

$$k_{it1} = \vartheta_j x_{it1} + \tau_j x_{it1}k_{it3} + \omega_j \hat{A}_{it1} + \gamma_j \hat{A}_{it1}k_{it3} + r_{i1} + k_{it3}(\overline{\mathrm{G}})r_1 + k_{it3}(\overline{\mathrm{G}})\varepsilon_{it1} + \varepsilon_{ijt} \qquad [5]$$

where τ_j is a vector of the differences $(\vartheta_1 - \vartheta_2)$ of the coefficients of household and farm-level explanatory variables in the two regimes of the SLM adoption (Murtazashvili and Wooldridge, 2016). The $(\overline{\mathrm{G}})$ is the Mundlak device, which is the mean of the explanatory variables, while ε_{ijt} is a vector of idiosyncratic errors of the Mundlak relationship (Mundlak, 1978). Other parameters and variables in equation (4) are as prior discussed. The treatment effect, γ_j reduces to the difference $(\omega_1 - \omega_2)$ in intercepts between the two regimes if the SLM adoption is a random practice (Lokshin and Sajaia, 2004). After incorporating the Chamberlain-Mundlak technique, the study derives the treatment effect, which is the expected value from a panel based ESR correction model (Murtazashvili and Wooldridge, 2016) as in equation (6):

$$\mathrm{E}\left(k_{ijt} \middle| k_{it3}, x_{ijt}\right) = h\left(\vartheta_j x_{it1} + \tau_j x_{it1}k_{it3} + \omega_j \hat{A}_{it1} + \omega_j \hat{A}_{it1}k_{it3} + r_{i1} + k_{it3}(\overline{\mathrm{G}})r_1 + k_{it3}(\overline{\mathrm{G}})\varepsilon_{it1} + \varepsilon_{ijt}\right)$$

$$= k_{it3}\lambda\big(\vartheta_j x_{it1} + \tau_j x_{it1}k_{it3} + \omega_j \hat{A}_{it1} + \omega_j \hat{A}_{it1}k_{it3} + r_{i1} + k_{it3}(\overline{\mathrm{G}})r_1 + k_{it3}(\overline{\mathrm{G}})\varepsilon_{it1} + \varepsilon_{ijt}\big)$$
$$- (1 - k_{it3})\lambda(-\vartheta_j x_{it1} - \tau_j x_{it1}k_{it3} - \omega_j \hat{A}_{it1} - \omega_j \hat{A}_{it1}k_{it3} - r_{i1} - k_{it3}(\overline{\mathrm{G}})r_1$$
$$- k_{it3}(\overline{\mathrm{G}})\varepsilon_{it1} - \varepsilon_{ijt}) \qquad [6]$$

where $h(.)$ is the generalized residual function, $\lambda(.)$ is the IMR function while other parameters and variables in equation (5) are as previously defined. The IMR term is characterized with zero mean and does not correlate with any of the model explanatory variables. The study also estimates the impact of SLM adoption through generating the conditional actual and counterfactual expectations as in equation (7) and (8) (Wooldridge, 2010).

$$\mathrm{E}(k_{it1}|k_{it3}, x_{1it} = 1) = \sigma_{\mu 1}\frac{\phi(\vartheta_1 x_{it1} + \tau_1 x_{it1}k_{it3} \dots)}{\Phi(\vartheta_1 x_{it1} + \tau_1 x_{it1}k_{it3} \dots)}$$
$$\equiv \vartheta_1 x_{it1} + (\overline{\mathrm{G}})r_1 + \Gamma_1 \hat{A}_{it3} \qquad [7]$$
$$\mathrm{E}(k_{it2}|k_{it3}, x_{2it} = 0) = \sigma_{\mu 2}\frac{\phi(\vartheta_2 x_{2it} + \tau_2 x_{2it}k_{it3} \dots)}{(1 - \Phi)(\vartheta_2 x_{it2} + \tau_2 x_{it2}k_{it3} \dots)}$$
$$\equiv \vartheta_2 x_{2it} + (\overline{\mathrm{G}})r_2 + \Gamma_2 \hat{A}_{it3} \qquad [8]$$

where $\phi(.)$ and $\Phi(.)$ are standard normal density functions (Manda et al., 2015; Wooldridge, 2010). Where $\hat{A}_{it3}$ is the generalised residuals which account for the endogeneity of the selection variable, while x_{itj} represents household and farm -level explanatory variables. The $\vartheta, r,$ and Γ are vectors of unknown parameters to be estimated by the model, that is after bootstrapping the standard errors to control for inclusion of $h(.)$ (Murtazashvili and Wooldridge, 2016). Other parameters and variables in equation (7) and (8) are as previously defined. The study examines the role of the TCRFs and the SLM adoption on farm productivity, through estimating the average treatment effect on the treated (ATET) and the average treatment effect on the untreated (ATU). Following Midongoyi et al. (2019) and Murtazashvili and Wooldridge (2016), the study estimates the ATET and ATU as in equation (9) and (10):

$$\mathrm{ATET} = \mathrm{E}\big(k_{ij1}\big|k_{it3}, x_{ijt} = 1\big) - \mathrm{E}\big(k_{ij1}\big|k_{it3}, x_{ijt} = 0\big) \qquad [9]$$
$$\mathrm{ATU} = \mathrm{E}\big(k_{ij2}\big|k_{it3}, x_{ijt} = 1\big) - \mathrm{E}\big(k_{ij2}\big|k_{it3}, x_{ijt} = 0\big) \qquad [10]$$

In practice, households adopt at least one of the SLM practices in the same farm, which arises to a multivariate binary or multinomial choice regression (Teklewold et al., 2013). On the one hand, any Poisson model is suitable when the treatment or the dependent variable is a count data (Wooldridge, 2010). It is appropriate when the adoption of one SLM practice does not alter the likelihood of an alternative practice

(Plan, 2014; Wollni et al., 2010). In this study, the adoption of one SLM practice may likely alter the likelihood of adopting any alternative. For example, cereal –legume intercropping may alter the likelihood of practicing agroforestry related SLM techniques. On the other hand, this study employ the panel-based ESR model to capture the effect of SLM adoption on farm productivity (Kassie et al., 2018).

The study fits the ESM model using the full information to estimate the maximum likelihood (FIMLM), instead of the two-step least square or the limited information maximum likelihood estimators. The later methods result in heteroskedastic residuals and are potentially cumbersome (Lokshin and Sajaia, 2004). While the FIMLM uses the joint normality of the error terms and simultaneous estimation to derive consistent standard errors (Wooldridge, 2010). For robustness of the results, the study run binary probit, multinomial ordered probit, and panel-based ESR, Cobb Douglass, fixed and random effect models.

Empirically, the study' s selection equation takes on the probit regressions and the outcome equation assumes the continuous or ordered regression (Kibira et al., 2015). Previous studies (Katengeza et al., 2018; Khataza et al., 2018; Teklewold et al., 2013) have informed the specification of the ESR model for the study. Accordingly, the study includes factors of production (such as fertilizer, labour, seeds), farm characteristics (i.e. soil quality, type, and slope), and TCRFs as explanatory variables in the outcome equation, where farm productivity is the dependent variable. Studies by Muyanga and Jayne (2019) and Aragon et al (2019) include farm size and personal-days as the most critical explanatory factors for farm productivity. In addition, this study uses education, gender, age, mobile-phones, credit access, and household size as additional explanatory variables in the selection equation, where the adoption decision of SLM –related practices is the dependent variable. Following Midingoyi et al. (2019), the study uses access to extension services as an exclusion restriction variable, which provides information on the benefits of various SLM practices (MoAWID, 2018).

4.3 Results and Discussion

4.3.1 Summary of household characteristics in Malawi

Malawi has very diverse households with different socioeconomic and agricultural profiles (NSO, 2020). Table 4.1 shows the summary statistics of socioeconomic and farm-level characteristics of household affected (TAH) and not affected (NTAH) by the TCRFs in the study area. Seven out of ten households are headed by male, who are, on average, aged 43 years. About 80 percent of household heads have attended some formal education, where slightly above 60 percent of them properly can read and write in any local language, like Chewa, Tumbuka, Kyangonde, Sena, and Lhomwe. On average, household heads have attend formal education. The majority of household heads in the study area have a mobile phone, which they use to access information from fellow farmers, relatives, and extension workers. Accordingly, about 60 percent of households have accessed agricultural extension services. Households have about five members, determining available family agricultural labour (NSO, 2020). Based on the studentized t-statistics in Table 4.1, the study observes no statistical differences in terms of socioeconomic characteristics between TAH and NTAH households and the study findings are in line with NSO (2020) and McCarthy et al. (2021).

Furthermore, households, in the study area, cultivated on 0.50 ha, implying that households have small farm holding sizes for crop production, which may never allocation expansion of agricultural activities. In other words, households may only invest in agricultural –related practices that intensify farm productivity. These results are statistically not difference between TAH and NTAH households (see Table 4.1). Moreover, the study finds that households have fragmented farm sizes due to population pressure, which is in line with the NSO (2020). Besides, slightly above half of the farms have loamy soils, seconded by sandy (26%), and clay soil type (21%). Fifty percent of the farms have good soil quality, followed by fair (37%) and poor (14%) soil quality. Approximately 55 percent of the cultivated farms have flat slope, followed by gentle (36%) and steep (10%) slope. These results determine the type of agricultural practices, which households may adopt to augment farm productivity and are consistent with Pangapanga and Mungatana (2021) and Asfaw et al. (2016).

Additionally, households plant approximately 10 kg per acre of maize seeds equivalent and the application seed rate is not significantly different between TAH and NTAH households. In terms of chemical fertilizer, households apply slightly above 50kg per acre in the study areas, with TAH households applying 20 kg less than what NTAH apply, indicating resource constrained for TAH households. On the one hand, households derive a farm value of 132000 MWK/ha in the study area, where TAH and

NTAH generate 160000MWK/ha and 146000 MWK/ha, respectively. This implies that TCRFs have a negative effect on farm productivity. The t-test also confirms a significant difference in crop output value obtained between TAH and NTAH households. On the other hand, after SLM adoption, adopters have higher crop output values than non-adopter, where SLM adopters and non-adopters obtain 141,000 MWK/ha and 112,000 MWK/ha, respectively (see Table 4.1). This income helps households to procure inputs, necessary for inducing farm productivity.

