ENVIRONMENTAL GREENHOUSE GAS HOTSPOTS AND CLIMATE CHANGE ADAPTATION IN SMALLHOLDER SORGHUM CROPPING SYSTEMS IN SIAYA COUNTY, KENYA

COLLINS MUIMI MUSAFIRI (MSc)

A THESIS SUBMITTED IN PARTIAL FULFILLMENT FOR THE AWARD OF THE DEGREE OF DOCTOR OF PHILOSOPHY IN SOIL SCIENCE OF THE UNIVERSITY OF EMBU

SEPTEMBER 2022

DECLARATION

This thesis is my original work and has not been presented elsewhere for a degree or any other award.

Signature……………………………… Date ……………………

Collins Muimi Musafiri
Department of Water and Agricultural Resource Management
A806/276/2020

This thesis has been submitted for examination with our approval as the university supervisors.

Signature……………………………… Date ……………………

Dr Onesmus Ng'etich
Department of Water and Agricultural Resource Management
University of Embu

Signature……………………………… Date ……………………

Dr Milka Kiboi
Division of Research, Innovation and Outreach
KCA University

Signature……………………………… Date ……………………

Dr Joseph Macharia
Department of Geography
Kenyatta University

Signature……………………………… Date ……………………

Prof Felix Kipchirchir Ngetich
Department of Plant, Animal and Food Sciences
Jaramogi Oginga Odinga University of Science and Technology

DEDICATION

To my mentors, Prof Felix Ngetich and Dr. Milka Kiboi.

ACKNOWLEDGEMENT

Glory to the Almighty God for the grace during my Ph.D. study. I acknowledge Prof Felix Ngetich for allowing me to conduct my research under the World Bank-funded project through Kenya Climate-Smart Agriculture Project (KCSAP), a multi-disciplinary collaborative project titled "*Validating Sustainable Land Management Technologies for Enhanced Carbon Sequestration and Improved Smallholder Farmer's Livelihoods."* I highly appreciate my supervisors, Dr. Onsemus Ng'etich, Dr. Milka Kiboi, Dr. Joseph Macharia, and Prof Felix Ngetich, for the academic guidance during the study. You instilled invaluable skills during the study through concept development, proposal writing, data collection, statistical analysis, manuscript writing, and publication and thesis development. I also appreciate the other KCSAP project team: Dr. Betty Mulianga, Dr. David Kosgei, and Dr. Michael Okoti, for their amiable support during the project implementation. It was a privilege working with you during my study, and indebted for the scientific guidance you accorded me during my publications. I appreciate my colleagues Esphorn Kibet, Franklin Mairura, Pamella Asule, Jane Omenda, and Miriam Githongo for their impeccable support. I thank the smallholder farmers in Alego-Usonga and Ugenya sub-counties for providing the data used in this study. Finally, I appreciate my family for their social and spiritual support.

"*God's Grace was sufficient*."

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS AND ACRONYMS

AEZs	Agro-Ecological Zones
ANOVA	Analysis of Variance
ASALs	Arid And Semi-Arid Lands
ATT	Average Effects on Treated
ATU	Average Effects on Untreated
C: N	Carbon Nitrogen Ratio
CA	Conservation Agriculture
CCAFSMOT	Climate Change, Agriculture, Food Security Mitigation Options Tool
CFP	Carbon Footprint
CFT	Cool Farm Tool
CGA	Cereal Growers Association
CIAT	International Center For Tropical Agriculture
CSAPs	Climate-Smart Agricultural Practices
EABL	East Africa Breweries Limited
EABL	East African Breweries Ltd
ESR	Endogenous Switching Regression
FIML	Full Information Maximum Likelihood
FT	Farm Types
FtMA	Farm to Market Alliance
GDP	Gross Domestic Product
GHG	Greenhouse Gas
HC	Hierarchical Clustering
HSD	Honestly Significance Difference
IMR	Inverse Mills Ratio
IPCC	Intergovernmental Panel on Climate Change
IPW	Inverse Probability Weighting
KMO	Kaiser Mayer-Olkin
KNBS	Kenya National Bureau Of Statistics

KNBS	Kenya National Bureau Of Statistics
LM	Lower Midlands
LR	Long Rains
MFT	Monetary Footprint
MoALF	The Kenya Ministry of Agriculture, Livestock and Fisheries
MVP	Multivariate Probit
NCCRS	National Climate Change Response Strategy
NDCs	Nationally Determined Contributions
NNM	Near Neighbor Matching
ODK	Open Data Kit
PCA	Principal Components Analysis
PCI	Problem Confrontation Index
PCs	Principal Components
PSM	Propensity Score Matching
SDA	Stochastic Dominance Analysis
SR	Short Rains
SSA	Sub Saharan Africa
SSA	Sub-Saharan Africa
TH	Transitional Heterogeneity
TLU	Tropical Livestock Unit
UM	Upper Midlands
UNFCCC	United Nations Convention Framework on Climate Change
VIFs	Variance Inflation Factors
WAI	Weighted Average Index

LIST OF APPENDICES

ABSTRACT

Sorghum (*Sorghum bicolor L.)* is an essential drought-resistant crop that could enhance food security. However, its productivity remains relatively low in Kenya. Efforts to increase sorghum productivity through the application of external inputs could increase greenhouse gas (GHG) emissions. The study aimed to assess environmental GHG emission hotspots, effects of minimum tillage and inorganic fertilizer adoption on sorghum yields, and the determinants of adopting climate-smart agriculture and climate change adaptation practices. The study employed a cross-sectional survey of 300 smallholders in Siaya County, Kenya. Principal component analysis and hierarchical clustering were used in farm typologies construction. Using Cool Farm Tool software, a carbon footprint assessment approach was performed to identify environmental GHG emissions hotspots. One-way analysis of variance was used to test the influence of farm types on sorghum yields, GHG balance, carbon footprint, and monetary footprint in SAS 9.4 software. Descriptive statistics were used to describe the survey data. The impact of minimum tillage and inorganic fertilizer adoption were analyzed using propensity score matching and endogenous switching regression. Socioeconomic, institutional and biophysical determinants of adopting climate-smart agricultural practices (CSAPs) were analyzed using multivariate and ordered probit regression. Binary and Poisson regression models were used to evaluate the determinants of adopting climate change adaptation strategies. The results showed five farm types. The study showed that sorghum cropping systems were net sinks of soil GHGs. The GHG balance, carbon footprint, and monetary footprint significantly varied across the farm types at $p=0.025$, $p=0.018$, and $p=0.004$, respectively. The GHG balance ranged from -818.76 kg CO2 eq. ha^{-1} in manure intensive and low fertilizer intensity small farms to 174.29 kg CO2 eq. ha^{-1} in fertilizer intensive and moderate manure application rates on small farms. Adoption of minimum tillage and inorganic fertilizer improved sorghum yields. The study showed both complements and substitutes between CSAPs. The multivariate probit analysis revealed that the household head's gender, education, age, family size, contact with extension agents, weather information, arable land, livestock owned, perceived climate change, infertile soil, and persistent soil erosion influenced CSAPs adoption. Gender, arable land, livestock owned, soil fertility, and constant soil erosion were crucial determinants of CSAPs adoption intensity. Membership in agricultural associations, study location, progressive farming, literacy, remittance, access to credit, farm size, weather forecast information, and perceived climate changes significantly determine the adoption of climate change adaptation strategies. The study revealed that the judicious integration of inorganic fertilizers with animal manure could significantly improve sorghum yields while reducing yield-scaled greenhouse gas emissions. The findings on adopting agricultural innovations have incredible implications on rural livelihood. Enhanced productivity could promote food security and improve purchasing power, thus enhancing smallholder farmers' capacity to cope with declining soil fertility and climate change-related challenges.

CHAPTER ONE

GENERAL INTRODUCTION

1.1 Background

Producing adequate food to feed the growing population is a significant hurdle across global agro-ecosystems (Niza-Ribeiro, 2022). Population growth is a major threat to global food production (Askew, 2017). Global food production needs to be increased by approximately 70% to feed the estimated population of 9.1 billion by 2050 (FAO, 2009). Against the backdrop of rising population, soil fertility decline and climate change are significant factors affecting agricultural productivity in sub-Saharan Africa (SSA) (Kiboi et al., 2019; Thierfelder et al., 2022) and in Western Kenya (Wetende et al., 2018; Kanyenji et al., 2022). The soil fertility decline results from continuous cultivation with no or minimal soil fertility replenishment (Mairura et al., 2022a). Additionally, climate change indicators such as prolonged drought, erratic and unreliable precipitation, floods, variations in the length of the cropping calendar, and the outbreak of pests and diseases lead to reduced crop yields or total failure (Mairura et al., 2021). To improve agricultural productivity in SSA and Western Kenya, ameliorating soil fertility decline coupled with climate change mitigation and adaptation is essential (Ngetich et al., 2014; Donkor et al., 2019; Musafiri et al., 2020a).

Sorghum is an essential climate-smart crop for enhancing food security in arid and semi-arid lands (ASALs) (Muui et al., 2013; Hadebe et al., 2017). According to the Kenya Ministry of Agriculture, Livestock, and Fisheries (MOALF), (2016), approximately 80% of the total-farming households grow sorghum, which ranks second in importance among smallholder farming systems in Western Kenya. Despite the high adoption of sorghum (a climate-smart crop), its productivity remains relatively low (Okeyo et al., 2020a). The main challenges facing sorghum farming includes low soil fertility, poor varieties, climate change, and bird menace (ICRISAT, 2019). Therefore, soil fertility management and climate change adaptation practices are essential for enhancing sorghum productivity.

Agricultural intensification practices such as the application of inorganic fertilizer, Animal manure and its integration enhance soil health and crop productivity (Kiboi et al., 2019; Musafiri et al., 2020b). The soil amendments improve nutrient availability, organic matter, and water holding capacity, thus enhancing crop yields (Kiboi et al., 2021). However, the application of external inputs in smallholder farms leads to the increased atmospheric concentration of greenhouse gas (GHG) such as carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) (Ortiz-Gonzalo et al., 2018; Macharia et al., 2020). Smallholder farming systems are highly heterogeneous (Musafiri et al., 2020a). Intensifying the already heterogeneous smallholder farming systems complicates agricultural intervention targeting (Alvarez et al., 2018; Kamau et al., 2018). Characterizing smallholder farming systems in Western Kenya is important for enhanced GHG emissions mitigation and food security.

Documentation of Nationally Determined Contributions (NDCs) of GHG emissions is essential in meeting Kenya’s obligation to the United Nations Framework Convention on Climate Change (UNFCCC) and the 2015 Paris agreement on climate change (Pauw et al., 2018). Directly quantifying GHG emissions to inform NDCs is expensive and impractical on a national and regional scale (Giltrap et al., 2010; Musafiri et al., 2021). Estimation approaches such as carbon footprint (CFP) assessment have been widely used to investigate the impacts of agricultural management practices on the GHG balance (Rakotovao et al., 2017). The intensification approaches result in environmental GHG emissions hotspots and hot moments (Ortiz-Gonzalo et al., 2017). However, there is scanty information on the influence of agricultural management practices on the GHG balances and environmental GHG emissions hotspots among sorghum cropping systems in Western Kenya.

Minimum tillage and inorganic fertilizer could improve sorghum productivity. Adopting conservation agriculture practices (CA) such as minimum tillage could enhance sorghum productivity among sorghum cropping systems. Minimum tillage enhances soil organic matter build-up and structure, thus increasing soil fertility and reducing soil erosion (Alam et al., 2014), therefore improving crop yields (Thierfelder et al., 2015). The use of minimum tillage is limited by slow gains in crop yields (Giller et al., 2009). Inorganic fertilizers enhance soil health and agricultural productivity through increased nitrogen availability (Amujoyegbe et al., 2007). However, the nitrogen application rates in Kenya are low (Pasley et al., 2019), thus limiting the yield gains. Therefore, there is a pressing need to assess the influence of minimum tillage and inorganic fertilizer adoption on sorghum yields.

Smallholder farmers are faced with a decision to adopt multiple climate-smart agricultural practices (CSAPs) for coping with climate change. Smallholder farmers' awareness of climate change indicators, causes, and impacts is essential in selecting the appropriate adaptation practice (Wetende et al., 2018). However, smallholder farmers will only adopt CSAP if the utility of adopting is higher than not adopting (Streletskaya et al., 2020). The adoption level and intensity of the CSAPs vary widely among smallholders and range from low to high (Musyoki et al., 2022). Therefore, smallholders can adopt no, single or a bundle of agricultural technologies (Mairura et al., 2021). The decision to adopt multiple agricultural practices is influenced by myriad factors, including socioeconomics, institutional, and biophysical (Kanyenji et al., 2020; Ogada et al., 2020). Thus, the socio-economic, institutional, and biophysical determinants of CSAPs adoption level and intensity need to be investigated to determine the smallholders' mitigation and adaptation practices to climate change in Western Kenya.

1.2 Statement of the problem

Climate change and soil fertility decline are the significant challenges facing smallholder farmers in Western Kenya. Adopting climate-smart crops such as sorghum and using external inputs such as inorganic fertilizers and animal manure improves crop yields. However, smallholders apply limited amounts of external inputs in sorghum cropping systems. The smallholders are highly heterogeneous. This makes the implementation of best-fit agricultural management practices complicated. Agricultural intensification results in increased concentration of GHGs such as carbon dioxide, methane, and nitrous oxide leading to environmental hotspots. There are limited studies quantifying environmental GHG emissions hotspots in Kenya. There is a dearth of data on the contribution of climate-smart crops such as sorghum to the national GHG emission budget. Therefore, an understanding of the contribution of climate-smart crops to the GHG balance is urgently needed.

Smallholders adopt soil fertility management practices and conservation agriculture to enhance crop yields. The adoption of inorganic fertilizer and minimum tillage could improve crop yields. However, smallholders hardly use the recommended inorganic fertilizer amounts. To enhance soil health and crop yields, there is a need to promote inorganic fertilizer and minimum tillage. Adoption of multiple CSAPs is essential for climate change mitigation and adaptation. Climate change awareness and in-depth understanding of its causes, indicators, and impacts are necessary for choosing coping strategies. To cope with the vagaries of climate change, there is a pressing need to adopt a bundle of agricultural practices to benefit from their complementary benefits. However, there is inadequate information on the adoption level and intensity of CSAPs and their determinants in the study area.

1.3 Justification of the study

Adopting soil fertility management and climate-smart agricultural practices could be used to improve soil fertility and cope with climate change among smallholder farmers. Although adopting soil fertility management practices improves crop yield (Macharia et al., 2020; Musafiri et al., 2020b), it leads to GHG emissions. Although GHG emissions have been quantified from diverse cropping systems, including maize, and coffee-diary systems (Ortiz-Gonzalo et al., 2017; Githongo et al., 2022), estimating GHG hotspots from sorghum cropping systems is important. Additionally, understanding the effects of inorganic fertilizer and minimum tillage on sorghum yields, is essential. Understanding the determinants of adoption level and intensity of climate change adaptation practices is important in promoting mitigation and adaptation practices. Therefore, this study seeks to evaluate the environmental GHG emissions hotspots, effects of inorganic fertilizer, and minimum tillage adoption on sorghum yields and determinants of adopting climate change adaptation practices.

1.4 Research objectives

The broad objective of the study was to evaluate the environmental GHG emissions hotspots, effects of inorganic fertilizer, and minimum tillage adoption on sorghum productivity and determinants of climate change adaptation among smallholder farms in Western Kenya.

The following specific objectives guided this study:

1. To assess environmental greenhouse gas emission hotspots among smallholders' sorghum cropping systems in Siaya County.
2. To evaluate the effects of minimum tillage adoption on sorghum productivity among smallholder farmers in Siaya County.
3. To evaluate the effects of inorganic fertilizer adoption on sorghum productivity among smallholder farmers in Siaya County.
4. To assess the determinants of climate-smart agricultural practices adoption level and intensity among smallholder farmers in Siaya County
5. To assess the climate change perceptions and determinants of adaptation among smallholder sorghum farmers in Siaya County.

1.5 Outline of the thesis

The thesis is structured into seven chapters. Chapter one (General Introduction) highlights the background of the study, statement of the problem, justification of the study, and research objectives. Following the general introduction, there are five chapters (Chapters two to six), each a manuscript submitted to a peer-reviewed journal.

Chapter two presents the carbon footprint of smallholder sorghum cropping systems in Western Kenya. The smallholders' sorghum cropping systems in Western Kenya were characterized. Environmental GHG emissions hotspots were estimated using Cool Farm Tool (CFT), an excel program. The study presented the GHG balance, environmental GHG balances, and mitigation opportunities across different farm types.

Chapter three describes the effects of minimum tillage adoption on sorghum yields. The study highlights the adoption level of minimum tillage, determinants of minimum tillage adoption, and sorghum yields for both adopters and nonadopters.

Chapter four describes the effects of inorganic fertilizer adoption on sorghum yield among smallholder farmers in western Kenya. The research describes the determinants of inorganic fertilizer adoption and sorghum yield for adopters and nonadopters.

Chapter five presents the adoption level and intensity of smallholder CSAPs among smallholder farmers in Western Kenya. The socioeconomics, institutional and biophysical determinants of animal manure, soil water conservation, agroforestry, crop diversification, and crop-livestock integration are presented with the adoption intensity.

Chapter six presents the smallholder farmers' awareness of climate change and its causes, indicators, and effects. The smallholder farmers' climate change adaptation practices are presented. The study describes the problems encountered by smallholder farmers in coping with climate change. The study underscores the socioeconomic, biophysical, and institutional factors determining the adoption of climate change adaptation practices. Lastly, chapter seven outlines the synthesis, conclusion, recommendations, and areas of further research.

CHAPTER TWO

THE CARBON FOOTPRINT OF SMALLHOLDER RAIN-FED SORGHUM CROPPING SYSTEMS OF KENYA: A TYPOLOGY-BASED APPROACH

Abstract

Agriculture is a major source of greenhouse gas (GHG) emissions in sub-Saharan Africa, Kenya included. To feed the growing population, there is a need to identify agricultural management practices to increase food production while reducing GHG emissions for climate change mitigation and adaptation. This study assessed environmental hotspots among smallholders' sorghum cropping systems in Siaya County. The study was based on the hypothesis that different intensification levels influence the GHG balance. Three hundred smallholder farms in western Kenya were surveyed. Principal component analysis and hierarchical clustering were used in farm typologies construction. The study revealed five farm types that ranged from no or minimal external inputs and highly intensified, small to large, and low to highly endowed in tropical livestock units. Cool Farm Tool excel program model was used to estimate GHG balances. The study showed that sorghum cropping systems were net sinks of soil GHGs. The GHG balance, carbon footprint, and monetary footprint significantly varied across the farm types at p=0.03, p=0.02, and p=0.004, respectively. The GHG balance ranged from -818.76 kg CO_2 eq. ha^{-1} in manure intensive and low fertilizer intensity small farms to 174.29 kg CO_2 eq. ha^{-1} in fertilizer intensive and moderate manure application rates on small farms. Fertilizer production and direct and indirect emissions (fertilizer application) were the environmental hotspots accounting for 63 and 30 % of the GHG emissions. The carbon and monetary footprints ranged from -1.29 to 0.45 kg CO_2 eq. kg^{-1} sorghum and -2.02 to 0.13 kg CO_2 eq. US^{-1} generated, respectively. This study highlights that judicious integration of animal manure and inorganic fertilizer offers opportunities for GHG mitigation among smallholder sorghum cropping systems in western Kenya.

Keywords: carbon footprint, smallholder sorghum farms; intensification; green production;
farm-scale; Kenya

2.1 Introduction

The global greenhouse gas (GHG) concentrations (carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) have significantly increased over the last decades (IPCC, 2007; IPCC, 2014; Ntinyari & Gweyi-Onyango, 2021). The GHGs, CO_2, CH_4, and N_2O contribute approximately 60%, 20%, and 6% of global warming, respectively (Dalal & Allen, 2020). Agriculture contributes to about 14-17% of the anthropogenic GHG emissions (Ciais et al., 2013; Paul et al., 2017). Consequently, agriculture has been identified as an essential entry point in GHG emissions mitigation (Ogle et al., 2014; Leahy et al., 2020; Sapkota et al., 2021). Few studies have quantified GHG emissions in most developing countries, including Kenya (Rosenstock et al., 2016; Pelster et al., 2017). The direct quantification of agricultural GHG fluxes to inform the national and regional GHG budget is expensive and impractical (Giltrap et al., 2010; Musafiri et al., 2021). The dearth of studies constrains the identification of GHG mitigation opportunities in smallholder farming systems. Moreover, smallholder farming systems are highly heterogeneous (Alvarez et al., 2014; Kamau et al., 2018; Musafiri et al., 2020a). Therefore, constructing farm typologies and using GHG emissions estimation approaches is essential for identifying GHG emissions hotspots and mitigation options.

Climate change is the main challenge facing smallholder farming systems in African countries, including Kenya (Musafiri et al., 2020a; Mairura et al., 2022a). In the African countries, the main hurdle is to feed the growing population projected to double by 2050 from the current 1.3 billion persons (United Nations Population Division, 2022) while mitigating and adapting to climate change. To feed the growing population, there is a need to shift from land expansion to intensification (Ortiz-Gonzalo et al., 2017). The growth of climate-smart crops such as sorghum also provides novel opportunities for enhancing food security (Mwadalu & Mwangi, 2013; Ogeto et al., 2013). Smallholder farmers use soil fertility management practices, including manure, inorganic fertilizer, integration of animal manure and inorganic fertilizer, and mulching to enhance crop yields (Musafiri et al., 2022a, b). However, the nitrogen application rates among smallholder farming systems are low (Waithaka et al., 2007; Tittonell et al., 2008; Musafiri et al., 2020a; Mairura et al., 2022b). Given the differences in intensification among smallholder farms, the smallholders' sorghum cropping systems are highly heterogeneous. The construction of farm typologies is essential to group the smallholder sorghum cropping systems into homogenous farm types. Homogenous farm types could enhance the identification of GHG hotspots and mitigation options.

Given that direct quantification of GHG fluxes for informing National and regional budgets is expensive, previous studies have used a modeling approach to quantify the carbon footprint (CFP) to assess the impact of management practices on climate change (Rakotovao et al., 2017; Ortiz-Gonzalo et al., 2017). The Cool Farm Tool (CFT) has been used to evaluate the GHG balance at the farm level (Farm-gate), as influenced by different agricultural management activities (Yan et al., 2015; Zhang et al., 2017; Chen et al., 2020a). Using the CFP methodology, agriculture has been evaluated for GHG mitigation through different management practices (Rakotovao et al., 2017; Huang et al., 2017). Documentation of Nationally Determined Contributions (NDCs) of GHG emissions is essential in meeting Kenya's obligation to the United Nations Framework Convention on Climate Change (UNFCCC) and the 2015 Paris agreement on climate change (Pauw et al., 2018). Product carbon footprint (CFP) estimation could be used to report the GHG budget.

In western Kenya, sorghum is grown by approximately 80% of the farming households (MoALF, 2016). Though sorghum farming is mainly subsistence, there are concerted efforts by different organizations such as One Acre Fund, Cereals Growers Association (CGA), and *Farm* to Market Alliance (FtMA) to commercialize sorghum farming (MoALF, 2016; CGIAR, 2021). The commercialization of sorghum productivity leads to increased use of soil amendments such as mineral and organic inputs. Though the external inputs lead to increased sorghum yields, they come with additional costs of GHG emissions, thus increasing climate variability. The climate disturbance due to the increased use of soil amendments could further threaten food security and smallholders' livelihoods. To enhance greener production, sustainable utilization of soil amendments is essential. The GHG balances under different intensification levels will be necessary to inform potential GHG mitigation options among sorghum cropping systems.

There is limited information on the influence of intensification levels on farm-scale GHG balances in sorghum cropping systems of Western Kenya. The objective of this study was to assess environmental hotspots among smallholders' sorghum cropping systems (no external inputs to highly intensified systems) in Siaya County, Western Kenya. The study hypothesized that farm-level GHG balances varied across different intensification levels defined as farm types. Secondly, the study identified environmental GHG emissions hotspots by assessing the contributions of various components to the GHG balance. Finally, mitigation options across farm types were specified.

2.2 Methodology

2.2.1 Study area description

The study was conducted in Alego-Usonga and Ugenya sub-Counties, Siaya County, Western Kenya. Alego-Usonga and Ugenya sub-Counties cover 599 km^2 and 324 km^2 and have a population of 224,343 and 134,354 persons (KNBS, 2019). The population density is 375 and 415 persons per km^2, for Alego-Usonga and Ugenya, respectively. The sub-Counties lie at an altitudinal range of 1,140 and 1,500 m above sea level in Siaya County. Alego-Usonga and Ugenya sub-Counties experience similar climatic conditions with six agro-ecological zones that are Lower midland (LM 1-5) and upper midland (UM1) (Jaetzold et al., 2010). The sites receive bimodal precipitation with long rain (LR) season experienced between March and June and the short rain season between September and December. The annual precipitation amounts range from 800 and 2,200 mm. The long-term temperature annual ranges from 20.9 to 22.3 °C. The primary soil type is *Ferrasol*, with moderate to low soil fertility.

2.2.2 Smallholders' cropping systems

The main economic activities in Alego-Usonga and Ugenya sub-Counties are agriculture, fishing, and livestock rearing. The sites experience climatic conditions varying from semi-humid to semi-arid. The smallholders grow climate-smart crops, including sorghum (Sorghum bicolor), cassava (*Manihot esculenta*), green gram (*Vigna radiata*), cowpea (Vigna unguiculata), groundnuts (*Arachis hypogaea*), millet (Panicum miliaceum) and chickpea (*Cicer arietinum).* Other crops grown in the sub-Counties include maize (*Zea mays*), beans (*Phaseolus vulgaris*), and sugarcane (*Saccharum officinarum*). Sorghum, a drought-resistance crop, is grown by approximately 80 % of the farmers in Siaya County (Ministry of Agriculture, Livestock, and Fisheries (MoALF), 2016). The crop is grown under rain-fed systems. Low soil fertility and climate change, including low rainfall amounts and erratic precipitation, affect sorghum production in the study area. Smallholders implement different soil fertility management and climate change adaptation mechanisms, including animal manure, inorganic fertilizer, and their integration, and minimum tillage to enhance productivity against declining soil fertility and changing climate. Most sorghum growing areas are affected by waterlogging, impeding farm operations, including ploughing, planting, weeding, and harvesting. Animal manure (cattle, goat, and poultry) is acquired from domestic livestock or nearby households. Fertilizers are expensive for smallholder sorghum farmers, thus applied in small quantities.

2.2.3 Data collection

A cross-sectional survey of 300 farms was conducted using interview schedules to construct farm typologies and estimate GHG emissions and removal. The interview schedule targeted the households' heads. Additionally, fieldwork observation and measurements of soil samples, fertilizer amounts, manure quantity, and harvested grains were implemented to complement the survey. The smallholder farms were selected based on the following criteria: within Alego-Usonga and Ugenya sub-Counties who grew sorghum. The survey covered ten wards.

The data collected included (i) farm description including georeferenced coordinates, sub-county, and ward, (ii) farmer gender, (iii) farm characteristics such as farm size, seed quantity planted, tropical livestock unit, and crop variety, (iv) soil fertility management technologies such as the use of animal manure, inorganic fertilizers, integration of animal manure and inorganic fertilizer, no inputs application, and tillage practices, (v) inputs such as quantity and type manure and fertilizer applied, (vi) management practices such as tillage, cover crop, compost, animal manure, and crop residues application, duration of application and proportion of land and (vii) output including yields and price per kilo of sorghum. Each farm was georeferenced using the Global Positioning System. The quantity of fertilizer, manure, and yields was determined by weighing ten tools used by smallholders (wheelbarrow, bag, debe, tin, and Korogoro).

Fifteen farms were selected for composite soil sampling. Five soil samples were taken from each farm at 0-20 cm depth and mixed to form a composite sample. Soil texture was analyzed using the hydrometer method, soil organic carbon using the Walkley-Black method, soil pH using a 1:2 soil water ratio, and the suspension measured using HANNA Instruments (pH meter) (Okalebo et al., 2002). Eight storage heaps (four for goats and four cattle) were selected for composite manure sampling. A composite sample was obtained by sampling five points from each manure heap. The manure from the five points was then mixed to form a composite sample. The total C and N were determined using C /N analyzers.

2.2.4 Data analyses

Rain-fed smallholders farm are highly diverse due to variations in farmer, farm, and input characteristics. Farm typologies construction is widely used to group heterogeneous farms into homogeneous categories (Gil et al., 2019; Hammond et al., 2020). The farm typologies are valuable for enhancing smallholder farm innovations and policy implementation (Alvarez et al., 2018). The farm typologies are highly influenced by the factors included in the construction (Alvarez et al., 2014). Therefore, the research objectives should guide the variables to be included in the farm typology construction (Pacini et al., 2014). Musafiri et al. (2020a) found that farm typologies could be pivotal in estimating GHG balance. The study hypothesized that due to differences across farm typologies, GHG balance could significantly differ across them.

Farm typologies can be constructed using Step by step comparison of farm functioning (Landais, 1998), Expert knowledge (Pacini et al., 2014), Participatory rankings (Kebede, 2007), and Multivariate analysis (Alvarez et al., 2018; Musafiri et al., 2020a). The multivariate analysis allows for statistical reduction of explanatory variables to homogeneous farm types. In this study, multivariate analysis (principal components analysis (PCA) and hierarchical clustering (HC) was performed in R software as described by Alvarez et al. (2014) using the ade4 package (Mangin et al., 2012). The key variables included in the analysis were land size under sorghum (ha^{-1}), seed quantity planted (kg ha^{-1}), tropical livestock unit (TLU units), fertilizer amount applied during planting (kg ha^{-1}), fertilizer amount during top dressing ((kg ha^{-1}), manure quantity (t ha^{-1}), sorghum yields (kg ha^{-1}) and sorghum income (Dollars ha^{-1}), Table 2.1). Box plots were used to check for normal distribution. To ensure normal distribution, manure quantity, fertilizer amounts, yields, and revenue data were log-transformed.

Table 2.1 Description of the study variables

Variable description	Description	Units
Number of farms	Number of smallholders	count (%) hh
Farm typology description	Classification of the farm type	
Categorical variables *		
Site	Number of the smallholders who resident in Ugenya	count (%) hh
Gender	Number of the male smallholders	count (%) hh
Control	Number of smallholders not using soil fertility management practices	count (%) hh
Manure	Number of smallholders who applied manure	count (%) hh
Fertilizer	Number of smallholders who applied fertilizer	count (%) hh
Fertilizer and Manure integration	Number of smallholders who integrated manure and fertilizer	count (%) hh
Minimum tillage	Number of smallholders who implemented minimum tillage	count (%) hh
Continuous variables		
Land size	Land size under sorghum production	ha
Seed quantity	The quantity of seeds planted	kg ha^{-1}
Tropical livestock unit	The units of livestock kept	TLU
Fertilizer planting	The quantity of fertilizer applied during planting	kg ha^{-1}
Fertilizer top dressing	The quantity of fertilizer applied during top dressing	kg ha^{-1}
Manure quantity	The quantity of manure applied	kg ha^{-1}
Yields	Sorghum productivity	kg ha^{-1}
Revenue	Sorghum revenue	US$ ha^{-1}

*Only continuous variables were used in the multivariate analysis

The principal components (PCs) were selected based on Kaiser Mayer-Olkin (KMO), Alvarez et al., 2014; Musafiri et al., 2020a). The Principal Components with eigenvalues greater than one were retained. The sample size was greater than 250, so the KMO resulted in many PCs (Field, 2011). Therefore, critical PCs were selected if the cumulated percentage of explained variability accounted for 70 % or more of the total variance (Hair et al., 2010). The resultant PCs were subjected to HC analysis similar to Kamau et al. (2018). The barplot (height = 40) and dendrogram suggested five categories (k=5), Figure 2.1). Correlation circles were generated for farm types visualization and interpretations (Figure 2.2). A one-way analysis of variance was performed to assess whether there was a significant difference between the factors and the farm types (Table 2.2).

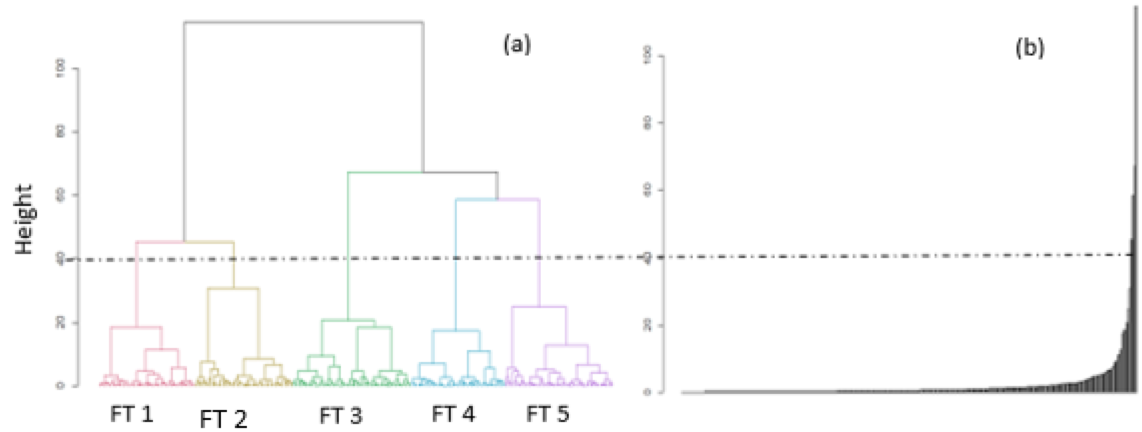

Figure 2.1 Dendrogram (a) and bar plot (b) indicate the number of farm types resulting from multivariate analysis. The dotted horizontal line indicates the cut-off points that resulted in five farm types (FT 1-5). The vertical axis represents the distance or 'height' between the farm types.

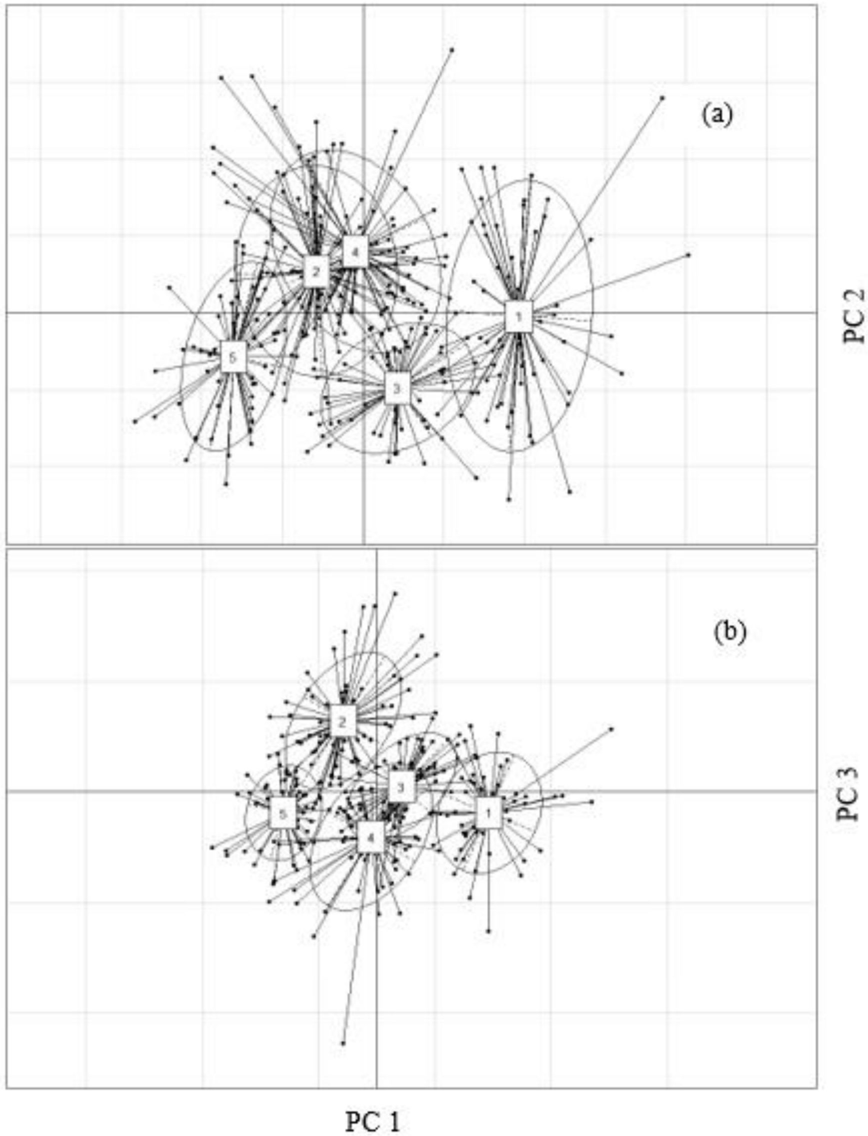

Figure 2.2 Visualization of farm types by Principal Component Analysis. The farm types are indicated in PC1-PC2 (a) and PC1-PC3 (b).

Several tools, including Cool Farm Tool (CFT), EX-ACT and Climate Change, Agriculture, Food Security Mitigation Options Tool (CCAFSMOT), have been developed, tested, and validated for estimating GHG balance in tropical conditions. The GHG tools estimate global GHG emissions with minimal data requirements (Lata et al., 2020). The CFT has been used to quantify GHG balance across different systems in Africa, including Seebauer (2014 from smallholder farms in Western Kenya, Svubure et al. (2018) from potato cropping systems in Zimbabwe, Ortiz-Gonzalo et al. (2017) from crop-livestock systems in Central Kenya and Vervuurt et al. (2022) from cacao production in the Republic of Côte d'Ivoire. The CFT (Hillier et al., 2011) is an open-source Spreadsheet program that estimates the GHG emissions from different input levels and management practices. Therefore, CFT combines other empirical models and uses them to calculate GHG emissions as carbon dioxide equivalents (Hillier et al., 2011). The CFT model uses empirical equations and the IPCC Tier 1 and 2 approaches. In this study, the CFT was used to estimate GHG balance across the different farm types in Western Kenya.

The CFT could be sensitive to input variables. Previous studies have found that the CFT model has lower sensitivity (Clavreul et al., 2017). Given the nitrogen application rate (0-89 kg N ha^{-1}) in the study was lower than 66–506 kg N ha^{-1} used by Clavreul et al. (2017), the uncertainty in the study could be much lower. Vervuurt et al. (2022) employed a similar analysis approach on cocoa cropping systems with a nitrogen application rate of (0- 250 kg N ha^{-1}). The GHG balance calculation requires a set system boundary (Alam et al., 2019; Chen et al., 2020b). The system boundary was set up to the farm gate. Therefore, emissions beyond the farm gate were not considered. The system boundary is used to assess the GHG balance based on sources and sinks. Figure 2.3 highlights the GHG emissions sources and sinks considered in the research. The overall GHG balance is expressed as CO_2 eq. The CO_2 eq. is calculated using the global warming potential conversation factor of 265 for N_2O and 28 for CH_4 over a 100-year time horizon (IPCC, 2014).

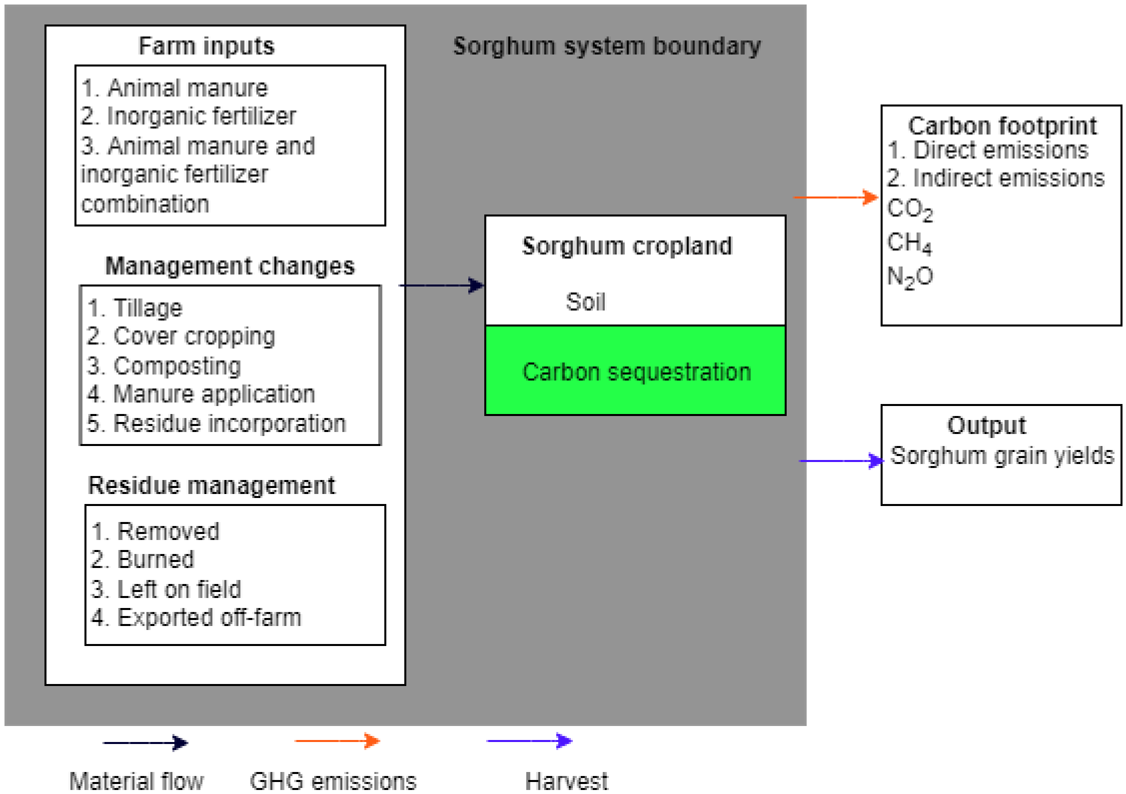

Figure 2.3 Sorghum cropping system boundary

The GHG balances comprised fertilizer production, background soil process, crop residue management, and carbon sequestration. This study did not consider emissions from trees, electricity, farm machinery, or sorghum processing. Smallholder sorghum cropping systems mostly use animals for farm labor, such as land preparation. In addition, including livestock emissions could lead to biased estimation due to overestimation of the GHG fluxes. Therefore, the study did not include emissions from livestock systems—background emissions results from soil biogeochemical processes. The soil emissions from the background processes include soil pH, texture and soil organic matter, drainage, and climate (Hillier et al. 2011). The net GHG balance is expressed as CO_2 eq. A positive sign indicates a source, and a negative sign indicates a sink. The soil characteristic data such as pH (5.2), SOM (2.8%), and texture (medium) were included in the model from the laboratory analysis. The C and N concentrations for manure were included in the laboratory analysis, while the manufacturer-specific concentrations of inorganic fertilizers were used for the input in the CFT model.

The environmental hotspots were determined by calculating the smallholders' sorghum cropping system to the GHG balance. The environmental hotspots were expressed as area-scaled emissions (kg CO_2 eq. ha^{-1}), yield-scale emissions (Kg CO_2 eq. kg $sorghum^{-1}$), and monetary-scaled emissions (Kg CO_2 eq. $US\$^{-1}$ generated). A heatmap analysis was performed to identify the environmental hotspots using R software. The environmental hotspots across different farm types were compared using one-way analysis of variance (ANOVA) and mean separation using Tukey's HSD when $P < 0.05$ in R software.

2.3. Results and discussion

2.3.1 Farm typology

Five farm types were identified through PCA and HC (Figure 2.2-2.3). The descriptive characteristics of each farm type (FT) are described in Tables 2.2-2.3. Farm type 1 (FT1) comprises small farms (0.22 ha), sole fertilizers, and manure and fertilizer integrating farming households. The FT1 also had a high resource endowment in TLU (0.54 units). FT1 had a high fertilizer (143.29 kg ha^{-1}) and moderate manure (502.39 kg ha^{-1}) use intensity. The FT1 was categorized as fertilizer intensive and moderate manure intensity on small farms. The FT2 comprised small farms (0.17 ha), sole manure and manure and fertilizer integrating farming households. The FT2 had high manure (1918.53 kg ha^{-1}) and low fertilizer (18.78 kg ha^{-1}) use intensity. The FT2 had a high TLU (0.63 units) regarding resource endowment. Therefore, the FT2 was grouped as manure intensive and low fertilizer intensity small farms.

Farm type three (FT3) comprised small farms (0.15 ha-1) with sole fertilizer and manure and fertilizer integrated farming households. The FT3 had moderate manure (195.84 kg ha^{-1}) and fertilizer (68.76 kg ha^{-1}) application rates. The farming households in FT3 had a low resource endowment of 0.27 units of TLU. The FT3 was classified as moderate fertilizer and manure intensifying on small farms. On the contrary, farm type 4 (FT4) had large (0.38 ha) and predominantly adopters of mineral fertilizer. The FT4 was characterized by low fertilizer (37.86 kg ha^{-1}) and manure (110.44 kg ha^{-1}) use intensity. Regarding resource endowment, FT4 had a high of 0.65 TLU units. The FT4 was grouped as low fertilizer and manure intensity on large farms.

Table 2.2 Descriptive characteristics of the five farm types in Western Kenya

Typology description/ Variables	**FT 1**	**FT 2**	**FT 3**	**FT 4**	**FT 5**	**P-Value**	**Pooled**
Number of farms	57 (19.0)	69 (23.0)	56 (18.7)	63 (21.0)	55 (18.3)		300
Categorical Variables							
Site	31(26.1)	14 (11.8)	28 (23.5)	29 (24.4)	17 (14.3)	0.000	119
Gender	26 (22.8)	29 (25.4)	12 (10.5)	28 (24.6)	19 (16.7)	0.044	114
Control	0 (0)	12 (23.5)	0 (0)	4 (7.8)	35 (68.6)	0.000	51
Manure	0 (0)	37 (82.2)	0 (0)	2 (4.4)	6 (13.3)	0.000	45
Fertilizer	45 (29.2)	0 (0)	50 (32.5)	47 (30.5)	12 (7.8)	0.000	154
Fertilizer and Manure integration	12 (24.0)	20 (40.0)	6 (12.0)	10 (20.0)	2 (4.0)	0.002	50
Minimum tillage	11 (19.0)	9 (15.5)	16 (27.6)	15 (25.9)	12 (7.1)	0.128	58
Continuous Variables							
Land size	0.22 ± 0.05^{b1}	0.17 ± 0.01^{b}	0.15 ± 0.02^{b}	0.38 ± 0.05^{a}	0.24 ± 0.02^{b}	0.000	0.23±0.02
Seed quantity	20.12 ± 1.63^{a}	17.48 ± 1.08^{a}	15.35 ± 1.08^{ab}	11.38 ± 1.72^{b}	11.62 ± 1.16^{b}	0.000	15.23±0.64
Tropical livestock unit	0.54 ± 0.05^{a}	0.63 ± 0.04^{a}	0.27 ± 0.04^{b}	0.65 ± 0.04^{a}	0.28 ± 0.04^{b}	0.000	0.49±0.02
Fertilizer planting	143.29 ± 16.28^{a}	18.78 ± 4.46^{cd}	68.76 ± 7.59^{b}	37.86 ± 3.93^{bc}	3.31 ± 1.03^{d}	0.000	52.94±4.59
Fertilizer top dressing	88.25 ± 10.91^{a}	0.36 ± 0.36^{b}	10.28 ± 3.33^{b}	13.28 ± 3.78^{b}	0.22 ± 0.15^{b}	0.000	21.60±2.97
Manure quantity	502.39 ± 161.08^{b}	1918.53 ± 242.36^{a}	195.84 ± 96.08^{b}	110.44 ± 38.15^{c}	90.87 ± 48.41^{c}	0.000	613.13±78.90
Yields	1565.62 ± 93.88^{a}	1105.24 ± 55.14^{bc}	1333.58 ± 85.27^{ab}	1061.62 ± 63.50^{c}	688.28 ± 33.77^{d}	0.000	1149.73±34.70
Revenue	702.48 ± 53.10^{a}	434.46 ± 25.24^{b}	531.97 ± 37.99^{b}	440.29 ± 31.06^{b}	269.70 ± 13.55^{c}	0.000	474.60±17.15

[1] Mean values with different superscripts across rows are significantly different at $P < 0.05$.
FT indicates the farm types
Values in parenthesis are the percentage
The ± showed the standard error of the mean
The soil fertility inputs, sorghum yields, and revenue are for one cropping season.

Table 2.3 Farm type distribution in Ugenya and Alego-Usonga sub-Counties

Pooled sample (n=300)			**Ugenya (n=119)**		**Alego-Usonga (n=181)**	
Farm type description	Farm type	Percent (%)	frequency	Percent (%)	Frequency	Percent (%)
Fertilizer intensive and moderate manure intensity small farms	1 (n=57)	19.0	31	26.1	26	14.4
Manure intensive and low fertilizer intensity small farms	2 (n=69)	23.0	14	11.8	55	30.4
Moderate fertilizer and manure intensity small farms	3 (n=56)	18.7	27	22.7	29	16.0
Low fertilizer and manure intensity large farms	4 (n=63)	21.0	29	24.4	34	18.8
No or minimal soil fertility replenishment small farms	5 (n=55)	18.3	18	15.1	37	20.4

Farm type five (FT5) was characterized by small farms (0.24 ha) with minimal utilization of soil fertility management technologies. The FT5 had very low fertilizer (3.31 kg ha^{-1}) and low manure (90.87 kg ha^{-1}) application rates. Additionally, the FT5 had a low resource endowment of 0.28 TLU units. The FT5 was grouped as no or minimal soil fertility replenishment on small farms.

2.3.2 Sorghum yields and revenue

The sorghum yields ranged from 688.28 to 1565.62 kg ha^{-1} under FT5 and FT1, respectively (Table 2.2). The sorghum yields significantly ($p \leq 0.0001$) differed across the FTs. The average sorghum productivity was 1149.73 kg ha^{-1}. The sorghum yields were lower in FT2, FT4, and FT5 and higher in FT1 and FT3. The FT1 had the highest sorghum yields, 2.27 times higher than FT5. The average revenue across the FTs was 474.60 US\$ ha^{-1} (Table 2.2). The sorghum revenues significantly ($p \leq 0.000$) differed across the FTs with FT5 having the lowest (269.70 US\$ ha^{-1}), and FT1 the highest income (702.48 US\$ ha^{-1}). The sorghum revenues in FT2, FT3, and FT4 were not statistically different.

The quantity of 688 to 1566 kg ha^{-1} of sorghum grain yields observed in the study agreed with 300 to 4300 kg ha^{-1} reported under drier conditions in Kenya (Okeyo et al., 2020; Kimaru-Muchai et al., 2021; Tegemeo Institute, 2021). However, the sorghum yields were much lower than the production potential of 2000 to 5000 kg ha^{-1} (Karanja et al., 2014). The higher crop yields in FT1, FT2, and FT3 than FT 4 and FT4 could be attributed to the higher nutrient application rates. Increased application of soil amendments such as mineral fertilizer and animal manure leads to improved soil fertility (Macharia et al., 2020; Musafiri et al., 2020b), thus enhancing crop productivity. Additionally, the application of animal manure in the drylands of Western Kenya could have resulted in better soil properties such as water content, organic carbon, and reduced degradation, thus enhancing crop yields. The findings indicated that external inputs such as animal manure and soil fertility improved sorghum yields.

2.3.3 Farm GHG environmental hotspots

Table 2.4 shows a heat map visually interpreting GHG balance and yield scaled emissions across farm types. The heat map interpretation is based on color intensity. The darker colors suggested hotspots and hot moments at multiple scales. FT1 and FT2 had the darkest colors for GHG balance, and yield scaled emissions, thus highlighted as environmental GHG hotspots among smallholder sorghum cropping systems in Western Kenya. Fertilizer production and application were the main contributors to the GHG hotspots.

Table 2.4 Heat map of environmental GHG hot moments and hotspots

Category	Sources of emissions	FT1	FT2	FT3	FT4	FT5
Product Footprint ($kg\ CO_2$ eq. ha^{-1})	Fertilizer Production					
	Fertilizer application					
	Crop Management					
	Carbon sequestration					
Carbon Footprint ($kg\ CO_2$ eq. kg^{-1} yields)	Fertilizer Production					
	Fertilizer application					
	Crop Management					
	Carbon sequestration					

Darker colors indicate higher emissions, FT is farm type

Differences in GHG balance were found across farm types, p=0.046 for fertilizer production, p=0.010 for fertilizer application, p≤0.0001 for crop management, and p=0.023 for carbon sequestration (Table 2.5). FT1 (1208.52 kg CO_2 eq. ha^{-}) and FT2 (1187.52 kg CO_2 eq. ha^{-}) had the highest GHG emissions from fertilizer production, while FT5 (86.23 kg CO_2 eq. ha^{-}) had the lowest. Both FT3 (416.15 kg CO_2 eq. ha^{-}) and FT4 (336.89 kg CO_2 eq. ha^{-}) contributed the same amount to the GHG balance. FT2 (400.00 kg CO_2 eq. ha^{-1}) had the highest contribution regarding fertilizer application, while FT5 (288.77 kg CO_2 eq. ha^{-1}) had the lowest. The FT1 (81.70 kg CO_2 eq. ha^{-1}) had the highest while FT5 (61.50 kg CO_2 eq. ha^{-1}) had the lowest contribution to GHG balance resulting from crop management. Different management practices resulted in soil carbon sink. The FT2 (-2478.77 kg CO_2 eq. ha^{-1}) had the highest soil carbon sink, while FT5 (-577.07 kg CO_2 eq. ha^{-1}) had the lowest. The overall contribution of different sources to GHG balance was ranked as; crop management (7%), fertilizer application (30%), and fertilizer production (63%), Figure 2.4).

An estimated -577 to -2478 kg CO_2 eq. ha^{-1} of carbon was stored in sorghum cropping systems (Table 2.5). The carbon sequestration falls within the range documented by previous studies range, between -1530 and -3830 kg C ha^{-1} in Western Kenya (Karanja, 2020), -1300 to -2300 kg C ha^{-1} in the Central highland of Kenya (Ortiz-Gonzalo et al., 2017), and -700 to -1150 kg C ha^{-1} in Brazil (Corbeels et al., 2006). Considering farm type, the highest amount of carbon (2478 kg CO2 eq. ha^{-1}) was stored in the FT2, while the lowest amount of carbon was stored in FT5. It is noteworthy that FT2 had the highest manure application rates (1919 kg ha^{-1}) and FT5 the lowest (91 kg ha^{-1}). Therefore, the highest and lowest carbon sequestration observed in FT2 and FT5 could be endorsed to the differences in manure application rates. The findings agreed with Ortiz-Gonzalo et al. (2017), who reported the highest manure application rates stored higher carbon.

Table 2.5 The GHG balance and yield-scaled emissions for different GHG sources and sinks

Farm type description	**The GHG balance (kg CO_2 eq. ha^{-1})**			
	Fertilizer production	**Fertilizer application**	**Crop Management**	**Carbon sequestration**
FT1	1208.52^{a}±360.32	313.78^{ab}±10.20	81.7^{a}±78	-1429.71^{b}±275.44
FT2	1187.52^{a}±297.82	400.00^{a}±47.46	72.5^{ab}±2.46	-2478.77^{c}±277.69
FT3	416.15^{b}±120.89	295.19^{b}±2.51	72.29^{ab}±2.28	-832.00^{ab}±120.69
FT4	336.89^{b}±120.92	311.56^{ab}±10.27	64.28^{bc}±1.76	-780.06^{ab}±107.98
FT5	86.23^{c}±44.51	288.77^{b}±6.48	61.51^{c}±2.06	-577.07^{a}±86.62
p-Value	0.046	0.010	0.000	0.023
Mean	666.98±104.96	325.09±11.56	70.46±1.20	-1266.74±100.05
	The yield-scaled emissions (kg CO_2 eq. kg sorghum $^{-1}$)			
FT1	1.90^{a}±0.42	0.31^{d}±0.03	0.07^{c}±0.01	-1.87^{b}±0.15
FT2	2.05^{a}±0.25	0.64^{c}±0.10	0.09^{c}±0.01	-4.05^{d}±0.16
FT3	0.71^{b}±0.12	0.39^{d}±0.04	0.08^{c}±0.01	-1.10^{a}±0.06
FT4	0.77^{b}±0.15	0.77^{b}±0.12	0.13^{b}±0.02	-3.69^{c}±0.52
FT5	0.56^{c}±0.12	1.02^{a}±0.20	0.18^{a}±0.03	-2.05^{b}±0.18
p-Value	0.015	0.000	0.000	0.027
Mean	1.23±0.11	0.63±0.05	0.11±0.01	-2.65±0.13

[1] Mean values with different superscripts across columns are significantly different at $P < 0.05$.
FT indicates the farm types
The ± indicated the standard error of the mean

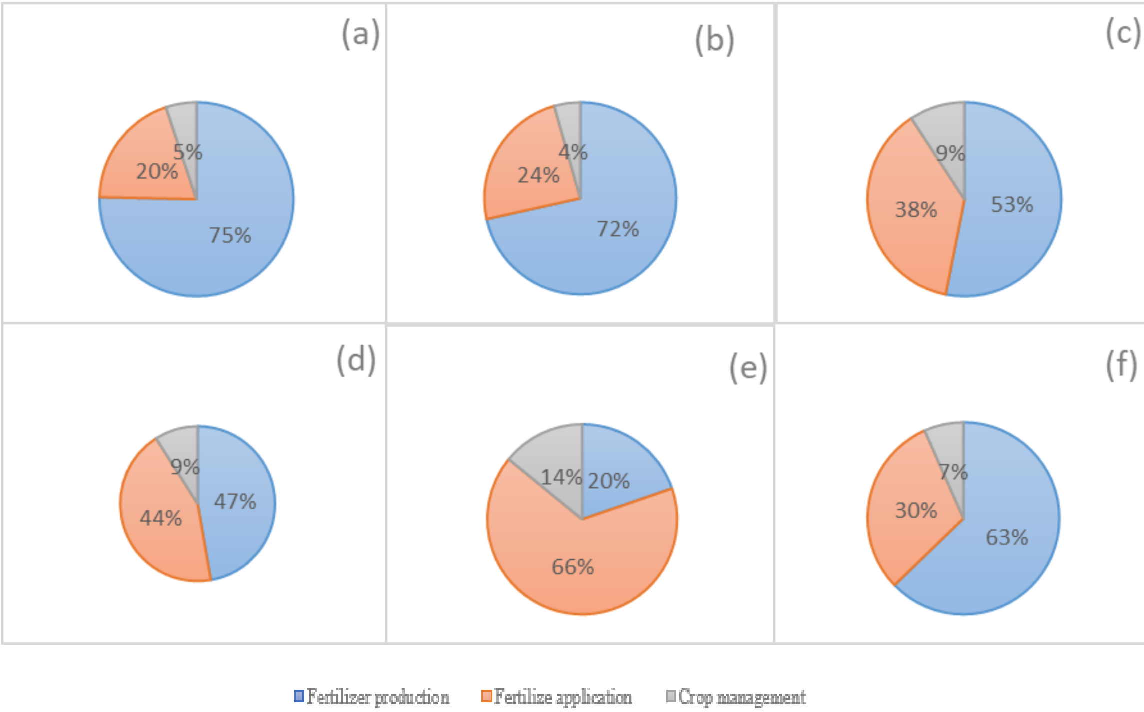

Figure 2.4 The contribution of different sources to GHG balance across the farm types (FT 1-5) and the overall. a) farm type 1, b) farm type 2, c) farm type 3, d) farm type 4, e) farm type 5 and f) overall.

The study revealed statistical differences in yield scaled emission across different farm types; p=0.015 for fertilizer production, p≤0.0001 for fertilizer application, p≤0.0001 for crop management, and p=0.027 for carbon sequestration (Table 2.5). Considering fertilizer production, the average carbon footprint was 1.23 kg CO_2 eq. kg sorghum $^{-1}$. The lowest CFT were observed under FT5 (0.56 kg CO_2 eq. kg sorghum $^{-1}$) and the highest in FT2 (2.05 kg CO_2 eq. kg sorghum $^{-1}$). FT1 (0.31 kg CO_2 eq. kg sorghum $^{-1}$) had the lowest and FT5 had the highest (1.02 kg CO_2 eq. kg sorghum $^{-1}$) CFT resulting from fertilizer application. The average CFT from fertilizer application was 0.63 kg CO_2 eq. kg sorghum $^{-1}$. On average, crop management had a CFT of 0.11 kg CO_2 eq. kg sorghum $^{-1}$. The lowest CFT was recorded in FT1 0.07 kg CO_2 eq. kg sorghum $^{-1}$ and the highest in FT5 at 0.18 kg CO_2 eq. kg sorghum $^{-1}$. Regarding carbon sequestration, smallholder farms in Siaya sequestered -2.65 kg CO_2 eq. kg sorghum $^{-1}$. The lowest carbon sequestration was observed in FT3 -1.10 kg CO_2 eq. kg sorghum $^{-1}$ and the highest in FT2 -4.05 kg CO_2 eq. kg sorghum $^{-1}$. The overall contribution of different sources to CFT was in rank; crop management (6%), fertilizer application (32%), and fertilizer production (62%), Figure 2.5).

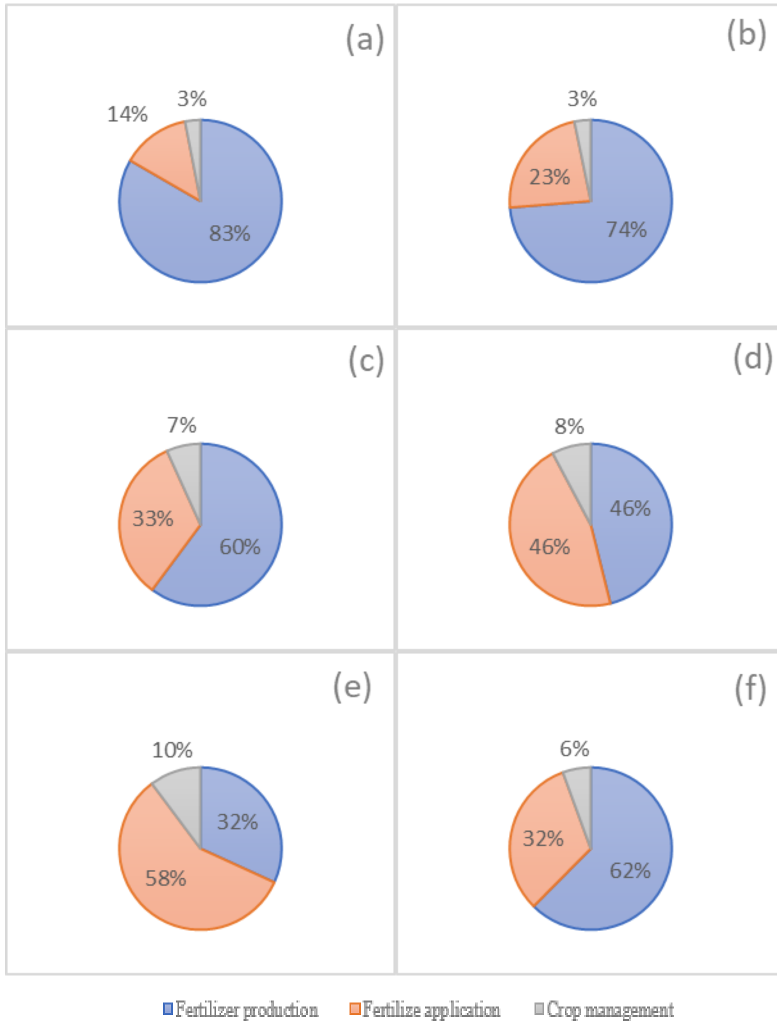

Figure 2.5 The contribution of different sources to yield-scaled emissions, the farm types (FT 1-5), and the overall. a) farm type 1, b) farm type 2, c) farm type 3, d) farm type 4, e) farm type 5 and f) overall.

The smallholder sorghum cropping system is an integration of different management components. The management components contribute differently toward the GHG balance. The results showed that the primary GHG emission hotspots were fertilizer production, fertilizer application (background soil emissions), and crop management. The influence of specific components varied across the farm types. Fertilizer production dominated the GHG balance in FT1, FT2, and FT5, while in FT3 and FT4, its contribution was relatively low. The indirect and direct emissions significantly contributed to the GHG balance in FT3 and FT4. The increased contribution of fertilizer production in FT3 and FT4 could be attributed to the low fertilizer application rates. Given the interactions between the components, rational approaches are essential to identify potential GHG mitigation options across the farm typologies.

2.3.4 Area, yield, and monetary-scaled footprint

Smallholder sorghum farms in Siaya County were predominantly GHG sinks (Table 2.6). This implies that the GHG emissions were less than the carbon sequestration. The GHG balance varied ($p=0.025$) across farm types. The mean GHG balance across farm types was -205.54 kg CO_2 eq. ha^{-1}. The lowest GHG balance was observed in FT2 -818.76 kg CO_2 eq. ha^{-1} while the highest was in FT1 at 174.29 kg CO_2 eq. ha^{-1}. FT1 had the highest GHG balance among the five FTs, which was 5.7 folds higher than FT2.

The sorghum cropping systems in Western Kenya were mostly net sinks of soil GHGs. The magnitude of GHG emissions and removal among the smallholder sorghum cropping systems was influenced by soil fertility management intensification. The smallholder sorghum farms with higher fertilizer rates produced higher area scaled emissions than manure application rates. The GHG balance ranged from -818.76 kg CO_2 eq. ha^{-1} under FT2 (high manure application rates) to 174.29 kg CO_2 eq. ha^{-1} under FT1 (high fertilizer application rates). The findings suggested that high manure application increased soil carbon sequestration, thus reducing the overall amount of GHG balance. The GHG balance was lower than Ortiz Gonzalo et al. (2017) of 4.5 to 12.5 t CO_2 eq ha^{-1} yr^{-1} in the Central Highlands of Kenya, though they included trees and livestock. The findings were lower than 4 and 6.5 t CO2 eq ha^{-1} yr^{-1} reported by Seebauer (2014), in Western Kenya though they included household energy consumption. The low GHG balance in sorghum cropping systems of Western Kenya could be attributed to the failure to include GHG removal by trees and enteric fermentation from livestock. The GHG balance was lower than 1946 kg CO2 eq./ha to 6211 kg CO2 eq./ha as reported under the potato cropping system in Zimbabwe (Svubure et al., 2018). Additionally, the findings on GHG balances were lower than the field measurements reported in the Central Highlands of Kenya

(Ortiz-Gonzalo et al., 2018; Macharia et al., 2020; Musafiri et al., 2020b). However, the field measurements did not consider carbon removal through soil sequestration. Considering soil carbon sequestration, Githongo et al. (2022) found that GHG balances ranged from -14700 to 3390 kg CO_2 eq ha^{-1} yr^{-1}. The findings indicated that the smallholders' sorghum cropping systems acted as GHG sinks. Thus, they could significantly contribute to climate change mitigation and adaptation. However, it is noteworthy that the diversity of variables included in the CFT GHG estimation methodology limits comparing the study findings with those reported in the literature.

Table 2.6 The area, yield, and monetary-scaled footprint across different farm types in Siaya County

Farm type	Area-scaled footprint (kg CO_2 eq. ha^{-1})	Yield-scaled footprint (kg CO_2 eq. kg sorghum $^{-1}$)	Monetary-scaled footprint (kg CO_2 eq. US^{-1} generated)
FT1	174.29a±62.79	0.45a±0.24	0.13a±0.04
FT2	-818.76d±57.64	-1.29d±0.19	-2.02d±0.20
FT3	-49.00b±25.18	0.07b±0.07	-0.01b±0.01
FT4	-67.34b±16.79	-1.86e±0.49	-0.01b±0.01
FT5	-147.88c±20.86	-0.30c±0.19	-0.46c±0.07
p-Value	0.025	0.018	0.004
Mean	-205.54±19.37	-0.64±0.13	-0.53±0.06

[1] Mean values with different superscripts across columns are significantly different at $P < 0.05$.
FT indicates the farm types
The ± showed the standard error of the mean

Differences in yield-scaled emissions (CFT) were observed across farm types at p = 0.018 (Table 2.6). The smallholder sorghum farm resulted in a CFT of -0.64 kg CO_2 eq. kg sorghum $^{-1}$. The highest CFT was observed in FT2 -1.29 kg CO_2 eq. kg sorghum $^{-1}$ and the highest in FT1 0.45 kg CO_2 eq. kg sorghum $^{-1,}$ which was 3.9 times higher. The CFT of -0.64 to -1.29 kg CO_2 eq. kg sorghum $^{-1}$ was lower than those reported by (Ortiz-Gonzalo et al., 2017). According to SGS North America (2015) the sorghum CFT ranged 0.05 kg CO_2 eq up to 0.74 kg CO_2 eq per kg of sorghum, with an average of 0.25 kg CO_2 eq. kg sorghum $^{-1}$ in the United States. Additionally, the low CFT of sorghum could be attributed to the limited soil fertility management intensity.

The study determined monetary footprint (MFT) as influenced by the five farm types (Table 2.6). The study showed significant ($p=0.004$) variation in MFT across the farm types. The smallholder sorghum farms had a mean of -0.53 kg CO_2 eq. US$$^{-1}$ generated. The lowest MFT was recorded in FT2 -2.02 kg CO_2 eq. US$$^{-1}$ and the highest in FT1 0.13 kg CO_2 eq. US$$^{-1}$. Manure intensification did not increase CFT and MFT. Smallholders' sorghum farming in Western Kenya is mainly subsistence (ICRISAT, 2017; Okeyo et al., 2020). Most of the sorghum yields are consumed by the farmers without selling. However, the farmers reported the prevailing market prices which were used to calculate the market value of the produced sorghum. Therefore, the study allocated the GHG balance to the market value of the sorghum grain yields produced.

2.4 Conclusion

Smallholder sorghum cropping systems showed lower CFT mainly due to the low use of external inputs in Western Kenya sorghum farms. In the study, sorghum cropping systems showed net sinks of GHG emissions. The primary GHG emissions hotspots were fertilizer production and application in moderate to high fertilizer manure use intensity. Integrating animal manure and inorganic fertilizer resulted in increased yields. Smallholder farmers in Western Kenya had already integrated animal manure and inorganic fertilizer for increased soil organic carbon and fertility for enhanced crop productivity. Therefore, the smallholders are contributing to the sink of GHG emissions. The study underscored the low contribution of smallholders' sorghum cropping systems in western Kenya to GHG emissions mitigation through integrated soil fertility management.

CHAPTER THREE

DOES THE ADOPTION OF MINIMUM TILLAGE IMPROVE SORGHUM YIELD AMONG SMALLHOLDERS IN KENYA? A COUNTERFACTUAL ANALYSIS[1]

Abstract

Climate change is an essential drawback to food security in most developing countries. Promoting minimum tillage and climate-smart crops is critical for mitigating and adapting to climate shocks. However, information on the impacts of minimum tillage on crop productivity under farmers' conditions is limited in Western Kenya. The study assessed the effects of minimum tillage adoption on sorghum productivity among smallholder sorghum farmers in Western Kenya. The study used household survey data from 300 smallholder farmers, and an endogenous switching regression model was performed to analyze the effects of minimum tillage adoption on sorghum yields. The results revealed that the adoption of minimum tillage increased sorghum yields by 11%, from 1146 to 1163 kg ha^{-1}. The occupation of the household head, acreage, soil fertility perception, and farm credit significantly and positively determined minimum tillage adoption. The remittance, agricultural associations, weather information, and site negatively and significantly determined minimum tillage adoption. The findings suggest that minimum tillage adoption under drought-tolerant crops such as sorghum could improve community wellbeing through increased crop productivity, notwithstanding the changing climate and associated weather shocks.