Table 4. 1 : Summary descriptive statistics of household characteristics between TAH and NTAH in Malawi

	TCS –RELATED FLOODS		SLM		POOLED		DIFFERENCE (T-TEST)	
	NTAH	TAH	NON-ADOPTOR (NAD)	ADOPTOR (AD)	MEAN	STD. DEV.	NTAH v TAH	NAD v AD
GENDER	0.760	0.727	0.744	0.735	0.738	0.44		
AGE	43.09	42.2	40.77	43.26	42.484	16.947		
EDU_CLASS	5.825	5.896	6.334	5.665	5.873	4.598		
MOBILE PHONE	0.853	0.851	0.974	0.797	0.852	1.109		
CREDIT ACCESS	0.164	0.144	0.142	0.154	0.15	0.357		
ACCESS EXTENSION	0.64	0.576	0.551	0.617	0.597	0.491		**
HHSIZE	5.024	4.939	4.976	4.962	4.967	2.262		
OWN LAND	0.591	0.695	0.687	0.650	0.662	0.473		**
LITERACY	0.716	0.688	0.7	0.696	0.697	0.459		
ATTENDED SCHOOL	0.832	0.82	0.817	0.827	0.824	0.381		**
CLAY SOIL	0.227	0.203	0.144	0.241	0.21	0.408	**	
LOAMY SOIL	0.543	0.525	0.367	0.605	0.531	0.499		**
SANDY SOIL	0.275	0.245	0.165	0.295	0.255	0.436		**
GOOD SOIL QUALITY	0.541	0.473	0.347	0.562	0.495	0.5	**	
FAIR SOIL QUALITY	0.363	0.372	0.26	0.418	0.369	0.483		**
POOR SOIL QUALITY	0.159	0.123	0.08	0.159	0.135	0.341	**	**
FLAT SLOPE	0.574	0.545	0.46	0.596	0.554	0.497	**	**
GENTLE SLOPE	0.386	0.347	0.179	0.441	0.359	0.48		**
STEEP SLOPE	0.113	0.086	0.04	0.119	0.095	0.293		**
MULTIPLE ADAPTATION	4.983	4.274	2.56	5.379	4.503	2.216	**	**
OUTPUT VALUE	159,800	146,880	111,690	141,015	131,896.37	55,924.35	**	**
SEED QUANTITY	9.313	9.405	9.233	9.439	9.375	4.049		
NPK FERTILIZER	69.24	61.32	41.26	74.07	63.872	230.5	**	**
FARM SIZE IN HA	0.52	0.483	0.437	0.544	0.495	0.381		

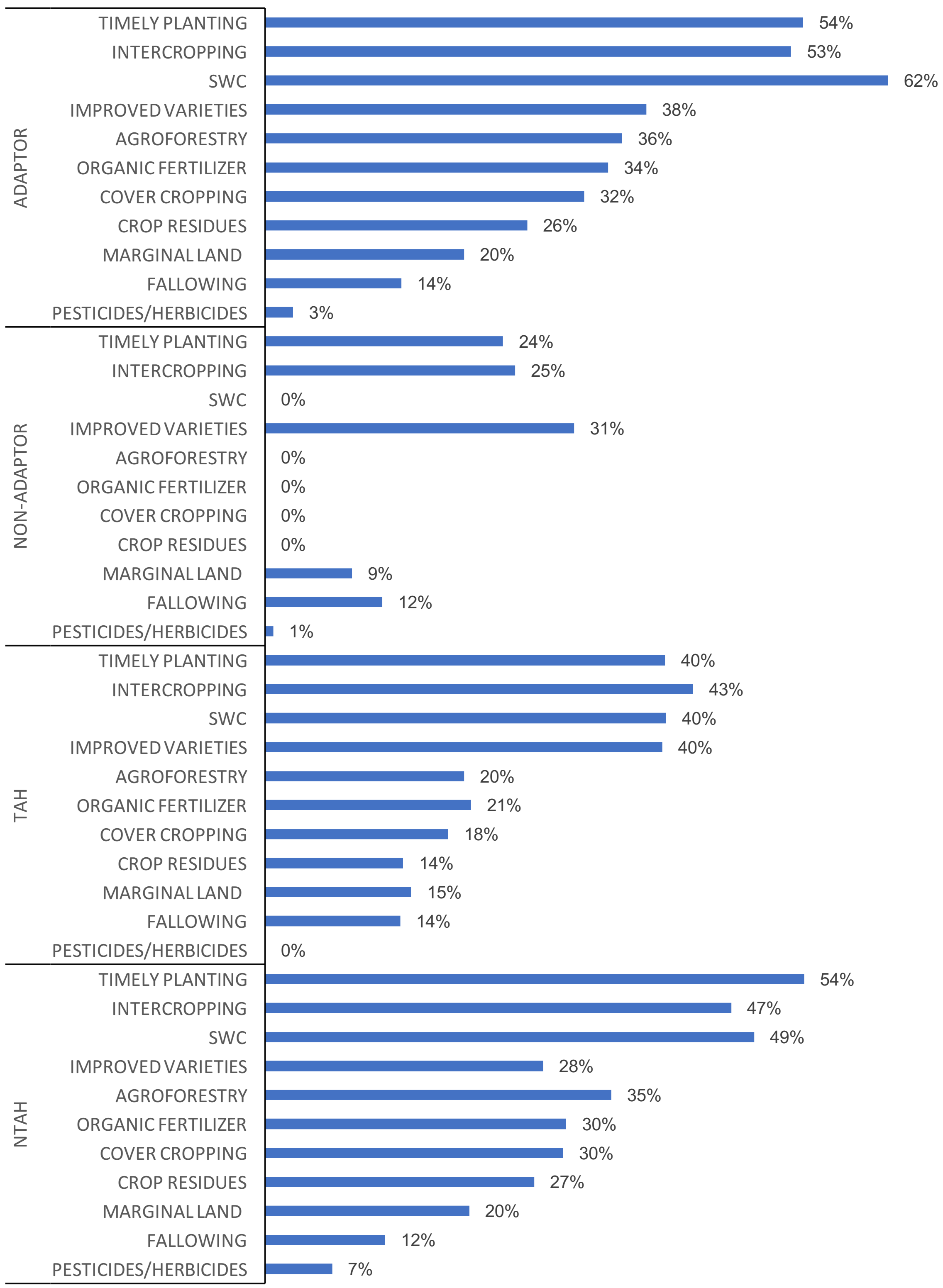

Figure 4.1 Proportional distribution of households adopting SLM practices by TAH, NTAH, Adopters and Non-Adopters

Figure 4.1 presents proportional distribution of households adopting various SLM –related practices across TAH, NTAH, Adopters, and non-adopters. Timely planting, SWC, and intercropping are the most adopted SLM –related practices in the study area. The larger proportion of households adopting SLM practices in NTAH can be attributed to the role of extension services, through government, civil services, farmer to farmer, lead farmers, and mobile phones, in informing households on the fundamental role of SLM under different TCRFs (McCarthy et al., 2021). Among SLM adopters, the study notes that at least one third of the households affected by TCRFs have adopted SWC, timely planting, intercropping, improved varieties, agroforestry, and cover cropping. This indicates that the SLM –related practices have an influence important role in augmenting farm productivity in the study area (McCarthy et al., 2021; MoAIWD, 2018).

Similarly, Figure 4.2 shows various SLM -related practices adopted at household level between 2010 and 2020. The study finds that soil and water conservation (SWC) measures (67%), namely, erosion control bunds and vetiver grasses are the most adopted practice to manage the effect of TCRFs in the study area, followed by intercropping (45%), improved varieties (41%), timely planting (40%), organic manure (23%), cover cropping (21%), agroforestry (20%), cultivation in marginal land (19%), crop residues (16%), and fallowing (14%). Interestingly, there is an increase in the proportion of households implementing various SLM –related practices in managing the adverse effects of TCRFs between 2010/2011 and 2019/2020. For example, the proportion of households using the SWC to contain the effect of TCRFs has increased from 50 percent in 2010 to slightly above 70 percent in 2019/2020. The number of households timely planting various crops has also increased from under one percent in 2010 to 40 percent in 2019/2020. Community interviews reveal that household previous experience of the TCRFs force them to opt for timely planting to avoid crop being submerged with water once TCRFs occur, further delaying crop planting. These results are similar to Kassie et al. (2015), where SLM practices are used to manage adverse effects of TCRFs.

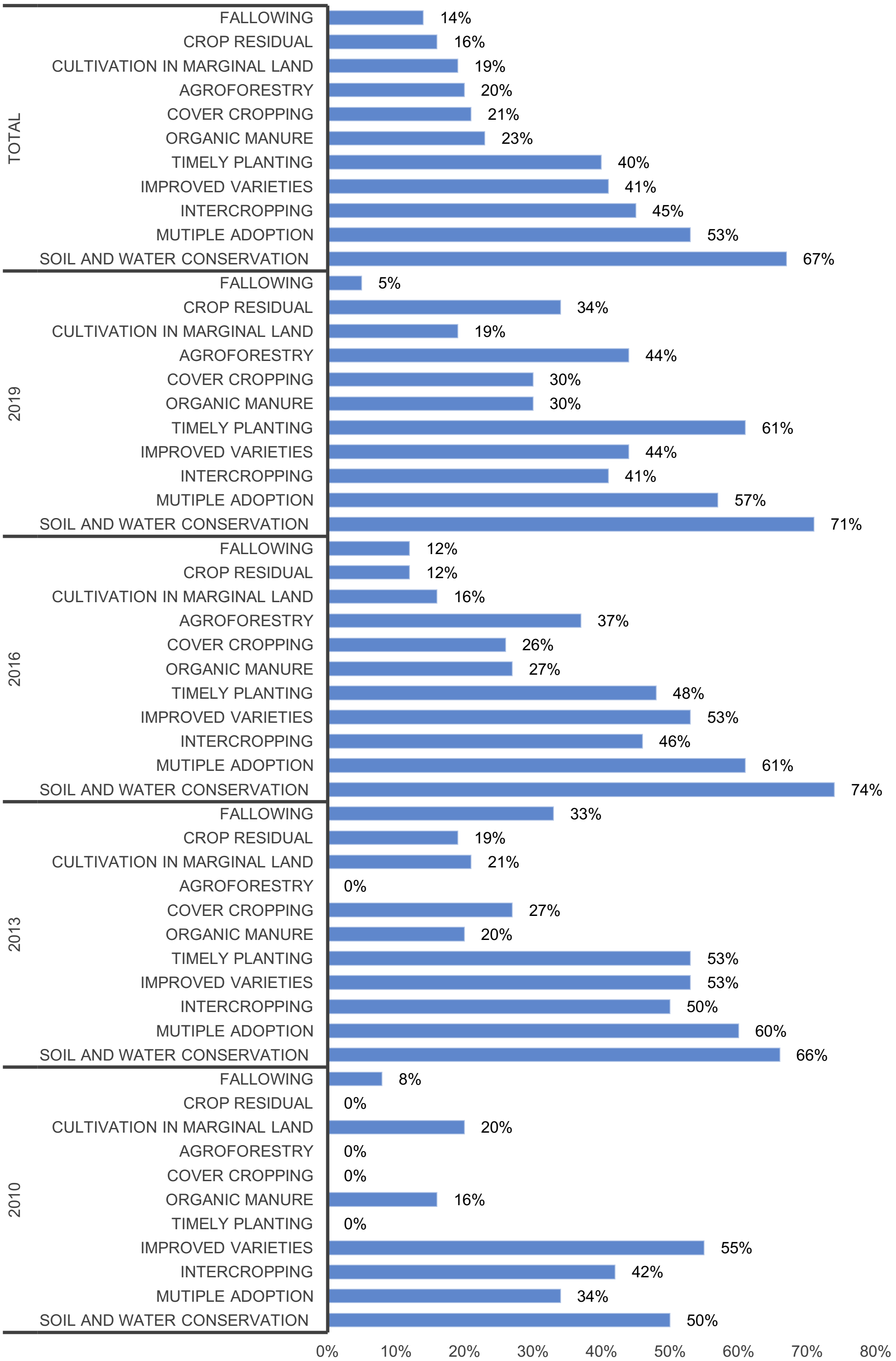

Figure 3. 2 Proportional distribution of households adopting SLM practices: 2016 - 2020

4.3.2 What factors affect the adoption of SLM –related Practices?

Several factors affect the adoption of SLM –related practices. Households adopted various SLM related practices, namely, minimum tillage, crop residues, cover cropping, organic manure application, timely planting, agroforestry, and SWC measures (see Table 4.2). Columns (1), (2), and (3) present regression results from a ESR model, based on a maximum likelihood estimation (MLE), two staged ESR model, and the Wooldridge control function, respectively. Column (4) shows results from the full information maximum likelihood estimation based on Lokshin and Sajaia (2004). Column (5) and (6) presents results for the multinomial ESR (MESR) and the panel based ESR (PESR) models, respectively. Interpretation of the results is based on Column (6) of Table 4.2.