Keywords: Food security; Conservation tillage; Endogenous switching regression; Propensity score matching; Sub-Saharan Africa

[1] Musafiri, C.M., Kiboi, M., Macharia, J., Ng'etich, O.K., Okoti, M., Mulianga, B., Kosgei, D.K. & Ngetich, F.K., (2022). Does the adoption of minimum tillage improve sorghum yield among smallholders in Kenya? A counterfactual analysis. *Soil and Tillage Research*, *223*, 105473. https://doi.org/10.1016/j.still.2022.105473

3.1 Introduction

Conservation agriculture (CA) can be defined as agricultural practices for improved agricultural production while conserving resources and protecting the environment (FAO, 2012). The main innovation in CA is reduced soil disturbance. Reducing soil disturbance enhances time, energy, and labor savings, thus promoting the conservation of soil, water, and nutrients for improved crop yields (Fredenburg, 2015). CA is one of the approaches promoted for enhanced agricultural productivity and making smallholder farming systems resilient to climate change (Findlater et al., 2019; Kassam et al., 2019). The three CA principles are minimum tillage, permanent soil surface cover, and crop diversification (Sommer et al., 2014; Vanlauwe et al., 2014). Minimum tillage, a conservation agriculture principle, involves minimal soil disturbance for improved crop productivity. Minimum tillage enhances soil organic matter build-up and structure, thus increasing soil fertility and reducing soil erosion (Alam et al., 2014; Kiboi et al., 2017; Kiboi et al., 2019; Seitz et al., 2019). The improved soil properties and fertility increase crop productivity (Thierfelder et al., 2015; Grabowski et al., 2016). Conventional tillage involves rigorous soil disturbance, reduces soil organic matter, and destroys soil structures, thus promoting soil erosion and degradation (Busari et al., 2015; Komissarov and Klik, 2020). However, there is low adoption of minimum tillage in sub-Saharan Africa (SSA) due to low initial yields coupled with a lack of technical know-how, increased weeds menace, and climatic conditions (Giller et al., 2009; Awada et al., 2014; Marenya et al., 2017; Ntshangase et al., 2018).

Minimum tillage adoption shows mixed results in improving crop productivity. Minimum tillage has been reported to significantly influence crop yields (Kassie et al., 2015; Jaleta et al., 2016; Ngoma, 2018). Experimental findings indicate that minimum tillage provides mixed results on crop yields (Kiboi et al., 2019). Long-term implementation of minimum tillage significantly improved maize yields in the Central Highlands of Kenya (Kiboi et al., 2019). Despite the novel gains of minimum tillage adoptions, quasi-experimental studies show that its adoption has no significant influence on crop yields in Kenya (Jena 2019). However, minimum tillage adoption saves labor and increases crop profitability (Jena, 2019; Osewe et al., 2020). Additionally, minimum tillage reduces the labor burden among women (Gatzweiler & Von Braun, 2016). Thus, there is a need to assess the influence of minimum tillage on crop yields across diverse socioeconomic, environmental and climatic conditions in Western Kenya.

Promoting climate-smart crops (such as cassava, millet, groundnuts, and sorghum) can foster smallholder farmers' enhancement of the adaptive capacity to climate change in SSA. Climate-smart agriculture is an approach to enhancing sustainable agricultural technical, policy, and investment techniques for achieving food security whilst the changing climate (FAO, 2014). The climate-smart crops flourish under low rainfall; thus, they have a high potential to promote food and nutritional security while mitigating and adapting to the changing climate (Mabhaudhi et al., 2019). Increasing sorghum production, a "climate-smart crop" in most developing countries, including Kenya, could significantly contribute to food security and alleviate poverty (MoALF, 2016; Okeyo et al., 2020). However, Kenya records low sorghum yields of approximately 1000 kg ha^{-1} despite the potential above 2,800 kg ha^{-1} (Tegemeo Institute, 2021). In Western Kenya, the sorghum productivity is about 700 kg ha^{-1} despite the potential of 2,000 to 5,000 kg ha^{-1} (Karanja et al., 2014). Sorghum productivity remains relatively low due to the low-yielding varieties, unreliable rains, low soil fertility, bird menace, Striga infestation, and reduced adoption of agricultural technologies (Mwadalu & Mwangi, 2013; Kavoi et al., 2014; Mutisya et al., 2016). Assessing the impacts of climate-smart agricultural technology on sorghum productivity is indispensable in guiding agricultural policies on food security and climate change adaptation and mitigation. The adoption of climate-smart crops and minimum tillage could enhance the achievement of Sustainable Development Goals (SDGs), including (1) ending poverty, (2) zero hunger, and (13) climate action coupled with the actualization of Kenyan vision 2030 economic pillar (Government of the Republic of Kenya, 2007; United Nations, 2016).

Minimum tillage adoption on sorghum cropping systems could improve crop yields, thus closing Kenya's yield gap. However, there is limited literature on the influence of minimum tillage on sorghum yields in Kenyan conditions. Zero tillage improved sorghum yields by 25% compared to conventional tillage in the drylands of Nigeria

(Agbede & Ojeniyi, 2009). The results implied that smallholders implementing conservation tillage could close the yield gap by 25% relative to conventional tillage. The influence of minimum tillage adoption on crop yields could be influenced by climatic and soil conditions (Busari et al., 2015; Githongo et al., 2021).

In addition to the inconsistent results on the influence of minimum tillage on crop yields, there are limited studies that have quantified the determinants and impacts of minimum tillage on sorghum yields. Moreover, socioeconomic, biophysical, and institutional determinants influencing sorghum yields under minimum tillage in Western Kenya have not been considered. This study assessed the determinants and impacts of minimum tillage on sorghum yields in Western Kenya. The study's specific objectives were to; i) assess the determinants of minimum tillage adoption, ii) assess the determinants of sorghum yields for adopters and non-adopters, and iii) quantify the impacts of minimum tillage adoption on sorghum yields in Western Kenya. The study hypothesized that i) socioeconomic factors influenced the adoption of minimum tillage, ii) socioeconomic factors influenced the sorghum yields for adopters and non-adopters, and iii) minimum tillage adoption significantly influenced sorghum yields among smallholder farmers in Western Kenya.

3.2 Methodology

3.2.1 Description of the study area

The study was conducted in Alego Usonga and Ugenya sub-Counties, Siaya County, Western Kenya. The Alego Usonga and Ugenya sub-Counties have 224343 and 134354 persons and a population density of 375 and 415 persons per km^2, respectively (Kenya National Bureau of Statistics (KNBS), 2019). The average land size is 1.02 ha in Alego Usonga and 0.96 ha in Ugenya. The high population density and increased land sub-division pressure available land (County Government of Siaya, 2019). Climate-smart agriculture (CSA) is necessary to increase agricultural productivity to feed the increasing population under harsh climatic conditions in Siaya due to climate change. *Ferrasols* are the predominant soils exhibiting moderate soil fertility, thus unsuitable for production without amendments (Jaetzold et al., 2010). The County experiences a bimodal rainfall distribution with long rains between March and June and short rains between September and December. The long-term annual rainfall ranges from 800 to 1600 mm and 1600 to 2000 mm, in Alego Usonga and Ugenya sub-Counties. The average long-term yearly average temperature ranges between 20.9 and 22.3 °C. The sub-Counties share similar agro-ecological zones (AEZs) of Lower Midlands (LM1, LM2, LM3) (Jaetzold et al., 2010). The LM2 is the predominant AEZ in both Alego-Usonga and Ugenya sub-Counties. The rainfall distribution varies across the agro-ecological zones, with most areas receiving less than 700 mm annually (County Government of Siaya, 2019). However, the rains are generally erratic and unreliable, thus suitable for climate-smart crops like sorghum. The sub-Counties experience high rainfall variability between the two seasons of approximately 66% (County Government of Siaya, 2019). The main food crops grown in the area include maize (*Zea mays)*, beans (*Phaseolus vulgaris*), sorghum (*Sorghum bicolor*), millet (*Panicum miliaceum*), cowpeas (*Vigna unguiculata*), sweet potatoes (*Ipomoea batatas*), and groundnuts (*Arachis hypogaea*). Sorghum is grown by approximately 80% of the residents in the study area (MoALF, 2016). The climate-smart crop is raised twice a year. However, the majority of the farmers grow sorghum during the long rains.

The study used primary data collected in June-July 2020 among smallholder sorghum farmers in Western Kenya's Alego Usonga and Ugenya sub-Counties of Siaya County. The reference cropping season was long rain 2019. Siaya County is a central sorghum-growing region in Kenya, and the two sub-Counties are the main sorghum-growing sites in the County. Sorghum is no longer a poor man's crop in Western Kenya, but an essential source of income among smallholders and has a great potential to enhance food security and nutritional wellbeing of their families (Kenya News Agency, 2019; Okeyo et al., 2020). Despite the great significance of sorghum in the study area, the productivity remains relatively low, at approximately 700 kg ha^{-1}. The low productivity is attributed to low-yielding crop varieties, erratic rains, bird menace, and limited climate-smart agriculture technologies (MoALF, 2016, ICRISAT,2019). The main sorghum varieties grown in the study area include Seredo, Gadam, Sila, KARI Mtama 1 (CGA, 2019).

3.2.2 Sample size and sampling procedure

Three hundred (300) smallholder sorghum farming households were sampled based on a 5.65 % allowable error at a 95% confidence level (Cochran, 2007). The sample size was determined following equation 3.1.

$$ss=\frac{z^2pq}{E^2}=\frac{1.96^2\times 0.5(1-0.5)}{0.0565^2}=300 \qquad (3.1$$

whereby: *ss* = Sample size, *z* = *z* value of 1.96 for 95% confidence level, *p* = probability of picking a choice, expressed as decimal (0.5), *q* = 1-p and *E* = 5.65 % allowable error, expressed as decimal (0.0565). Therefore, the sample size comprised of 300 smallholder sorghum farmers.

The study employed a multistage sampling procedure to select farming households for the survey. The smallholder farming households were sampled using a simple random sampling procedure. The first stage involved a purposive selection of the study locations, Siaya County, and the two sub-Counties based on sorghum’s growing prevalence among smallholder farmers. This was achieved through a reconnaissance survey and discussion with agricultural officers. The sampling frame was smallholder sorghum farming households in the study area. The second stage involved selecting wards in the two sub-Counties. The whole sampling procedure was employed to select all the ten wards in the study area's. Thirdly, the proportionate population size (PPS) sampling technique was used to calculate the number of sorghum farming households sampled from each ward. Finally, a simple random sampling procedure was implemented. The sampling frame was smallholder sorghum farming households from each ward. The households in each ward were obtained from the ward agricultural officer.

3.2.3 Data source, data types, and data collection procedures

A semi-structured interview schedule was used to collect the empirical data. First, pre-testing the interview schedule was done. Pre-testing feedback was used in modifying the interview schedule by specifying the units of measurement, such as the area in acres and harvested sorghum in kgs. The study collected data on sorghum yields (independent variables) and minimum tillage adoption (treatment variable) (Table 3.1). The sorghum grain yields were based on farmer-reported yields on their pieces of land. The yields were calculated following equation 3.2.

$$Y = \frac{Yi \times 2.47}{A} \tag{3.2}$$

Where Y is the sorghum yields in kg ha^{-1}, Yi is the farmer-reported yields, A is the sorghum land size in acres, and 2.47 is the conversion rate to hectares.

The study employed two treatment variables that are minimum tillage and conventional tillage. Minimum tillage adoption was considered for a farmer who had implemented minimum tillage in the same piece of land for six consecutive cropping seasons. Minimum tillage is the form of tillage that minimizes soil disturbance. This study defined minimum tillage as no-till, strip-till, ridge-till, or mulch till. Conventional tillage was defined as the farming household implementing ploughing that results in soil disturbance. Trained enumerators collected the empirical data using an Open Data Kit software. The enumerators were trained on data handling, questions interpretation, and sampling protocol.

3.2.4 Conceptual framework

A conceptual framework was developed to assess the impacts of minimum tillage on sorghum yields (Figure 3.1). The conceptual framework demonstrates the linkage between minimum tillage adoption and improving sorghum yields alongside explanatory variables. Adopting minimum tillage (1) is a binary farmer choice that multiple factors could influence. The determinants of minimum tillage adoption were categorized as household and farm, smallholders soil perception, institutional, and location characteristics.

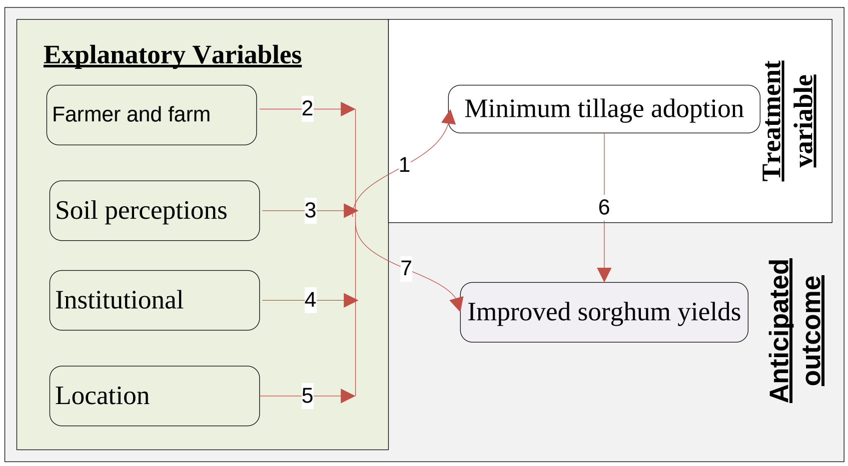

Figure 3.1 Conceptual framework displaying hypothesized determinants of minimum tillage adoption and sorghum yields

Household and farm characteristics (2) included sex, education, experience, occupation, and age of household head, farm, and household size. Evidence shows that household and farm characteristics determine the adoption of agricultural technologies (Macharia et al., 2014; Ngoma, 2018; Jena, 2019; Mwaura et al., 2021; Yigezu et al., 2021). Gender significantly impacts agricultural technologies' adoption (Coulibaly et al., 2017; Kpadonou et al., 2017). However, gender exhibits mixed results, with males dominating the adoption of most agricultural technologies. This underlines gender disparities in technology adoption. Male household heads are more likely to adopt because they mainly control the farming resources such as land. Education is an essential factor driving the adoption of agricultural innovations. Previous studies have reported mixed results on the influence of education on agricultural technology adoption (Asfaw & Neka, 2017;

Donkor et al., 2019; Ojo & Baiyegunhi, 2020; Musafiri et al., 2022a). Education could positively influence minimum tillage adoption since educated farmers could easily comprehend new agricultural technologies, thus increasing adoption (Donkor et al., 2019). However, education could negatively influence the adoption of minimum tillage as literate farmers could focus on salaried employment and pay for limited agriculture. Experience positively and age negatively impacts minimum tillage adoption, similar to El-Shater et al. (2016) and Ngoma (2018) studies. Experienced farmers could adopt minimum tillage due to the lessons learned in labor savings and increased revenue. Older farmers are risk-averse, thus, less likely to adopt agricultural technologies. However, old farmers could have accumulated experience in changing climate and need to adopt new technologies for enhanced productivity. Household size is an essential variable in negatively influencing the adoption of minimum tillage as it requires minimum labor. Therefore, the propensity to adopt minimum tillage could decrease with the increase in household size. The households with few family members could adopt minimum tillage compared to those with larger family sizes. Farmers with larger farm sizes could experiment with minimum tillage, thus increasing the likelihood of adoption (Jena, 2019). Finally, household head occupation is an essential predictor of minimum tillage adoption. Households whose main occupation is farming are more likely to receive training and implement new technologies (Jawid & Khadjavi, 2019).

Smallholder soil perceptions (3) on soil statuses, such as fertility and erosion, are fundamental in sharpening technology adoption. A farmer's holistic approach to identifying soil status drives the motivation to adopt improved management. Therefore, smallholders who perceive their soil as problematic, such as highly eroded and of poor fertility, could adopt agricultural technologies to improve land productivity. Previous studies have found soil perception a vital variable in defining the adoption of farming technologies (Ngoma, 2018; Jena, 2019; Belachew et al., 2020; Essougong et al., 2020).

Institutional factors (4) are vital in supporting smallholder farmers' adoption of agricultural innovations. Institutional factors such as membership in farming associations, extension, credit access, and weather forecast information were included in the study.

The institutional factor improves smallholders' human or financial capacity, thus promoting the adoption of agricultural technologies (Macharia et al., 2014; Donkor et al., 2019; Amadu et al., 2020). Therefore, access to the aforementioned institutional factors could enhance the adoption of minimum tillage among smallholder farmers in Western Kenya.

Location (5) captures differences in the environmental, institutional, and farmers' characteristics, thus highlighting differences in agricultural technologies adoption (Ndiritu et al., 2014; Marenya et al., 2017; Martey and Kuwornu, 2021). Farmers in a given study area could experience varied adoption rates due to differences in supportive services and environmental conditions.

The study was based on the hypothesis that minimum tillage adoption (6) and the explanatory variables (7), including household and farm, soil perceptions, and institutional and location, influenced sorghum yields. More importantly, minimum tillage adoption improves sorghum yields. The minimum tillage adoption is expected to improve soil organic carbon build-up, soil structure, and soil physio-chemical properties, increasing land productivity. Therefore, increased crop productivity contributes to food, nutritional security, and poverty alleviation.

3.2.5 Econometric description

Minimum tillage adoption is a binary variable for smallholder sorghum farmers who maximize the expected utility. Farmers could adopt minimum tillage to better their productivity. However, the minimum tillage adoption decision could be an endogenous variable influenced by selection biases involving observable and unobservable characteristics. Thus, controlling the observable and unobservable biases is key in determining the impact of adoption on sorghum productivity. An endogenous switching regression (ESR) was employed in data analysis to control the cofounding factors, similar to Amadu et al. (2020) and Martey et al. (2021). The ESR is a robust analysis methodology that predicts the determinants of technology adoption (selection) and outcome for adopters and non-adopters (Asfaw et al., 2012; Manda et al., 2019; Martey et al., 2019). Further, the ESR computes for both actual (adopter and non-adopters) and counterfactual (adopter if they did not adopt and non-adopters if they adopted), thus superior to propensity score matching (Di Falco et al., 2011; Ngoma, 2018).

Following utility maximization theory, it is assumed that smallholder sorghum farmers are risk-averse in reality which affect technology adoption decisions. The farmers could adopt or not adopt minimum tillage based on expected gains in yields. Therefore, minimum tillage adoption is a pre-determined production decision by farmers' perceptions of increasing or decreasing sorghum yields. The yield difference (P_i*) is a latent variable computed by subtracting observed yield for minimum tillage's non-adopters (Y_{0i}) from for adopters (Y_{1i}), Equation 3.3.

$$P_i^* = Y_{1i} - Y_{0i} > 0 \tag{3.3}$$

Therefore, a farmer will adopt minimum tillage if Y_{1i} exceeds Y_{0i}. However, the latent variable describing expected utility could be influenced by observable factors such as farmer, farm, soil perceptions, institutional and location characteristics, and unobservable variables such as motivation Equation 3.4.

$$P^*_i = X_i \alpha + \varepsilon_i \text{ with } P_i = \begin{cases} 1 \text{ if } P^*_i > 0 \\ 0 \text{ otherwise} \end{cases} \tag{3.4}$$

Where P_i* is a latent variable describing the expected utility, X_i is the vector of minimum tillage adoption, α is a vector of parameters to be estimated, ε_i is a vector of unobserved factors affecting the adoption decision, and a random error term. However, only observe P_i, which is indicated by 1 for minimum tillage adopters and 0 for minimum tillage non-adopters. Since sorghum yield is conditional on smallholder farmers' adoption of minimum tillage (Di Falco et al., 2011; Amadu et al., 2020; Martey et al., 2021), the sorghum yields could be displayed as two endogenous switching regimes Equation 3.5a and 3.5b.

$$\text{Regime 1 (Minimum tillage adopters)}: y_{1i} = X_{1i}\beta_1 + e_{1i} \text{ if} P_i = 1 \tag{3.5a}$$

$$\text{Regime 2 (Minimum tillage non}-\text{adopters)}: y_{0i} = X_{0i}\beta_0 + e_{0i} \text{ if} P_i = 0 \quad (3.5b)$$

Where Y_{1i} and Y_{0i} are sorghum yields for minimum tillage adopters and non-adopters, respectively. β_1 and β_0 vectors of parameters to be estimated, X_{1i} and X_{0i} are the vector determinants of the sorghum yields from i^{th} household while e_{1i} and e_{01} are the error terms. The three error terms $\varepsilon_i, e_{1i}, e_{0i}$ are assumed to have a trivariate normal distribution with mean vector zero and covariance matrix Equation 3.6.

$$\text{cov}(\varepsilon,\ e_1,\ e_2) = \begin{pmatrix} \sigma_\varepsilon^2 & \sigma_{e1\epsilon} & \sigma_{e0\epsilon} \\ \sigma_{e1\epsilon} & \sigma_{e1}^2 & \sigma_{e1e0} \\ \sigma_{e0\epsilon} & \sigma_{e1e0} & \sigma_{e0}^2 \end{pmatrix} \quad (3.6)$$

where $\sigma^2\varepsilon$ = var (ε_i), $\sigma^2 e_1$ = var (e_1), $\sigma^2 e_0$ = var(e_0), $\sigma e_1\varepsilon$ = cov (e_1,ε), and $\sigma e_0\varepsilon$ = cov (e0, ε). In this study, the covariance between e_1 and e_0 is not defined since Y_1 and Y_0 are never observed simultaneously (Maddalla, 1983). Therefore, the expected values of the error terms e_1 and e_0 can be expressed as described by Fuglie and Bosch (1995) equation 3.7a and 3.7b.

$$E(e_1|P_i = 1) = \sigma_{e1\epsilon}\lambda_1 \text{ (Minimum tillage adopters)} \quad (3.7a)$$

$$E(e_0|P_i = 0) = \sigma_{e0\epsilon}\lambda_0 \text{ (Minimum tillage non-adopters)} \quad (3.7b)$$

The inverse mills ratios or selectivity terms (λ_1 and λ_0) can be included in equation 3 to correct for selection bias two-step estimation procedure known as the endogenous switching treatment regression model (Maddala 1983) equation 8a and 8b.

$$Y_{1i} = \beta_1 X_{1i} + \sigma_{e1\epsilon}\lambda_1 + \omega_1 \text{ if } P_i = 1 \text{ (Minimum tillage adopters)} \quad (3.8a)$$

$$Y_{0i} = \beta_0 X_{0i} + \sigma_{e0\epsilon}\lambda_0 + \omega_0 \ if \ \ P_i = 0 \text{ (Minimum tillage non-adopters)} \quad (3.8b)$$

If the $\sigma_{\varepsilon 1\epsilon}$ and $\sigma_{\varepsilon 2\epsilon}$ are significant, indicate the presence of an endogenous switching. However, full information maximization likelihood (FIML) is more effective than the two-step procedure (Lee and Trost, 1978; Lokshin and Sajaia, 2004). Recent studies have employed the FIML to estimate the selection (first-stage) and outcome (second-stage) equations simultaneously (Donkor et al., 2019; Manda et al., 2019; Martey et al., 2021; Yigezu et al., 2021). A falsification test was performed to identify instrumental variables using F statistics.

The study estimated the treatment effects on outcome variables (sorghum yields) of minimum tillage adoption under two scenarios, i.e., actual and counterfactual while accounting for selection bias Equation 3.9a –3. 9d.

Minimum tillage adopters (actual)

$$E(Y_{1i}|P_i = 1;\ X) = \beta_1 X_{i1} + \sigma_{\varepsilon 1\epsilon} \boldsymbol{\lambda}_{i1} \tag{3.9a}$$

Minimum tillage non-adopters (actual)

$$E(Y_{0i}|P_i = 0; X) = \beta_0 X_{i0} + \sigma_{\varepsilon 0\epsilon} \boldsymbol{\lambda}_{i0} \tag{3.9b}$$

Minimum tillage adopter if they decided not to adopt (counterfactual)

$$E(Y_{0i}|P_i = 1;\ X) = \beta_0 X_{i1} + \sigma_{\varepsilon 0\epsilon} \boldsymbol{\lambda}_{i1} \tag{3.9c}$$

Minimum tillage non-adopters if they decided not to adopt (counterfactual)

$$E(Y_{1i}|P_i = 0; X) = \beta_1 X_{02} + \sigma_{\varepsilon 1\epsilon} \boldsymbol{\lambda}_{02} \tag{3.9d}$$

After that, the average treatment effect on minimum tillage adopters was computed, the average treatment effect on the Treated (ATT), and the average treatment effects on untreated (ATU) as described in Equations 3.10a and 3.10b.

$$ATT = (a) - (c) = (\mathrm{Y}_{1i}|\mathrm{A}_i = 1;\ \mathrm{X}) - (\mathrm{Y}_{0i}|\mathrm{P}_i = 1;\ \mathrm{X}) = \mathrm{X}_{i1}(\beta_1 - \beta_0) + \boldsymbol{\lambda}_{i1}(\sigma_{e1\epsilon} - \sigma_{e0\epsilon}) \quad (3.10a)$$

$$ATU = (d) - (b) = (\mathrm{Y}_{1i}|\mathrm{A}_i = 0;\mathrm{X}) - (\mathrm{Y}_{0i}|\mathrm{P}_i = 0;\mathrm{X}) = \mathrm{X}_{i0}(\beta_1 - \beta_0) + \boldsymbol{\lambda}_{i0}(\sigma_{e1\epsilon} - \sigma_{e0\epsilon}) \quad (3.10b)$$

Further, base heterogeneity following equations 3.11a and 3.11b was computed. The base heterogeneity compares the actual and counterfactual results, that is, whether actual adopters could have higher yields than non-adopters if they decided to adopt and if adopters decided not to adopt could have higher yields than actual non-adopters. Finally, transitional heterogeneity was determined by subtracting ATU from ATT.

$$H_1 = \text{(a)-(d)} = \mathrm{E}(\mathrm{Y}_{1i}|\mathrm{P}_i = 1;\ \mathrm{X}) - \mathrm{E}(\mathrm{Y}_{1i}|\mathrm{P}_i = 0;\mathrm{X}) = \beta_1(X_{il} - X_{i0}) + \boldsymbol{\lambda}_{i1}(\sigma_{e1\epsilon} - \sigma_{e0\epsilon}) \quad (3.11a)$$

$$H_2 = \text{(c)} - \text{(b)} = E(\mathrm{Y}_{0i}|\mathrm{P}_i = 1;\ \mathrm{X}) - \mathrm{E}(\mathrm{Y}_{0i}|P_i = 0;\mathrm{X}) = \beta_0(X_{il} - X_{io}) + \sigma_{e0\epsilon}(\lambda_{i1} - \lambda_{i0}) \quad (3.11b)$$

A stochastic dominance analysis (SDA) was performed to evaluate overlap, common support region, and the the superiority of minimum tillage adopters over non-adopters (Martey et al., 2021). The SDA assumes smallholders are risk-neutral and could only adopt minimum tillage if the expected utility dominates conventional tillage (the traditional farming).

Propensity score matching is a quasi-experimental analysis that pairs treated and control groups based on similarity in propensity score matching and possibly covariate but removing the unmatched units (Donkor et al., 2019; Manda et al., 2019; Martey et al., 2019). The propensity score matching does not account for unobserved biases (Rosenbaum & Rubin, 1983). Due to the PSM weakness in accounting for other confounding factors, the study only used the PSM to check the robustness of ESR, similar to studies by Shiferaw et al. (2014a) and Martey et al. (2021). A detailed presentation of the PSM framework can be found in Rosenbaum and Rubin, (1985) &Martey et al. (2019). Matching methods such as kernel, radius, near neighbor, and local linear methods were employed to estimate the average treatment effects on the treated.

3.2.6 Data analysis

The statistical analysis was performed in STATA 15 software. Before actual data analysis, Variance inflation factors (VIFs) were used to test multicollinearity. The VIFs of the independent variables were less than 4, and tolerance factors (1/VIF) were greater than 0.2 (Appendix 1), thus no problem of multicollinearity (Hair et al., 2010). The results indicated that the data was not highly correlated, therefore plausible for the analysis. Descriptive analysis was performed, such as mean and standard error of the mean of dependent, independent, and treatment variables. Before performing the endogenous switching regression, the data were tested for an instrumental variable using a falsification test. To assess the influence of minimum tillage on sorghum yields, propensity score matching, and endogenous switching regression were performed. Stochastic dominance analysis evaluated an overlap between minimum and conventional tillage farming households.

3.3 Results and discussion

3.3.1 Descriptive characteristics of sampled households in Western Kenya

Descriptive statistics showed variations between conventional tillage and minimum tillage among smallholder sorghum farming households in Western Kenya (Table 3.1). Fifty-eight (19%) of the interviewed sorghum farmers adopted minimum tillage, while 242 (81%) practiced the conventional tillage. Remittance, seed quantity, fertility poor, agricultural associations, weather information, and site significantly differed between adopters and non-adopters. The conventional tillage farming households were better in remittance receipt and seed quantity. The average seed quantity for minimum tillage farmers was 3.97 kg acre^{-1} and 4.75 kg acre^{-1} for conventional tillage farmers. The seed rate was consistent with the recommended seed rate of 3 - 4 kg per acre (Karanja et al., 2014). Smallholder farmers' soil perception significantly differed between minimum tillage adopters and non-adopters at a 1% significance level (Table 3.1). The findings showed that institutional factors, including membership in agricultural associations and receipt of weather forecast updates, significantly differed between the minimum and conventional tillage farmers at 10% and 5% levels of significance, respectively. More conventional tillage farmers (21%) were members of agricultural associations than the minimum tillage farming households. Most conventional tillage farmers (86%) received weather forecast information compared to minimum tillage farmers 74%. Most minimum tillage farmers, 53% lived in the Ugenya sub-County than conventional tillage farmers, 47%.

Table 3.1 Descriptive statistics of sampled households by the tillage adoption decision

Variables	Description	sign (+/-)	Minimum tillage (A) (N=58)		Conventional tillage (B) (N=242)		Diff
			Mean	SE	Mean	SE	(A-B)
Dependent variable							
Sorghum yields	Harvested sorghum yields (kg ha^{-1})		1163.62	82.17	1146.40	38.33	17.42
Explanatory Variables							
Household and farm characteristics							
Gender	Gender of household head (1=Male)	+/-	0.31	0.06	0.40	0.03	-0.09
Literacy	Education of household head (1=formal, 0=otherwise)	+/-	0.90	0.04	0.85	0.02	0.05
Age	Age of household head in years	+/-	50.84	1.85	52.16	0.88	-1.32
Occupation	The main occupation of the household head (1=farming, 0=otherwise)	+	0.90	0.04	0.85	0.02	0.05
Experience	Farming experience of the household head in years	+	22.69	1.75	22.54	0.95	0.15
Household size	Number of residences in the family	+	6.26	0.40	5.72	0.18	0.54
Remittance	Household received remittance (Yes=1)	+	0.10	0.04	0.40	0.03	-0.30***
Acreage	Land size under sorghum production in acres	+	0.58	0.07	0.54	0.03	0.04
Seed type	Planted sorghum seeds (1=improved,	+	0.12	0.04	0.10	0.02	0.03

	0=local)						
Seed quantity	Seeds planted per unit area (kg acre^{-1})	-	3.97	0.29	4.75	0.14	-0.78**
Perceptions of soil status							
Fertility poor	Farmer perceived soil fertility as poor (Yes=1)	+	0.36	0.06	0.21	0.03	0.15***
Erosion high	Farmer perceived soil erosion as high (Yes=1)	+	0.05	0.03	0.06	0.02	-0.01
Institutional	**factors**						
Agricultural association	Household member to agricultural association (Yes=1)	+	0.12	0.04	0.21	0.03	-0.09*
Farm credits	Household received credit (Yes=1)	+	0.09	0.04	0.07	0.02	0.02
Extension	Household received extension services (Yes=1)	+	0.09	0.04	0.15	0.02	-0.06
Weather information	Household received weather updates (Yes=1)	+	0.74	0.06	0.86	0.02	-0.12**
Geographical	**Location**						
Site	Household located in Alego Usonga sub-County (1), Ugenya (0)	±	0.47	0.07	0.63	0.03	-0.17**

Significance at 10%, 5%, and 1% indicated by *, **, *** respectively, SE indicates the Standard error of the mean

The average sorghum yield under minimum tillage was 1163.62kg ha $^{-1,}$ while conventional tillage was 1146.40kg ha^{-1}. The sorghum yields were not significantly different between the minimum and conventional tillage. Table 3.2 shows the quantile distribution of sorghum yields between minimum tillage and conventional tillage. The first quantile had similar sorghum yields for minimum and conventional tillage farmers. Minimum tillage adopters had higher sorghum yields at the second and third quantile than the conventional tillage quantile. Sorghum yields were higher under conventional tillage than in minimum tillage farming households in the fourth quartile.

Table 3.2 Quartile distribution of sorghum yields among minimum and conventional tillage farmers

Quartile	**Minimum tillage**		**Conventional tillage**	
	Sorghum yields (kg ha^{-1})	**% farmers**	**Sorghum yields (kg ha^{-1})**	**% farmers**
First	790.4	31.03	790.4	28.93
Second	938.6	18.97	889.2	23.14
Third	1407.9	24.14	1333.8	23.97
Forth	2,668	25.86	4,446	23.97

The findings showed insignificant sorghum yields differences between minimum and conventional tillage farming households. However, the bivariate mean differences did not account for self-selection biases, which could have confounding effects on the yields. The mean results could not automatically be attributed to the minimum tillage adoption without controlling the confounding factors.

3.3.2 Distribution of sampled households: Stochastic dominance results

The findings highlighted a substantial overlap in the estimated probability of minimum and conventional tillage farming households (Figure 32a-b). Visualizing the distribution of propensity scores between the minimum and conventional tillage demonstrates fulfillment of the common support condition. The findings were consistent with Wossen et al. (2017), who documented satisfaction of common support conditions between treated and untreated sampled households.

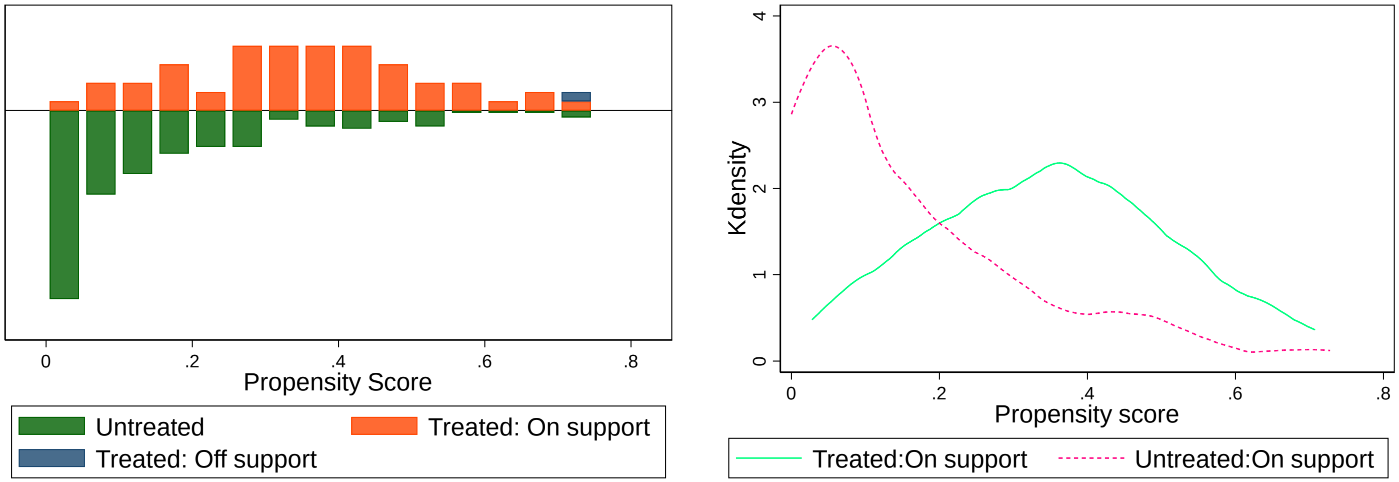

Figure 3.2 Propensity score density distribution and common support region for minimum tillage adoption

3.3.3 Determinants of minimum tillage adoption

The first stage for the endogenous switching regression model showed the determinants of minimum tillage adoption (Table 3.3). Household heads whose main occupation was farming had a positive and significant **(β=0.778, p=0.014)** higher propensity to adopt minimum tillage at a 5% significance level than their counterparts who implemented conventional tillage. The significantly higher propensities of minimum tillage among smallholder farming households whose main occupation was farming make sense in Kenya. The plausible explanation for this could be that the main occupation being farming, farmers depend on agriculture for their livelihoods and may adopt new technologies to improve the livelihoods of their households. Household whose main occupation is farming has a higher potential to learn and implement new technologies on their farms compared to their counterparts whose main occupation is not farming. The households have full-time interests in improving crop yields and saving labor. The increased adoption of minimum tillage among farmers whose main occupation was farming showed increased interest in experimenting with new technologies. The findings were in line with Marenya et al. (2017) and are intuitive because salaried employment negatively influenced minimum tillage adoption among smallholder farmers in Ethiopia. Households whose main occupation is farming could be willing to adopt agricultural innovation for improved productivity to meet their livelihoods demands.

Minimum tillage adoption significantly decreased with remittance receipt at a 1% significance level. The findings implied that smallholder farming households that received remittance had a lower propensity to adopt minimum tillage. The propensity to adopt minimum tillage increased with acreage under sorghum production. The negative prediction of minimum adoption by remittance receipt is intuitive since it is crucial for domestic household consumption and mainly been used to buy seed and fertilizers. Therefore, smallholder farming households receiving remittance could use it to purchase farm inputs such as fertilizer and improved seeds.

The positive estimate of acreage on minimum tillage adoption is consistent with Jena (2019) andMartey and Kuwornu (2021). The strong influence of acreage on minimum tillage underscores the importance of additional land to experiment with new technologies among smallholder farming households. Smallholders farming households with larger land sizes could experiment with new technologies, including minimum tillage (Martey and Kuwornu, 2021). This was attributed to the probability of practicing minimum tillage in some plots while performing conventional tillage in others.

Soil fertility perception of the smallholder farming household had a positive and significant (**β=0.615, p=0.011)** influence on minimum tillage adoption. This implied that if a farming household perceived low soil fertility in the sorghum cropping systems had a higher likelihood of adopting minimum tillage. The positive and significant prediction of soil fertility perceptions was consistent with Kpadonou et al. (2017) and Essougong et al. (2020). Being mindful of declining soil fertility, smallholders could explore various agricultural technologies to alleviate the declining soil problem. The adoption of minimum tillage among smallholders' who perceived soil fertility as poor could be attributed to the need to improve agricultural productivity using climate-smart technologies. Minimum tillage improves soil fertility through improved aggregate stability and soil carbon stock (Busari et al., 2015).

Membership in an agricultural association exerted a negative and significant (β=-0.955, p=0.026) influence on minimum tillage adoption. This implied that smallholder sorghum farmers who belonged to agricultural associations were less likely to adopt minimum tillage technology. The negative and significant effect of agricultural associations was inconsistent with current research highlighting agricultural associations as vital platforms for knowledge sharing among members (Macharia et al., 2014; Musafiri et al., 2020a). The finding mirrors the descriptive characteristics (Table 3.1) that showed higher agricultural association membership among conventional tillage farming households. Smallholder farmers who join agricultural associations could pool resources and access facilitation, including loans to implement improved agricultural technologies. The lower adoption of minimum tillage among smallholder sorghum farmers who belonged to agricultural associations could be attributed reduced effectiveness of the agricultural organizations. The findings agreed with Ahmed and Anang (2019), who found that group membership was associated with lower adoption of improved maize varieties in Ghana due to increased politicization, reduced effectiveness, and low public and private support of the smallholders' groups.

Table 3.3 **Determinants of minimum tillage adoption: First-stage results of the FIML ESR results**

Variables	Coefficient	Standard error	p value
Household and farm characteristics			
Gender	-0.331	0.226	0.143
Literacy	0.569	0.355	0.109
Age	-0.001	0.010	0.900
Occupation	**0.778****	0.316	0.014
Household size	0.026	0.037	0.477
Experience	-0.004	0.009	0.657
Remittance	**-0.986*****	0.264	0.000
Acreage	**0.817****	0.457	0.044
Seed quantity	0.042	0.249	0.867
Seed type	0.549	0.348	0.114
Perceptions of soil status			
Fertility poor	**0.615****	0.241	0.011
Erosion high	-0.357	0.460	0.437
Institutional factors			
Agricultural association	**-0.955****	0.428	0.026
Farm credits	**1.118****	0.521	0.032
Extension	-0.440	0.365	0.228
Weather information	**-0.619****	0.248	0.013
Geographical location			
Site	**-0.641*****	0.214	0.003
Constant	-0.165	0.883	0.852

FIML indicates full information maximization likelihood, ESR represents endogenous switching regression, *, **, *** indicates 10%, 5% and 1% level of significance.

Farm credit access significantly increased the probability of minimum tillage adoption among smallholder sorghum farmers in Kenya at a 5% significance level. Smallholder sorghum farming households that received farm credit had a higher likelihood of adopting minimum tillage technology. The positive relationship between minimum tillage adoption and credit access was in line with previous studies that found that credit access increased the propensity of adopting conservation farming practices (Ng'ombe et al., 2014). The findings were in line with descriptive characteristics (Table 3.1) that showed higher farm credit access among minimum tillage than conventional tillage farming households. Sorghum markets in Western Kenya are imperfect, triggering organizations such as One Acre Fund and East African Breweries Ltd **(**EABL) to provide farm credit to streamline market access (MoALF, 2016). Farm credit is used for agricultural investment instead of remittance used in family consumption. However, the descriptive statistics show low credit and remittance receipt (Table 3.1).

Weather forecast information receipt precipitated a negative and significant (β=-0.619, p=0.013) influence on minimum tillage adoption. This implied that minimum tillage adoption decreased with weather forecast information receipt. The negative prediction of minimum tillage adoption among smallholder farming households that received weather forecast information could be attributed to their utilization of cropping calendar management relative to agricultural inventions. Though weather forecasts provide essential information that could influence agricultural decisions (Bloodhart et al., 2015; Kumar et al., 2020), the information is mainly used for seasonal planning, such as sowing, crop protection from pests and diseases, and harvesting based on the cropping calendar (van der Burgt et al., 2018).

Geographical location negatively and significantly (β=-0.641, p=0.003) influenced minimum tillage adoption. Smallholder sorghum farmers in the Alego Usonga sub-County had a lower likelihood of adopting minimum tillage than their counterparts in the Ugenya sub-County. The geographical location highlights differences in supportive services such as credit, extension, and group membership, culminating in variations in technologies' receptive capacities. The findings underscore the importance of site-specific considerations in promoting the adoption of conservation farming.

3.3.4 Determinants of sorghum production among minimum and conventional tillage farmers

The covariance term **(**rho 1, -0.778***) was negative and significantly different at a 1% significance level (Table 3.4). This implied that the use of ESR analysis was justified. The chi-square statistics for the likelihood ratio (LR) test of independent equations for sorghum yields (14.95***) was significant at the 1% level. This implied that the estimation of determinants of minimum tillage adoption sorghum yields for adopters and non-adopters using FIML was plausible. Further, the results rejected the hypothesis that equations 3, 4a, and 4b were independent. The Wald chi-square (57.91***) was significant at a 1% level. The finding implied that the parameters used in ESR jointly explained the variations in sorghum yields. The instrumental variables (occupation, remittance, and weather forecast information receipt) were significant in the selection model (Table 3.3) but insignificant in the validity test (Table 3.5), therefore credible to be used as instrumental variables.

The gender of the household head showed a negative and significant effect on sorghum yields for minimum tillage adopters at a 1% significance level. The findings showed that female-headed farming households harvested 672.865 kg ha^{-1} higher than the male counterparts for minimum tillage adopters. The significantly higher sorghum yields among female-headed farming households over male-headed households are interesting because when women implement minimum tillage, they would save labor for other household chores (Yigezu et al., 2021). Additionally, females mostly grow low-value crops, "women's crops," such as sorghum, possibly due to limited access to resources, while cash crops, mainly for export, are regarded as men's crops. The results corroborate with Martey et al. (2019), who found that gender negatively predicted land productivity in Ghana. Contrary to the findings, Martey et al. (2021) documented higher cowpea yields among male-headed households than women in Ghana. These findings highlight the gendered disparities in promoting agricultural technologies in sub-Saharan Africa.

Literacy exhibited a positive and significant effect on sorghum yields for minimum tillage adopters at a 1% significance level. The finding implied that minimum tillage adopters who received formal education harvest higher sorghum yields than illiterate ones. The findings signified that literate minimum tillage adopters harvested 710.298 kg ha^{-1} greater sorghum yields than illiterate counterparts. The positive effect of literacy on sorghum yields is intuitive since literate farming households can understand and appreciate new agricultural technologies for increasing crop yields. Educated household heads are more likely to implement other agronomic activities, including herbicides and pesticides, thus improving productivity. The findings were consistent with Ngoma (2018) and Donkor et al. (2019), who found that adopting agricultural technologies such as minimum tillage and fertilizer had significantly high returns among educated farmers.

Seed type positively and significantly impacted sorghum yields for both adopters and non-adopters. Utilization of improved seeds increased sorghum yields by 242.307 kg ha^{-1} and 500.010 kg ha^{-1} for non-adopters and adopters, respectively. Improved sorghum seeds are bred to promote agricultural productivity against changing climate. Increased sorghum yields among smallholders' who utilized improved varieties could be attributed to the potential of improved seeds in enhancing production. The finding agreed with Ngoma (2018), who reported that utilization of improved seeds increased crop yields for both minimum tillage adopters and non-adopters in Zambia.

Table 3.4 Determinants of sorghum production among minimum tillage adopters and non-adopters: Second-stage results of the FIML ESR results

Variable	Conventional tillage			Minimum tillage		
	Coefficient	**Standard error**	**p-value**	**Coefficient**	**Standard error**	**p-value**
Household and farm characteristic						
Gender	-33.609	85.161	0.693	**-672.865*****	229.557	0.003
Literacy	152.268	131.718	0.248	**710.298****	329.150	0.031
Age	-0.795	3.673	0.829	12.550	8.919	0.159
Family size	-3.888	14.706	0.792	0.998	30.606	0.974
Experience	-1.620	3.391	0.633	-12.654	8.840	0.152
Acreage	-99.798	92.615	0.281	16.702	235.784	0.944
Seed quantity	176.202	185.457	0.342	160.298	432.581	0.711
Seed type	**242.307***	144.772	0.094	**500.010***	272.154	0.066
Perceptions of soil status						
Fertility poor	**192.771***	102.004	0.059	-196.543	294.172	0.504
Erosion high	**450.908*****	169.178	0.008	568.767	399.041	0.154
Institutional factors						
Agricultural association	**204.654***	120.096	0.088	-410.358	455.273	0.367
Farm credits	**-393.078****	181.916	0.031	656.331	505.740	0.194
Extension	19.948	131.695	0.88	395.425	307.382	0.198
Geographical location						
Site	-34.674	86.243	0.688	**591.491****	266.730	0.027
Constant	**947.067*****	334.092	0.005	678.504	748.128	0.364
Sigma (0,1)	**564.185*****	27.291	0.000	**658.146*****	125.160	0.000
rho (0,1)	-0.181	0.274	0.156	**-0.778*****	0.188	0.007
Summary statistics						
LR test of independent equations	14.95***					
Wald chi-square	57.9***					
Log-likelihood	-1119.6					

FIML indicates full information maximization likelihood, ESR represents endogenous switching regression, *,**,*** indicates 10%, 5% and 1% level of significance.

Soil fertility perception positively impacted sorghum yields among non-adopters. The findings implied poor soil fertility perception increased sorghum yields by 192.771 kg ha^{-1}. The decline in soil fertility is the main challenge facing smallholders in SSA (Kiboi et al., 2019; Musafiri et al., 2020a). The smallholders link low agricultural productivity and poor soil fertility (Essougong et al., 2020). Smallholders who perceived low soil fertility status among minimum tillage adopters could integrate soil fertility management, thus increasing farm productivity. This could lead to nutrient replenishment, thus surging crop performance.

The perception of soil erosion positively and significantly affected sorghum minimum tillage non-adopters. The finding implied that smallholder farmers who perceived the soil to have high erosion rates harvested 450.908 kg ha^{-1} higher than their counterparts. Soil erosion significantly degrades soil fertility, culminating in reduced crop yields, thus advancing the need to adopt soil erosion management technologies (Moges and Holden, 2007; Odendo et al., 2010). The increased yields among minimum tillage non-adopters who perceived soil erosion as high could be attributed to implementing preventive measures such as erosion control, thus increasing sorghum yields. The finding conforms with previous studies that endorsed soil erosion leads to reduced agricultural production (Ngetich et al., 2014; Okeyo et al., 2014; Mihretie et al., 2021), prompting the need for agricultural innovation, including minimum tillage and mulching.

Table 3.5 Test of the validity of instrumental variables (falsification test)

Variable	Coefficient.	Standard error	P value
Household and farm characteristics			
Gender	-63.659	81.552	0.436
Literacy	104.837	123.861	0.152
Age	-0.264	3.532	0.941
Occupation	-167.977	104.192	0.108
Family size	-8.220	13.311	0.537
Experience	-0.803	3.157	0.799
Remittance	20.817	78.667	0.791
Acreage	**200.023***	86.559	0.077
Seed quantity	**246.573***	167.118	0.051
Seed type	**471.582*****	126.580	0.007
Perceptions of soil status			
Fertility poor	-84.973	87.801	0.334
Erosion high	**503.687*****	157.527	0.002
Institutional factors			
Agricultural association	**414.538****	111.649	0.035
Farm credits	**-278.539***	163.225	0.089
Extension	113.832	120.615	0.346
Weather information	-127.294	100.838	0.208
Geographical location			
Site	-18.854	73.045	0.797
Constant	**1048.651*****	321.226	0.001
F statistic	2.040		
Prob. > F	0.009		

FIML indicates full information maximization likelihood, ESR represents endogenous switching regression, *, **,*** indicates 10%, 5%, and 1% significance level.

Agricultural associations' membership positively and significantly impacted sorghum yields of minimum tillage non-adopters. The finding suggests that agricultural association increased yields by 204.654 kg ha^{-1} among minimum tillage adopters. Agricultural associations positively influenced sorghum yields and were consistent with Donkor et al. (2019), who documented that being an association member enhanced cassava yields and income of the smallholder farmers in Nigeria. Siaya County has strong sorghum organizations, including Cereal Growers Associations (governmental) and Farm to Market Alliance (non-governmental organization), promoting agricultural innovation through groups. Smallholders gain insights into agricultural innovations during the organizations' training, thus improving sorghum yields. Sorghum is ranked as a low-value crop, i.e., "poor man's crop," The credit received could be diverted to other valuable crops. The findings were consistent with Martey et al. (2021), who found that loans from associations negatively impacted cowpeas yields among trained farmers in Ghana.

Against the expectations, farm credits negatively affected sorghum yields of minimum tillage non-adopters. The finding implied farm credit access reduced sorghum yields by 393.078 kg ha^{-1} among minimum tillage non-adopters. The credit could be used to implement agricultural innovations, including minimum tillage. The increased adoption of minimum tillage among smallholders who received farm credit could be attributed to utilizing the revenues to implement agricultural innovation for improved sorghum yields. Therefore, access to farm credit increases the propensity of adopting agricultural innovation.

Minimum tillage adopters in the Alego Usonga sub-County harvested 591.491 kg ha^{-1} lower sorghum yields than those in Ugenya sub-County. The findings suggested that minimum tillage adopters in the Ugenya sub-County had higher sorghum productivity than their counterparts in the Alego Usonga sub-County. The positive influence of geographical location on sorghum yields is intuitive because it underscores the importance of smallholder residence. The differences in yields between minimum tillage adopters in Ugenya and Alego-Usonga sub-Counties could be attributed to differences in rainfall amounts. This implies that the one-size-fits-all approach is not applicable across geographical locations and the need to consider site-specific characteristics in promoting agricultural practices. Additionally, the study location could highlight differences in socioeconomics and institutional factors. The disparities in the institutional factors such as credit access, extension agent and group membership could significantly determine yields.

3.3.5 Impacts of minimum tillage adoption on sorghum yields

3.3.5.1 Propensity score matching results

The propensity score matching analysis revealed insignificant effects of minimum tillage adoption on sorghum yields (Table 3.6). Though insignificant, the findings were consistently positive across evaluation algorithms signifying that minimum tillage adopters had better yields than a non-adopter. However, the PSM results do not include counterfactual outcomes. Therefore, a more robust methodology like ESR is viable to account for the unobserved biases.

Table 3.6 Average impact of minimum tillage adoption on adopters: PSM results

Outcome variable	**Matching algorithm**	**Minimum tillage**	**Conventional tillage**	**ATT**	**SE**	**T-stat**
Sorghum yields	Kernel	1175.37	1149.37	26.01	105.89	0.25
(kg ha^{-1})	Radius	1175.37	1152.58	22.80	106.19	0.21
	Near Neighbor	1175.37	1149.22	26.16	112.80	0.23
	Local linear	1175.37	1142.42	32.95	150.37	0.22

ATT indicates average treatment effects; SE represents the standard error.

The descriptive statistics and propensity score matching algorithms showed that minimum tillage adoption had insignificant effects on sorghum yields. The findings were consistent with Jena (2019), who found that various matching algorithms such as 5-nearest neighbor matching, kernel matching, and radius matching showed that minimum tillage had insignificant effects on maize yields in Kenya. The latter does not account for the influence of the confounding factors. Therefore, suitable models are needed to account for confounding factors such as endogenous switching regression.

3.3.5.2 Endogenous switching regression results

The ESR results showed that minimum tillage adoption positively and significantly impacted sorghum yields (Table 3.7). The ATT results indicated that sorghum yields of minimum tillage adopters 1167.99 kg ha^{-1} were superior to adopters if they decided not to adopt (1046.79 kg ha^{-1}). Further, the ATU results demonstrated that sorghum yields for non-adopters, if they did adopt minimum tillage (1805.87 kg ha^{-1}), were higher than the actual non-adopters (1148.99 kg ha^{-1}). The ATT suggested that the adoption of minimum tillage improves sorghum yields by 11.58%. The ATU findings suggest that if non-adopters decided to adopt minimum tillage, they could increase sorghum yields by 58%. The findings are substantial, based on the low adoption rate of minimum tillage among smallholder farming households and the highlighted potential of improving yields if they choose to adopt.

The endogenous switching regression revealed that minimum tillage adoption significantly influenced sorghum yields. The findings were consistent with Ngoma (2018), who reported increased crop yields with minimum tillage among smallholder farmers in Zambia. The treatment effect analysis shows substantial implications for non-adopters to adopt minimum tillage. If the non-adopters decided to adopt, there could be a 58% increment in sorghum yields; thus, the study is plausible in improving food security.

Minimum tillage is a component of conservation agriculture. In Kenya, smallholders have adopted conservation agriculture principles at varying rates. Some adopt one, others two or three conservation agriculture practices. Adopting one or more conservation agriculture practices could contribute to improved crop yields. Minimum tillage improves soil fertility which leads to increased crop yields. The increment in crop yields shows the potential of minimum tillage in improving food security.

Table 3.7 Average treatment effects of minimum tillage adoption on sorghum yields

Sample	**Decision Stage**		**Average treatment effect**	**Average treatment effects (%)**
	Adopt	**Not to adopt**		
Minimum tillage	1167.99	1046.79	121.2**	11.58
Conventional tillage	1805.87	1148.99	656.87***	58.01
Heterogeneity effects	-638.50	-102.21	535.67	

Values in parenthesis are standard error, **, *** significance and 5% and 1%.

The study revealed a negative base heterogeneity effect for sorghum yields. The BH_1 suggested that sorghum yields for non-adopters were higher than for actual adopters if they decided to adopt. The findings highlight that if non-adopters decide to adopt minimum tillage could attract higher benefits than the actual adopters. Further, the BH_2 suggested that actual non-adopters had higher yields than adopters if they chose not to adopt. This finding disclosed that if adopters decided to abandon minimum tillage, they could attract lower yields than the actual non-adopters. The transitional heterogeneity (TH) was negative, suggesting that had minimum tillage non-adopters decided to adopt, they could have higher sorghum yields than the actual adopters.

The counterfactual analysis showed that minimum tillage adoption could increase sorghum yields in Kenya (Table 3.7). The findings were consistent with previous studies (Ngoma, 2018; Yigezu et al., 2021). The finding highlights the importance of promoting minimum tillage adoption among non-adopters for increased yields. The results provide the basis for quasi-experimental studies investigating labor savings of minimum tillage and economic gains among smallholder farmers.

3.4. Conclusion and policy implications

The study evaluated factors determining smallholder sorghum farmers' adoption of minimum tillage and the impacts on sorghum yield. The study revealed low adoption level of minimum tillage among smallholder sorghum farmers. The findings confirm the low adoption level of conservation agriculture principles in Western Kenya. The descriptive comparison revealed the insignificant difference between minimum tillage adopters and non-adopters. However, the bivariate mean comparison does not account for the confounding factors. An endogenous switching regression model was used to correct the selection biases.

Households whose main occupation was farming, perceived poor soil fertility status, had large acreage and accessed farm credit were likelier to adopt minimum tillage. Household heads who received remittance, members of agricultural associations, weather forecast information and residents in Alego Usonga were less likely to adopt minimum tillage. The ESR results showed that minimum tillage significantly improved sorghum productivity among smallholder sorghum farmers in Western Kenya. Different factors affect sorghum productivity among minimum tillage adopters' s non-adopters.

The findings established that could the non-adopter decide to adopt minimum tillage; they could improve sorghum productivity by 58%. Given the low adoption of minimum tillage in the study area, if non-adopters decide to adopt they could substantially enhance food security. Enhancing sorghum productivity through minimum tillage is pertinent for social development. The improved productivity could reduce malnutrition, food insecurity, and poverty while improving access to social services, including health and education, through income obtained from selling the surplus. Therefore, promoting minimum tillage adoption non-adopters in Western Kenya could enhance the actualization of sustainable development goals, including zero hunger and poverty alleviation and Kenyan vision 2030.

Based on the findings, the study draws two folds' key policy recommendations. First, minimum tillage adoption should be promoted among smallholder sorghum farmers for improved agricultural productivity. Government and stakeholders should disseminate minimum tillage importance among smallholders. Second, agricultural policies targeting minimum tillage adoption should consider key determinants such as enhancing credit access to agricultural association membership while paying attention to the farmer, farm, and site-specific characteristics for enhanced acceptability and increased productivity. These policies could promote the three pillars of climate-smart agriculture: food security, climate change adaptation, and mitigation.

CHAPTER FOUR

POTENTIAL OF INORGANIC FERTILIZER AND CLIMATE-SMART CROPS IN RESPONDING TO SOIL FERTILITY DECLINE AND CLIMATE CHANGE IN WESTERN KENYA

Abstract

Adoption of inorganic fertilizers and careful selection of climate-resilient crops such as sorghum could improve the livelihoods of smallholder farmers through improved soil health and food security. However, information on the effects of inorganic fertilizer adoption on sorghum productivity remains scanty, especially in SSA. The study objective was to evaluate the effects of inorganic fertilizer adoption on sorghum productivity among smallholder farmers in Siaya County, Western Kenya. A cross-sectional survey was conducted to collect data from 300 smallholder sorghum farmers. The study employed endogenous switching regression (ESR) modeling to control observed and unobserved biases in predicting the effects of inorganic fertilizer adoption on productivity. Smallholder farmers applied a limited amount of inorganic fertilizer. The study established that hired labor, agricultural training, and farmers' perception of soil erosion were significant positive determinants of inorganic fertilizer adoption. Site and access to weather forecast information were key negative determinants of inorganic fertilizer adoption. The adoption of inorganic fertilizer increased crop yields by 14%. The findings have incredible implications on rural livelihood as enhanced productivity could promote food security and improve purchasing power, thus enhancing smallholder farmers' capacity to cope with declining soil fertility and climate change-related challenges. Therefore, agricultural policies targeting improved productivity of smallholder sorghum farmers could enhance inorganic fertilizer adoption while considering the determinants.

Keywords: Community welfare, Counterfactual analysis, Propensity score matching, drought-tolerant crop

4.1 Introduction

Low soil fertility and climate change are significant global challenges facing smallholder farming systems (Morton, 2007; Rapsomanikis, 2015; Mugi-Ngenga et al., 2016). Evidence shows that the dominant climate change indicators include increased drought frequency and severity causing crop water stress and reduced yields in sub-Saharan Africa (SSA) (Shiferaw et al., 2014b; Mubiru et al., 2020). The fertility status of the soil could be determined through testing and farmer perceptions. Most smallholder farmers in SSA exhibit high poverty, approximated at 53% (Alliance for a Green Revolution in Africa (AGRA), 2014). The impacts of climate change and soil fertility decline could be adverse in most developing sub-Saharan African countries (SSA) due to the lack of capacity by most of the community members to cushion themselves against these impacts (Karienye and Macharia, 2020). The over-dependence by most smallholder farmers on rain-fed agriculture aggravates the situation culminating in reduced agricultural productivity and increased food insecurity (Devendra, 2012; Raimi et al., 2017). The high poverty levels could exacerbate the effects of climate change and soil fertility decline due to the low capacity to invest in adopting new agricultural technologies. Therefore, promoting the adoption of climate-resilient crops and inorganic fertilizer could be a good entry point in enhancing the twin agenda of climate change adaptation and soil fertility amelioration.

Against the above challenges facing smallholder farming systems and the need to feed the growing population, there is a need to improve productivity. The "orphan crops" are crops that researchers have neglected, play a central role in enhancing food security and spurring sustainable agriculture under the changing climate (Mabhaudhi et al., 2019). In Kenya, one of the "orphan crops" is sorghum (*Sorghum bicolor* (L.), commonly grown in arid and semi-arid lands (ASALs) and referred to as "poor man's crop." The ASALs face numerous challenges, including severe and frequent drought, water scarcity, and soil degradation, which culminate in high poverty, food insecurity, and malnutrition (Karienye and Macharia, 2020). The growth of climate-smart crops such as sorghum could be vital in promoting food security and community wellbeing. Traditionally, sorghum has been grown for subsistence purposes in Kenya (Muui et al., 2013;

Chepng'etich et al., 2015). The crop is predominantly grown in Western Kenya by approximately 80% of the smallholder farming households (Kenya Ministry of Agriculture, Livestock, and Fisheries), MOALF, 2016). Recently, there have been concerted synergies by both governmental and non-governmental organizations, including County Governments, One Acre Fund, Cereals Growers Association (CGA), and *Farm* to Market Alliance (FtMA), towards sorghum commercialization (MOALF, 2016; Njagi et al., 2019). Despite the synergies to enhance sorghum access to the market, its productivity remains low.

Sorghum is the second most important cereal crop after maize across Kenyan agro-ecosystems (Mitaru et al., 2006). Sorghum could enhance the agricultural productivity of smallholders living in ASALs. However, sorghum productivity in Western Kenya remains relatively low (Muuii et al., 2013; Okeyo et al., 2020a), probably due to continuous cropping without nutrient replenishment. The low sorghum productivity is exacerbated by numerous challenges including limited utilization of inorganic fertilizer and socioeconomic, biophysical, and institutional factors (Kebeney et al., 2015; Mbanda-Obura et al., 2017; Okeyo et al., 2020a; Okeyo et al., 2020b). Promoting inorganic fertilizer adoption while considering smallholders' dynamics in policy implementation could enhance the livelihoods of the sorghum producers.

Adopting inorganic fertilizer could considerably enhance community welfare, as Donkor et al. (2019) reported in Nigeria. However, there is a shortage of literature on the determinants and effects of inorganic fertilizer adoption on productivity among smallholder sorghum cropping systems in most developing countries, including Kenya. Though adoption of inorganic fertilizer could upsurge productivity, the low application rates recorded among smallholder farmers could contradict outputs (Kibunja et al., 2017; Mairura et al., 2022a). Further, the high cost of inorganic fertilizer limits adoption among smallholder farmers in Kenya (Mugwe et al., 2009; Jena et al., 2021). Therefore, the objective was to evaluate the effects of inorganic fertilizer adoption on sorghum productivity among smallholder farmers in Siaya County, Western Kenya. This study assessed i) the determinants of inorganic fertilizer adoption and sorghum productivity and

ii) the effects of inorganic fertilizer adoption on sorghum yields. The study hypothesized that i) socioeconomic, biophysical, and institutional factors significantly determine inorganic fertilizer adoption and sorghum yields of adopter and nonadopters, and ii) inorganic fertilizer adoption significantly increases sorghum yields among smallholder farmers in Western Kenya.

4.2 Methodology

4.2.1 Study location

The research used primary data collected from smallholder sorghum farmers of Alego Usonga and Ugenya sub-Counties of Siaya County, Western Kenya (Figure 4.1). The sub-Counties lie under low midlands (LM1, LM2, LM3, LM4, and LM5) and upper midland (UM1), (Jaetzold et al., 2010). The site experiences bimodal rainfall, with long rains occurring between March to June and short rains between September and December every year. The long-term annual rainfall amount ranges between 800 to 2000 mm, while the average long-term yearly temperature ranges between 20.9 and 22.3 °C. The primary soil type is *Ferrasols*, with low to moderate inherent soil fertility and thus cannot sustain crop production without external inputs. The main food crops grown in the study area include sorghum (*Sorghum bicolor*), maize (*Zea mays*), beans (*Phaseolus vulgaris*), cassava (*Manihot esculenta*), sweet potato (*Ipomoea batatas*), and cowpea (*Vigna unguiculata*). The Alego-Usonga and Ugenya sub-Counties have 224,343 and 134,354 persons (Kenya National Bureau of Statistics (KNBS), 2019), with a population density of 375 and 415 persons per km^2, respectively. The smallholder farmers in the study area face high poverty levels, food insecurity, and increased population density challenges.

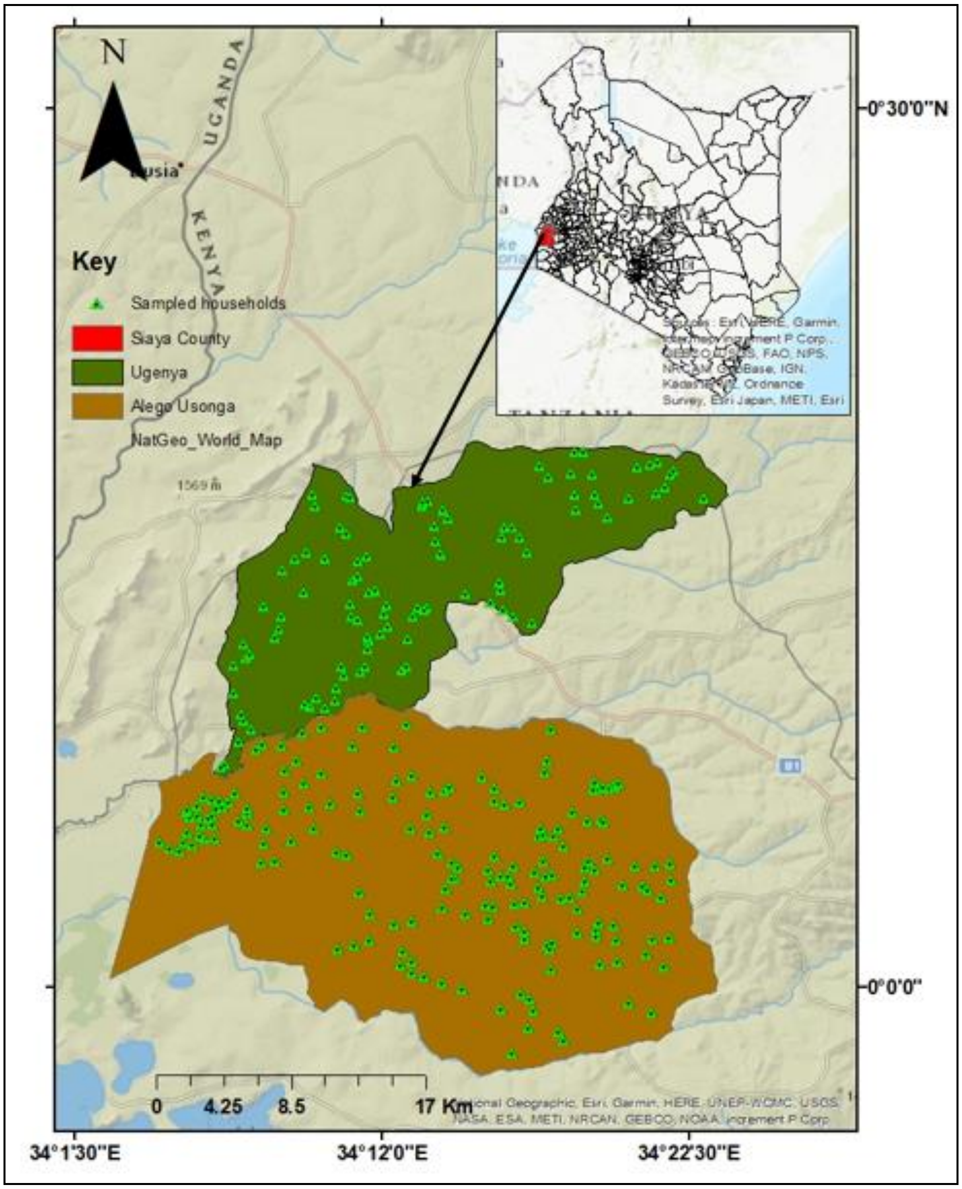

Figure 4.1 Map of the study area indicating sampled households

4.2.2 Sampling procedure

The study used cross-sectional survey in implementation and a multistage sampling procedure to select the farmers included in the survey. First, Siaya County was selected based on the predominance of sorghum production and previous efforts to commercialize sorghum production. Secondly, a meeting was held with the County Government of Siaya agricultural officers drawn from the Agricultural Department to select the dominant sorghum-growing sub-Counties and settled on the Alego-Usonga and Ugenya sub-Counties. Thirdly, the study employed total sampling to collect data from all the ten wards in the sub-Counties. Fourth, the number of households sampled in each ward was determined using a proportionate to size sampling procedure. Finally, the individual households were sampled using a random sampling procedure. The sampling frame was obtained from the ward agricultural officers. The sample size was determined following the method described by Cochran (2007), Equation 4.1.

$$ss = \frac{z^2pq}{E^2} = \frac{1.96^2 \times 0.5(1-0.5)}{0.0565^2} = 300 \qquad (4.1)$$

Whereby: *ss* = Sample size, *z* = *z* value of 1.96 for 95% confidence level, *p* = probability of picking a choice, expressed as decimal (0.5), *q* = 1-p and *E* = 5.65 % allowable error, expressed as decimal (0.0565). Therefore, the sample size comprised of 300 smallholder sorghum farmers.

A semi-structured interview schedule was administered face-to-face during data collection. Five enumerators were recruited and trained from the local community in each sub-County who were eloquent in English and vernacular. They were taught how to use the Open Data Kit (ODK) mobile App and question interpretation. Before the actual data collection, the research tool was pretested and modified. The final semi-structured interview schedule had questions on sorghum cropping systems, inorganic fertilizer adoption, and explanatory variables, including socioeconomic, institutional, and biophysical factors (Table 4.1).