Based on the PESR model, the estimates reveal that TCRFs induce SLM adoption by 27 percent, ceteris paribus (Column 6). Besides, improved crop varieties enhance the probability of adopting SLM –related practices by 2 percent, holding all other factors constant. Similarly, marginal change in farm size by one acre increases the chances of adopting SLM –related practices by 8 percent, ceteris paribus. However, the study finds chemical fertilizer reducing the adoption of SLM practices by 4 percent. This suggests limited complementarity between NPK fertilizer and SLM –related practices. These results are in line with Timothy et al. (2017) findings.

In terms of farm-level characteristics, loamy (37%) and sandy (32%) soils enhance the probability of adopting SLM -related practices by slightly over one-third, ceteris paribus (Column 6). These results are the same across all models (see Column 1-5). Quality soils play an important role in influencing household decision to practise SLM –related practices. The study observes that household with poor soil quality are 33 percent more likely to adopt SLM –related practices than households with good soil quality, while holding all other factors constant. Similarly, households with fair soil quality are 22 percent significantly more likely to undertake any of the SLM -related practices than household farms with good soil quality. The study results show that poor soils require investment in SLM –related practices, which likely improve soil organic matter and texture. Furthermore, gentle and steep slopes are 51 and 60 percent more probable to have SLM –related practices in the study area, respectively. Qualitative data shows that SLM control surface run off, thereby limiting soil erosion and leaching of soil nutrients. These results are consistent across all the models and in line with Thierfelder et al. (2016) and McCarthy et al. (2021).

Socioeconomic characteristics also influence household decision in adopting the SLM -related practices (Column 5). In this study, the adoption decision of the SLM practices improves with the age of the household head by 3 percent, implying the role of long-term experience of TCRFs in changing farming behaviours, ceteris paribus. SLM practices are labour intensive (McCarthy et al., 2021) hence the study find household size to have a positive effect on the adoption rate of SLM –related practices. Information plays a very critical role in influencing household decision to adopt various practices. Accordingly, households with mobile phones are 6 percent more likely to adopt any of the SLM –related practices than their counterparts, while holding all other factors constant. Mobile phones help households have access to climate and weather -related information, especially, on the merits and demerits of various SLM -related practices from fellow farmers, lead farmers, relatives, and extension workers (NSO, 2020). These study results conforms to findings by Chinseu et al. (2018) and Fisher et al. (2018).

Table 4. 2 : Results of the ESR models: Factors influencing the SLM adoption in Malawi

	(1)	(2)	(3)	(4)	(5)	(6)
	ESR-MLE	**ESR-2SLS**	**ESR-CONTROL**	**ESR-FMLE**	**MESR**	**PESR**
LN(FARM SIZE)	0.0812**	0.0468	0.0468		0.0342	0.0896
	(2.63)	(1.50)	(1.49)		(1.52)	(0.41)
LN(LABORDAYS)	0.231***	0.249***	0.249***		0.0822***	0.260***
	(6.71)	(7.17)	(7.38)		(-3.38)	(21.60)
LN(FERTILIZER)	-0.115***	-0.113***	-0.113***		-0.0891***	-0.0351***
	(-14.83)	(-14.47)	(-14.85)		(15.05)	(3.81)
LN(SEED)	0.0359	0.0295	0.0295		0.0471	0.241***
	(0.92)	(0.75)	(0.73)		(1.67)	(15.52)
LOAMY SOIL	0.556***	0.586***	0.586***	0.706***	0.557***	0.371***
	(14.81)	(15.50)	(15.61)	(19.62)	(19.67)	(8.30)
SANDY SOIL	0.523***	0.554***	0.554***	0.643***	0.470***	0.320***
	(12.06)	(12.65)	(12.26)	(14.58)	(15.07)	(6.23)
FAIR SOIL	0.208***	0.222***	0.222***	0.274***	0.223***	0.223***
	(5.82)	(6.15)	(6.07)	(7.61)	(8.55)	(5.35)
POOR SOIL	0.342***	0.363***	0.363***	0.396***	0.298***	0.327***
	(6.47)	(6.79)	(6.52)	(7.17)	(8.19)	(5.39)
GENTLE SLOPE	0.551***	0.542***	0.542***	0.594***	0.296***	0.515***
	(14.88)	(14.48)	(14.15)	(15.88)	(11.21)	(12.01)
STEEP SLOPE	0.585***	0.579***	0.579***	0.612***	0.404***	0.597***
	(9.03)	(8.80)	(8.33)	(8.90)	(9.65)	(7.96)
MALE	-0.0160	-0.0203	-0.0203	-0.0309	-0.121***	
	(-0.44)	(-0.51)	(-0.51)	(-0.79)	(-4.22)	
AGE	0.0254**	0.0371***	0.0371***	0.0369***	0.0330***	
	(2.65)	(3.58)	(3.55)	(3.64)	(4.31)	
AGE_SQUARE	-0.0080**	-0.0153***	-0.0153***	-0.0337		
	(-2.56)	(-3.49)	(-3.41)	(-1.07)		
EDUCATION	0.0736	0.0647	0.0647	0.0292	0.0126***	
	(1.85)	(1.50)	(1.51)	(0.71)	(4.00)	
OWN MOBILE-PHONE	0.0998***	0.0738***	0.0738***	0.0630***	0.0821***	
	(6.14)	(4.24)	(4.47)	(3.74)	(6.21)	
CREDIT ACCESS					0.0993**	
					(2.95)	
HH SIZE	0.0533	0.0472	0.0472	0.0671	0.0532	
	(0.74)	(0.06)	(0.06)	(0.89)	(0.92)	
TCRFs	0.395***	0.426***	0.426***	0.349***	0.483***	0.266***
	(9.07)	(9.49)	(9.85)	(8.20)	(15.56)	(6.18)
LR(χ^2)	5655.26***	3299.76***	16.90***	1408.67***	***	***
N	3090	3090	3090	3090	3090	3090

Note: t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$

4.3.3 What are the effect of the TCs –related floods and SLM adoption on the farm productivity?

Table 4.3 highlights the effect of TCRFs and adoption of SLM –related practices on farm productivity using various ESR model. Columns (1), (2), and (3) report the regression estimates of the ESR model, based on maximum likelihood estimator, a two-step, and control function, respectively. Column (4) and (5) presents the results based on the ESR command in Stata for SLM non-adopters (4) and adopters (5), following Lokshin and Sajaia (2004). Lastly, Column (6) and (7) reports outputs from the multinomial ESR (MERS) model and panel-based ESR (PESR) model, correspondingly. Columns (8), (9), and (11) presents results from panel-based fixed, random, and CD production function, respectively. All variables across all models show similar expected signs with slight difference in magnitude of marginal effect and the study interprets the empirical results based on Column 7 of Table 4.3.

From Column (7), the study finds that TCRFs reduce farm productivity by 31 percent in the study area, 10 percent among SLM adopters and 7 percent among non-adopters, ceteris paribus. TCRFs wash away and submerge already matured crops, especially in areas occupied by SLM –related adopters (DoDMA, 2018). Accordingly, this implies that any crop that is submerged by water may not yield maximum results. The World Bank (2018, 2020) reports that TCRFs of 2018 reduced maize production by 30 percent in Southern Malawi, which resulted into over a million households reporting food insecure and destitute for food assistance.

Nonetheless, the study notes that households, which have adopted SLM practices, are 27 percent more likely to improve farm productivity than the non-adopters (column 7), while holding all other factors constant. Results from the MESR model reveal that the improvements in farm productivity increase with the number of the adopted SLM –related practices, ceteris paribus. Households which undertake at least one SLM practice significantly enhance farm productivity by almost 126 percent, holding all other factors constant. In other words, households which have adopted at least one SLM –related practices substantially derive higher returns than households adopting only one practice. After interacting SLM with TCRFs, the study finds a positive effect of SLM adoption on farm production by 24 percent, ceteris paribus (see Column 7). This implies that SLM –related practices cushion households from the adverse effect of TCRFs on farm productivity and these results are consistent with Amadu et al. (2020), Midingoyi et al. (2019), and Khonje et al. (2018).

Physical farm input like farm holding size, labour, seed, and fertilizer, also have positive and noticeable influence on farm productivity (Column 7). Marginal increase in farm holding size by one acres increases farm productivity by 40 percent in the study area, 20 percent for adopters, and 23 percent for non-adopters, ceteris paribus.

Similarly, marginal increase in labour by one personal day insignificantly improves farm productivity by 10 percent for SLM adopters and 19 percent for the non-adopters, holding all other factors constant. Equally, marginal increase in inorganic fertilizer by one percent enhances farm productivity by 16 in study area, where it augments farm productivity for SLM adopters and non-adopters by 10 and 4 percent, ceteris paribus, respectively. Furthermore, marginal increase in improved crop varieties seeds considerably enhance farm productivity 18 percent in the study area, 3 percent for adopters, and 7 percent for non-adopters. These results are also consistent with estimates from the PESR model, Kansanga et al. (2020), and Kassie et al. (2015).

Farm-level characteristics, namely, soil quality, type, and slope, enhance farm productivity but differently (Column 7). On the one hand, farms with loamy soils are 11 percent more likely to improve farm productivity than farms with clay soils. Though sandy soils are 8 percent more likely to augment farm productivity, their contribution was not substantive. Similarly, farms with gentle slope are noticeably 13 percent more probably to increase farm productivity. A similar trend is observed among SLM adopters (13%) and non-adopters (10%). On the other hand, households with fair and poor soil qualities are less likely to have improved farm productivity than good soil quality. In other words, the study results agree to FAO (2021) and Kassie et al. (2015), where it is suggested that farm with poor soils should adopt the SLM practices to enhance soil fertility.

Table 4. 3 : Results of the ESR models: The impact of the TCRFs and SLM adoption on farm productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ESR MLE	ESR 2SLS	ESR CONTROL	ESR NAD	ESR AD	MESR	PESR	FE	RE	CD
LNFARM SIZE	0.248***	0.252***	0.252***	0.198***	0.230***	0.232***	0.397***	0.0760	0.110**	0.480***
	(16.44)	(14.76)	(14.39)	(7.26)	(13.07)	(16.16)	(18.87)	(1.49)	(2.90)	(20.07)
LNLABORDAYS	0.098***	0.0597**	0.0597**	0.193***	0.0963***	0.138***	0.0991	0.163	0.165*	0.100*
	(5.89)	(2.86)	(2.90)	(4.45)	(5.36)	(8.90)	(0.84)	(1.88)	(2.48)	(2.21)
LNFERTILIZER	0.094***	0.111***	0.111***	0.0429***	0.0925***	0.0849***	0.155***	0.278***	0.292***	0.189***
	(21.55)	(17.35)	(16.19)	(5.44)	(18.74)	(18.94)	(18.47)	(13.14)	(18.14)	(17.97)
LNSEED	0.0392*	0.0361	0.0361	0.0708	0.0321	0.0362*	0.181***	0.833***	0.882***	0.175***
	(2.02)	(1.65)	(1.47)	(1.62)	(1.35)	(1.96)	(9.85)	(27.89)	(38.26)	(13.49)
LOAMY SOIL	0.089***	0.181***	0.181***	0.0121	0.121***	0.0764**	0.114**	0.984***	0.886***	0.479***
	(4.17)	(5.58)	(5.50)	(-0.33)	(4.39)	(2.93)	(2.81)	(9.50)	(11.35)	(8.97)
SANDY SOIL	0.101***	0.186***	0.186***	0.00199	0.127***	0.0815**	0.0774	0.792***	0.683***	0.490***
	(4.40)	(5.67)	(5.53)	(0.04)	(4.47)	(3.15)	(1.80)	(6.79)	(7.91)	(8.09)
FAIR SOIL	-0.053**	-0.0170	-0.0170	-0.153***	-0.0209	-0.0549**	-0.0817*	0.548***	0.488***	0.0936
	(-2.89)	(-0.76)	(-0.74)	(-4.13)	(-0.98)	(-2.93)	(-2.30)	(5.79)	(6.80)	(1.93)
POOR SOIL	-0.078**	-0.0254	-0.0254	-0.234***	-0.0439	-0.0855**	-0.0832	0.670***	0.573***	0.0422
	(-3.05)	(-0.81)	(-0.78)	(-4.19)	(-1.51)	(-3.27)	(-1.74)	(4.97)	(5.72)	(0.62)
GENTLE SLOPE	0.131***	0.211***	0.211***	0.101	0.126***	0.0846***	0.133***	0.271**	0.201**	0.0794
	(6.50)	(7.14)	(7.09)	(0.24)	(5.26)	(4.15)	(3.55)	(2.80)	(2.71)	(1.61)
STEEP SLOPE	-0.116***	-0.191***	-0.191***	-0.0521	-0.106**	0.0992**	0.0499	-0.112	-0.0483	-0.145
	(-3.87)	(-4.99)	(-4.93)	(-0.68)	(-3.09)	(3.16)	(0.93)	(-0.73)	(-0.42)	(-1.91)
TCRFS	-0.0382	-0.0180	-0.0180	-0.070*	-0.109***	-0.260*	-0.312***	-0.572***	-0.912***	-0.566***
	(-1.76)	(-1.64)	(-1.68)	(-2.22)	(-4.39)	(-2.10)	(-7.51)	(-4.40)	(-10.04)	(-8.72)
SLM*TCRFS	0.093**	0.101**	0.101**		0.116*	0.728***	0.238***	0.037	0.484*	0.484*
	(2.91)	(3.01)	(2.84)		(2.64)	(4.78)	(4.45)	(0.911)	(2.26)	(2.45)
SLM										
ONE PRACTICE	0.693***(12.97)	1.184***(9.09)	1.184***(9.28)			0.288***(6.83)	0.271***(4.35)	0.055 (0.54)	0.016(0.20)	0.022(0.44)
2 PRACTICES						0.369***(6.24)				
3 PRACTICES						0.471***(5.85)				
4 PRACTICES						0.609***(5.81)				
5 PRACTICES						0.767***(5.82)				
6 PRACTICES						1.073***(6.39)				
7 PRACTICES						1.259***(3.97)				
LR(χ^2)	5655.26***	3299.76***	16.90***	1408.67***	1408.67***	***	***	133.56***	2851.94***	2653.50***
N	3865	3865	3865	3865	3865	3865	3865	3865	3865	3865

Note: t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$

Table 4.4 shows the effect of various individual SLM –related practices on farm productivity using the linear regression with endogenous household adoption decision. The study finds varying effect of SLM –related practices on farm productivity. For instance, the study notes that SWC, herbicides application, fallow cultivation, timely planting, agroforestry, improved varieties, intercropping, and multiple adoption of SLM –related practices positively influence farm productivity, on the one hand. Interestingly, the study observes that the application of herbicides significantly enhances farm productivity under different TCRFs due to minimum soil disturbances (Chinseu et al., 2018). On the other hand, the study results reveal that cultivation along marginal land, cover cropping, and incorporation of crop residues with ploughing reducing farm productivity.

Table 4. 4 : What are the effects of various SLM -related practices on farm productivity?

	Unit of measurem ent	NON-ADOPTERS	ADOPTE RS	DIFFEREN CE	%TAGE CHANGE
HERBICIDES	Yes=1	11.2	15.5	4.3	38.3%
SWC	Yes=1	10.3	11.6	1.3	12.8%
MULTIPLE ADAPTATION	Counts	10.4	11.5	1.2	11.1%
INTERCROPPING	Yes=1	10.9	12.1	1.2	10.2%
IMPROVED VARIETIES	Yes=1	10.9	11.9	1.0	9.3%
TIMELY PLANTING	Yes=1	10.9	11.8	1.0	9.0%
FALLOWING	Yes=1	11.2	11.9	0.7	6.0%
AGROFORESTRY	Yes=1	11.2	11.7	0.5	4.6%
MARGINAL LAND	Yes=1	11.6	10.3	-1.2	-10.7%
COVER CROPPING WITH PLOUGHING	Yes=1	11.7	10.2	-1.5	-13.2%
PLOUGHING	Yes=1	12.0	08.2	-3.8	-31.3%

4.4 Conclusion and Key Policy Recommendations

This study examines the effect of TCs –related floods (TCRFs) on farm productivity. The study further investigates factors affecting household adoption of SLM -related practices, namely, minimum tillage, crop residual, cover crop, organic manure application, soil and water conservation measures, terracing, and agroforestry. The study uses household data, collected by the NSO and the World Bank Living Standard Measurement Study team between 2010 and 2020. The study accounts for the selection bias and unobserved heterogeneity through employing the panel –based ESR model. The study results reveal that a number of factors influence the adoption of the SLM –related practices. Particularly, the TCRFs enhance the adoption of SLM practices by 27 percent, ceteris paribus. Households with access to credit markets are also 10 percent more likely to undertake the SLM practices than their counterparts, holding other factors constant. Furthermore, socioeconomic factors such as age, education and mobile phone positively influenced the adoption rate of the SLM –related practices.

However, the study finds TCRFs substantially reducing farm productivity by 31 percent, ceteris paribus, justifying the adoption of the SLM –related practices to cushion farm productivity. Based on a panel ESR model, the SLM practices enhance farm productivity by 27 percent, holding other factors constant. Similarly, households that interacted SLM –related practices with TCRFs augment farm productivity by 24 percent, ceteris paribus. Accordingly, multiple adoption of the SLM –related practices substantially improve farm productivity by 126 percent. In other words, households adopting more than one SLM –related practices obtain higher returns than households, adopting only one SML practice. This implies that multiple adoption of SLM –related practices has higher likelihood of cushioning farm productivity from adverse effect of TCRFs. Generally, farms with poor soil quality and steep slope are less likely to have improved farm productivity, suggesting the need to invest in SLM practices. Moreover, female farmers less likely to adopt SLM practices in this study because they do not have access to productive resources. Hence, the study findings propose the need of gender targeted extension services, accompanied by some affordable SLM package. Besides, the study results reveal a competing relationship between chemical fertilizer and the SLM practices, suggesting the need to sensitize farmers on the inorganic fertilizer and SLM practices complementarities.

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CHAPTER FIVE

Understanding the impact of climate-induced rural – urban migration on the technical efficiency of maize production in Malawi

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Abstract

This study estimates the effect of the climate induced rural-urban migrants (RUM) on the maize productivity. It uses panel data, gathered by the National Statistics Office and the World Bank to understand the effect of RUM on farm productivity in rural Malawi. The study runs the two-stage Tobit regression to isolate the real effect of rural-urban migration on the farm productivity. The results show that RUM significantly reduce the technical efficiency of maize production. However, the interaction of RUM and climate-smart agriculture have a positive and significant influence on the technical efficiency of maize production, suggesting the need of re-investing migrants' remittances in agricultural activities.

Key Words: Climate Smart Agriculture, Farm Productivity, Rural-urban migration, Panel Stochastic Frontier Models.

5. Introduction

In this Chapter five, the study lays-out the context, regarding the impact of rural-urban migration (RUM) on maize farm productivity as adaptive strategy towards different extreme weather events. It also presents the chapter research motivation; the objectives, and questions guiding the chapter. The chapter further discusses the specific theoretical and empirical framework, viz., the two-stage panel based Tobit regression. Lastly, this chapter highlights the results and discussion, the conclusion and the key policy recommendations of the study.

5.1 Study Context

Agricultural production is globally increasing with maize almost tripling from 476.8 million tonnes in 1989 to over 1100.8 million tonnes in 2016 (Food and Agricultural Organization [FAO], 2018). Similarly, in Africa, maize production has doubled from 41.6 million tonnes in 1989 to over 84.2 million tonnes in 2016 (Binswanger and Townsend 2000, FAO, 2014). Binswanger and Deininger (2005) and FAO (2018) attribute the increase in agricultural production to augment the use of inorganic fertilizers and improved crop varieties. In Africa, agriculture accounts for at least 20 percent of the GDP, contributes about 60 percent of employment, and forms half of the total export earnings (World Bank 2018). However, in Sub-Sahara Africa (SSA), literature shows declining agricultural production from 12.8 million tonnes in 1989 to 8.0 million tonnes in 2016 (Benin et al., 2016). This is partly because of low use of inorganic fertilizer, traditional crop varieties, rain-fed agriculture, fragmented farm sizes and extreme weather events (Chauvin et al., 2012). Accordingly, SSA has aligned its agricultural agendas with continent agricultural programme to boost agricultural production and productivity, where countries appropriate 10 percent of the total national budget to agricultural programmes.

Like other developing countries in SSA, Malawi economy is predominantly agriculture, contributing 30 percent of the GDP, 80 percent of the total export earnings, and 85 percent of the livelihood to the rural population (MoAIWD, 2018), employing 64 percent of total workforce, where women form over 70 percent of its labour-force (NSO, 2020). Furthermore, the agricultural sector is dualistically categorized into smallholder (78%) and estate (22%) sub-sectors (NSO, 2020), where smallholders farm on 3.3 million communal hectarage and mostly rural. The smallholder agriculture highly relies on rain-fed agriculture and over 90 percent of them cultivate maize (MoAIWD, 2018). Land user rights are disproportionally distributed, along the lines of gender, with women cultivating on less than 0.45 hectares (NSO, 2018), where the majority of households cultivate local maize varieties, have increasing land fragmentation and only 4 percent is under irrigation (NSO, 2018). Amare et al. (2015), Ravallion and Datt (1999), and NPC (2020) argue that improving agricultural productivity is thus the main pathway out of poverty for developing countries like Malawi and achieving SGD target on poverty reduction and zero hunger.

Despite the role maize play in poverty reduction in Malawi, over the past decades, the country has experienced erratic maize production and productivity because of declining soil fertility, land fragmentation, communal land tenure system, unsustainable agricultural practices, and underdeveloped infrastructure (McCarthy et al., 2021; Katengeza et al., 2019; Kilic et al., 2015; MoAIWD, 2018; FAO, 2018). Lately, extreme weather events, namely, droughts, floods, and pest outbreak, such as fall armyworms, have amassed discussions around agricultural productivity (McCarthy et al., 2018; Asfaw et al., 2016; Mwase et al., 2013), where it is highly correlated with volatility in agricultural productivity. Mwase et al. (2013) report increased maize production during the years of 2010/2011 and 2013/2014, and reduction in 2004/2005 and 2015/2016, where extremes weather events were absent and present, respectively.