Regarding institutional factors, a low proportion of 7%, 13%, and 19% of sampled sorghum farmers received inputs on credit, was agriculturally trained, and were members of sorghum associations. However, a higher proportion, 84%, received weather forecast information. The majority of the sampled sorghum farmers perceived soil fertility as moderate (63%), soil erosion low (57%), and resided in the Alego Usonga sub-County (60%), Table 4.1).

Table 4.1 Description of study variables

Variable	Definition	Mean	SE#	Minimum	Maximum
Dependent variables					
Sorghum productivity	Sorghum yields in (kg ha^{-1})	1118.32	46.66	32.93	4446.00
Log sorghum productivity	Log of sorghum yields (kg ha^{-1})	3.05	1.67	1.52	3.65
Treatment variable					
Inorganic fertilizer adoption	Household adopted inorganic fertilizer (1=yes)	0.68	0.03	0	1
Predictor variables					
Sex	Sex of the household head (1=male)	0.38	0.03	0	1
Literate	Household head had schooled (1=yes)	0.86	0.02	0	1
Family size	Household size	5.78	0.17	1	15
Main occupation hhh	Household head main occupation farming (1=yes)	0.86	0.02	0	1
Farming experience	Household head farming experience (years)	22.56	0.84	1	70
Hired labor	Household employed hired labor (1=yes)	0.48	0.03	0	1
Remittance receipt	Household received remittance (1=yes)	0.34	0.03	0	1
Group membership	Household was a member of agricultural association (1=yes)	0.19	0.02	0	1
Credit access	Household received agricultural credit (1=yes)	0.07	0.02	0	1
Agricultural training	Household received agricultural training (1=yes)	0.13	0.02	0	1
Sorghum price	Prevailing market sorghum price (KES [a])	43.70	0.66	25	100
Weather information receipt	Household received weather forecast information (1=yes)	0.84	0.021	0	1
Sorghum land holding	Total farm size under sorghum (ha)	0.22	0.01	0.04	1.21
Perceived change in climate	Household head perceived change in climate (1=yes)	0.96	0.01	0	1
Perceived soil fertility poor	Household head perceived soil fertility status as poor (1=yes)	0.24	0.03	0	1
Perceived soil fertility moderate	Household head perceived soil fertility status as moderate (1=yes)	0.63	0.03	0	1
Perceived soil fertility is good	Household head perceived soil fertility status as good (1=yes)	0.12	0.02	0	1
Perceived soil erosion low	Household head perceived soil erosion as low (1=yes)	0.57	0.03	0	1
Perceived soil erosion high	Household head perceived soil erosion as high (1=yes)	0.06	0.01	0	1
Sorghum variety improved	Household planted improved sorghum seeds (1=yes)	0.10	0.02	0	1
Sorghum seeds quantity	The quantity of seeds planted per acre (Kg ha^{-1})	11.49	0.32	1.24	29.64
Site	Household located in Alego Usonga sub-County (1) and Household located in Ugenya (0)	0.60	0.03	0	1

SE indicates the standard error, [a]KES is Kenya shilling at exchange rate was US $1 = KES 109.68.

The descriptive characteristics of the sampled sorghum farmers were expressed as mean (Table 4.1). All the variables included in this study were selected based on literature (Coulibaly et al., 2017; Donkor et al., 2019; Martey et al., 2019; Marenya et al., 2020). The average sorghum productivity was 1118.32 kg ha^{-1}. The inorganic fertilizer adoption rate was 68%. The summary statistics indicated that 38% of the sampled sorghum farmers were male, while both literate and farmers whose main occupation was farming were 86% (Table 4.1). The descriptive socioeconomic statistics indicated that the average family size, farming experience, sorghum prices, sorghum landholding, and sorghum seed quantity were 5.78, 22.56 years, 43.70 KES (0.40 US$), 0.22 ha, and 11.49 kg ha^{-1} respectively (Table 4.1). The low proportion of households, 10%, 34%, and 48%, used improved seeds, remittance, and hired labor in sorghum production.

4.2.3 Conceptual framework and estimation strategies

Smallholder sorghum farmers in Western Kenya are experiencing the challenge of declining soil fertility (Kebeney et al., 2015). To enhance sorghum productivity while facing declining soil fertility, the smallholder farmers adopt soil fertility ameliorating technologies such as inorganic fertilizer application. A conceptual framework was developed to illustrate the effects of inorganic fertilizer adoption on sorghum yield. It is noteworthy that smallholder sorghum farmers could adopt inorganic fertilizer if the utility arising from adoption is greater than not adopting (Meyer, 2002; Montes de Oca Munguia et al., 2021). Therefore, the adoption of inorganic fertilizer is a decision process influenced by various factors, including socioeconomic, biophysical, and institutional factors (Figure 4.2).

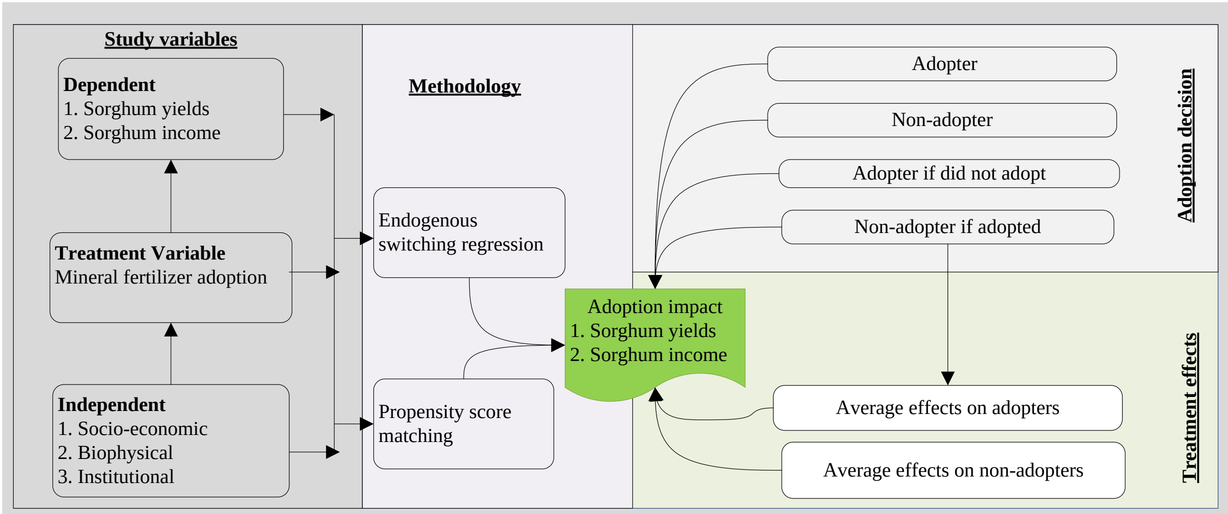

Figure 4.2 Conceptual framework for inorganic fertilizer adoption effect on sorghum yields: Modified from Donkor et al. (2019)

Adopting inorganic fertilizer and socioeconomic, institutional, and biophysical factors influence sorghum yields. Inorganic fertilizer adoption increases soil fertility, thus hypothesized to increase sorghum yields. Due to the high cost, the low application rates of inorganic could lower the full potential of yield improvement. The effects of inorganic fertilizer adoption on sorghum yields could be modeled using propensity score matching (Rosenbaum and Rubin, 1983). However, the propensity score matching doesn't control for unobserved bias. Therefore, this study is more appropriate to use endogenous switching regression that could control for both observable and unobservable biasness. The modeling approach would estimate the actual and counterfactual implication of inorganic fertilizer adoption on both sorghum yields, i.e. if an adopter chose not to adopt and if non-adopters decided to adopt. The counterfactual scenario is essential for estimating the average treatment effects of both treated and untreated.

Adopting inorganic fertilizer among smallholder sorghum farmers is a decision process based on utility maximization theory. Therefore, smallholder sorghum farmers could only adopt inorganic fertilizer if the benefits are superior to not adopting. This could be expressed in an equation as a farmer decides to adopt inorganic fertilizer if the utility of adopting (U_{iy}) exceeds that of not adopting (U_{iz}). The difference(A_i^*) between the two utilities is described in equation 4.2.

$$A_i^* = U_{iy} - U_{iz} > 0 \qquad (4.2)$$

The A_i^* is a latent variable indicating the expected benefits of inorganic fertilizer adoption. The latent variables can be described using observable variables, as shown in equation 4.3.

$$A^*_i = W_i\alpha + \varepsilon_i \text{ with } A_i = \begin{cases} 1 \text{ if } A^*_i > 0 \\ 0 \text{ otherwise} \end{cases} \qquad (4.3)$$

Where A is a binary variable of the decision to adopt inorganic fertilizer as 1 indicates adopters and 0 non-adopters. W is a vector of factors influencing the decision to adopt inorganic fertilizer, such as socioeconomic, institutional, and biophysical; α is a vector of parameters to be estimated, and ε is a random error term.

Similar to Donkor et al. (2019) and Martey et al. (2019), it was expected the adoption of inorganic fertilizer to influence smallholder farmers' sorghum yield. The productivity is expressed as a function of a vector, X, of variables including socioeconomic, institutional, and biophysical factors and an endogenous variable (A) of inorganic fertilizer adoption Equation 4.4

$$Y_i = \omega X_i + ðA_i + \mu_i \qquad (4.4)$$

Whereby Y_i indicates outcome variables, sorghum yields, A shows the binary variable of the decision to adopt inorganic fertilizer, ω *and* ð indicates parameters to be estimated, and μ represents the error term.

Various methodologies have been used to evaluate the impact of agricultural technology adoption on farmers' well-being, including crop yields (Donkor et al., 2019; Jena, 2019; Martey et al., 2019). However, the best method is tailored to treatment allocation, i.e., whether the fertilizer adopters and non-adopters were randomized. In this study, the adoption of inorganic fertilizer among sorghum farmers was not randomized. This implied that both adopters and non-adopters were not equally and randomly exposed to inorganic fertilizer technology. Therefore, the sampled sorghum farmers across the study area could have different characteristics. Because adopters and non-adopters could have different characteristics, a direct comparison of means was not plausible (Rosenbaum and Rubin, 1985).

Further, the sorghum yields are influenced by inorganic fertilizer adoption and socioeconomic, institutional, and biophysical factors as described in the conceptual framework (Figure 4.2). Therefore, predicting sorghum yields using a linear model such as ordinary least square (OLS) could be biased. Previous studies have highlighted suitable models for this kind of data, including propensity score matching (PSM) and endogenous switching regression (Jena, 2019; Martey et al., 2021). The main drawback with propensity score matching is its inability to account for unobservable bias (Khonje et al., 2015). Therefore, the study used the empirical research's endogenous switching regression (ESR) analysis and the propensity score matching for robustness check similar to Martey et al. (2021).

4.2.4.1 Robust check

The study employed a second-order stochastic dominance (SD) analysis to evaluate the superiority of inorganic fertilizer adoption on sorghum yields. The analysis is used to test for the common support condition. The SD analysis assumes that smallholder farmers are risk-averse and adopt superior technology to maximize the expected utility. Therefore, the SD analysis shows the dominance of adoption relative to non-adoption graphically (Mutenje et al., 2019; Martey et al., 2021).

Propensity score matching (PSM) is an analytical technique that mimics an experiment design by matching the treated with untreated units based on the propensity of adopting superior technology while accounting for covariates and removing all the unmatched units (Rosenbaum and Rubin, 1983; Donkor et al., 2019; Martey et al., 2019). Previous studies (Shiferaw et al., 2014a; El-Shater et al., 2016; Jena, 2019) have used PSM to examine the effects of agricultural technologies on yield. The first stage in PSM estimates the propensity score of inorganic fertilizer adoption using the probit model.

The second step involves estimating the average treatment effects on treated (ATT), in this case, the sorghum yields for adopters and non-adopters using matching techniques including PSM, inverse probability weighting (IPW), and near neighbor matching (NNM). The propensity score is defined as the conditional probability of receiving treatment, i.e., inorganic fertilizer, given the pre-treated characteristics described in Equation 4.5

$$P(X) = \Pr\{\mathrm{Ai} = 1|\mathrm{X}\} = \mathrm{E}\{\mathrm{Ai}\ |\mathrm{X}\} \quad (4.5)$$

Where Ai = (0, 1) is the indicator of exposure to inorganic fertilizer treatment, and X is the multidimensional vector of pre-treatment characteristics. Therefore, the ATT can be estimated as shown in equation 4.6.

$$\mathrm{ATT}=\mathrm{E}(Y_{1i}A = 1\ ,P(X)) - \mathrm{E}(Y_{2i}A = 0\ ,P(X)) \quad (4.6)$$

Where ATT is the average treatment effect on treated, Y_{1i} indicates the outcome when the household *i* adopted inorganic fertilizer (*A*=1), and Y_{2i} shows the outcome when the household *i* did not adopt inorganic fertilizer (A=0). However, the PSM cannot estimate the counterfactual effects, including if non-adopters adopted or adopters did not adopt (Maina et al., 2020; Aweke et al., 2021; Habtewold, 2021).

4.2.4.2 Endogenous switching regression

The study employed endogenous switching regression (ESR) modeling to account for the selection bias similar to previous studies (Manda et al., 2019; Habtewold, 2021) on agricultural technology adoption effects on wellbeing. The sorghum yields can be expressed based on two ESR regimes; 1 inorganic fertilizer adoption and 2 inorganic fertilizer nonadoption Equation 4.7a & 4.7b.

$$\text{Regime 1 (inorganic fertilizer adopters)}: y_{1i} = X_{1i}\beta_1 + e_{1i} \text{ if} A_i = 1 \qquad (4.7a)$$

$$\text{Regime 2 (inorganic fertilizer nonadopters)}: y_{2i} = X_{2i}\beta_2 + e_{2i} \text{ if} A_i = 0 \qquad (4.7b)$$

Where Y_{1i} and Y_{2i} are the outcome variables of productivity for inorganic fertilizer adopters and non-adopters, respectively, β_1 and β_2 vectors of parameters to be estimated, X_{1i} and X_{2i} are the vector determinants of the productivity from i^{th} household. At the same time, e_{1i} and e_{2i} are the error terms.

An exclusion restriction variable is introduced in the choice model (Eq. 3). Like Martey et al. (2019), weather forecast information receipt was used as an instrumental variable. Weather forecast information receipt can make farmers anticipate potential adverse effects, including yield loss, and could adopt agricultural technologies. Therefore, it could directly influence the adoption of inorganic fertilizer but is unlikely to affect sorghum yields directly. The admissibility of the instrument was assessed by a falsification test similar to Donkor et al. (2019). The falsification test is used to confirm the use of a selection instrument. If the selected variable is valid, it significantly influences the decision variables but with no significant influence on outcome variables. The study revealed that weather information receipt significantly influenced inorganic fertilizer adoption (eq. 3) but did not influence sorghum yields (eq. 7b), Appendix 2). Thus, the instrumental variable was valid.

The three error terms for Equations 3, 7a, and 7b are assumed to have a trivariate normal distribution with mean vector zero and covariance matrix described by Di Falco et al. (2011) Equation 4.8.

$$\text{cov}(\varepsilon,\ e_1,\ e_2) = \begin{pmatrix} \sigma_\varepsilon^2 & \sigma_{e1\varepsilon} & \sigma_{e2\varepsilon} \\ \sigma_{e1\varepsilon} & \sigma_{e1}^2 & \sigma_{e1e2} \\ \sigma_{e2e} & \sigma_{e1e2} & \sigma_{e2}^2 \end{pmatrix} \qquad (4.8)$$

Whereby $\sigma^2\varepsilon$ = var (ε_i), $\sigma^2 e_1$ = var (e_1), $\sigma^2 e_2$ = var(e_2), $\sigma e_1\varepsilon$ = cov (e_1,ε), and $\sigma e_2\varepsilon$ = cov (e2, ε). In this study, the covariance between e_1 and e_2 is not defined since Y_1 and Y_2 are never observed simultaneously (Maddalla, 1983). Following Martey et al. (2021), the two error terms can be expressed as described in equation 4.9a – 4.9b.

$$\mathrm{E}(e_1|A_i = 1) = \sigma_{e1\varepsilon}\lambda_1 \text{ for inorganic fertilizer adoption} \qquad (4.9a)$$

$$\mathrm{E}(e_2|A_i = 0) = \sigma_{e2\varepsilon}\lambda_2 \text{ for inorganic fertilizer non-adoption} \qquad (4.9b)$$

Here λ_1 and λ_2 are the inverse mill ratio (IMR) estimated from equation 3 and further incorporated in regime Equations7a and 7b to account for the selection bias in the ESR. Therefore, the regimes for the outcome variable can be described as shown in Equations 4.10a &4.10b.

$$Y_{1i} = \beta_1 X_{1i} + \sigma_{e1\varepsilon}\lambda_1 + \omega_1 \text{ if } A_1 = 1 \text{ for inorganic fertilizer adoption} \qquad (4.10a)$$

$$Y_{2i} = \beta_2 X_{2i} + \sigma_{e2\varepsilon}\lambda_2 + \omega_2 \; if \;\; A_1 = 0 \text{ for inorganic fertilizer non adoption} \qquad (4.10b)$$

If the $\sigma_{e1\varepsilon}$ and $\sigma_{e2\varepsilon}$ are significant and indicate the presence of an endogenous switching. Full information maximization likelihood (FIML) is superior to the two-step procedure (Lee and Trost, 1978; Lokshin and Sajaia, 2004). The ESR framework was used to estimate the average treatment effects on inorganic fertilizer adopters (ATT) and non-adopters (ATU) by associating both actual and counterfactual outcomes similar to Donkor et al. (2019) as illustrated in equations 4.11a –4.11d.

Inorganic fertilizer adopters (actual)

$$E(Y_{1i}|A_i = 1;\ X) = \beta_1 X_{i1} + \sigma_{e1\epsilon}\lambda_{i1} \tag{4.11a}$$

Inorganic fertilizer non-adopters (actual)

$$E(Y_{2i}|A_i = 0; X) = \beta_2 X_{i2} + \sigma_{e2\epsilon}\lambda_{i2} \tag{4.11b}$$

Inorganic fertilizer adopters if they decided not to adopt (counterfactual)

$$E(Y_{2i}|A_i = 1;\ X) = \beta_2 X_{i1} + \sigma_{e2\epsilon}\lambda_{i1} \tag{ 4.11c}$$

Inorganic fertilizer nonadopters if they decided not to adopt (counterfactual)

$$E(Y_{1i}|A_i = 0; X) = \beta_1 X_{i2} + \sigma_{e1\epsilon}\lambda_{i2} \tag{4.11d}$$

The average treatment on treated (ATT) was calculated as equation 4.11a – 4.11c and average treatment effects on untreated as 4.11d -4.11b as shown in equations 4.12a & 4.12b.

$$ATT= (Y_{1i}|A_i = 1;\ X) - (Y_{2i}|A_i = 1;\ X) = X_{i1}(\beta_1 - \beta_2) + \lambda_{i1}(\sigma_{e1\epsilon} - \sigma_{e2\epsilon}) \tag{4.12a}$$

$$ATU = (Y_{1i}|A_i = 0; X) - (Y_{2i}|A_i = 0; X) = X_{i2}(\beta_1 - \beta_2) + \lambda_{i2}(\sigma_{e1\epsilon} - \sigma_{e2\epsilon}) \tag{4.12b}$$

The overall average treatment effects on adopters and non-adopters are expressed in Table 4.2. The transitional heterogeneity H_3 was calculated to determine whether the actual inorganic fertilizer adopters affected sorghum yields compared with the non-adopters if they decided to adopt. Further, H_1 and H_2 the base heterogeneity were calculated to compare the effects of inorganic fertilizer adoption decisions described in Equations 4.13a & 4.13b.

$$H_1 = E(Y_{1i}|A_i = 1;\ X)\text{-}E(Y_{1i}|A_i = 0; X) = \beta_1(X_{il} - X_{i2}) + \lambda_{i1}(\sigma_{e1\epsilon} - \sigma_{e2\epsilon}) \qquad (4.13a)$$

$$H_2 = E(Y_{2i}|A_i = 1;\ X)\text{-}E(Y_{2i}|A_i = 0; X) = \beta_2(X_{il} - X_{i2}) + \sigma_{e2\epsilon}(\lambda_{i1} - \lambda_{i2}) \qquad (4.13b)$$

Table 4.2 Estimation of average treatment and heterogeneity effects

Sampled households	**Inorganic fertilizer adoption decision stage**		**Average treatment effect**
	To adopt	**Not to adopt**	
Inorganic fertilizer adopters	11a $(Y_{1i}|A_i = 1; X)$	11c $(Y_{2i}|A_i = 1; X)$	ATT=(11a-11c)
Inorganic fertilizer nonadopters	11d $(Y_{1i}|A_i = 0; X)$	11b$(Y_{2i}|A_i = 0; X)$	ATU=(11d-11b)
Heterogeneity effects	H_1 (11a-11d)	H_2 (11c-11b)	H_3 = (ATT-ATU)

Slightly modified from Di Falco et al. (2011) and Martey et al. (2019). H_1 and H_2 are the base heterogeneity on inorganic fertilizer adopter and nonadopters. H_3 is the transitional heterogeneity, ATT is the average treatment effects on adopters and ATU is the average treatment effects on nonadopters.

4.3. Results and discussion

4.3.1 Descriptive statistics on inorganic fertilizer adoption

The findings indicated that 68% (204 out of 300) sampled smallholder sorghum farmers adopted inorganic fertilizer (Table 4.3). The inorganic fertilizer adoption rates were similar to previous SSA studies (Mugwe et al., 2009; Macharia et al., 2014; Ricker-Gilbert, 2020). The fertilizer application rate (15.41 kg N ha^{-1}) was low across the sorghum cropping systems. The low application rate of inorganic fertilizer among smallholder farmers could be attributed to its high cost (Mugwe et al., 2009). Inorganic fertilizer adopters obtained significantly higher yields than non-adopters (Table 4.3). The observed mean sorghum yields of 1118.32 kg ha^{-1} were consistent with Okeyo et al. (2020), who reported sorghum yields of 1370.85 kg ha^{-1} in Western Kenya but lower than the productivity potential of 2000 to 5000 kg ha^{-1} (Karanja et al., 2014). Inorganic fertilizer adopters and non-adopters were significantly differentiated by several explanatory variables: family size, hired labor, household head main occupation, soil fertility perceptions, group membership, access to inputs on credit, agricultural training, and improved sorghum varieties, farmer soil perceptions, and site.

Table 4.3 Descriptive statistics by inorganic fertilizer adoption

Variable	Adopters (IA) N=204		Nonadopters (IN) N=96		Diff (IA-IN)
	Mean	SE	Mean	SE	
Dependent variables					
Sorghum productivity	1183.20	58.32	980.42	75.41	202.79**
Log sorghum productivity	3.07	1.77	2.99	1.88	0.08**
Predictor variables					
Sex	0.38	0.03	0.39	0.05	-0.01
Education	0.88	0.02	0.82	0.04	0.05
Family size	6.05	0.20	5.19	0.31	0.87**
Main occupation hhh	0.86	0.02	0.86	0.04	-0.01
Farming experience	21.31	0.98	25.21	1.56	-3.89**
Hired labor	0.54	0.03	0.36	0.05	0.18***
Remittance receipt	0.33	0.03	0.36	0.05	-0.03
Group membership	0.22	0.03	0.14	0.04	0.08*
Credit access	0.09	0.02	0.02	0.02	0.07***
Agricultural training	0.16	0.03	0.08	0.03	0.07*
Sorghum price#	44.79	0.89	41.40	0.75	3.39***
Weather information receipt	0.82	0.03	0.87	0.03	-0.05
Sorghum land holding	0.23	0.02	0.22	0.02	0.01
Perceived soil fertility poor	0.29	0.03	0.14	0.04	0.16***
Perceived soil fertility moderate	0.58	0.03	0.75	0.04	-0.17***
Perceived soil fertility good	0.13	0.02	0.11	0.03	0.01
Perceived soil erosion low	0.55	0.03	0.59	0.05	-0.04
Perceived soil erosion high	0.05	0.02	0.07	0.03	-0.02
Sorghum variety improved	0.12	0.02	0.05	0.02	0.07**
Sorghum seeds quantity	11.39	0.40	11.71	0.57	-0.32
Site	0.49	0.04	0.84	0.04	-0.36***

#Exchange rate was US $1 = KES 109.68.
***, **, * significant at 1%, 5% and 10% level of significance

4.3.2 Determinants of inorganic fertilizer adoption

Inorganic fertilizer adoption was significantly determined by hired labor, access to agricultural training on sorghum production, soil fertility perception, weather forecast information receipt, and site (Table 4.4). Hired labor positively influenced the adoption of inorganic fertilizer at a 1% significance level. The findings implied that the likelihood of sorghum farmers adopting inorganic fertilizer increased with the increased utilization of hired labor. Meticulous application of inorganic fertilizer in its right amounts, from the suitable sources, at the right time, and in the right place calls for additional labor (Johnston and Bruulsema, 2014). Higher adoption of inorganic fertilizer among households who had access to hired labor could be attributed to the increased labor requirements. However, it is worth noting that hired labor comes with additional costs that could reduce the benefits attributed to inorganic fertilizer adoption. The finding agreed with several studies across SSA (Mugwe et al., 2009; Udimal et al., 2017; Mwaura et al., 2021) that hired labor is a significant positive determinant of agricultural productivity technologies adoption.

Agricultural training significantly and positively influenced the adoption of inorganic fertilizer in Western Kenya. The findings implied that the likelihood of adopting inorganic fertilizer increased with better access to agricultural training. The increased adoption n of inorganic fertilizer could be attributed to agricultural training that transfers reliable knowledge to farmers on the benefits and timing of inorganic fertilizer application. Further, agricultural training improves farmers' know-how on the sources of agricultural inputs and plays an essential component in instilling agricultural skills and building the target group's capacity (Macharia et al., 2014; Musafiri et al., 2020a; Musafiri et al., 2022a). Several studies have found the training to be a significant positive predictor of adoption of agricultural technologies, attributed to the transfer of knowledge on best management practices (Jawid and Khadjavi, 2019; Okeyo et al., 2020b; Mucheru-Muna et al., 2021; Mairura et al., 2021).

Soil fertility perception had a significant and positive influence on inorganic fertilizer adoption. Farmers' perception, especially on soil fertility, plays a central role in shaping the adoption of technologies to alleviate the status. Smallholder farmers could directly connect their reduced agricultural productivity to poor soil fertility. Declining soil fertility is the main drawback of agricultural productivity in SSA (Kiboi et al., 2019; Mwaura et al., 2021); thus, farmers who perceived the soil fertility as poor could have adopted inorganic fertilizer to enhance crop production. The adoption of inorganic fertilizer among smallholder farmers who perceived soil fertility as poor could be attributed to the need to improve sorghum yields. The finding agreed with Odendo et al. (2010) and Musafiri et al. (2022a), who reported that most households in Western Kenya perceived soil fertility as declining, thus affecting crop yields. Further, the findings collaborated with Desbiez et al. (2004), who found smallholder farmers' perceptions of soil fitness to be holistic to the field condition and thus could directly determine the adoption of soil fertility ameliorating practices, including inorganic fertilizer.

Weather forecast information receipt significantly and negatively influenced inorganic fertilizer adoption. This implied that the likelihood of adopting inorganic fertilizer increased with a reduction in weather forecast information receipt. This condition suggests using weather forecast information, including rainfall amount, onset, and cessation, to manage the cropping calendar. The weather forecast information could be used in agronomic activities such as land preparation, planting, pesticide application, and harvesting. Though the weather forecast information could not improve inorganic fertilizer adoption, it could be utilized to enhance agricultural productivity through climate change adaptation (Musafiri et al., 2022b).

Site negatively determined inorganic fertilizer adoption among smallholder farmers. Smallholder farmers residing in the Alego-Usonga sub-County had a lower likelihood of inorganic fertilizer adoption than their counterparts in the Ugenya sub-County. The lower adoption of inorganic fertilizer in Alego-Usonga could be attributed to differences in climatic conditions. Additionally, the geographical location highlights differences in institutional, socioeconomic, and biophysical characteristics that could influence the adoption of agricultural innovations. Similar findings were reported by Donkor et al. (2019) and Mairura et al. (2022a), who found that site significantly influences the adoption of agricultural technologies in Nigeria and Kenya, respectively.

Table 4.4 Determinants of inorganic fertilizer adoption and sorghum productivity among smallholder farmers in Western Kenya

Variable	**Log yield (Kg ha^{-1})**		
	Selection	**Non-adopters**	**Adopter**
Sex	-0.173(0.207)	-0.035(0.079)	0.032(0.043)
Education	0.288(0.313)	**0.328***(0.10)**	0.041(0.065)
Education	0.134(0.413)	0.169(0.141)	0.032(0.091)
Farming experience	-0.411(0.311)	**0.275**(0.121)**	-0.044(0.060)
Hired labor	**0.857***(0.22)**	-0.026(0.088)	0.078(0.053)
Remittance receipt	-0.131(0.203)	-0.047(0.071)	-0.009(0.044)
Group membership	0.023(0.294)	0.100(0.109)	0.018(0.060)
Credit access	0.229(0.503)	-0.333(0.230)	-0.058(0.082)
Agricultural training	**0.510***(0.39)**	0.201(0.142)	0.058(0.065)
Sorghum land holding	-0.086(0.240)	**-0.245*** (0.088)**	**-0.131*** (0.049)**
Sorghum variety improved	0.304(0.339)	-0.218(0.135)	**0.193***(0.066)**
Sorghum seeds quantity	0.258(0.438)	0.243(0.157)	**0.225**(0.094)**
Perceived soil erosion low	-0.237(0.188)	-0.035(0.071)	**-0.129***(0.041)**
Perceived soil fertility poor	**0.723***(0.24)**	-0.099(0.127)	-0.031(0.053)
Site	**-1.439***(0.22)**	0.192(0.129)	0.081(0.067)
Weather information receipt	**-0.848*** (0.28)**		
Constant	**2.420***(0.93)**	**1.38*** (0.31)**	**2.386***(0.159)**
rho_1		-0.582** (0.29)	
rho_2			0.029(0.404)
Summary statistics			
LR test of independent equations	12.05***		
Wald chi2	49.50***		
Prob>chi2	0.0000		
Log likelihood	-154.567		

Value is parenthesis are standard error, *. **. *** Significance at 10%, 5%, and 1% level of significance.

4.3.3 Determinants of sorghum yields

The findings showed a Likelihood ratio test of independent equations of 12.05*** for sorghum productivity (Table 4.4). The results implied that the three equations 3, 7a, and

7b were dependent, and if it was assumed the equations were independent, could have obtained biased estimates. The rho_1 (-0.582**) for non-adopters was significant at a 5% significance level. Thus, the application of ESR was plausible. The Wald chi-square test value of 49.50 for sorghum yields was significant at a 1% significance level, indicating independent variables included in the model jointly explained variations in sorghum yields.

Education of the household head exerted a significant positive effect on sorghum yields at a 1% significance level for inorganic fertilizer non-adopters. The finding implied that educated inorganic fertilizer noadopters were likely to have higher sorghum yields. Literate inorganic farmers could have improved technical know-how and external source of income to purchase farm inputs, consequently improving land productivity. The increased sorghum yields among non-adopters could be attributed to improved knowledge of other agronomic management practices such as organic farming. Theoretically, educated farmers are more likely to access information about agricultural innovations (Mulwa et al., 2017). The finding agreed with Paudel et al. (2019), who reported an increase in crop yield with an increase in education years among rice farmers of Nepal. However, the findings contradict Ojo and Baiyegunhi (2019), who found education negatively predicted the net returns of rice farmers in southwest Nigeria.

Farming experience significantly affected sorghum yields among inorganic fertilizer non-adopters at a 5% level of significance. The findings indicated that an increase in farming experience increased sorghum yields among inorganic fertilizer non-adopters. Agricultural farming is an engaging exercise, and as farmers gain experience, they become knowledgeable on the management practices to increase yield. The increased yield among non-adopters who had higher farming experience could be attributed to utilizing the gained expertise and technical knowledge in integrating farm inputs and overall management. The findings agreed with Donkor et al. (2019) and Martey et al. (2019), who indicated that experience positively influenced cassava and rice yields in Nigeria and Ghana.

Sorghum land holding negatively determined yields for adopters and non-adopters of inorganic fertilizer. This implied that sorghum yields among inorganic fertilizer adopters and non-adopters increased with a decline in land holding. Farmers with smaller land sizes could practice intensification practices, thus increasing their productivity. The lower yields among farmers with larger land sizes could be attributed to the inability to apply required nitrogen rates due to the high cost. The findings were similar to Paudel et al. (2019), who documented that land size had a negative effect on rice yields in the mid-hills of Nepal.

Improved sorghum variety utilization positively influenced sorghum yields for inorganic fertilizer adopters. The findings implied that inorganic fertilizer adopters who utilized improved sorghum varieties had higher yields than those who did not. Improved verities are developed to increase agricultural productivity more than the local ones. Therefore, the higher yields among smallholder farmers who adopted improved sorghum varieties could be attributed to their suitability to promote food security. Several studies in SSA have found that adopting enhanced crop varieties significantly improves the welfare of smallholder farmers including increased yields (Shiferaw et al., 2014a; Khonje et al., 2015; Manda et al., 2019).

The number of seeds planted significantly positively influenced sorghum yields among inorganic fertilizer adopters. The findings implied that an increase in seed quantity increases sorghum yields among inorganic fertilizer adopters. Increased seed quantity leads to enhanced plant population per unit area, thus increased productivity. However, high seed quantity beyond recommended planting density could lead to lower productivity due to the increased competition for resources, including nutrients. Agricultural training should be enhanced to educate farmers on the recommended seed quantity.

Smallholders' soil erosion perceptions significantly negatively affected sorghum yields among inorganic fertilizer adopters. This implied that the likelihood of increasing sorghum yields decreased with low soil erosion perceptions. Soil erosion leads to a reduction in soil fertility as the topsoil is eroded together with the nutrients. The reduced yields among smallholders who perceived the soil erosion to be low could be attributed to limited utilization of conservation practices leading to poor soil fertility, culminating in lower yields. The findings were consistent with Saguye (2017) and Tesfahunegn et al. (2020), who found farmers' perceptions of soil erosion influential in adopting conservation practices, thus improving land productivity.

4.3.4. Inorganic fertilizer adoption effects on sorghum yields

The results showed that inorganic fertilizer adoption had positive significant average treatment effects on sorghum yields at a 1% level (Table 4.5). Inorganic fertilizer adopters had a higher log of sorghum yields (2.97) than if they did not adopt (2.55).

Table 4.5 Inorganic fertilizer adoption effects on sorghum yields: ESR results

Outcome variable	Sampled household type	Household adoption decision stage		Average treatment effect
		To adopt	**Not to adopt**	
Log sorghum yield (kg $acre^{-1}$)	Inorganic fertilizer Adopters (IA)	2.97	2.55	ATT=0.42(0.02)***
	Inorganic fertilizer non-adopters (IN)	2.96	2.88	ATU=0.09(0.03)***
	Heterogeneity effect (IA-IN)	H_1=0.01	H_2=-0.33	H_3=0.33

*** indicate significance at 1%, ATT is the average treatment effects on treated, ATU represents average treatment effects on untreated, H_1 and H_2 are base heterogeneity, and H_3 represent transitional heterogeneity, ESR is the endogenous switching regression

Inorganic fertilizer adoption increased sorghum yields by 14%. The results implied that inorganic fertilizer adoption improved community welfare through enhanced sorghum yields. The findings corroborate with several studies across SSA Donkor et al. (2019), Khonje et al. (2018) and Martey et al. (2019) that found that the adoption of agricultural technologies significantly improved smallholder farmers' yields.