Adverse effects of extreme weather events have disrupted rural livelihoods forcing households indigenously adopt rural-urban migration, as an extreme weather event adaptive strategy (RUM) (DoDMA, 2018; World Bank, 2018). NSO (2020) reported that over 40 percent of the population in rural areas migrated to urban areas to generate remittances for investing in climate resilient agricultural activities for household members left behind. Undoubtedly, RUM presents an important opportunity as an adaptive strategy to increasing weather events in Malawi (Zhang et al., 2020; NSO, 2020; MoAIWD, 2018; FAO & IOM, 2017). Through remittances, the climate induced RUM can help households invests in climate induced –related adaptation practices, thereby building household resilience to varying extreme weather events. RUM has increased the frequency and the amount of remittances trickling down to rural households from US$0.84 million in 2002 to about US$ 40.0 million in 2016 (Dinkelman and Marriott, 2016; Truen et al., 2016). Generally, remittance receipts have increased from under one percent in early 2000s to over 23 percent in 2020, with Covid-19 increasing the number of household receiving remittance to approximately two-third of the rural households (World Bank, 2020). Households have invested migrants' remittances in climate-smart agricultural (CSA) –related practices, viz., soil and water conservation (SWC) practices, drought tolerant varieties, fallow cultivation, agroforestry practices, and conservation agriculture to boost agricultural productivity (NSO, 2020; FAO, 2018; McCarthy et al., 2016).

Unfortunately, existing literature offers mixed results on the role of RUM and remittances on agricultural productivity (Anglewicz et al., 2017; Asfaw et al., 2016; McCarthy et al., 2016; Adams and Cuecuecha, 2013; Anderson, 2011), thereby failing to inform agricultural policies. Elsewhere, scholars have demonstrated negative and positive effects of urban migration (de la Fuente, 2010; World Bank, 2018). For example, in Ghana, urban migration has reduced family labour, land tenure security and changes headships (Tshikala et al., 2014; Massey et al., 2012), resulting in reduced agricultural production. Also, in Mexico, households have invested migrants' remittance in non-productive activities, namely, food consumption (Adams and Cuecuecha, 2012; de la Fuente, 2010). However, migrants' remittances sometimes are used to cushion households from credit and risk constraints (Stark and Davie, 1985). Furthermore, migrants' remittances have also enhanced the adoption of CSA practices, where migrants have shared innovative ways of farming through existing media platforms (Stark and Davie, 1985). Yet, literature on the effect of RUM on farm productivity, as an adaptive strategy to extreme weather events, is still scanty (Katengeza et al., 2018; Khataza et al., 2018), failing to present the real effect of RUM on the farm productivity, which has been annually fluctuating between 2.37 and 3.98 million (MoAIWD, 2018; FAO, 2018).

This study contributes to policy making process on farm productivity by assessing the effect of RUM on the technical efficiency of maize production. Usually, households use RUM as an adaptive strategy to extreme weather events. Eventually, the study results are relevant to the debate on SDGs and Malawi Vision 2063 on agricultural productivity under different weather extremes. The study adopts the maize crop because it is cultivated by over 90 percent of the households (NSO, 2020, 2018). The study further applies a two-stage panel based Tobit regression to isolate the effect of RUM on the technical efficiency of maize production in the study area. Data from the three-wave IHPS, conducted by the NSO and the World Bank between 2010 and 2016/2017 is used in this study.

5.2 Research Methodology

5.2.1 Study Area, Sampling Strategy and Data Acquisition

This study is implemented in Malawi, which is a landlocked country, located in Sub-Sahara Africa (SSA) bordering Tanzania to the North, Mozambique to the East, South and West, and Zambia to the North West (see Figure 1.5). The country is divided into three regions, which are further divided into districts. There are 28 districts in total, with four urban centres. The country has one rainy season, which runs from October to April. Variations in altitude, ranging between under 500 to over 1500 m above sea-level, have led to the wide differences in the country' s mean temperature and precipitation during the agricultural cropping season (World Bank, 2020). The mean temperature ranges from 23 to 25 degree Celsius, while precipitation has averaged between 85.90 and 238.40 mm annually.

The study data is based on the Integrated Household Panel Survey (IHPS), collected by the NSO and the World Bank between 2010 and 2017 (NSO, 2020). Using the IHPS, about 3865 households are randomly selected using the multi-stage sampling procedure (Kilic, 2014; Kilic et al., 2021). First, the country is divided into district, then sub-divided into traditional areas, and lastly into enumeration areas, where households are systematically and randomly picked for the survey (NSO, 2012, 2013, 2017; 2020). There are 1300 households, which are matched across 2010/2011, 2013 (n=1272), and 2016/2017 (n=1289) sample to form a balanced panel. The survey captures data on household characteristics, including education, labour and time use, food security, income, credit accessibility, expenditure, consumable and durable goods, migration, and household enterprises. Additionally, the survey collects data on institutional factors, such as credit, input and output markets, land acquisition, and extension services. Furthermore, the survey gathers data on farm-level characteristics, inputs, production, storage and sales. Households also receive a questionnaire on whether they have someone who migrated to other areas, including urban centres. In this study, any households, which respond to have had a migrant, does or does not receive any form of remittance, is labelled household with migrant (HWM), and otherwise, a household without migrant (HNM). The NSO and the World Bank have followed these households in 2010/2011, 2013, and 2016/2017. Table 1.1 highlights definitions, measurements, and expected signs of variables used in this study (NSO, 2020; Katengeza et al., 2018; Khataza et al., 2018).

5.2.2 Theoretical and Empirical Framework

Discourses on rural-urban migration (RUM) have existed in the literature since 1900s, where households have used RUM as one of the sources of income (Lee, 1966; De Haas, 2014; Bakewell, 2010). However, literature has partially discussed the effect of climate–induced RUM on the technical efficiency of maize production (Vermeulen et al., 2012; McKinley et al., 2015; van Dijik et al., 2015; FAO and IOM, 2017; Tshikala et al., 2014; World Bank, 2018; Lipper et al., 2014; Asfaw et al., 2016). Figure 5.1 illustrates the relationship for extreme weather events, climate induced RUM, CSA, and related effect on the technical efficiency of maize productivity. Figure 5.1 also displays that household and farm level characteristics have an effect on the climate-induced RUM, the adoption of CSA, and the technical efficiency of maize production.

The study uses the panel-based Cobb-Douglass Stochastic Frontier and two-stage Tobit regression model (Kumbhakar et al., 2015; Pangapanga and Mungatana, 2021). The study casts the research objective into the household decision making model, where it assumes a household is driven by expected random utilities. In other words, a household member migrants to urban areas only when the resultant presents higher returns than staying in rural areas. The study further postulates rural areas experience frequent and varying extreme weather events, which have an effect on rain-fed maize production. Following RUM, households receive remittances which is invested in CSA –related practices (see Pangapanga and Mungatana, 2021 for CSA definition and examples).

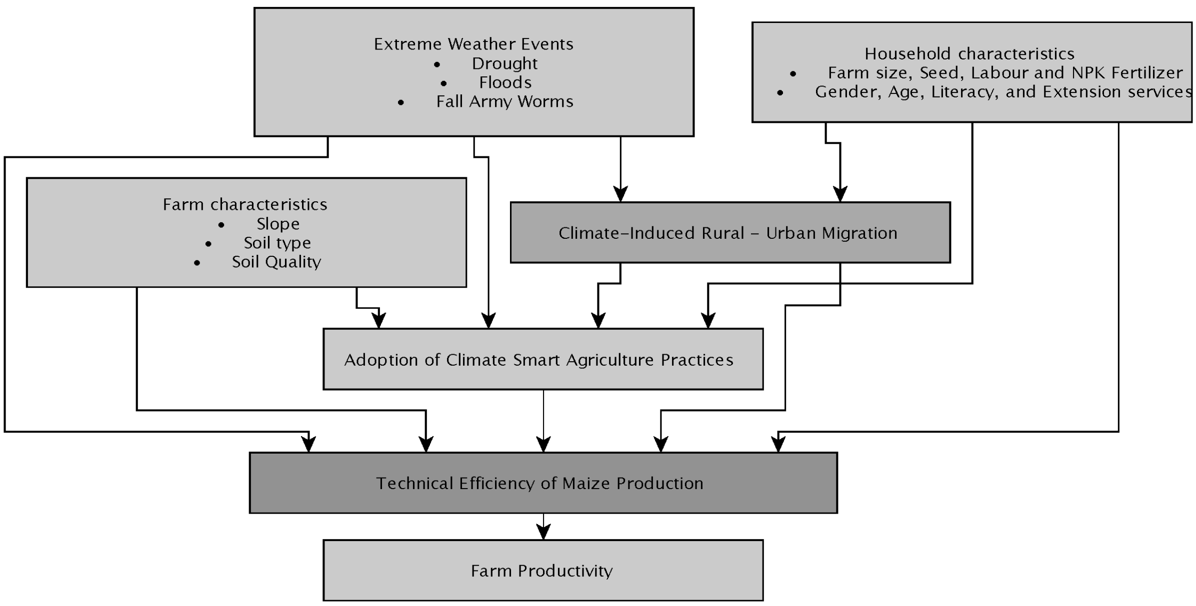

Figure 5. 1 : Conceptual framework of the relationship for Extreme Weather Events, Climate-induced Rural Urban Migration, and Adoption of Climate Smart Agriculture

Determinants of farm production can be analysed using either non-parametric or parametric frontiers (Kumbhakar et al., 2015). In simplicity terms, non- parametric frontiers do not specify any functional form on the error term (Chirwa, 2007) and the Data Envelopment Analysis is the most prominent non-parameter techniques. While, the parametric frontiers impose a functional form and distribution assumptions on the error term (Woodridge, 2016; Kumbhakar et al., 2015). Most common forms of production functions include the Cobb-Douglas (CD), Generalised, Transcendental and Translog Production Function.

Production functions represent maximum output, generated given some inputs combination and available technology. The study builds our theoretical framework and discussion following Kumbhakar et al. (2015), Chirwa (2007), Battese and Coelli (1995), and Battese (1992). We assume all production processes are input-output transformative. We call the maximum output as "frontier of production". It is aware that a production function is in itself devoid of any economic intuition (Kumbhakar et al., 2015). However, the study uses the production function to model optimization problems because it demonstrates some forms of weak monotonicity, quasi-concavity, non-negativity, and essentiality properties. Optimization model in our case is a latent utility function, which is maximised given the maize-based Translog production technology subject to various inputs' constraints in space and over time, such as capital and labour.

Farrell (1957) first motivates the econometric modelling of production functions to estimates the technical efficiency (Batiese, 1992). Later, Aigner et al (1977) and Meeusen and van den Broeck (1977) independently extend and propose the SFA use, which can be specified as in equation 1.

$$y_{ijt} = f\left(x_{ijkt}, \beta, t\right) \equiv lny_{ijt} = \beta_j \sum x_{ijt} + \beta_t t, \qquad (1)$$

where y_{ijkt} denote non-negativity farm productivity (k) of household (i) and at time (t), $x_{ijt} : (i = 1,2 \ldots., J)$ represents a vector of inputs (j) used by household (i) in farm (k) and at time (t), including rural-urban migration, and β is a vector unknown parameters to be estimated by the model. We derive margins, namely, ${dy_{ijt}}/{dx_{jt}} \geq 0$ and ${d^2 y_{ijt}}/{dx_{jt}^2} < 0$, of one input while fixing the other inputs (Fuss et al., 1978). We observe that technical inefficiency results into household failing to derive the maximum output along the production frontier, which is therefore the difference between potential and actual productivity (Kumbhakar et al., 2015; Mango et al., 2015). Customarily, a household is technically inefficient if a higher level of output (y) bundle is technically attainable given the inputs (x) combination or the observed farm productivity (y) can be achieved, using a lower set of (x) input bundle (Kumbhakar et al., 2015).

The study derives the economic effects from the production technology (Varian, 2016 and Fuss et al., 1978). First, we examine the homogeneity and return to scales of output over increasing level of inputs. It further assumes that a production function is homogeneous if it satisfies the monotonicity assumption, which is a mathematical construct of a product of a scalar factor (λ) and the farm productivity (y) as presented in equation 2:

$$\lambda^{\gamma} y_{ijkt} = f(\lambda x_{1ikt}, \dots, \lambda x_{nikt}), \qquad (2)$$

If all inputs are increased by a factor of (λ) and the farm productivity augmented by a factor of (λ^{γ}), then the production function is called a homogenous of degree γ in x (Kumbhakar et al, 2015; Aneani, 2011). If $\gamma = 1$, then households operate at constant returns to scale, $\gamma > 1$ denotes increasing returns to scale, while $\gamma < 1$ represents decreasing returns to scale. Returns to scale (RTS) only depends on x if the production function is not homogenous. We can also the Marginal Rate of Technical Substitution (MRTS), σ_{ij} , as specified in equation 3:

$$\sigma_{ij} = \sigma_{ji} = \frac{\sum_i x_{ijkt} f_i}{x_{1ikt} x_{2ikt}} * \frac{F_{ji}}{F}, \qquad (3)$$

In general, the value of σ_{ij} lies between zero and infinity for convex isoquants. Perfect substitution between inputs is observed when σ_{ij} is infinity, complementary substitution is depicted when σ_{ij} is negative, and always positive when inputs are just substitutes. Besides having a separable property, production functions exhibit technical change. In our study, this may be highly observed following rural-urban migration having some intertemporal characteristics, where farm managers learn and apply different management styles over time. However, technical change [$TC(.)$] adopts a Hicks Neutral-where the shift does not depend on any input and otherwise (Simwaka et al., 2011, Tchale, 2009) and can be written as in equation 4.

$$TC(x,t) = \frac{d ln f(x.\exp(-\theta), t)}{dt} \equiv \frac{\partial \ln y}{\partial t} = \beta_t \qquad (4)$$

where the $e\text{xp}(-\theta)$ can be treated as either a neutral or non-neutral multiplicative or augmented agent factored to the panel-based stochastic production function. We factor time and derive output with respect to time to capture technical change. Following Kumbhakar et al. (2015), the study generates the elasticity of output with respect to input x_j as in equation 5.

$$\varepsilon_j = \frac{\partial ln y_{ijkt}}{\partial ln x_{ijkt}} = \beta_j, \qquad (5)$$

On the one hand, the study can apply a cross sectional SFA procedure to estimate the effect of RUM on the technical efficiency of maize production. However, it suffers from the endogeneity issues and may not capture the intertemporal technical change (Kumbhakar and Lovell, 2002). Unless the study adopts the corrected ordinary least square (COLS), the cross-sectional models require distribution assumption and assumes non-existence of the white noise (Simwaka et al., 2011). On the other hand, the panel data models account for the true state dependence, the endogeneity and the unobserved heterogeneity (Kumbhakar et al., 2015), by controlling for the unobservable individual and times effects.

The Cobb-Douglass production function forms the empirical strategy of the study because it is flexible, interpretable, and executable (Kumbhakar et al., 2015; Pangapanga et al., 2012; Tchale, 2009). In its linearized forms, the function isolates the effect of RUM on the technical efficiency of maize production among households with (HWM) and without migrants (HNM). The panel-based SFA function is specified as in equation 6.

$$lny_{itk} = \beta_0 + \sum_{i=1}^{N} \beta_j lnx_{itk} + \emptyset T - u_{itk} - v_{it} \qquad (6)$$

where y_{itk} denotes maize productivity by individual HWM and HNM, i, in time period, t, in farm, k; x_{it} represents a vector of physical factors of production such as labour, quantity of seeds, total available farm size, amount of fertilizer, slope, soil type, and soil quality. The $\beta, \emptyset$ and Ω denotes unknown parameters to be estimated by the model. Vector T captures the time trend for technical change, indicating retrogressive or progressive production. While v_{it} represents the white noise, having zero mean and constant variance and u_{it} is the technical inefficiency of maize production. The study adopts a half normal distribution to run the model (see detail in Ng' ombe, 2017; Chirwa, 2003). Let Z_{itk} be the household characteristics affecting the technical inefficiency of maize production as demonstrated in equation 7

$$u_{itk} = \beta_0 + \sum_{i=1}^{N} \beta_j lnP_{itk} + \sum_{i=1}^{N} \beta_j lnZ_{itk} + \omega RUM_{it} + \Omega \mathrm{CSA} * RUM_{it} + e_{it} \qquad (7)$$

where u_{itk} and Z_{itk} are as prior defined. The Ω and ω are the unknown parameters to be estimated by the model. The P_{itk} is a vector of physical factors of production like labour in personal days, quantity of seeds in kg, total available farm size in ha, and amount of fertilizer in kg. The $\mathrm{CSA} * RUM$ is the interaction between RUM and CSA adoption. While, the e_{it} is the error terms, with zero mean and constant variance. The study examines the effect of RUM on the technical efficiency of maize production through adoption of the two-stage Tobit regression (see Pangapanga and Mungatana, 2021). In the first stage, technical efficiency scores are predicted through the CD-SFA of the Battese and Coelli (1995). While in the second stage, the Tobit regression is applied to assess the effect of RUM on the technical efficiency of maize production in the study area.

5.3 Results and Discussions

5.3.1 Descriptive statistics of household characteristics

Table 5.1 presents summary descriptive statistics of household and farm-level characteristics between the households with migrant (HWM) and households without migrant (HNM) for the period 2010 – 2016/2017. Approximately, 40 percent of the households have at least one person migrating to urban areas for various economic reasons. Male heads about 75 percent of households, which has further dropped from almost 78 percent in 2010 to about 72 percent in 2016/2017, implying the effect of RUM at household level. The heads of the households are aged 46 years, with HWM and HNM headed by members aged 57 and 38 years, respectively. HWM are headed by elder people, indicating that most productive members of the household may likely migrate to urban areas for potential green areas. There is also an increasing trend of RUM from 35 percent in 2010 to slightly above 40 percent in 2016/2017. Above two-third of the households have attended some formal education, with the highest education grade being five. Almost, 70 percent of households have a mobile phone for communication, where households owning mobile phones has increased from 58 percent in 2010 to 88 percent in 2016/2017. In terms of remittances, the study observes that 33 percent of HWM received remittance from household members who have migrated to urban areas, representing 13 percent of the total sampled households. These results are in line with the NSO (2020) and Chilimapunga (2006).

Table 5. 1 : Summary statistics of the household characteristics between HNW and HWM in Malawi

	HNM		HWM		POOLED		HNM vs HWM
VARIABLES	Obs	Mean	Obs	Mean	Mean	Std. Dev.	P-value
SEED IN KG	2533	9.588	1332	10.56	9.974	9.519	***
YIELD IN/HA	2533	1463	1332	1538	1,493.251	1,144.091	**
PERSONAL LABOUR DAYS	2533	27.01	1332	30.58	28.438	20.358	***
FERTILIZER IN KG	2533	46.43	1332	47.52	46.864	59.554	
FARM SIZE IN HA	2533	0.478	1332	0.550	0.507	0.473	***
AGE OF HH HEAD IN YEARS	2533	37.93	1332	57.17	45.614	15.369	***
CREDIT ACCESS	2533	0.127	1332	0.116	0.123	0.329	
DISTANCE TO THE ADMARK IN KM	2533	7.497	1332	7.500	7.498	5.163	
DISTANCE TO THE MAIN ROAD IN KM	2533	9.369	1332	9.676	9.492	9.867	
ATTENDED EDUCATION	2533	0.876	1332	0.751	0.826	0.379	***
HIGHEST EDUCATION CLASS	2533	6.001	1332	4.368	5.349	4.262	***
EXTENSION ACCESS	2533	0.628	1332	0.674	0.646	0.478	***
GENDER OF THE HH HEAD	2533	0.804	1332	0.674	0.752	0.432	***
HH SIZE	2533	5.459	1332	5.156	5.338	2.301	***
ORGANIC FERTILIZER IN KG	2533	110.6	1332	147.9	125.5	2.513	***
MOBILE PHONE	2533	0.722	1332	0.678	0.705	1.022	
REMITTANCE RECEIPT	2533	0.00	1332	0.334	0.133	0.340	***
FLAT SLOPE	2533	0.673	1332	0.650	0.664	0.472	
GENTLE SLOPE	2533	0.264	1332	0.275	0.269	0.443	
STEEP SLOPE	2533	0.0460	1332	0.0590	0.051	0.221	*
VERY STEEP SLOPE	2533	0.0160	1332	0.0160	0.016	0.126	
GOOD SOIL QUALITY	2533	0.493	1332	0.499	0.495	0.500	
FAIR SOIL QUALITY	2533	0.377	1332	0.389	0.382	0.486	
POOR SOIL QUALITY	2533	0.130	1332	0.112	0.123	0.328	
CLAY SOIL TYPE	2533	0.211	1332	0.210	0.210	0.408	
LOAMY SOIL TYPE	2533	0.545	1332	0.519	0.535	0.499	
SANDY SOIL TYPE	2533	0.218	1332	0.243	0.228	0.420	*
LOAMY SANDY SOIL TYPE	2533	0.0250	1332	0.0280	0.026	0.160	

Note: t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$

The study also interrogates the amount of physical productive resources allocated to agricultural activities. HWM and HNM cultivate maize on 0.55 and 0.48 of a hectare, respectively. Data shows that households produce a minimum of 1493 kg per hectare, where HWM and HNM have 1556 kg and 1463 kg per hectare, respectively. HWM produce 83kg per acre more maize grain than HNM. HWM and HNM allocate about 30 and 27 personal-days on the farm, respectively. Households apply, on average, one 50kg bag of inorganic fertilizer and there is no noticeable difference in the amount of NPK fertilizer applied between HWM (48 kg) and HNM (46 kg). In terms of organic fertilizer, households apply about 125 kg of organic fertilizer in the farms, where HWM and HNM use approximately 148 kg and 110 kg, respectively. Besides, the study finds that 65 percent of households accessed extension services.

Figure 5.2 shows summary of household and farm level characteristics between 2010 and 2016. Accordingly, study notes a positive trend in terms of households accessing extension services between 2010 and 2016/2017, where 41 percent of households have accessed extension services in 2010, 70 percent in 2013 and 90 percent in 2016. In terms of farm characteristics, about 66 percent of households have flat slopped farms, while only 27 percent have gentle slopped farms. Almost 50 percent of the visited households report having farms with good soil quality, followed by 38 percent of households with fair soil quality. However, the study notes that soil quality improved over the years. This can be explained by investments in sustainable land management practices which enhance soil fertility of the farm. Fifty-four (54) percent of households reported having farms with loamy soil type, while 23 percent have farms with sandy soil type.