The findings revealed a positive base heterogeneity for adopters (H_1) and negative for non-adopters (H_2) for sorghum yields (Table 4.5). The findings for H_1 implied the influence of inorganic fertilizer adoption was greater for adopters than non-adopters if they decided to adopt. The negative H_2 indicated that the effect of inorganic fertilizer on adopters, if they chose not to adopt, was lower than non-adopters. The transitional heterogeneity (H_3) was positive for sorghum yields. This implied that inorganic fertilizer adopters had higher yields than non adopters could if they adopted. The finding indicated that adopting agricultural technologies, including inorganic fertilizer, positively affected sorghum yields. Therefore, smallholder farmers in Western Kenya could cope with a high poverty rate, climate change, and soil fertility decline by adopting inorganic fertilizer to enhance their livelihoods. The income generated could be used to uplift the rural livelihoods through increased food security and purchasing power.

4.3.5 Robustness check

The study revealed a good overlap of propensity scores for inorganic fertilizer adopters and non-adopters (Figure 4.3). The propensity score distribution highlighted that the common support region condition was satisfied. This implied that the use of propensity score matching (PSM) was plausible similar to Wossen et al. (2017) and Mojo et al. (2017).

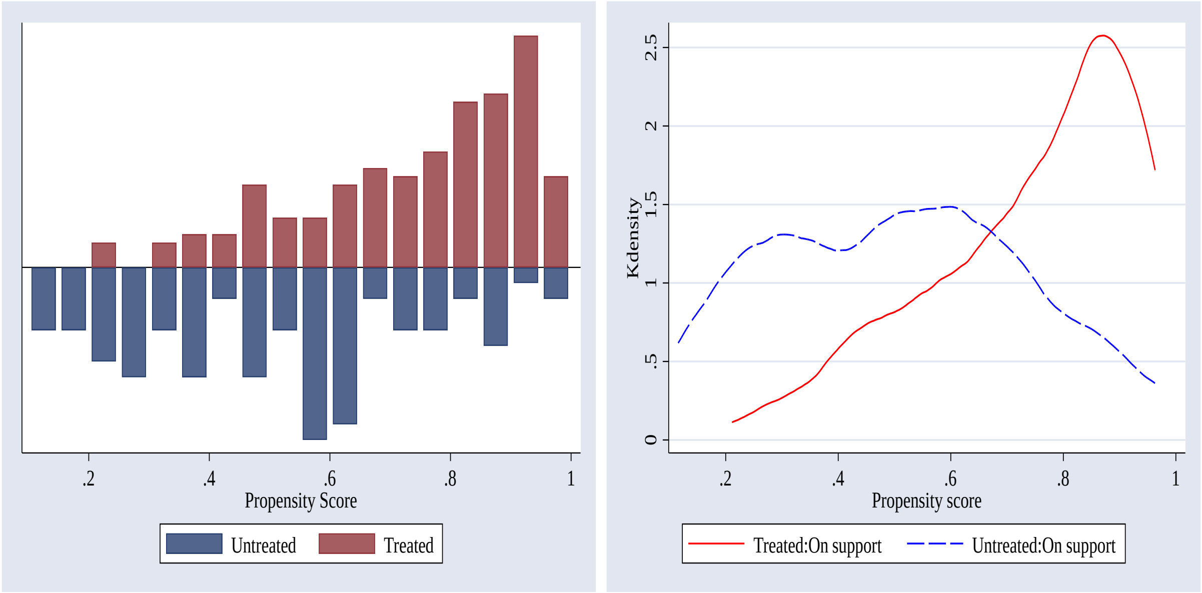

Figure 4.3 Distribution of inorganic fertilizer adopters and nonadopters for sorghum yields a) propensity score distribution, b) common support region

Table 4.6 Treatment effects from different matching algorithms

Matching algorithm	Log productivity (Kg ha^{-1})	
	ATT	**Robust Std. Error**
Propensity score matching	0.105	0.039***
Inverse probability weighing	0.079	0.041*
Nearest Neighbor Matching	0.074	0.044*

Significance at 10% and 1% level of significance is indicated by *. ***, respectively

Different matching algorithms showed a significant positive increase in sorghum yields under inorganic fertilizer adoption (Table 4.6). This implied that inorganic fertilizer adoption increased sorghum yields among smallholder farmers. The increased productivity could improve the rural households through enhanced food and nutritional security. The findings were consistent with previous studies by Donkor et al. (2019), Martey et al. (2019), and Marenya et al. (2020), who highlighted the adoption of agricultural technologies improved yields, including cowpeas, cassava, and maize across SSA countries.

4.4 Conclusion and policy implications

Soil fertility decline and climate change are significant hurdles facing smallholder farmers in Western Kenya. The study assessed the determinants and effects of inorganic fertilizer adoption on sorghum yield. The main determinants of inorganic fertilizer adoption among sorghum farmers were hired labor, agricultural training, farmers' soil perceptions, site, and weather forecast information receipt. The average treatment effects on treated (ATT) indicated that inorganic fertilizer adoption increased sorghum yields by 14%. The findings showed a positive transitional heterogeneity thus, inorganic fertilizer adopters had higher productivity than non-adopters if they decided to adopt. The results highlight the importance of inorganic fertilizer adoption on increasing food security among smallholder farmers. The study revealed that different factors influence sorghum productivity among adopters and non-adopters. The research recommends agricultural subsidies enhance inorganic fertilizer adoption and improve application rates among sorghum farmers. Policymakers need to target promoting agricultural training and consider farmers' perceptions of soil fertility and site to enhance inorganic fertilizer adoption and sorghum productivity.

CHAPTER FIVE

ADOPTION OF CLIMATE-SMART AGRICULTURAL PRACTICES AMONG SMALLHOLDER FARMERS IN WESTERN KENYA: DO SOCIOECONOMIC, INSTITUTIONAL, AND BIOPHYSICAL FACTORS MATTER?[2]

Abstract

Rigorous efforts should be channeled to the current low adoption of climate-smart agricultural practices (CSAPs) in sub-Saharan African countries to improve food production. The question is, what determines the adoption level and intensity of CSAPs among smallholder farmers in Kenya? Hence, the objective was to assess the determinants of climate-smart agricultural practices adoption level and intensity among smallholder farmers in Siaya County. The study used data collected from 300 smallholder farmers in Western Kenya to assess smallholders' CSAPs adoption determinants while considering their joint adoption. The CSAPs considered were animal manure, soil water conservation, agroforestry, crop diversification, and crop-livestock integration. Multivariate and ordered probit models was used to assess the determinants of joint adoption of CSAPs in Western Kenya. The study established complements and substitutes between CSAPs. The multivariate probit analysis revealed that the household head's gender, education, age, family size, contact with extension agents, access to weather information, arable land, livestock owned, perceived climate change, infertile soil, and persistent soil erosion influenced CSAPs adoption. The ordered probit model revealed that gender, arable land, livestock owned, soil fertility, and constant soil erosion were crucial determinants of CSAPs adoption. The findings implied that policymakers and relevant stakeholders should consider farmer, institutional, and biophysical factors in upscaling or promoting the adoption of CSAPs.

Keywords: Soil fertility decline, Climate-smart agriculture, Climate change, Multivariate probit model, Ordered probit model

---

[2] Musafiri, C.M., Kiboi, M., Macharia, J., Ng'etich, O.K., Kosgei, D.K., Mulianga, B., Okoti, M. & Ngetich, F.K. (2022). Adoption of climate-smart agricultural practices among smallholder farmers in Western Kenya: do socioeconomic, institutional, and biophysical factors matter? *Heliyon*, *8*(1), p.e08677. https://doi.org/10.1016%2Fj.heliyon.2021.e08677

5.1 Introduction

Climate change is a major significant hurdle to agricultural production globally. The climate change impacts on agricultural production are predominant in developing countries such as sub-Saharan Africa (SSA), where agriculture is rain-fed dependent (OECD & FAO, 2016; Van Ittersum et al., 2016). Climate change manifests as dry spells, meteorological droughts, flooding, unreliable rainfall, cropping calendar changes, and increased atmospheric temperature (Bryan et al., 2013; Ochieng et al., 2017). Climate change induces crop failure and livestock losses culminating in food insecurity and posing severe threats to society's wellbeing (Thornton & Herrero, 2015). Despite the climate change impacts on the agricultural sector, producing more food is essential for the increasing population in SSA countries, Kenya included. Therefore, interventions such as adopting climate-smart agricultural practices (CSAPs) among smallholder farmers are crucial.

Smallholder farmers are faced with multiple climate change shocks, including floods, erratic rains, dry spells, and drought, among others (Bozzola et al., 2018; Mairura et al., 2021). The climate change shocks significantly affect their agricultural productivity, including total crop failure and livestock losses. Therefore, smallholder farmers adopt single or multiple agricultural practices to cope with the impacts of climate change (Thornton & Herrero, 2015; Mairura et al., 2021). The CSAPs such as animal manure, soil water conservation, agroforestry, crop diversification, and crop-livestock integration improve food security and community welfare (Ngetich et al., 2014; Thornton & Herrero, 2015; McCord et al., 2015; Kiboi et al., 2019; Reppin et al., 2020). The above CSAPs were selected based on the literature and expert knowledge of the study area. Despite the novel gains from CSAPs in enhancing food security and community wellbeing, their adoption levels remain relatively low (Ogada et al., 2014). This adoption varies across practices, and regions and the rates range from low to high (Bryan et al., 2013; Ndiritu et al., 2014; Kanyenji et al., 2020; Mogaka et al., 2021). However, there is limited literature on adopting the combination of agricultural practices such as animal manure, soil water conservation, agroforestry, crop diversification, and crop-livestock integration in Western Kenya to mitigate the impacts of climate change. Therefore, assessing the adoption levels and intensity of CSAPs is vital in promoting policy formulation, technology dissemination, and improving livelihoods.

Smallholder farmers adopt CSAPs to cope with climate change shocks. Smallholder farmers are faced with complex decisions either not to adopt or adopt a single or combination of technologies for climate change mitigation and adaptation (Ndiritu et al., 2014). The adoption of CSAPs is mainly driven by expected utility (Rabin,2013), where a farmer could adopt a practice if the pay-off is better than not adopting. However, smallholder farmers are also faced with the decision to adopt a bundle of CSAPs (Kpadonou et al., 2017; Mulwa et al., 2017). The adoption of a specific practice could be conditioned to another. Therefore, assessing the determinants of the adoption of CSAPs should test the assumption of the interdependencies between them (Oyetunde-Usman et al., 2021). Previous studies found interdependencies between practices while estimating determinants of simultaneous adoption of agricultural innovation, thus assuming independence between them could produce biased outcomes (Teklewold et al., 2013; Ndiritu et al., 2014; Mulwa et al., 2017; Ehiakpor et al., 2021). Adopting CSAPs could be influenced by geographical location, farmer demographics, institution traits, biophysical factors, and the practice under consideration. Since smallholders could consider the combination of technologies, exploring the determinants of adoption intensity is equally essential.

Despite the potential of integrating CSAPs to improve food security and community wellbeing, adopting a bundle of practices is limited by various factors such as high initial cost and technical know-how. Therefore, a smallholder farmer could adopt none, single, or several practices based on the ability. This justifies the need to evaluate determinants of CSAPs adoption among smallholder farmers across diverse locations to design pro-farmer policies that could foster intervention adoption and improve food security against the backdrop of changing climate. The objective was to assess the determinants of climate-smart agricultural practices adoption level and intensity among smallholder farmers in Siaya County. The study responded to the following research question: what determines the smallholders' adoption of multiple interrelated CSAPs in Western Kenya?

5.2 Methodology

5.2.1 Study area

The study was conducted in Alego-Usonga and Ugenya sub-Counties in Siaya County, Western Kenya. Alego-Usonga and Ugenya sub-Counties cover 599 km^2 and 324 km^2, respectively, 36.48% of Siaya County. Alego-Usonga and Ugenya are inhabited by 224,343 and 134,354 persons, respectively, 36.11% of the Siaya County population (KPHC, 2019). The study area is located in diverse agro-ecological zones, including Upper midland (UM1) and low midlands (LM1-5) (Jaetzold et al., 2010)

The elevation ranges from 1140 to 1500 m above sea level. The site experience long-term annual temperature and rainfall ranging from 20.9 to 22.3 °C and 800 to 2000 mm (Jaetzold et al., 2010). The rainfall is bimodally distributed, where long rains occur from March to June and short rains from September to December each year. This results in two full cropping seasons per year. The main economic activity is crop and livestock farming. However, the rainfalls are highly erratic and unpredictable, leading to crop-livestock losses and food insecurity. The main climatic hazards in the study area include dry spells, flooding, and heat stress (Mairura et al., 2021). The threats significantly affect crop and livestock production. Therefore, smallholder farmers are forced to explore different CSAPs to mitigate the adverse climate change impacts. Most of the smallholder farmers in the area grow orphan crops such as cassava (*Manihot esculenta*), millet (*Panicum miliaceum*), sorghum (Sorghum bicolor), cowpea (*Vigna unguiculata*), chickpea (*Cicer arietinum*), and groundnut (*Arachis hypogaea*). They also grow food crops such as common bean (*Phaseolus vulgaris*) and maize (*Zea mays*). The predominant livestock reared includes goat, sheep, cattle, and poultry. Fishing is also a joint economic activity in the study area.

5.2.2 Study variables description

Smallholder farmers were requested to explain their encounters with the changing climate over the last ten years. Following the experience of smallholder farmers with climate change, they were asked to enumerate CSAPs they had adopted. The main CSAPs adopted by smallholder farmers to improve agricultural productivity and cope with climate change included the use of animal manure, agroforestry, soil water conservation, crop diversification, and crop-livestock integration (Table 5.1). The practices mentioned were consistent with literature (Bryan et al., 2013; Kpadonou et al., 2017; Mulwa et al., 2017; Ochieng et al., 2017; Oyetunde-Usman et al., 2021). The five CSAPs were used as the outcome variables. The adoption intensity indicates the number of CSAPs adopted by a smallholder farmer (Table 5.2).

The relied on available literature on CSAPs adoption in selecting independent and dependent variables (Mutoko et al., 2014; Ndiritu et al., 2014; Kassie et al., 2015; Mulwa et al., 2017; Sileshi et al., 2019; Ehiakpor et al., 2021). The five CSAPs, animal manure, agroforestry, soil water conservation, crop diversification, and crop-livestock integration, were measured as 1 if the smallholder farmer adopted a specific practice and 0 if otherwise. Specifically, socioeconomic, institution and biophysical factors were incorporated as determinants of CSAPs adoption (Table 5.3).

5.2.3 Sampling procedure and sample size

The study employed a cross-sectional survey and multi-stage sampling procedure in sampling the smallholder farmers. First, Siaya County in Western Kenya at the first stage was purposely selected due to the high poverty levels, food insecurity, and climate-related shocks (MoALF, 2016). At the second stage, two sub-Counties: Alego-Usonga and Ugenya, from the six total sub-Counties, including Bondo, Gem, Rarienda, and Ugunja in Siaya County were selected because of climate risk dominance. Whole sampling procedure was implemented to collect data from the six and four wards in Alego-Usonga and Ugenya sub-Counties at the third stage. The study used proportionate to size sampling procedure in determining household heads sampled per ward. Finally, random sampling procedure was employed to collect data from 300 smallholder farming households in the two sub-Counties. The target population was 57, 553 and 33, 565 smallholder households in Alego-Usonga and Ugenya sub-Counties. Cochran formula was used in sample size calculation. The sample size of the 300 smallholders was sampled based on a 5% level of significance, and a 5.65% confidence interval, as described by Cochran (2007).

5.2.4 Household interview

The study used a semi-structured interview schedule for data collection. Before the actual data collection, the interview schedule was pre-tested using ten randomly selected smallholder farmers. Following feedback from the pre-testing, the interview schedule was modified and adjusted. The interview administration involved ten recruited and trained enumerators. The interview schedule had questions on CSAPs adopted, and smallholder farmers' socioeconomic, institutional, and biophysical variables. Smallholder farmers were requested to voluntary consent before participating in the study. The interview was administered to the household head.

5.2.5 Multivariate probit model

Smallholder farmers could decide to adopt multiple CSAPs to improve food production and mitigate climate change impacts. To evaluate determinants of CSAPs adoption, the study assumed interdependencies between error terms of different practices, including animal manure (M), agroforestry (A), soil water conservation (S), crop diversification (D), and crop-livestock integration (L). Therefore, using a model that could simultaneously estimate the determinants of practices is imperative. A multivariate probit (MVP) model was used to assess the determinants of smallholders' simultaneous adoption of CSAPs. The MVP model estimates the determinants of simultaneous CSAPs adoption while the individual probit model considers one practice at a time (Belderbos et al., 2004). The correlation of error terms where a positive sign represents complements or a negative sign indicates substitutes across different CSAPs (Mulwa et al., 2017; Oyetunde-Usman et al., 2021). The MVP model can be presented in two systems equations. Following Kpadonou et al. (2017) let U_a indicate the utility of adopting jth practice and U_n otherwise. Smallholders can adopt the jth approach if $Yij=U_a-U_o>0$. Therefore, net utility Y*ij, a farmer obtains for adopting the jth practice, is a latent variable that can be predicted by the experimental factors and the multivariate normally distributed error terms (ε_i) equation 5.1:

$$Y_{ij}^{*} = \beta_j X_i + \varepsilon_i \qquad (5.1)$$

Where X_i indicates a vector of independent variables, j climate-smart agriculture practice, $\boldsymbol{\beta}_j$ Vector coefficient, and ε_i error term.

According to utility maximization theory, smallholder farmers could adopt CSAPs if the expected benefits are higher than non-adoption. This can be presented as an observable dichotomous outcome for each choice of CSAPs adopted by smallholder farmers could be described as shown in equation 5.2:

$$Y_{ij} = {}^{1\ if Y_{ij}^{*}}_{0\ otherwise} Where\ j = M, S, A, D, L \qquad (5.2)$$

Where, Y_{ij} Indicates a binary observable variable for the adoption of jth practice by the ith farmer. Suppose adoption of CSAPs is assumed to co-occur; the error terms of the equation can be described using a variance-covariance matrix (equation 5.3).

$$\pi = \begin{pmatrix} 1 & \delta MS & \delta MA & \delta MD & \delta ML \\ \delta Sm & 1 & \delta SA & \delta SD & \delta SL \\ \delta AM & \delta AS & 1 & \delta AD & \delta AL \\ \delta DM & \delta DS & \delta DA & 1 & \delta DL \\ \delta LM & \delta LS & \delta LA & \delta LD & 1 \end{pmatrix} \qquad (5.3)$$

Where rho (δ) is a pairwise correlation between any two CSAPs, the sign between the two practices shows the relationship. As stated earlier, a positive sign represents complements, and a negative one indicates substitutes.

5.2.6 Ordered probit model

From the MVP model, smallholder farmers adopt CSAP with higher utility than non-adoption. The MVP model considers smallholder farmers' adoption of specific CSAP conditional to other practices based on expected utility. The intensity of adoption is a count data that could be analyzed using Poisson regression. The Poisson regression is based on the assumption that all the events have the same probability of occurrence. However, the adoption intensity of CSAPs doesn't have the same chance of happening.

The propensity of adopting the first CSAP could be different from the subsequent adoption of the practices (second to fifth) because smallholder farmers gain experience upon the first adoption. The smallholder farmers could have achieved better pay-off upon adopting the first practice and could be willing to adopt a combination of approaches to maximize the utility. Notably, the adoption of the practices could also differ based on their nature, including labor requirements, practical knowledge requirements, initial investments, and whether the benefits expected are in the short term or long term. However, smallholder farmers combine multiple CSAPs to increase the utility than those who adopt none, single, or few practices (Kpadonou et al., 2017). The adoption intensity (number of CSAPs adopted by *i*th farmer) was considered as an ordinal variable that could be analyzed using the ordered probit model. The model allows for estimating determinants of ordinal variables (adoption intensity that 1, 2, 3, 4, and 5 CSAPs). The ordered outcome could be assessed as a latent variable Y*, where Y* is the unobservable measure of smallholders' CSAPs adoption intensity (Cameron & Cameron, 2015; Oyetunde-Usman et al., 2021) as described in equation 5.4.

$$Y_j^* = X_j'\beta + u_j \qquad 5.4$$

For the i_{th} smallholder farmer where normalization is that the regressors x do not include and intercept, the adoption intensity increases with Y*. The probability of observing a j outcome could be described by equation 5.

$$\Pr(outcome\ i = j) = \Pr(n_{j-1} < X_j'\beta + u_j \leq \boldsymbol{\alpha}_j \qquad 5.5$$

The coefficient β_1, β_2… β_{j-1} were estimated jointly with the cut points α_1, α_2, …, α_j where j is the number of the possible outcomes. U_i is assumed to be normally distributed with a standard normal cumulative distribution function. The ordered probit model is pooled and works under the assumption that the unobserved heterogeneity is uncorrelated with the independent variables. Previous studies have adopted plot-level analysis to control unobserved heterogeneity that may affect the estimates using fixed or pseudo- fixed-effect models (Kpadonou et al., 2017). However, using plot-level analysis is not feasible in this study because of the nature of the data.

5.3 Results and discussions

5.3.1 Descriptives of the smallholders

The descriptive characteristics of variables used in modeling are presented in Table 5.1 and Table 5.2. The study revealed a wide range of smallholders' CSAPs adoption rates in Western Kenya (Table 5.1). The adoption level of individual CSAPs ranged between 30% for agroforestry to 78% for crop diversification. The findings indicate that the adoption of individual CSAPs widely varies among smallholder farmers. The results were consistent with Ogada et al. (2014), who reported a varied adoption rate of agricultural practices in Western Kenya.

Table 5.1 Climate-smart agricultural practices adopted by smallholder farmers.

CSA practices	Description	Mean	Std Dev.
Animal manure	Dummy=1 if the household adopted animal manure, 0 otherwise	0.32	0.27
Soil water conservation	Dummy=1 if the household adopted soil water conservation, 0 otherwise	0.65	0.48
Agroforestry	Dummy=1 if the household adopted agroforestry, 0 otherwise	0.30	0.46
Crop diversification	Dummy=1 if the household adopted crop adjustments, 0 otherwise	0.78	0.42
Crop-livestock integration	Dummy=1 if the household adopted crop livestock integration, 0 otherwise	0.44	0.30

The adoption intensity of CSAPs ranged between zero to five (Table 5.2). Though some farmers (2.7%) adopted all the five CSAPs, a few farmers (2%) did not utilize any of the practices. Approximately 98% of the smallholder farmers practiced at least one CSAP. The findings agreed with Ndiritu et al. (2014), Kpadonou et al. (2017), Sileshi et al. (2019), and Ehiakpor et al. (2021), who reported high adoption rates of at least one CSAP. However, the adoption rates and intensity widely varied across the specific practice. Most (80%) of the smallholder farmers adopted one to three CSAPs, and 15% implemented four of the five practices. Only 2.7% of the sampled farmers adopted all the five CSAPs. The findings implied a great potential to improve the adoption of agriculture practices for enhanced food and nutritional security, coping with climate change, reducing soil erosion, and uplifting economic gains among smallholder farmers. The simultaneous adoption of CSAPs needs to be interwoven with socioeconomic, institutional, and biophysical characteristics to improve society's welfare.

Table 5.2 Adoption intensity of climate-smart agriculture practices among smallholders.

Intensity of adoption (Number of technologies)	**Frequency**	**Percentage (%)**
0	6	2.00
1	45	15.00
2	105	35.00
3	91	30.33
4	45	15.00
5	8	2.67
Total	**300**	**100**

The socioeconomic, institutional, and biophysical variables displayed the profile of the sampled respondents (Table 5.3). The results showed that 38% of the sampled household heads were male and 68% female. These results implied that most of the farming population in Siaya County were female. Additionally, most (86%) of the sampled household heads were literate. The literacy level implied that most smallholder farmers residing in Western Kenya could effectively comprehend new agricultural innovations. Results revealed that smallholders had an average age of 51.9 years. This is consistent with previous studies in Western Kenya of Mutoko et al. (2014) and Wetende et al. (2018), who found the sampled households' heads were still in the active age bracket. However, the population was beyond the youths' frame of 35 years and below, implying that youths were not actively participating in agricultural production. Additionally, smallholder farmers had an average family size of 5.78 members, an essential variable indicating farm labor availability.

The findings demonstrated a low access to extension agents of 13% (Table 5.3). However, most sampled household heads received weather forecast information (86%) and perceived change in climate (96%). The smallholder farmers had small landholdings (1.23 acres) and tropical livestock units (3.35). Additionally, only a few household heads perceived their soil status as problematic, that is, 24% infertile soil and 6% persistent soil erosion.

Table 5.3 Descriptive statistics of the sampled households among smallholder farmers in Western Kenya

Variable	Description	Mean	Std Dev.
Gender of the household head (hhh)	Dummy=1 if male, 0 female	0.38	0.49
Education status of the household head(hhh)	Dummy=1 if attained formal education, 0 otherwise	0.86	0.35
Age of the household head (hhh)	Age of the household head in years	51.91	13.74
Family size	Number of family members	5.78	2.91
Contact with extension agent	Dummy= 1 if yes, 0 otherwise	0.13	0.34
Access to weather information	Dummy= 1 yes, 0 otherwise	0.84	0.37
Arable land size	Total arable land size in acres	1.23	0.90
Owned livestock	Total livestock unit#	3.35	3.83
Perceived climate change	Dummy=1 yes, 0 otherwise	0.96	0.19
Soil fertility	Dummy=1 infertile, 0 fertile	0.24	0.43
Persistent soil erosion	Dummy=1 yes, 0 otherwise	0.06	0.24

Total livestock unit for cow, sheep, goat, and chicken calculated using a conversion of 0.7, 0.1,0.1, and 0.01 following Jahnke (1982).and Musafiri et al. (2020a).

5.3.2 The compliments and substitutes of climate-smart agricultural practices

The likelihood ratio test ($chi^2 = 658.201$, $p < 0.0001$) of the error terms of different CSAPs equations from the MVP model was significant at a 1% level of significance, thus rejecting the null hypothesis that the equations were independent (Table 5.4). The results indicated that the equations for adopting individual CSAP were interdependent. Therefore, alternative hypothesis of the interdependence between error terms of CSAPs was accepted. The results justified using the MVP model in analyzing the determinants of adopting the CSAPs. The findings showed both positive and negative correlation coefficients indicating both complements and substitutes between CSAPs. The findings were similar to Ndiritu et al. (2014), who reported complements and substitutes between sustainable intensification practices among smallholders in Kenya. The research established compliments between soil water conservation and animal manure, agroforestry and animal manure, crop diversification and soil water conservation, crop-livestock integration, and crop diversification. The complements of CSAPs could be attributed to the desire to improve agricultural productivity, adapt to climate change, and enhance income (Oyetunde-Usman et al., 2021). The CSAPs used as substitutes among the smallholder farmers included crop diversification and animal manure, crop-livestock integration and soil water conservation, crop-livestock integration, and agroforestry. Crop diversification and crop-livestock integration involve agricultural intensification. To boost farming revenues, farmers may find it less economical to combine farming revenues with animal manure, agroforestry, and soil water conservation.

Table 5.4 Correlation coefficients of the climate-smart agricultural practices (estimation from multivariate probit model)

CSA practice	Coefficient	Std. Err.	p value
Soil water conservation and animal manure (rho21)	0.127***	0.095	0.008
Agroforestry and animal manure (rho31)	0.118**	0.098	0.048
Crop diversification and animal manure (rho41)	-0.122***	0.104	0.003
Crop-livestock integration and animal manure (rho51)	-0.087	0.092	0.435
Agroforestry and soil water conservation (rho32)	0.028	0.103	0.786
Crop diversification and soil water conservation (rho42)	0.474***	0.090	<0.001
Crop-livestock integration and soil water conservation (rho52)	-0.124***	0.096	0.001
Crop diversification and agroforestry (rho43)	0.044	0.107	0.682
Crop-livestock integration and agroforestry (rho53)	-0.173***	0.089	0.001
Crop-livestock integration and crop diversification (rho54)	0.178***	0.100	0.003

Likelihood ratio test of rho21 = rho31 = rho41 = rho51 = rho32 = rho42 = rho52 = rho43 = rho53 = rho54 = 0: $chi^2(10) = 125.5427$ Prob > $chi^2 = 0.0001$

** $p<0.05$

*** $p<0.01$

5.3.3 Determinants of climate-smart agriculture practices adoption

The study assessed factors that determined individual or simultaneous adoption of CSAPs. The Wald $chi^2 = 102.63$, p=0.0001 was significant (Table 5.5), justifying the plausibility of MVP analysis. Therefore, the null hypothesis that CSAPs such as animal manure, soil water conservation, agroforestry, crop diversification, and crop-livestock integration were independent, was rejected. The results indicated that the practices were interdependent, and using the individual probit model produced biased estimates.

The adoption of CSAPs is influenced by socioeconomic, institutional, farmer perceptions, and biophysical factors (Table 5.5). Household head's gender negatively influenced agroforestry adoption. The finding suggests that females had a higher propensity to adopt agroforestry than males. The negative prediction was against the previous literature that male dominates farming resources and could be attributed to female empowerment (Kiptot and Franzel, 2012; Oyetunde-Usman et al., 2021). Given that the dominant cropping enterprise in the study area is sorghum, female households' increased adoption of agroforestry could be attributed to the crop being referred to as a poor man's crop'. The finding agreed with Kiptot and Franzel (2012), who found that women highly practice agroforestry with crops of little or no commercial value. Smallholder farming in Western Kenya is women-dominated (Table 5.3). Most agricultural empowerment programs target women (Diiro et al., 2018) thus enhancing good farming practices among female farmers. The findings underscore the responsibility of women in climate change adaptation and sustainable agriculture.

The results revealed that the household head's education level positively determined animal manure adoption (Table 5.5). This implied that literate smallholder farmers had higher chances of applying animal manure in their farms than illiterate ones. The observation may be because the educated farmers may know the correct methods and amounts of animal manure application. The findings agreed with Kassie et al. (2015) and Kanyenji et al. (2020), who highlighted the importance of education in adopting animal manure. However, the findings contradicted Oyetunde-Usman et al. (2021), who found education determinant of organic manure adoption.

Table 5.5 Determinants of climate-smart agricultural practices adoption among smallholder farmers in Western Kenya

Variable	**Multivariate probit estimates**					**Individual probit estimates**				
	M Coeff. (S.E)	**S Coeff. (S.E)**	**A Coeff. (S.E**	**D Coeff. (S.E**	**L Coeff. (S.E**	**M Coeff. (S.E)**	**S Coeff. (S.E)**	**A Coeff. (S.E**	**D Coeff. (S.E**	**L Coeff. (S.E**
Gender of the hhh	-0.172 (0.177)	0.031 (0.176)	-0.511*** (0.182)	0.317 (0.192)	-0.248 (0.170)	-0.166 (0.177)	0.013 (0.177)	-0.502*** (0.183)	0.361* (0.197)	-0.252 (0.170)
Education status hhh	0.555** (0.276)	-0.407 (0.279)	0.120 (0.276)	-0.431 (0.307)	0.086 (0.261)	0.549** (0.276)	-0.389 (0.279)	0.128 (0.276)	-0.428 (0.310)	0.089 (0.261)
Age of the hhht	0.012* (0.006)	0.000 (0.006)	-0.005 (0.007)	-0.003 (0.007)	0.005 (0.006)	0.012* (0.006)	0.000 (0.006)	-0.005 (0.007)	-0.003 (0.007)	0.005 (0.006)
Family size	-0.046 (0.030)	0.035 (0.029)	-0.056* (0.030)	0.043 (0.033)	0.001 (0.028)	-0.046 (0.030)	0.036 (0.030)	-0.060** (0.031)	0.042 (0.033)	0.002 (0.028)
Contact with extension agent	-0.440* (0.250)	0.715*** (0.256)	-0.257 (0.246)	1.094*** (0.351)	-0.194 (0.225)	-0.450* (0.251)	0.736*** (0.257)	-0.251 (0.247)	1.147*** (0.361)	-0.180 (0.225)
Access to weather information	-0.308 (0.215)	-0.269 (0.231)	0.467* (0.243)	-0.451* (0.267)	0.234 (0.216)	-0.311 (0.216)	-0.229 (0.230)	0.472* (0.246)	-0.477* (0.269)	0.224 (0.216)
Arable land	-0.041 (0.100)	-0.005 (0.096)	0.145 (0.098)	-0.096 (0.104)	0.171* (0.096)	-0.039 (0.099)	-0.010 (0.097)	0.150 (0.098)	-0.109 (0.104)	0.167* (0.095)
Livestock owned	-0.018 (0.022)	0.023 (0.021)	0.013 (0.021)	-0.014 (0.022)	0.051** (0.021)	-0.018 (0.022)	0.020 (0.021)	0.014 (0.021)	-0.011 (0.023)	0.051** (0.021)
Perceived climate change	0.838 (0.550)	-1.069* (0.581)	0.852 (0.562)	-4.631 (1.622)	0.440 (0.421)	0.834 (0.549)	-1.130* (0.587)	0.971* (0.570)	-	0.477 (0.418)
Soil fertility	0.515*** (0.181)	-0.333* (0.184)	-0.013 (0.188)	-0.339* (0.195)	-0.223 (0.183)	0.512*** (0.186)	-0.378** (0.190)	0.064 (0.194)	-0.274 (0.199)	-0.227 (0.184)
Persistent soil erosion	-0.210 (0.334)	1.429*** (0.516)	0.534* (0.322)	0.123 (0.345)	-0.105 (0.326)	-0.223 (0.338)	1.351*** (0.500)	0.586* (0.321)	0.080 (0.352)	-0.082 (0.324)
Constant	-1.741** (0.757)	1.698** (0.770)	-1.316* (0.794)	6.077 (2.623)	-1.300** (0.660)	-1.713** (0.755)	1.645** (0.774)	-1.303 (0.799)	1.699*** (0.585)	-1.349** (0.659)

Number of observations = 300 Log likelihood = -848.359 Wald chi2 (56) = 102.63, Prob>chi2 =0.0001, *p<0.1 **p<0.05 ***p<0.01, robust standard error in parenthesis, M = Animal manure, S = Soil water conservation, A = Agroforestry, D = crop diversification, L = crop livestock integration.

Household head's age positively predicted animal manure adoption. The findings suggested that the propensity to adopt animal manure increased with age. This could be attributed to the possibility that old farmers have evaluated the benefits of animal manure application over the long term. Further, the older farmers could have larger livestock herds compared to their young counterparts. The results corroborated with Oyetunde-Usman et al. (2021), who found that adoption of animal manure was positively influenced by age. However, the findings contradict the hypothesis that old farmers are risk-sensitive and reluctant to adopt agricultural innovations (Macharia et al., 2014; Musafiri et al., 2020a).

Family size negatively predicted agroforestry adoption. The findings implied that large families were less likely to adopt agroforestry. Family size is an important variable as it signifies the availability of labor to adopt an agricultural practice. The pessimistic prediction of family size on the adoption of agroforestry was unanticipated because large family sizes could be in a position to supply labor. After all, agroforestry is a labor-intensive technology. The results could be due to the probability of small family sizes using hired labor in implementing agricultural innovations. The findings corroborated with Kpadonou et al. (2017) and Ehiakpor et al. (2021), who reported that family size negatively determines agricultural practices adoption. However, the findings disagreed with Bryan et al. (2013), Kassie et al. (2015), and Mwaura et al. (2021), who found that family size positively influenced agricultural technologies utilization.

The findings revealed that contact with extension agents positively influenced soil water conservation and crop diversification, while animal manure was negative. Extension agents help smallholder gain more insights into the implementation of agricultural technologies (Syahza, 2021). The findings could be linked to the need for technical know-how in implementing soil water conservation practices and crop diversification instead of animal manure, one of the traditional practices. The extension agents' contacts could have played a central role in equipping the farmers with practical skills of soil water conservation implementation and selecting crop diversification practices to improve agricultural productivity and adapt to climate change. The findings agreed with

Anang et al. (2020) and Emmanuel et al. (2016), who underscored extension services implication in enhancing agricultural interventions adoption.