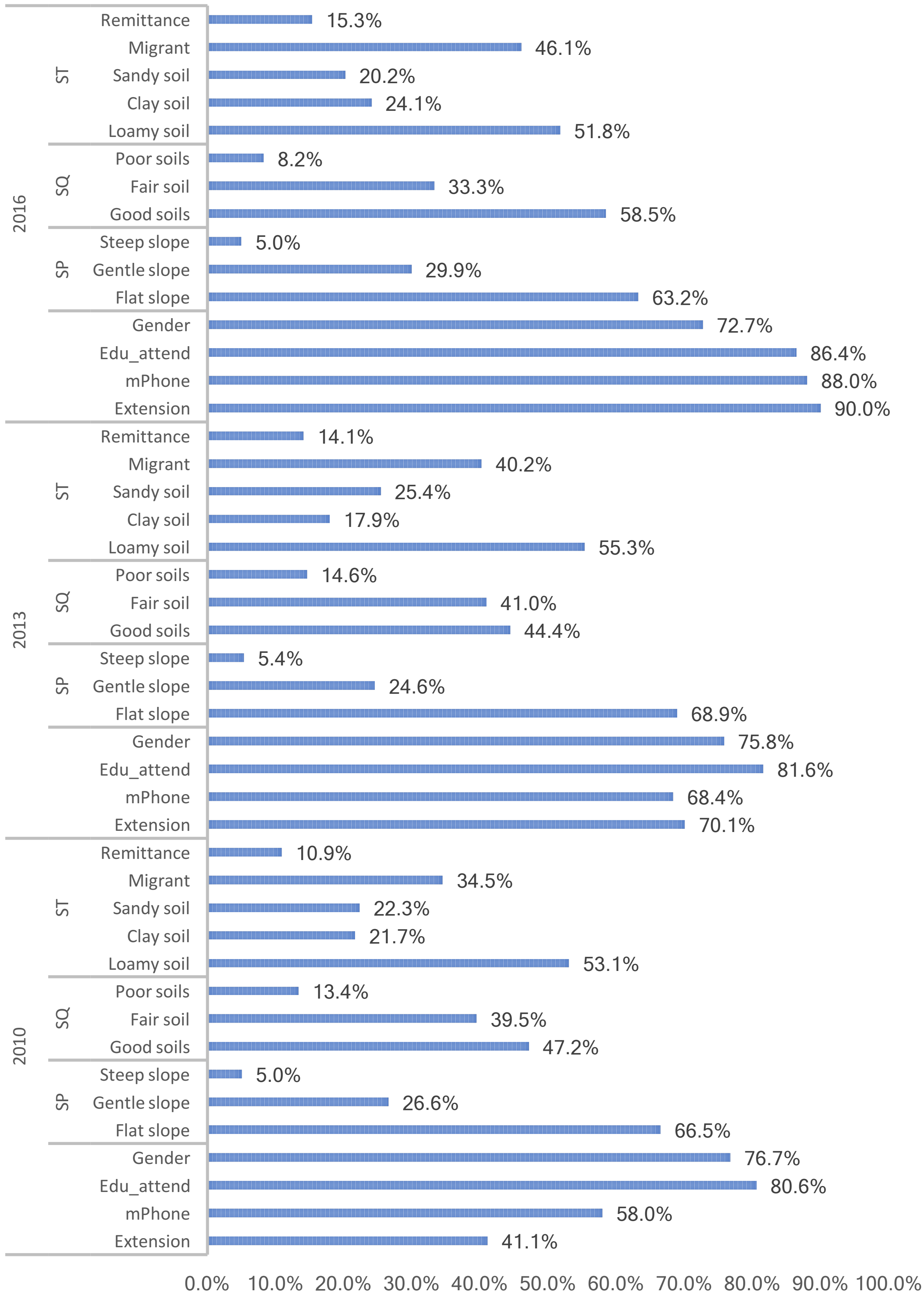

Figure 5. 2 : Proportion distribution of household and farm-level characteristics between 2010 and 2016.

5.3.2 Robustness of Stochastic Frontier Analytical (SFA) Models

Prior to estimating the empirical models, the study checks for the robustness of the data and models. It uses the Schmid and Lin (1984) proposed residual test to check for the validity of the stochastic frontier analytical (SFA) specification. For correct specification, the residual of the OLS has to be skewed to the left, i.e., negative skewness (Kumbhakar et al., 2015). In this study, Table 5. 2 shows skewness, kurtosis, and the log-likelihood ratio tests results. The study finds a negative sign of the skewness for the panel-based fixed and random effect models, implying that the data is fit for the SFA specifications. Accordingly, the study have enough evidence to support the rejection of the null hypothesis of no skewness, indicating the existence of the one-sided. Additionally, the study observes a positive kurtosis, indicating heavily tailed distributions of the technical inefficiency.

Table 5. 2 : Skewness, kurtosis and log-likelihood ratio tests

	HWM	HNM	POOLED
FIXED EFFECT MODEL			
SKEWNESS	-0.23.	-0.33	-0.84
KURTOSIS	6.41	4.83	6.44
RANDOM EFFECT MODEL			
SKEWNESS	-0.74	-0.59	-0.41
KURTOSIS	7.47	5.03	6.12
LIKELIHOOD RATIO TEST (LRT)			
BATTESE AND COELLI (BC)	43.89	65.73	430.94

Furthermore, the study checked for the specification of the SFA model via the log-Likelihood Ratio (LR) test, which assesses the presence of the inefficiency in the model by checking the null hypothesis of no-one sided error. The LR was only conducted after the Maximum Likelihood (ML) estimation of the model. At one percent level of significance level, the study finds log-LR tests, having larger values than the critical values (5.412) for both HWM and HNM. Similarly, the log-LRs out-rightly support the rejection of the null hypothesis of no technical inefficiency. Additionally, the study checks for the presence of panel-data unit roots using Harris-Tzavalis (1990) and Breitung and Das (2005) tests (see detail in Baltagi, 2005). Both tests do not find any unit root in the data at one percent level of significance.

5.3.3 What is the effect of rural-urban migration on maize productivity during varying extreme weather events?

The study presents in Table 5.3 the two-stage Tobit regression model to estimate the effect of RUM on the technical efficiency of maize production under extreme weather events. In the first step, the study runs the BC-1995 CD Stochastic Frontier Approaches (SFA) between households with (HWM) and without migrants (HNM) to analyse the effect of various physical production inputs on maize productivity. Thereafter, the study predicts the technical efficiency scores, which are used in the second step. In the second step, the study employs the panel based Tobit regression to assess the effect of RUM on the technical efficiency of maize production. According to qualitative data, households have used RUM to cushion maize productivity from the adverse effects of different extreme weather events, through reinvesting the remittances from RUM in CSA -related practices, which enhance maize productivity.

Columns (1 – 4) highlight results from the SFA estimations. Whereas, Columns (5 – 8) presents the results from the second step of the two-stage regression results, which are based on the Battese and Collie (BC-1995) specification. The study finds that the log-likelihood ratio test for the model highly significant at one percent. This implies that the model is substantively appropriate to evaluate maize productivity at household level for HWM and HNM. The study provides interpretation of the results, which are based on Column (1 - 3).

The study results reveal that farm holding size has an expected positive sign to maize productivity and significantly increases farm productivity at one percent, ceteris paribus. An increase in farm size by one acre enhances maize productivity by 12 percent, holding all other factors constant. Farm size has higher returns for HWM (45%) than for HNM (8%). Additionally, the study finds seeds having positive effect on maize productivity, where an increase in seed amount by 100 kg increases maize productivity by 8 percent in the study area, ceteris paribus. Also, inorganic fertilizer has an expected positive sign and significantly increases maize productivity by 36 percent, while holding all other factors constant. Personal-days further significantly augment maize productivity for HWM and HNM. However, HWM (3%) derive less gains from any invested personal-days than HNM (22%), ceteris paribus. This perhaps explains the effect of productive family labour for HWM (Tshikala et al., 2014). These results are consistent with previous findings by Asfaw et al. (2016) in Malawi and Mango et al. (2015) in Zimbabwe.

RUM may not directly affect influencing maize productivity, instead it may directly influence the technical efficiency of maize production. Table 5.3, from Columns (5 – 8) shows Tobit regression results, which highlight the effect of RUM on the technical efficiency of maize production. The study notes the Tobit regression output is substantial at one percent level of significance, implying that the model is fit enough to detect the minimum effect of RUM on the technical efficiency of maize production.

The study results reveal that RUM has a significant and negative influence on the technical efficiency of maize production. This could be explained through the reduced supply of productive family labour at household level, for labour intensive activities, namely, timely weeding, fertilizer application, organic manure, and others, which are critical for cushioning households from the negative effects of weather variability on maize productivity. Statistically, holding other factors constant, RUM influence the technical efficiency of maize production by nine (9) percent. Furthermore, RUM reduces the technical efficiency of maize production by 18 percent in 2010 - 2013 and seven (7) percent in 2016, ceteris paribus. This is in line with past findings by Stark (1999), Wouterse (2010), Fakhruddin (2018) and Tshikala et al. (2014).

However, the study finds a positive effect of RUM when interacted with CSA – related practices. For instance, RUM-CSA improves the technical efficiency of maize production by two (2) percent in study area, ceteris pluribus. The interaction enhances the technical efficiency by five (5) percent in 2010, four (4) percent in 2013, and one (1) percent in 2016. This implies that households re-allocate some of the remittance from migrants in CSA –related practices which fundamentally reduce the negative effect of weather events on maize productivity (de la Fuente, 2010). Unless remittances are invested in CSA –related practices (Shi, 2018; Huy and Nonneman, 2016), it can be speculated that most CSA-related practices demand family personal days, which are in low supply for HWM, whose members have migrated to urban areas. However, Singh et al. (2012) argue that lack of input markets in rural areas undermined the role of remittances. These results are in consistent with the findings by FAO (2018), Adams and Cuecuecha (2013), Zahonogo (2011), Jokisch and Pribilsky (2002) and Brauw (2010) and Singh et al. (2012) and Chilimapunga (2006).

Table 5. 3 : Results of the two-Stage regression: Impact of rural-urban migration on the technical efficiency of maize farm production in Malawi

		SFA (Farm productivity)				Tobit(Technical Efficiency)			
		1	2	3	4	5	6	7	8
		HNM	HWM	POOLED	POOLED	POOLED	2010	2013	2016
LOG(FARM SIZE)	Ha	0.447***	0.078***	0.116**	0.136***	0.019***	0.003	0.024***	0.057***
		(16.39)	(13.20)	(3.29)	(3.70)	(5.18)	(0.46)	(3.65)	(9.38)
LOG(SEED)	Kg	0.178***	0.890***	0.083***	0.072***	0.032***	0.014***	0.019***	0.101***
		(12.19)	(25.08)	(38.96)	(19.99)	(15.02)	(4.83)	(4.12)	(17.65)
LOG(LABOR)	Personal days	0.310***	0.216*	0.183**	0.186**	0.015*	0.011	0.013	-0.018
		(5.70)	(2.37)	(2.95)	(3.10)	(-2.14)	-0.84	(-1.05)	(-1.63)
LOG(FERTILIZER)	Kg	0.208***	0.360***	0.361***	0.286***	0.006***	0.001	0.008**	0.006*
		(18.17)	(15.36)	(25.37)	(19.93)	(4.43)	(0.21)	(3.02)	(2.52)
GENDER	Male=1					0.029***	0.040*	0.025	0.017
						(3.75)	(2.57)	(1.77)	(1.46)
AGE	Years					0.001	0.002	0.005*	0.002
						(0.66)	(0.94)	(2.25)	(1.83)
AGE SQUARE	Years					-0.000	-0.000	-0.000	-0.000*
						(-0.77)	(-0.89)	(-1.79)	(-2.21)
LITERACY	Yes = 1					0.01	0.024	0.019	0.042***
						(1.39)	(1.78)	(1.43)	(3.57)
EXTENSION	Access =1					0.012	0.01	0.058***	0.038***
						(1.90)	(0.80)	(4.77)	(3.29)
RUM	Yes=1					-0.085***	-0.178***	-0.183***	-0.068**
						(-5.89)	(-4.96)	(-6.43)	(-2.97)
RUM*CSA	Interaction					0.017***	0.047***	0.038***	0.009*
						(6.84)	(6.14)	(7.53)	(2.36)
YEAR	Number	-0.001***	-0.001***	-0.001***	-0.001***				
		(18.61)	(19.47)	(-33.33)	(-34.75)				
GENTLE SLOPE	Yes=1				0.227***				
					(-3.45)				
STEEP SLOPE	Yes=1				-0.016				
					(-0.15)				
LOAMY SOIL	Yes=1				0.090***				
					(14.32)				
SANDY SOIL	Yes=1				-0.721***				
					(9.12)				
FAIR SOIL TYPE	Yes=1				-0.451***				
					(-6.99)				
POOR SOIL TYPE	Yes=1				-0.487***				
					(-5.41)				
χ^2		1057.74***	471.61***	1922.12***	2672.14***	282.66***	30.02***	90.93***	622.70***
N		2533	1332	3865	3865	3827	1288	1266	1273