Access to weather forecast information positively influenced the adoption of agroforestry and negatively affected crop diversification. The findings implied that receiving weather forecast information accelerated the propensity to adopt agroforestry while decreasing the likelihood of implementing crop diversification. The receipt of weather forecast information help smallholder farmers choose CSAPs for climate change mitigation. The findings could be attributed to smallholders' need to implement long-term strategies for climate change adaptation, including agroforestry, instead of the short-term ones among smallholder farmers who received weather forecast information. Adopting agroforestry trees among smallholder farmers who received weather forecast information could be attributed to the multiple anticipated benefits, including improved soil carbon sequestration, food security, income, provision of shade and timber (Qazlbash et al., 2021).

Arable land size exhibited a significant positive influence on adopting crop-livestock integration. The findings suggested an increased likelihood of adopting crop-livestock integration with the increase of arable land size. The increased adoption of crop-livestock integration could be due to the need for larger farm sizes for livestock keeping and crop farming. The larger land size could also grow folder crops that could be used as animal feeds. The result could be attributed to smallholder farmers apportioning their farms to different technologies with more extensive farm holdings. The findings were confirmed by Darkwah et al. (2019), Ehiakpor et al. (2021) and Thinda et al. (2020). Notably, smallholder farmers with large landholdings benefit from the trade-off arising from crop-livestock integration, such as using the crop residue as animal feed and the livestock's application for soil fertility amelioration.

The TLU positively determined crop-livestock integration adoption. The findings suggested that the propensity of crop-livestock integration adoption increased with an increase in TLUs. The influence of TLU on crop-livestock integration could be attributed to the greater need for animal feeds among households with greater TLU, thus integrating crops and livestock to utilize the crop residues as animal feeds. Additionally, the manure produced from the livestock could also be incorporated into the agricultural land, thus enhancing soil fertility. The findings were consistent with Kanyenji et al. (2020) and Ndeke et al. (2021), who found that TLU was a significant positive determinant of improved technologies adoption.

Farmers' perceptions of climate change positively explained soil water conservation adoption. The findings implied that household heads who perceived climate change had a higher likelihood of adopting soil water conservation practices. The increased adoption among smallholders who perceived climate change can be attributed to the anticipated reduction in food production. Therefore, smallholders' awareness of climate change could have motivated them to implement CSAPs. The findings were in line with Joshi et al. (2017) and Ochieng et al. (2017). However, smallholder farmers could fail to adopt sustainable agricultural practices even if they perceive climate change due to the high investment cost required (Bryan et al., 2013).

Soil fertility significantly influenced animal manure adoption but negatively affected soil water conservation and crop diversification adoption. This implied that smallholders experiencing poor soil fertility had a higher likelihood of adopting animal manure and a lower propensity to utilize soil water conservation and crop diversification practices. The finding could be attributed to improving soil fertility by using animal manure to achieve food security and increase income. Further, the smallholder farmers can anticipate crop failure or lower yields from infertile plots, thus failing to implement high investment practices. Soil water conservation and crop diversification are not directly linked to soil fertility improvement. Therefore, smallholder farmers could find it suitable to implement animal manure for soil fertility amendment. The findings were consistent with Fosu-Mensah et al. (2012) and Mulwa et al. (2017), who reported that smallholders with fertile plots were less likely to utilize agricultural innovations. This was attributed to reduced chances of crop failure in fertile fields.

Persistent soil erosion positively determined agroforestry and soil water conservation adoption. This suggested that smallholders who perceived continued soil erosion had a higher propensity to adopt agroforestry and soil water conservation practices. The findings could be endorsed to control soil erosion through agroforestry and soil water conservation structures. Agroforestry and soil water conservation practices reduce soil erosion and improve soil water retention, leading to higher crop yields and income (Batjes, 2014; Sova, 2017). Additionally, smallholder farmers who perceived persistent soil erosion were more likely to experience crop failure, thus investing in CSAPs.

The discussion emphasized the MPV model results. The study's findings were compared with the individual probit model. The findings were pretty similar from individual and MVP models regarding coefficients, significance, and sign. However, the MVP model was more reliable than the individual probit as it explained the multiple CSAPs adoptions.

5.3.4 Determinants of climate-smart agriculture practices intensity

Adoption intensity is imperative among smallholder farmers to improve crop yields and income and mitigate climate change impacts (Ndiritu et al., 2014; Kpadonou et al., 2017; Oyetunde-Usman et al., 2021). The results revealed that the LR $Chi^2 = 125.05$, $Prob > chi^2 = 0.000$ was significant, suggesting that the ordered probit model was credible.

The household head's gender negatively predicted CSAPs adoption intensity (Table 5.6). The results suggested that female-headed smallholders had a higher propensity to intensify agricultural practices than male-headed households. The findings contradict the notion that male-headed strengthen agricultural practices since they control production resources such as labor and land. The results conformed with the simultaneous adoption of CSAPs (Table 5.5). These findings could be endorsed to the availability of women empowerment programs in the area (Diiro et al., 2018). The results contradicted Oyetunde-Usman et al. (2021), who reported that male-headed households intensified sustainable agricultural practices and attributed it to poor access to complementary inputs.

Table 5.6 Factors influencing the number of climate-smart agricultural practices adopted using an ordered probit model

Variables	Coefficient	Std Error	p-value
Gender of the hhh	-0.340**	0.144	0.018
Education status of hhh	-0.082	0.220	0.710
Age of the hhh	0.000	0.005	0.948
Family size	-0.007	0.023	0.752
Contact with extension agent	0.122	0.188	0.517
Access to weather information	0.184	0.180	0.308
Arable land size	0.142**	0.078	0.068
Livestock owned	0.040**	0.017	0.018
Perceived climate change	0.155	0.338	0.648
Soil fertility	-0.260*	0.150	0.083
Persistent soil erosion	0.669***	0.270	0.003
Number of observations = 300	LR Chi2 (11) = 125.05	Prob > chi2 = 0.000	
Log likelihood = -348.345	Pseudo R2 = 0.0347		

*p<0.1 **p<0.05 ***p<0.01

Arable land positively influences CSAPs' adoption intensity. The findings suggested that the propensity of adopting multiple CSAPs among smallholders increased with arable land size. The results corroborated with section 3.3, thus highlighting the importance of landholding in agricultural intensification. On the other hand, livestock ownership significantly influenced CSAPs intensification, thus substantiating results reported in Table 5.5 and highlighting the importance of livestock in agricultural intensification. The observation is that livestock dropping was used as the source of manure. The findings align with Ehiakpor et al. (2021) who established that livestock ownership significantly influenced sustainable agricultural practices adoption intensity. This was attributed to the probability of selling livestock to purchase farm inputs, including agrochemicals, fertilizers, and improved seeds.

The negative and significant prediction of soil fertility on adoption intensity implied that smallholder farmers who perceived infertile soil were less likely to intensify agricultural practices. Smallholder farmers under low soil fertility status are more likely to experience adverse effects of climate change, such as reduced crop yields. Poor soil fertility is a considerable drawback to agricultural production in SSA (Kiboi et al., 2018; Vanlauwe et al., 2015). Low soil fertility execrates the effects of climate change. Therefore, the smallholder farmers under deprived soil fertility intensify agricultural production to improve crop yields and lower crop failure risks. Notably, smallholder farmers experiencing good soil fertility anticipate fewer climate-related stocks, such as crop failure, thus intensifying their agricultural production (Mulwa et al., 2017)

Persistent soil erosion significantly influenced CSAPs adoption intensity, suggesting that smallholder farmers who perceived constant soil erosion had a higher propensity to intensify CSAPs. This is laudable because the smallholder farmers in erosion-prone areas could boost CSAPs adoption to reduce erosion compared with those in less erosion-prone areas. This is probably because CSAPs such as soil water conservation and agroforestry controls soil erosion. Hence, the joint adoption of CSAPs could reduce soil erosion prevalence, thus increasing crop yields and income. Therefore, the need to prioritize erosion control methods in agricultural fields to minimize (Irianti et al., 2020).

5.4 Conclusions

The adoption level and intensity of CSAPs varied because of differences in the socioeconomic, institution, and biophysical factors across sampled households. The study established positive and negative correlation coefficients between CSAPs, indicating that they acted as complements and substitutes. The critical determinants of multiple adoptions of CSAPs were household head's gender, education, age, family size, contact with extension agents, access to weather information, arable land, livestock owned, perceived climate change, infertile soil, and persistent soil erosion. The findings revealed that gender of the respondent, arable land, livestock owned, soil fertility, and continued soil erosion were crucial determinants of CSAPs adoption intensity. Female-headed households, farmers' asset base, and farm factors influenced smallholder farmers' adaptive capacity.

Against the above background, the study recommends that policymakers design pro-farmers policies that promote adopting multiple agricultural practices to complement each other in mitigating the adverse impacts of climate change. Given that numerous factors determine the adoption of various CSAPs, policymakers should innovatively consider smallholders' perceptions of soil fertility, soil erosion, and climate change in optimizing CSAPs adoption. Therefore, the policymakers should target smallholder farmers who perceive poor soil fertility, high soil erosion, and climate change to enhance the adoption of CSAPs. In upscaling the adoption of CSAPs, governments and stakeholders should promote extension services and agricultural training for improved capacity building among smallholder farmers.

CHAPTER SIX

SMALLHOLDERS' ADAPTATION TO CLIMATE CHANGE IN WESTERN KENYA: CONSIDERING SOCIOECONOMIC, INSTITUTIONAL AND BIOPHYSICAL DETERMINANTS[3]

Abstract
Climate change has stimulated detrimental threats to the global agricultural ecosystems. The study objective was to assess the determinants of climate change adaptation among smallholder sorghum farmers in Siaya County. Specifically, the study investigated i) the climate change perceptions, drivers, effects, and barriers, and ii) determinants of climate change adaptation among smallholder farmers in Western Kenya. The study interviewed 300 households using a semi-structured face-to-face interview schedule. The study employed two indices, i.e., weighted average and problem confrontation index, and two regression models, i.e., Binary logistic and Poisson regression. The findings indicated that smallholder farmers were aware of climate change, its drivers, and its effects. The main barriers to climate change adaptation were unpredictable weather patterns, financial constraints, and limited agricultural training. Group membership and site negatively influenced climate change adaptation. Household head's education, experience, remittance receipt, access to credit on inputs, climate change perception, access to weather information, and cultivated farm size positively influenced climate change adaptation. The findings underscore the importance of tailoring smallholder farmers' dynamics in climate change policies to enhance adaptation. The negative prediction of group membership needs to be emphasized to prevent demotivating farmers from joining community associations. The study highlights the need to incorporate farmers' perceptions of climate change, climate awareness creation, and monetary assistance to enhance climate change resilience among smallholder farmers.

Keywords: Sustainable agriculture; Farmers' perceptions; Adaptation strategies; Poisson regression

[3] Musafiri, C.M., Kiboi, M., Macharia, J., Ng'etich, O.K., Kosgei, D.K., Mulianga, B., Okoti, M. & Ngetich, F.K. (2022). Smallholders' adaptation to climate change in Western Kenya: Considering socioeconomic, institutional and biophysical determinants. *Environmental Challenges*, *7*, p.100489. https://doi.org/10.1016/j.envc.2022.100489

6.1 Introduction

Climate change coupled with the demand to feed the ever-growing population is a foremost challenge to global agricultural ecosystems and economic development (IPCC, 2014). The global agricultural ecosystems are significantly contingent on climate and susceptible to climate change (Kim, 2008). Agricultural productivity could be adversely impacted by the current and future projected changes in climate (Rudel et al., 2019). The world population is estimated to upsurge from 7.7 to 9.7 billion by 2050 (United Nations, 2019). The demand to feed the current and future projected population has triggered intensive agricultural transformation, including deforestation and agrochemicals' use for agricultural expansion, increasing anthropogenic greenhouse gas emissions, thus aggravating climate change (Arora, 2019). The impacts of climate change could be more pronounced in developing countries, especially sub-Saharan Africa, where smallholders' rain-fed agriculture is the principal source of livelihood (Cooper &. Coe, 2011; Abrams, 2018). Given the impacts of climate change on smallholder farming systems, assessing farmers' perceptions of drivers and climate change impacts. This could influence efficient and effective climate change adaptation and mitigation targeting, smallholder farmers, thus enhancing food security.

In Kenya, the agricultural sector is the mainstay of the economy, contributing about 51% of the Gross Domestic Product (GDP) and providing income to approximately 80% of the population (United Nations Environment Programme, 2015; World Bank Group, 2018). The Kenyan smallholder farming systems dominate the agricultural sector, accounting for approximately 75% of the agricultural production and over 75% of the employment (Salami et al., 2010; World Bank & International Center for Tropical Agriculture (CIAT), (2015). However, these smallholder farming systems are faced with a myriad of challenges, including climate change (Bryan et al., 2012; Mugi-Ngenga et al., 2016; Wetende et al., 2018).The increased effects of climate change among smallholder farmers call for enhanced adoption of adaptation and mitigation measures that result in improved food security (Ndiritu et al., 2014; Kimaru-Muchai et al., 2020; Musafiri et al., 2020a). Understanding smallholder farmers' perceptions of climate change, including its indicators, drivers, impacts, and barriers, is pertinent to enhance climate change adaptation.

Smallholder perceptions and awareness of climate change is the main stage in embracing adaptation practices (Masud et al., 2017). According to Tesfahunegn et al. (2016), farmers' awareness of climate change indicators and drivers is appropriate for selecting adaptation practices. Likewise, smallholder farmers' understanding of the impacts of climate change is essential in implementing adaptation practices (Kibue et al., 2016; Karienye & Macharia, 2020). The noticeable impacts of climate change in Kenya include reduced agricultural productivity, crop damage, reduced livestock production, and loss of property or life (Herrero et al., 2010; Parry et al., 2012; Wetende et ala., 2018). However, climate change perceptions, its drivers, and impacts vary with locations and socio-demographic characteristics (Toan et al., 2014; Haq & Ahmed, 2017). Hence, the need to contextualize climate change perceptions, drivers, and impacts among smallholder farmers in Western Kenya.

Smallholder farmers face various problems that restrain them from adopting climate change adaptation practices. As a result, the smallholder farmers continue experiencing various challenges, including low agricultural production (food and pastures), poor infrastructure, population displacement, extreme poverty, overall food insecurity, and tough livelihoods (Karienye & Macharia, 2020). In Kenya, National Climate Change Response Strategy (NCCRS) was established to address the challenges of climate change (Government of Kenya, 2010). To mitigate the impact of climate change in Kenyan socioeconomic development, the NCCSR developed a comprehensive and concerted suite of long-term strategies. Previous studies have pointed out poverty, unpredicted weather patterns, limited climate change information, high cost of inputs, funds, and high implementation costs as the main barriers of climate change adaptation (De Jalón et al., 2015; Masud et al., 2017; Ochieng et al., 2017; Khan et al., 2020). Understanding climate change barriers necessary for implementing adaptation policies among smallholder farmers – consequently, the need to study climate change barriers among smallholder farmers in Western Kenya.

Different socioeconomic, institutional, and biophysical factors determine farmers' adaptation practices. Previous studies detailed various socioeconomic characteristics such as gender, education, experience, occupation, income, and farm size, which influenced adaptation practices (Alemayehu & Bewket, 2017; Zulfiqar & Thapa, 2018; Ojo & Baiyegunhi, 2020; Qazlbash et al., 2020). Both institutional and biophysical factors, including credit access, agricultural training, information access, and group membership, have widely been documented to influence the adoption of adaptive practices (Kpadonou et al., 2017; Archie et al., 2018; Moroda et al., 2018; Dapilah et al., 2021; Kimaru-Muchai et al., 2020).This highlights the significance of diverse determinants consideration in designing and promoting climate change adaptation among smallholder farmers.

Although Western Kenya is incredibly vulnerable to the effects of the changing climate, scientific studies on climate change are scanty. The study objective was to assess the determinants of climate change adaptation among smallholder sorghum farmers in Siaya County. Specifically, the study aimed to; i) determine the climate change perceptions, drivers, and consequences, and ii) assess barriers and determinants of climate change adaptation among smallholder farmers in Western Kenya. The following hypotheses guided the study i) smallholder farmers were aware of climate change, its drivers, effects, and barriers, and ii) socioeconomic, biophysical, and institutional characteristics of the smallholder farmers influence climate change adaptation in Western Kenya.

6.2 Materials and methods

6.2.1 Study area description

The study was conducted in the Alego-Usonga and Ugenya sub-Counties of Siaya County at an altitude between 1140 and 1500 m above sea level in Western Kenya (Figure 6.1). According to the Kenya National Bureau of Statistics (KNBS), (2019), Alego Usonga and Ugenya sub-Counties recorded 224, 343, and 134 354 persons, a population density of 375 and 415 persons per km^2, respectively. The sub-Counties have six agro-ecological zones, including low midlands (LM1, LM2, LM3, LM4, and LM5) and Upper Midlands (UM1) (Jaetzold et al., 2010). The study area experiences a bi-modal rainfall where long rain seasons are experienced in March through June and short rain seasons between September and December. Annual long-term rainfall amounts vary considerably across the study area from 800 to 2000 mm (Jaetzold et al., 2010). The climatic conditions range from semi-humid to semi-arid. The study area is characterized by high food insecurity and poverty (MoALF, 2016). Long-term average temperature ranges between 20.9 and 22.3 °C. The predominant soil type in the area is *Ferrasol,* with moderate to low soil fertility. This implies that the soil cannot sustainably feed the local population without applying external amendments such as organic and inorganic fertilizers.

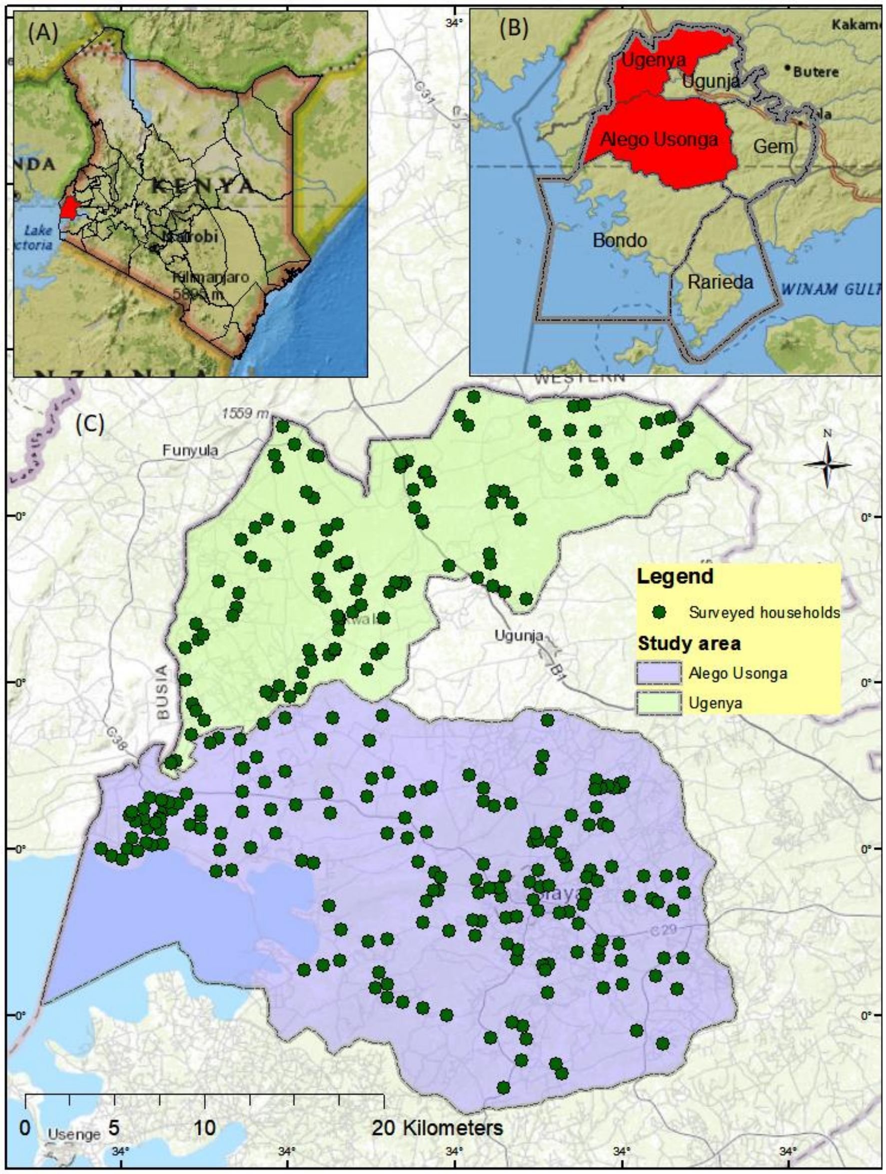

Figure 6.1 Map of the study area. Inset (A) shows the location of Siaya County on the Kenyan map, Inset (B) shows the location of Alego Usonga and Ugenya in Siaya county, and (C) shows the sampled household distribution across the study area.

The smallholders' land size is relatively smallscale at approximately 1.02 ha. Crop farming, fishing, and livestock keeping are the primary agricultural economic activities in the study area (MoALF, 2016). The primary food crops grown in the area include maize (*Zea mays*), beans (*Phaseolus vulgaris*), sorghum (*Sorghum bicolor*), millet (*Panicum miliaceum*), cowpeas (*Vigna unguiculata*), sweet potatoes (*Ipomoea batatas*), and groundnuts (*Arachis hypogaea*), while the main cash crops include; cotton (*Gossypium barbadense*), rice (*Oryza sativa*), and sugarcane (*Saccharum officinarum*). The majority of the farmers are rain-fed agriculture dependent, non-mechanized, and could adversely be affected by the vagaries of climate change. The main livestock reared in the study area includes cattle, goats, sheep, poultry, donkeys, and rabbits. The study area is characterized by a low livestock density of approximately 2.07 tlu per household (Kassie et al., 2014). The residents depend on Lake Victoria and Lake Kanyaboli for fishing.

6.2.2 Sampling and data collection

The study employed a cross-section survey design and multi-stage sampling procedure to collect data from 300 household heads. First, purposively, selected Siaya County and the sub-Counties were sampled due to previous studies on climate change's impacts (MoALF, 2016; Wetende et ala., 2018). Secondly, total sampling was implemented to collect climate change data from all the ten wards in the study area. Thirdly, a proportionate to size sampling procedure was utilized to determine the number of households sampled in each ward. As a result, this study interviewed 181 and 119 households from Alego Usonga and Ugenya sub-Counties, respectively. Finally, a simple random sampling procedure identified specific households sampled in each ward. The study relied on a sampling frame from the respective ward agricultural officer.

The sample size for empirical data collection was calculated using Eq. 6.1 as described by Cochran (2007).

$$n=\frac{z^2pq}{E^2}=\frac{1.96^2\times0.5(1-0.5)}{0.0565^2}=300 \tag{6.1}$$

Where: n = Sample size, z = z value (e.g. 1.96 for 95% confidence level), p = probability of picking a choice, expressed as decimal (0.5), q = 1-p and E = 5.65 % allowable error, expressed as decimal (0.0565). Therefore, a sample size of 300 smallholder farmers was selected.

A semi-structured face-to-face interview schedule was used during data collection. The interview schedule was divided into three categories – the first category comprised climate change perceptions questions. First, a farmer was asked to define climate change. This was a primary question to reveal smallholder farmers' understanding and awareness of climate change. To answer the study objective, smallholder farmers were informed of the actual definition of climate change, i.e., long-term (30 years) changes in average weather patterns. This was followed by closed and open-ended questions such as whether the farmer perceived change in climate, brainstorming on the indicators and drivers of climate change, and enumerating the effects of climate change. The second category was on barriers and adaptation to climate change. Based on literature the study developed questions on barriers to adopting climate change adaptation practices (Ochieng et al., 2017; Talanow et al., 2021) The respondents were asked to select the practice(s) they had adopted and using a Four-Likert scale (not important (0), less important (1), moderate important (2), and high important (3) to rank the importance of each of the adaptation practice (Masud et al., 2017) to determine the importance of adopting various climate change adaptation practices. Similarly, a four a Likert scale (no problem (0), less problem (1), moderate problem (2), and high problem (3) was used to rank the barriers of climate change adaptation. The third category had questions on household socioeconomic characteristics, including household heads', institutional, and farm variables. The questions were digitized in Open Data Kit (ODK) mobile App for pre-testing. After pre-testing, the interview schedule was reviewed and used in the empirical data collection.

Five enumerators were recruited based on their ability to speak both English and local dialect languages. This ensured they could comprehend the different questions and explain them in the local language to the respondents. To improve the quality of the survey, capacity building was done among the selected enumerators through training on question interpretation and use of the ODK mobile App. The data was collected under close supervision.

6.2.3 Variable description

The study had two dependent variables i) Adoption level, a dichotomous variable where 1 is the farmer had adopted at least one adaptation practice and 0 otherwise, and ii) adoption intensity that is a count variable indicating the number of adaptation practices adopted by the farmer. The independent variables were selected based on literature background and characteristics of the sampled households (Ochieng et al., 2017; Musafiri et al., 2020a; Ehiakpor et al., 2021). Table 6.1 shows the salient dependent and independent variables in Table 6.1.

Table 6.1 Description of variables used in the study

Variable	Description	Code	Sign
Dependent variables			
Adoption level	Binary: 1 if a farmer adopted at least 1 adaptation practice, 0 if otherwise		
Adoption intensity	Count: The number of adaptation practice adopted by a farmer		
Independent variables			
Gender of the household head	Binary: 1 if the household head was a male, 0 if female	Gend	±
Education of the household head	Binary: 1 if the farmer had attained formal education, 0 if otherwise	Educ	+
Household head size	Continuous: The number of dependents in the household	H.size	+
Main occupation of the household size	Binary: 1 if the household head main occupation was agriculture, 0 if otherwise	Occp	+
Farming experience of the household head	Continuous: duration the farmer has been in farming measured in years	Exp	+
Hired labour	Binary: 1 if the farmer used hired labour, 0 if otherwise	Lab	+
Remittance receipt	Binary: 1 if the farmer received remittance, 0 if otherwise	Rem	+
Group membership	Binary: 1 if farmer was a member of a community organization, 0 if otherwise	Grp	+
Inputs credit access	Binary: 1 if the farmer had received inputs credit, 0 if otherwise	Cred	+
Weather information access	Binary: 1 if the farmers had received weather information, 0 if otherwise	Info	+
Total cultivated land size	Continuous: The total cultivated land size in acres	Land size	±
Farmers' perceptions of climate change	Binary: 1 if farmer perceived change in climate, 0 if otherwise	Perc	+
Total Livestock Unit	Continuous: The total livestock units	TLU.	±
Ugenya sub-County	Binary: 1 if farmer sampled from Ugenya, 0 if otherwise	Ugenya	±
Alego Usonga sub-County	Binary: 1 if farmer sampled from Alego Usonga, 0 if otherwise	Alego	±

6.2.4 Statistical analysis

The data were analyzed using STATA 15.0 software. Before statistical analysis, data cleaning, coding, and transformations were performed. Tropical livestock unit (TLU) for samllholder farming household was calculated following Jahnke (1982) of cattle (0.7), sheep and goat (0.1), pig (0.2), chicken (0.01), and rabbit (0.02). The study employed descriptive statistics including mean and standard error, t-test. Further, Pearson's correlation, binary logistic regression, and Poisson regression analysis were implemented.

The constructs (18 for the importance of adopting various climate change adaptation practices and 15 for barriers of climate change adaptation) were subjected to Cronbach's alpha test (Cronbach, 1951).The constructs for the importance of adopting various climate change adaptation practices had a Cronbach's alpha coefficient of 0.80 and 0.86 for barriers of climate change adaptation that was greater than 0.7 (Bonett & Wright, 2015). Hence, all the constructs were reliable for the climate change adaptation analysis. To analyze for weighted average index (WAI) and problem confrontation index (PCI), the study adopted research by Masud et al. (2017) as described in equations 6.2 and 6.3.

$$WAI = \frac{\sum ni + li + \mathrm{mi} + hi}{N} \tag{6.2}$$

Where *WAI* is the weighted average index, *ni* is no important, *li* is less important, *mi* is moderately important, *hi* is highly important.

$$PCI = \sum np * 0 + \mathrm{lp} * 1 + \mathrm{mp} * 2 + \mathrm{hp} * 3 \tag{6.3}$$

Where PCI is problem confrontation index, np is no problem, lp is less problem, mp is a moderate problem, and hp is a high problem, and 0, 1, 2, and 3 is the frequency under each category ie., np, lp, mp, and hp.

A binary logistic regression model was used to estimate the likelihood of independent variables on adoption level similar to Mango et al. (2017), Asfaw and Neka (2017), and Haq & Ahmed (2017). The binary logistic regression model helps determine the effects of several independent variables on a dichotomous dependent variable. Before binary logistic regression analysis, model's credibility was tested using the correlation coefficients from the pair-wise correlation of independent variables and the Variance Inflation Factor from the multicollinearity test. The Pearson correlation analysis revealed correlation coefficients ≤ 0.32. The multicollinearity test revealed a variance inflation factor (VIF) that ranged from 1.23 to 1.48. Since the correlation coefficients were less than 0.5 and VIF less than 10, the independent variables were not correlated and could be used in the regression analysis. The binary logistic regression equation was as described in equation 6.4.

$$ln\frac{p}{1-p} = B_0 + B_1X_1 + B_2X_2 + \cdots + B_nX_n \tag{6.4}$$

Where p/(1-p) is the odd ratio, p is the probability of adopting at least one adaptation practice, i-p is the probability of the household not adopting the adaptation practice, B_0 is the intercept, B_1, B_2 … and B_n are regression coefficients while X_1, X_2 and … and X_n are the independent variables. The odd ratio explained the relationship between the independent variable(s) and adoption level ie., an odd ratio greater than 1 showed a positive relationship, and less than 1 indicated a negative relationship (Field, 2009).

The number of adaptation practices adopted by individual smallholder farmers is a discrete non-negative integer count variable with a Poisson distribution. The number of practices adopted by each smallholder farmer were defined as adoption intensity. Poisson regression model assumes equi-dispersion, i.e., variance equals to mean (Greene, 1997). Prior to Poisson regression, overdispersion was tested using Deviance and Pearson goodness-of-fit since it causes the standard deviation to exceed the mean (Cox et al., 2009). The deviance goodness-of-fit of 86.137 with pro>$chi^2(279)$ =1.000 and Pearson goodness-of-fit 89.765 with pro>$chi^2(279)$ =1.000. Both Deviance and Pearson goodness-of-fit were insignificant. This implied that the adoption intensity data was not overdispersed and had no excessive zeros, thus reliable for Poisson regression. The study utilized Poisson regression model as described by Nkegbe and Shankar (2014).

$$Prob\ (Y_i = Y_i|X_i)\frac{e^{-\lambda_i}\lambda_i^{Y_i}}{y_i^!}, \lambda_i \in \mathbb{R}^+, \qquad y_i = 0,1,2,3 \ldots n \qquad (6.5)$$

Where Y_i is the adoption intensity, $\lambda_i = E(y_i|x_i) = Var(y_i|x_i)$ and the mean is usually defined $\lambda_i = exp(x_i\beta)$ where x_i is a vector of characteristics specific to household i, and β is a vector of unknown parameters to be estimated. Binary logistic and Poisson regression analysis were subjected to marginal effects. The marginal effects describe the expected change in dependent variables due to a unit change of an independent variable (Cameron & Trivedi , 2013; Moroda et al., 2018).

6.3 Results and Discussion

6.3.1 Descriptive characteristics sampled households

The findings revealed that 94% (282 of 300 sampled households) had adopted at least one adaption practice (Table 6.2). Adopters had significantly higher (87%) formal education than non-adopters (67%). Adopters were significantly ($p<0.01$) more experienced in agricultural farming than non-adopters. Significantly higher numbers of adopters (97%) perceived climate change than non-adopters (72%).

Table 6.2 Descriptive characteristics the sampled smallholder farmers in Siaya County

Variable	Pooled (p)		Adopters (a)		Non-adopters (n)		Diff (a-n)
	Mean	SE	Mean	SE	Mean	SE	
Gend	0.38	0.03	0.39	0.03	0.22	0.10	0.17
Educ	0.86	0.02	0.87	0.02	0.67	0.11	0.21*
H.size	5.78	0.17	5.78	0.17	5.67	0.79	0.12
Occp	0.86	0.02	0.86	0.02	0.83	0.09	0.02
Exp	22.56	0.84	23.16	0.85	13.11	3.37	10.05**
Lab	0.48	0.03	0.49	0.03	0.39	0.12	0.10
Rem	0.34	0.03	0.36	0.03	0.17	0.09	0.19
Grp	0.19	0.02	0.19	0.02	0.33	0.11	-0.15
Cred	0.07	0.02	0.07	0.02	0.05	0.06	0.01
Info	0.84	0.02	0.84	0.02	0.77	0.10	0.07
L. size	1.23	0.05	1.24	0.92	1.03	0.65	0.22
Perc	0.96	0.01	0.98	0.01	0.72	0.11	0.26**
TLU	3.35	0.22	3.36	0.23	3.09	0.58	0.27
Ugenya	0.40	0.03	0.37	0.03	0.89	0.08	-0.52**
Alego	0.60	0.03	0.63	0.03	0.11	0.08	0.52**

*, ** significant at 5 and 1 %, SE is the standard error of the mean

6.3.2 Farmers' understanding and perceptions of local climate change

Majority of the smallholder farming households perceived changes across different indicators of climate change (Figure 6.2). The change ranged between 74% (flooding frequency) to 99% (temperature). Regarding the sign of change, majority of the smallholders farming households perceived that the climate was changing towards the negative including decrease in rainfall frequency (82%), length of cropping calender (95%), and rainfall amount (96%), and an increase in flooding frequency (63%), drought frequency (82%) and temperature (99%). The findings suggested that smallholder farming households understood the indicators of climate change. The findings were similar to recent studies by Mairura et al. (2021) in the Central Highlands of Kenya and Tesfahunegn et al. (2016) in northern Ethiopia. The findings implied that the smallholder farming households understood the indicators of climate change and could adopt different adaptation strategies.

The study revealed that deforestation (79%) was the main driver of climate change (Table 6.3). Smallholder farmers' perceptions of other drivers of climate change were low such as environmental pollution (mainly charcoal burning, 25%), industrialization and agrochemicals (13%), mining (4%), overstocking (4%), poor farming methods (3%) and spiritual beliefs (2%) (Table 6.3). However, 16% of the farmers were unaware of the drivers of climate change.