Note: *t* statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.4 Conclusion and Key Policy Recommendations

Households adopt rural-urban migration (RUM) as a climate and weather - related adaptation strategy. Through RUM, households receive remittance and innovative ideas from their migrant members, which in turn are invested in modern agriculture, including climate-induced agricultural practices. The study uses data from the IHPS (2010 – 2016/2017), compiled by the NSO and the World Bank. The Battese and Collie (1995) is used to unravel the effect of RUM on the technical efficiency of maize farm production. For robustness of the results, the study checked for the correct specifications using residual tests, skewness, kurtosis, and the likelihood tests. Unless, RUM is interacted with CSA adoption, the study finds that RUM has a significant and negative effect on the technical efficiency of maize production because of low supply of family labour. Statistically, RUM reduces the technical efficiency of maize production by nine (9) percent in the study area, 18 percent in 2010 and 2013, and seven (7) percent in 2016, ceteris paribus. Nonetheless, the interaction between RUM and CSA practices enhances the technical efficiency of maize production by two (2) percent in the study area, five (5) percent in 2010, four (4) percent in 2013, and one (1) percent in 2016, while holding all other factors constant. The study primarily recommends Government and other stakeholders to develop rural agricultural markets, which can allow the exchange of family labour within the rural set-up, and thereby containing RUM of agricultural labour.

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CHAPTER SIX

Summary, Conclusion and Policy Recommendations

6. Introduction

6.1 Study Context

Agricultural production and productivity in Malawi continues to deteriorate, and frustrate the food security agenda despite massive investments in the agricultural sector, including affordable input subsidy programmes, climate-smart agriculture (CSA), integrated pest (IPM) and sustainable landscape management (SLM) –related practices, agroforestry, improved crop varieties, and organic manure application. Furthermore, households have engaged in rural urban migration (RUM) to cushion maize productivity from the negative effects of extreme weather effects. High poverty levels, poor agricultural practices; fragmenting landholding sizes, and largely declining soil fertility are some of the fundamental constraints, limiting household agricultural productivity. Additionally, extreme weather conditions, viz., drought, fall armyworms (FAW), and tropical cyclones related floods (TCRFs), have recently exasperated the falling agricultural productivity, pushing people into being food insecure and trapping the majority into the poverty cycle.

The main objective of the study is to examine the effect of the adoption of CSA, IPM, and SLM –related practices on the farm productivity under different extreme weather events in Malawi. Specific objectives of this study are, thus, in four-folds: (i) evaluating the effect of varying extreme weather events on farm productivity; (ii) determining factors influencing adoption of CSA, IPM, and SLM –related practices in the study area; (iii) examining the influence of various CSA, IPM, and SLM -related practices on the farm productivity; and lastly (iv) unravelling the impact of RUM on the technical efficiency of maize productivity. The study uses the nationally represented data from the Integrated Household Panel Survey 2010 - 2020, compiled by the NSO and World Bank in Malawi.

6.2 Summary and Conclusions

This study poses four (4) major questions to thoroughly address the four researchable questions: (i) Do extreme weather events, viz., drought, TC –related floods, and fall armyworms substantially affect farm productivity and the adoption of CSA, IPM, and SLM -related practices? (ii) Do household (e.g. gender, education, mobile ownership, and credit accessibility) and farm-level (i.e. soil quality, type, and slope), drive the adoption of CSA-related practices? (iii) Do CSA, IPM and SLM-related practices (i.e. organic farming, intercropping, agroforestry, soil and water conservation, pesticides, and improved crop varieties) have any significant influence on the farm productivity? Finally, (iv) does RUM improve the technical efficiency of maize production under extreme weather events? The study groups these researchable questions into five (5) different chapters, where chapter one highlighted the study' s motivation, objectives, research questions, and general methodology.

In Chapter two (2), the study examines the drivers of CSA –related practices' adoption and their influence on the technical efficiency of maize production under different drought episodes. The conditional fixed effect logit regression is undertaken to determine factors driving the adoption of the CSA –related practices. The study further runs the panel-based Cobb-Douglas stochastic frontier analysis (SFA) to estimate the technical efficiency of maize production. Chapter two (2), lastly, applies the triple-hurdle panel-panel-based Tobit regression to evaluate the effect of drought and CSA –related practices on the technical efficiency of maize production. Based on the panel-based Conditional logit, the study finds that drought episodes significantly influence household decision to adopt CSA-related practices, particularly, organic manure application (76%) and soil and water conservation measures (29%), ceteris paribus. The study results reveal that households can increase the current level of farm productivity by 37 percent. Besides, the triple hurdle Tobit regression demonstrates that organic and inorganic fertilizer simultaneously enhance the technical efficiency of maize production, while holding all other factors constant.

In Chapter three (3), the thesis unravels the effect of FAW and IPM –related practices on the farm productivity and food security. The Chapter adopts the maximum likelihood estimated ESR model to isolate the impact of FAW and IPM –related practices on farm productivity, while controlling for potential endogeneity. Furthermore, the Chapter employs the panel-based ESR model to unpack the average treatment effect on the treated (ATET) of the IPM –related practices on the household food security. For robustness of the results, the study applies the multinomial ESR model to ascertain the effect of FAW and IPM –related practices on farm productivity. Accordingly, this study finds FAW reducing farm productivity by 12 percent, ceteris paribus. Interestingly, this study further depicts that the experience of FAW improved the adoption of the IPM -related practices by 6 percent, holding all other factors constant. Furthermore, the study results indicate a positive effect of IPM-related practices on farm productivity and food security. For instance, households, which adopt IPM-related practices, are 21 percent more likely to augment farm productivity than non-adopters, ceteris paribus. Moreover, this study observes that IPM practices have ten-fold returns on improving household food security.

In Chapter four (4), the study interrogates the effect of TCRFs and SLM –related practices on farm productivity. Similarly, this chapter uses the panel-based ESR models to control for the potential observable and unobservable heterogeneity, and further ascertain the effect of TCRFs and SLM –related practices on farm productivity. For checking the robustness of the model, the study fits the ESR using (i) the maximum likelihood, (ii) the two-step, (iii) the control function, and (iv) multinomial ordered probit procedures. The study results reveal that TCRFs have noticeably reduced farm productivity by 31 percent, ceteris paribus. Similarly, households, experiencing TCRFs, are 27 percent more likely to adopt various SLM –related practices, holding all other factors constant. After interacting SLM and TCRFs, the study finds SLM practices enhancing farm productivity by 24 percent, ceteris paribus.

In Chapter five (5), the study investigates the role of RUM on influencing the technical efficiency of maize production in the study area. Households adopt the RUM to cushion maize production activities from the negative effects of extreme weather events. Accordingly, the study adopts the panel-based SFA and the two stage Tobit regression model to estimate the influence of RUM on the technical efficiency of maize production. Unless households invested the remittance in CSA-related practices, the study finds RUM insignificantly reducing the technical efficiency of maize production. Statistically, RUM reduces the technical efficiency of maize production by nine (9) percent in the study area, 18 percent in 2010 and 2013, and seven (7) percent in 2016, ceteris paribus. Nonetheless, the interaction between RUM and CSA practices enhances the technical efficiency of maize production by two (2) percent in the study area, five (5) percent in 2010, four (4) percent in 2013, and one (1) percent in 2016, while holding all other factors constant.

In brief, this thesis concludes that droughts, FAW, TCRF, and RUM have significant and negative effects on the farm productivity. However, households, which are affected by any of the extreme weather events are markedly more likely to adopt any of the CSA, IPM, and SLM-related practices and RUM, which positively enhance farm productivity. Relevantly, these study results inform the existing policy making processes in Malawi in four broad ways. First, it presents drivers and the effects of CSA, IPM, and SLM -related practices on farm productivity in Malawi. Second, it minimises the dis-adoption of CSA, IPM and SLM –related practices through isolating efficient practices at household level. Third, it enhances the adoption of practices, which are climate resilient and have substantial effects on augmenting farm productivity under different extreme weather events. Ultimately, the study findings mainstream the indigenous knowledge and workable feedback in climate adaptation to ensure the CSA, IPM, and SLM-related practices' and RUM' s suitability, flexibility, and sustainability for rural households. Overall, the study results are further relevant to the existing debate on achieving the SDGs and the Malawi Vision 2063 on enhancing agricultural production and productivity under different extreme weather events.

6.3 Key Policy Recommendations

Despite using the secondary data, the study combines several methodologies to understand the drivers of CSA, IPM, and SLM-related practices' adoption and allied influence on the farm productivity, under different extreme weather events. Thus, the study partially contributes to the policy making process debate on the attainment of SDGs and Malawi Vision targets on agricultural productivity, and ultimately, ending hunger in the country. However, the study hardly tests some hypothesis, for example: what is the optimal amount of organic and inorganic fertilizer combination, which farmers should adopt to maximize the farm productivity.

Additionally, the study does not isolate the heterogeneous, persistent, and transient technical efficiency of the farm, which is temporary very critical for policy recommendations and implementations. This study therefore recommends future studies to unbundle the technical efficiency of the farm into heterogeneous, persistent, and transient under different extreme weather events. Furthermore, investment in most CSA, IPM, and SLM-related practices heavily depends on land tenure security. Moreover, most SLM –related practices are long term investments. Hence, the study proposes further studies to ascertain the performance of CSA, IPM, SLM –related practices under different land tenure security system. Besides, due to limited longitudinal data on Covid-19 at household level, which is one of the recent pandemic exasperated by climate and weather variability, this study further suggests future studies investigating the long-term effect of Covid-19 on farm productivity, food security, and household income in Malawi.

The IPM-related practices performed better than the chemical pesticides alone, in this study. Thus, this study recommends the promotion of IPM-related practices, which are found more affordable and profitable to resource constrained female farmers. The study further observes an increase in households adopting RUM, which eventually reduces farm productivity. This study therefore proposes to Government to establish appropriate institutional factors, such as rural markets to regulate RUM, rural labour supply, and related remittance receipts. For instance, the study suggests Government and other stakeholders providing input markets, which households can access to procure improved inputs for farm production. In addition, the study recommends provision of accessible credit markets, which can allow farmers procure farm inputs, like hired labour, inorganic fertilizer, and improved crop varieties, which are critical for the adoption of various CSA, or IPM, or SLM –related practices.