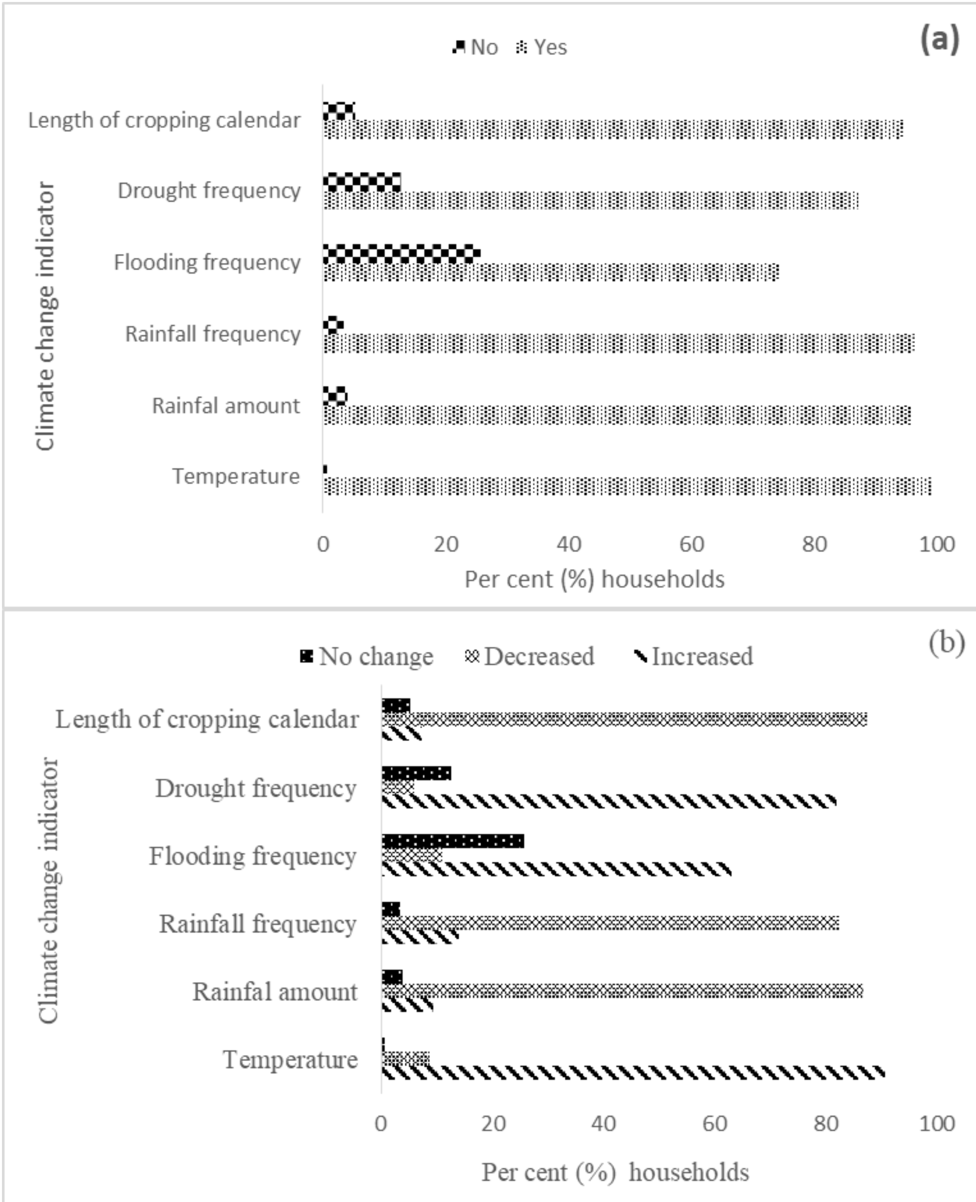

Figure 6.2 Smallholders understanding of climate change indicators a) perceived change in climate indicator, b) perceived direction of change

Table 6.3 Farmers' perception on the drivers of climate change

Drivers of climate change	Frequency	Per cent (%)
Deforestation	236	79
Environmental pollution	76	25
Farmer unaware of drivers of climate change	47	16
Industrialization/ agrochemicals	38	13
Mining	11	4
Overstocking	11	4
Poor farming methods	8	3
Spiritual beliefs	7	2

N= 300, A farmer could have enumerated various climate change drivers

Smallholder farmers' perception of climate change is pertinent in selecting adaptation practices (Gbetibouo, 2009; Mugi-Ngenga et al., 2016). Smallholder farmers' cognizance of changing climate acts as a baseline for decision-making on adaptation (Masud et al., 2017). The study revealed a high proportion (96%) of sampled households perceived change in the climate. This implied that smallholder farmers were aware of the changing climate. The findings were consistent with studies of Bryan et al. (2013), Tesfahunegn et al. (2016), and Alam et al. (2017), who reported a similar trend of climate change perception in Kenya, Ethiopia, and Bangladesh, respectively.

Understanding of climate change indicators and drivers among smallholder farmers is essential in improving adaptation. The findings imply that smallholder farmers in Western Kenya were aware of the drivers of climate change. These results were in agreement with the findings of previous studies that found deforestation as a main driver of climate change (Tesfahunegn et al., 2016; Yamba et al., 2019; Doggart et al., 2020). Further, smallholder farming households perceived environmental pollution particularly through charcoal burning, industrialization and agrochemicals as important drivers of climate change. These drivers are reported to increase carbon dioxide (CO_2) emissions (Ciais et al., 2014). Carbon dioxide emission is a critical agent of global warming and climate change (Fahey et al., 2017; Macharia et al., 2020; Musafiri et al., 2020b).

6.3.3 Farmers' perception of climate change effects

Resultsrevealed reduced crop productivity (53%), crop failure (28 %), and increased food insecurity (24%) were the main climate change impacts (Table 6.4). The findings showed low proportion of farmers (between 7 and 16 per cent) perceived property destruction/ displacement, loss of human life, increased soil erosion, increased food prices, invasion of pests, diseases, weeds, and worms, and reduced livestock production as effects of changing climate (Table 6.4). The findings indicated that smallholder farmers in Western Kenya understood the effects of climate change. Understanding climate change impacts is fundamental in appreciating adaption practices. The findings underscore the importance of smallholder farmers' perceptions of climate change impacts, thus informing adaptation. This was consistent with the findings of Wetende et al. (2018) in Western Kenya, Yamba et al. (2019) in Ghana, and Kibue et al. (2016) in China, who pointed out that climate change had significant impacts on agricultural productivity (livestock and crops) leading to increased food insecurity.

Table 6.4 Farmers' perception on the effects of climate change

Effect of climate change	Frequency	Percent (%)
Reduced crop productivity	159	53
Crop failure	85	28
Increased food insecurity	73	24
Property destruction/ displacement	47	16
Loss of human life	43	14
Increased soil erosion	42	14
Increased food prices	33	11
Invasion of pest, diseases, weeds, and worms	29	10
Reduced livestock production	22	7

N= 300, A farmer could have enumerated various climate change effects

6.3.4 Adoption level and intensity of adaptation practices

Theresults showed that the adoption of different climate change adaptation practices ranged between 2 and 64% (Table 6.5). The majority of the farmers adopted soil water conservation measures (64%), early maturing crop varieties (64 %), drought-tolerant crops (59%), and organic fertilizer (57%). A low proportion of the farmers (2%) opted to abandon farming (farming to no farming). The adoption of specific adaptation practices across SSA countries ranges from low to high, with most smallholder farmers adopting at least one practice (Mango et al., 2017). The findings on the adoption level of adaptation practice were consistent with various studies across SSA that found a high adoption rate of at least one agricultural innovation (Ndiritu et al., 2014; Nkegbe and Shankar, 2014; Darkwah et al., 2019).

Table 6.5 Adoption level of adaptation practices to climate change among smallholder farmers

Adaptation practice	Number of adopters	Per cent (%)
Soil and water conservation measures	193	64
Use of early maturing crop varieties	191	64
Planting drought-tolerant crops	176	59
Use organic fertilizer	172	57
Intensifying of crop production	144	48
Tree planting	130	43
Livestock rearing	125	42
Crop rotation	123	41
Timing harvesting	117	39
Changing planting dates	90	30
Crop diversification	88	29
Agroforestry	86	29
Use mineral fertilizer	75	25
Irrigation	73	24
Mixed cropping	69	23
Home gardening	44	15
Purchase of addition land	39	13
Reducing farm size	12	4
Farming to no farming	6	2

Six (6) percent of the sampled household did not adapt to climate change (Table 6.6). The majority of the sampled households (50 adopters, 17%) adopted 5 adaption practices. The study findings revealed that 86% of the sampled household adopted two or more climate change adaptation practices. Given the interdependence among adaptation practices, smallholder farmers could adopt multiple practices. The adoption of multiple technologies observed in this study could be endorsed to the need to mitigating the vagaries of climate change. The findings agreed with previous studies that found that smallholder farmers adopt multiple adaptation practices to benefit from the innovation (Ndiritu et al., 2014; Ojo & Baiyegunhi, 2020).

Table 6.6 Adoption intensity of climate change adaptation practices among smallholder farmers

Number of adaptation practices	**Number of adopters**	**Per cent (%)**
0	18	6
1	25	8
2	27	9
3	42	14
4	46	15
5	50	17
6	32	11
7	24	8
8	17	6
9	14	5
10	5	2
Total	**300**	**100**

Based on the weight average index, the use of early maturing crop varieties (2.54) was the most important adaptation practice, while abandoning farming (0.45) was the least important option among smallholder farmers (Table 6.7). Moreover, the use of organic fertilizer, soil and water conservation measures, and drought-tolerant crops were important adaptation practices. The findings revealed that reducing farm size and abandoning farming were not important adaptation practices. These results highlight the importance of crop adjustment, soil, fertility, and water conservation as key interventions for coping with climate change. The findings were consistent with previous studies in SSA that have document crop adjustments, soil fertility management, soil water conservation practices, and planting trees as essential adaptation practices (Bryan et al., 2009; Ochieng et al., 2017; Talanow et al., 2021).

Table 6.7 Farmers' perceptions on the importance of adaption practices among smallholder farmers

Adaptation practice	No important (ni)	Less important (li)	Moderate important (mi)	High important (hi)	*WAI	Rank
Use of early maturing crop varieties	3	33	63	201	2.540	1
Use organic fertilizer	6	35	69	190	2.477	2
Soil and water conservation	11	32	61	196	2.473	3
Planting drought tolerant crops	18	37	62	183	2.367	4
Tree planting	7	33	126	134	2.290	5
Intensifying of crop production	14	60	80	146	2.193	6
Crop rotation	16	46	103	135	2.190	7
Livestock rearing	33	47	90	130	2.057	8
Timing harvesting	29	50	99	122	2.047	9
Crop diversification	17	47	142	94	2.043	10
Mixed cropping	15	54	150	81	1.990	11
Agroforestry	25	56	129	90	1.947	12
Changing planting dates	41	77	86	96	1.790	13
Use mineral fertilizer	64	45	109	82	1.697	14
Irrigation	91	66	66	77	1.430	15
Home gardening	62	96	98	44	1.413	16
Purchase of addition land	92	63	105	40	1.310	17
Reducing farm size	139	71	77	13	0.880	18
Farming to no farming	211	50	30	9	0.457	19

*WAI indicate weighted average index

6.3.5 Barriers to adoption of adaptation practices

Smallholder farmers quoted unpredictable weather patterns (problem confrontation index, PCI of 732), as the primary hindrance to climate change adaptation (Table 6.8). Further, financial constraints and limited access to agricultural training were major drawbacks to adaptation. Though soil degradation, limited access to agricultural markets, credit and water, and limited farm size could impede adaptation, smallholder farmers perceived them as less problematic. The findings on climate change adaptation barriers implied that farmers had to highly confront the problems of unpredictable weather, financial constraints, and limited training in adapting to climate change. The results were consistent with Masud et al. (2017), Ochieng et al. (2017) Williams et al. (2019) and Antwi-Agyei and Stringer (2021), who found the main barriers of climate change adaptation comprised of unpredictable weather, high cost of inputs, financial constraints, and high implementation costs. Despite the challenges facing smallholder farmers in the study area, only 2% deserted farming. This underscores the need for adaptation among smallholder farming systems to increase their climate change resilience.

Table 6.8 Barriers to climate change adaptation among smallholder farmers

Barriers of adaptation	**No Problem (np)**	**Less Problem (lp)**	**Moderate Problem (mp)**	**High Problem (hp)**	***PCI**	**Rank**
Unpredictable weather patterns	5	34	85	176	732	1
Financial constraint	25	16	71	188	722	2
Limited access to agricultural training	6	35	111	148	701	3
High cost of inputs	22	40	77	161	677	4
Lack of agricultural subsidies	20	33	98	149	676	5
Limited access to agricultural extension	13	43	104	140	671	6
Labour intensive technologies	12	42	111	135	669	7
Poor soil fertility	27	43	70	160	663	8
Limited access to farm inputs	20	44	110	126	642	9
Limited weather information	29	36	115	120	626	10
Soil erosion and land degradation	28	59	115	98	583	11
Limited access to agricultural markets	27	65	112	96	577	12
Limited credit access	34	57	120	89	564	13
Limited access to water	39	88	103	70	504	14
Limited farm size	77	49	115	59	456	15

*PCI indicate problem confrontation index

6.3.6 Determinants of adaptation practices adoption level and intensity

The binary logistic regression analysis showed that six variables significantly predicted smallholder farmers' adoption level to climate change (Table 6.9). Education level, farming experience, household remittance, and climate change perceptions positively predicted adoption level of adaptation practices among smallholder farmers. Different from study hypothesis, group membership and site negatively predicted farmers' adoption level to adaptation practices.

The Poisson regression model had an estimated Pseudo R-squared of 5.1 %, Wald chi-squared value of 86.10, and $p<0.0001$ (Table 6.9). This shows the significance of the Poisson model that was used to assess determinants of adoption intensity of climate change adaptation practices. The Poisson regression analysis showed seven explanatory variables that significantly predicted adaptation practices' adoption intensity (Table 6.9). Household head's education level, farming experience, access to input on credit, access to weather information, and cultivated land size positively predicted adaptation practices adoption intensity. Similar to adoption level, group membership and site negatively predicted the adoption intensity.

The household head's education level increased the likelihood of both adoption level and intensity (Table 6.9). This implied that farmers with formal education were more likely to have a greater adoption level and intensity of climate change adaptation practices. A high education level could imply a greater level of knowledge acquisition and synthesis of the impacts of climate change. Therefore, farmers with higher education could adopt more climate change adaptation practices compared with their counterparts with lower education qualifications. The findings were consistent with Mahama et al. (2020), Mahmood et al. (2021), Masud et al. (2017) and Silvestri et al. (2012) who found education as a positive predictor of agricultural technologies adoption. However, the findings contradicted Qazlbash et al. (2020) who reported that education negatively predicted adaptation among communities in Pakistan. This was attributed to the increased dissemination of adaptation practices information among illiterate farmers.

Household head's farming experience increased the likelihood for both adaptation level and intensity among smallholder farmers in Western Kenya (Table 6.9). Experienced farmers could have reliable adaptation practices compared with those with low experience. Further, experienced farmers could have a higher capacity to evaluate the existing climate change adaptation and mitigation measures better than their counterpart younger farmers based on their interactions with the nature over the years. Additionally, the farming experience could influence risk perceptions and preferences about agricultural technologies and practices among farmers (Martey & Kuwornu, 2021). The findings were consistent with Macharia et al. (2014), Masud et al. (2017), Anang & Asante (2020) and Musafiri et al. (2020a), who documented that experience is a key determinant of smallholder households' decision making.

Table 6.9 Determinants of adaptation practices adoption level and intensity among smallholder farmers

Variable	Adoption level		Adoption intensity	
	Binary logistic regression		Poisson regression	
	Odd Ratio	Marginal effect	Coefficient	Marginal effects
Gend	2.870	0.037	0.030	0.205
	(2.614)	(0.032)	(0.051)	(0.345)
Educ	**8.221***	**0.075***	**0.211***	**1.420***
	(7.849)	(0.032)	(0.081)	(0.549)
H.size	0.995	0.005	-0.014	-0.095
	(0.118)	(0.004)	(0.009)	(0.058)
Occp	1.988	0.024	0.089	0.600
	(1.891)	(0.034)	(0.070)	(0.471)
Exp	**1.072***	**0.002***	**0.007****	**0.045****
	(0.034)	(0.001)	(0.002)	(0.012)
Lab	0.983	-0.001	0.087	0.585
	(0.739)	(0.027)	(0.051)	(0.343)
Rem	**8.796***	**0.077***	-0.004	-0.024
	(8.937)	(0.036)	(0.051)	(0.346)
Grp	**0.147***	**-0.068***	**-0.150***	**-1.010***
	(0.145)	(0.035)	(0.073)	(0.491)
Cred	1.930	0.023	**0.341****	**2.299****
	(2.896)	(0.053)	(0.101)	(0.684)
Info	3.116	0.040	**0.146***	**0.983***
	(2.920)	(0.033)	(0.069)	(0.467)
L. size	1.598	0.017	**0.097***	**0.654***
	(1.397)	(0.031)	(0.047)	(0.314)
Perc	**7.730***	**0.072***	0.250	1.687
	(7.570)	(0.034)	(0.151)	(1.016)
TLU	1.006	0.004	0.010	0.069
	(0.095)	(0.003)	(0.006)	(0.038)
Site	**0.039****	**-0.115****	**-0.207****	**-1.393****
	(0.044)	(0.040)	(0.049)	(0.334)
Constant	0.154		**1.145****	
	(0.254)		(0.181)	
Observations	300		300	
LR chi^2	55.630		86.100	
prob>chi^2	0.0000		0.0000	
Pseudo R^2	0.428		0.051	
log-likelihood	-37.139		-801.586	

Parenthesis are the robust standard errors, *, ** significant at 5 and 1 %.

Household heads who received remittance were more likely to adopt at least one adaption practice (Table 6.9). Remittance provides a supplement to farmers' earnings that could be used in the implementation of agricultural innovation. Therefore, smallholder farmers who received remittance could use the additional income to invest in agricultural technologies including climate change adaptation and mitigation measures. The findings were similar to Kpadonou et al. (2017), who found that remittance was a positive determinant of soil water conservation practice in West African Sahel. This was attributed to the provision of poor resourced farmers with cash that could be used to invest in agricultural technologies.

The significant prediction of institutional characteristics (group membership, inputs credit, and weather information) on adaptation practices adoption accentuates their relevance in climate change adaptation (Table 6.9). The negative prediction of group membership on the adoption level was unexpected as it is generally known that group membership increases knowledge of agricultural technologies, thus increased adoption (Musafiri et al., 2020a; Okeyo et al., 2020b). Further, groups offer training, knowledge sharing, increased information access, and credit access opportunities through collective resource pooling among farmers. It is noteworthy that farmers' groups are objective specific and work towards achieving collective agenda. Therefore, the negative prediction of group membership could be ascribed to varied objectives, including value addition and commercialization as opposed to climate change mitigation. Contrary to the findings, previous studies in SSA have reported group membership as a positive significant determinant of agricultural practices adoption (Mango et al., 2017; Kimaru-Muchai et al., 2020; Ehiakpor et al., 2021).

Access to inputs on credit positively and significantly increased the adoption intensity of adaptation practices (Table 6.9). Farmers who accessed inputs on credit adopted more climate change adaptation practices than those who did not. Access to inputs credit is mostly preceded by agricultural training to ensure attainment of maximum returns on the investment, which could include promotion of activities that result to climate change adaptation. Therefore, the increased adoption intensity among farmers who received inputs on credit could be attributed to increased exposure during the inputs utilization training. Further, the increased adoption intensity could be attributed to climate change adaptation inputs' availability among resource-poor farmers. The findings mirrored Tessema et al. (2018) in Ethiopia and Darkwah et al. (2019) in Ghana studies that articulated that credit access motivates farmers to adopt adaptation practices. Similarly, Kimathi et al. (2021) found credit as a positive determinant of climate resistance potato varieties in Meru county, Kenya, that was attributed to extension services on risk management that accompany credit access.

Access to weather information increased the likelihood of adoption intensity among smallholder farmers (Table 9). Weather information includes expected rainfall amounts, onset, and cessation. This information is important in planning the cropping calendar including the type of crop, when and how to plant. Therefore, the increased adoption intensity among farmers who received weather information could be endorsed to increased know-how of the climate dynamics compared to those who did not. In agreement with the results of Archie et al. (2018), Zulfiqar and Thapa (2018). Moroda et al. (2018) found that weather forecasts and climate change information access among smallholder farmers significantly predicted the adoption of adaptation practices.

The positive prediction of climate change perception implied that farmers who perceived climate change were more likely to adopt adaptation practices (Table 9). This could be attributed to the need to utilize climate change adaptation practices to mitigate its impacts. Further, the awareness of climate change is the first stage of appraising its impacts, thus adopting counter-strategies. The finding agreed with Kibue et al. (2016) and Ochieng et al. (2017) who reported that farmers who perceived change in climate adopted adaptation practices in China and Kenya.

Farming households with larger cultivated land size had a higher likelihood of adopting more adaptation practices (Table 9). Households with larger farm sizes are more likely to experience higher losses from climate change impacts than their counterparts. To counter the myriad of challenges, they could choose the adoption of multiple practices that increases their diversification potential and ability to spread risks over the large piece of land. On the contrary, smallholder farmers could be constraint in the adoption of new technologies due to their limited land sizes for trial implementation. The findings were consistent with various studies that found higher adoption among smallholder farming households with larger farm holdings (Alemayehu & Bewket, 2017; Esfandiari et al., 2020; Ehiakpor et al., 2021).

The study site negatively and significantly predicted both adoption level and intensity among smallholder farmers (Table 9). Farmers who lived in Ugenya sub-County were 4% for adoption level and 21% for adoption intensity less likely to adapt to climate change compared to those who lived in Alego-Usonga sub-County. This underscores the importance of site-specific consideration in promoting agricultural technologies. Therefore, there is a need to intensify the climate change adaptation campaign in Ugenya sub-County to increase the adoption of adaptation practices. Similar findings were reported by Kpadonou et al. (2017), who found that farmers who belong in Northern Sahel negatively determined climate-smart technologies adoption intensity. In agreement with the findings, Martey and Kuwornu (2021), found that site, i.e., smallholder farmers in the Northern region, were less likely to adopt integrated soil fertility management than those in the Upper East and Upper West regions of Ghana.

6.4 Conclusion and policy recommendations

Smallholder farmers in Western Kenya are significantly affected by climate change. The study assessed the climate change perceptions, drivers, effects, and barriers to adaptation and the determinants of climate change adaptation among smallholder farmers in Western Kenya. In line with the hypotheses, the findings showed that smallhoders' were aware of climate change, its drivers, and its effects and socioeconomics, environmental and institutional factors determined adoption of climate change adaptation practices. The key barriers to climate change adaptation among smallholder farmers were unpredictable weather patterns, financial constraints, and limited agricultural training. Household head's education level, experience, group membership significantly determined both adoption level and intensity of climate change adaptation practices. The findings underscore the importance of socioeconomic determinants in shaping farmers' adaptation to climate change. Further, the study highlights the significance of climate information, farmers' perceptions, and site on climate change adaptation.

Based on the findings, three policy recommendations are highlighted. First, policies targeting climate change adaptation should focus on strengthening farmers and institutions capacity. This could be actualized through enhancing farmers' education, agricultural training, and improved access to weather information. Second, climate change policies need to be site-specific and tailored to farmers' perceptions to enhance climate change adaptation. Third, policymakers should consider the establishment of agricultural credit kit to enhance climate change adaptation. Initiating the above recommendations could be instrumental in improving climate change resilience and mitigation.

CHAPTER SEVEN

SYNTHESES, CONCLUSIONS, AND RECOMMENDATIONS

7.1 Syntheses

The study's broad objective was to evaluate environmental GHG emissions hotspots, effects of inorganic fertilizer adoption and minimum tillage on sorghum yields, and determinants of climate change adaptation in Western Kenya. The objectives were achieved by estimating the carbon footprint using Cool Farm Tool (Chapter 2). The effects of the adoption of minimum tillage (Chapter 3) and inorganic fertilizer (Chapter 4) on sorghum yields were assessed. Identifying CSAPs adoption level and intensity (Chapter 5) and evaluating the determinants of adopting climate change adaptation strategies (Chapter 6) as presented in Chapters two to six.

Smallholder farming systems were grouped into five farm types. Smallholder sorghum cropping systems in Western Kenya had lower CFT than other cropping systems in Kenya (Chapter 2). This was mainly due to the low use of external inputs in sorghum farms. The sorghum cropping systems were estimated to be net sinks of GHG emissions. The primary GHG emissions hotspots were fertilizer production and application in moderate to high fertilizer manure use intensity and on intensifying farm types.

The adoption of minimum tillage and inorganic fertilizer was linked to socioeconomic, institutional, and biophysical determinants (Chapters 3 and 4). The study found low and high adoption rates of minimum tillage and inorganic fertilizer, respectively. Socioeconomics, institutional and biophysical factors were key drivers of minimum tillage and inorganic fertilizer adoption. Both minimum tillage and inorganic fertilizer adoption improved sorghum yields in Western Kenya.

Adopting climate-smart agricultural and climate change adaptation practices was influenced by socioeconomic, institutional, and biophysical factors (Chapters five and six). The study reviewed both complements and substitutes between CSAPs. Household head's gender, education, age, family size, contact with extension agents, access to weather information, arable land, livestock owned, perceived climate change, infertile soil, and persistent soil erosion influenced CSAPs adoption. Smallhoders' were aware of climate change and its drivers. The key barriers to climate change adaptation were unpredictable weather patterns, financial constraints, and limited agricultural training. Household heads' education level, experience, and group membership significantly determined both the adoption level and intensity of climate change adaptation practices.

7.2 Conclusions

Based on the study finds, the following conclusions are made:

- Smallholder sorghum cropping systems showed a low amount of GHG balances in Western Kenya.
- Minimum tillage adoption enhanced sorghum productivity among smallholder farmers.
- Inorganic fertilizer application improved sorghum yields among smallholder farmers.
- Smallholder farmers adopt multiple climate-smart agricultural practices to improve crop productivity and cope with climate shocks.
- Socioeconomic, institutional, and biophysical determinants influence the adoption of climate change adaptation practices.

7.3 Recommendations

The study recommends that:

- To enhance crop productivity and reduce greenhouse gas emissions, smallholder farmers should practice judicious integration of inorganic fertilizer and animal manure.
- Minimum tillage adoption should be promoted among smallhoder farming households for increased sorghum productivity.
- To improve sorghum yields, the use of adequate amounts of inorganic fertilizer should be promoted among smallholder farmers.

- Policymakers and relevant stakeholders should consider socioeconomic, institutional, and biophysical factors in upscaling or promoting adopting climate-smart agricultural practices.
- Smallholder farmers' perceptions of climate change, climate awareness creation, and monetary assistance should be considered to enhance climate change resilience.

7.4 Areas of further research

The study proposes the following areas of further research:

- Direct quantification of GHGs from different climate-smart crops such as cassava, sorghum, millet, groundnut, and cowpeas.
- Field studies to evaluate the influence of conservation agriculture and soil fertility management practices on sorghum yields.

REFERENCES

Abrams, L. (2018). Unlocking the potential of enhanced rain-fed agriculture. Stockholm: Stockholm International Water Institute.

Agbede, T. M., & Ojeniyi, S. O. (2009). Tillage and poultry manure effects on soil fertility and sorghum yield in southwestern Nigeria. Soil and tillage research, 104(1), 74-81. https://doi.org/10.1016/j.still.2008.12.014

Ahmed, H., & Anang, B. T. (2019). Does farmer group membership enhance technology adoption? Empirical evidence from Tolon district of Ghana. Review of Agricultural and Applied Economics (RAAE), 22(1340-2019-3700), 26-32. http://dx.doi.org/10.22004/ag.econ.293644

Ahmed, Z., Guha, G. S., Shew, A. M., & Alam, G. M. (2021). Climate change risk perceptions and agricultural adaptation strategies in vulnerable riverine char islands of Bangladesh. Land use policy, 103, 105295.https://doi.org/10.1016/j.landusepol.2021.105295

Alam, G. M., Alam, K., & Mushtaq, S. (2017). Climate change perceptions and local adaptation strategies of hazard-prone rural households in Bangladesh. Climate Risk Management, 17, 52-63.https://doi.org/10.1016/j.crm.2017.06.006

Alam, M., Islam, M., Salahin, N. & Hasanuzzaman, M., (2014). Effect of tillage practices on soil properties and crop productivity in wheat-mungbean-rice cropping system under subtropical climatic conditions. The Scientific World Journal, 2014, 1-15. https://doi.org/10.1155/2014/437283

Alam, M.K., Bell, R.W.& Biswas, W.K. (2019). Decreasing the carbon footprint of an intensive rice-based cropping system using conservation agriculture on the Eastern Gangetic Plains. Journal of Cleaner Production, 218, pp.259-272. https://doi.org/10.1016/j.jclepro.2019.01.328

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

Alliance for a Green Revolution in Africa (AGRA). (2014). Africa agriculture status report 2014: Climate change and smallholder agriculture in Sub-Saharan Africa.

Alvarez, S., Paas, W., Descheemaeker, K., Tittonell, P.A. and Groot, J.C., (2014). Typology construction, a way of dealing with farm diversity: General guidelines for Humidtropics. https://cgspace.cgiar.org/bitstream/handle/10568/65374/typology_guidelines.pdf?sequence=1

Alvarez, S., Timler, C.J., Michalscheck, M., Paas, W., Descheemaeker, K., Tittonell, P., Andersson, J.A. & Groot, J.C., (2018). Capturing farm diversity with hypothesis-based typologies: An innovative methodological framework for farming system typology development. PloS one, 13(5), p.e0194757. https://doi.org/10.1371/journal.pone.0194757

Amadu, F.O., McNamara, P.E. & Miller, D.C., (2020). Yield effects of climate-smart agriculture aid investment in southern Malawi. Food Policy, 92, 101869. https://doi.org/10.1016/j.foodpol.2020.101869

Amujoyegbe, B. J., Opabode, J. T., & Olayinka, A. (2007). Effect of organic and inorganic fertilizer on yield and chlorophyll content of maize (Zea mays L.) and sorghum Sorghum bicolour (L.) Moench. African Journal of Biotechnology, 6(16). https://doi.org/10.5897/AJB2007.000-2278

Anang, B. T., Bäckman, S., & Sipiläinen, T. (2020). Adoption and income effects of agricultural extension in northern Ghana. Scientific African, 7, e00219.https://doi.org/10.1016/j.sciaf.2019.e00219

Anang, B.T. and Asante, B.O., 2020. Farm household access to agricultural services in northern Ghana. Heliyon, 6(11), p.e05517.https://doi.org/10.1016/j.heliyon.2020.e05517

Antwi-Agyei, P., & Stringer, L. C. (2021). Improving the effectiveness of agricultural extension services in supporting farmers to adapt to climate change: Insights from northeastern Ghana. Climate Risk Management, 32, 100304.https://doi.org/10.1016/j.crm.2021.100304

Archie, K. M., Chapman, R., & Flood, S. (2018). Climate change response in New Zealand communities: Local scale adaptation and mitigation planning. Environmental development, 28, 19-31.https://doi.org/10.1016/j.envdev.2018.09.003

Arora, N. K. (2019). Impact of climate change on agriculture production and its sustainable solutions. Environmental Sustainability, 2(2), 95-96.https://doi.org/10.1007/s42398-019-00078-w

Asfaw, D., & Neka, M. (2017). Factors affecting adoption of soil and water conservation practices: the case of Wereillu Woreda (District), South Wollo Zone, Amhara Region, Ethiopia. International Soil and Water Conservation Research, 5(4), 273-279.https://doi.org/10.1016/j.iswcr.2017.10.002

Asfaw, S., Shiferaw, B., Simtowe, F. & Lipper, L. (2012). Impact of modern agricultural technologies on smallholder welfare: Evidence from Tanzania and Ethiopia. Food policy, 37(3), 283-295. https://doi.org/10.1016/j.foodpol.2012.02.013

Askew, K. (2017). Population growth 'a threat to food quality'. https://www.foodnavigator.com/Article/2017/11/10/Population-growth-a-threat-to-food-quality#

Awada, L., Lindwall, C. W., & Sonntag, B. (2014). The development and adoption of conservation tillage systems on the Canadian Prairies. International Soil and Water Conservation Research, 2(1), 47-65. https://doi.org/10.1016/S2095-6339(15)30013-7

Aweke, C. S., Hassen, J. Y., Wordofa, M. G., Moges, D. K., Endris, G. S., & Rorisa, D. T. (2021). Impact Assessment of Agricultural Technologies on Household Food Consumption and Dietary Diversity in Eastern Ethiopia. Journal of Agriculture and Food Research, 4, 100141. https://doi.org/10.1016/j.jafr.2021.100141

Batjes, N. H. (2014). Projected changes in soil organic carbon stocks upon adoption of recommended soil and water conservation practices in the Upper Tana River catchment, Kenya. Land Degradation & Development, 25(3), 278-287.https://doi.org/10.1002/ldr.2141

Belachew, A., Mekuria, W. & Nachimuthu, K. (2020). Factors influencing adoption of soil and water conservation practices in the Northwest Ethiopian highlands. International Soil and Water Conservation Research, 8(1), pp.80-89. https://doi.org/ 10.1016/j.iswcr.2020.01.005

Belderbos, R., Carree, M., & Lokshin, B. (2004). Cooperative R&D and firm performance. Research policy, 33(10), 1477-1492.https://doi.org/10.1016/j.respol.2004.07.003

Bloodhart, B., Maibach, E., Myers, T. & Zhao, X. (2015). Local climate experts: The influence of local TV weather information on climate change perceptions. PLoS One, 10, 1-14. https://doi.org/10.1371/journal.pone.0141526

Bonett, D. G., & Wright, T. A. (2015). Cronbach's alpha reliability: Interval estimation, hypothesis testing, and sample size planning. Journal of organizational behavior, 36(1), 3-15.https://doi.org/10.1002/job.1960

Bozzola, M., Smale, M., Di Falco, S. (2018). Climate, shocks, weather and maize intensification decisions in rural Kenya. In Agricultural Adaptation to Climate Change in Africa (pp. 107-128). Routledge

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

Bryan, E., Ringler, C., Okoba, B., Roncoli, C., Silvestri, S., & Herrero, M. (2013). Adapting agriculture to climate change in Kenya: Household strategies and determinants. Journal of environmental management, 114, 26-35.http://dx.doi.org/10.1016/j.jenvman.2012.10.036

Busari, M.A., Kukal, S.S., Kaur, A., Bhatt, R. & Dulazi, A.A. (2015). Conservation tillage impacts on soil, crop and the environment. International Soil and Water Conservation Research, 3(2), 119-129. https://doi.org/10.1016/j.iswcr.2015.05.002

Cameron, A. C., & Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. Journal of human resources, 50(2), 317-372.

CGA. (2019). CGA Encourages Siaya Farmers to Grow More Sorghum -. [online] Available at: <https://cga.co.ke/2019/01/28/siaya-farmers-grow-more-sorghum/> [Accessed 18 December 2021].

CGIAR (2021). Improving farmers' livelihoods through upscaling best performing sorghum varieties for seed production and commercial products in western Kenya. CGIAR . https://www.cgiar.org/news-events/news/improving-farmers-livelihoods-through-upscaling-best-performing-sorghum-varieties-for-seed-production-and-commercial-products-in-western-kenya/

Chen, R., Zhang, R., Han, H. & Jiang, Z. (2020a). Is farmers' agricultural production a carbon sink or source?–Variable system boundary and household survey data. Journal of Cleaner Production, 266, p.122108. https://doi.org/10.1016/j.jclepro.2020.122108

Chen, X., Xu, X., Lu, Z., Zhang, W., Yang, J., Hou, Y., Wang, X., Zhou, S., Li, Y., Wu, L. & Zhang, F. (2020b). Carbon footprint of a typical pomelo production region in China based on farm survey data. Journal of Cleaner Production, 277, p.124041. https://doi.org/10.1016/j.jclepro.2020.124041

Chepng'etich, E., Nyamwaro, S. O., Bett, E. K., & Kizito, K. (2015). Factors that influence technical efficiency of sorghum production: A case of smallholder sorghum producers in Lower Eastern Kenya. Advances in Agriculture, 1-11. https://doi.org/10.1155/2015/861919

Ciais, P., Bombelli, A., Williams, M., Piao, S. L., Chave, J., Ryan, C. M., & Valentini, R. (2011). The carbon balance of Africa: synthesis of recent research studies. Philosophical transactions of the royal society A: Mathematical, Physical and Engineering Sciences, 369(1943), 2038-2057.https://doi.org/10.1098/rsta.2010.0328

Clavreul J, Btunar I, Rubio V, & King H. (2017) Intra- and interyear variability of agricultural carbon footprints: a case study on field-grown tomatoes. J Clean Prod 158:156–164. https://doi.org/10.1016/j.jclepro.2017.05.004

Cochran, W. G. (2007). Sampling techniques. John Wiley & Sons.

Cooper, P. J., & Coe, R. (2011). Assessing and addressing climate-induced risk in sub-Saharan rainfed agriculture: Foreword to a special issue of experimental agriculture. Experimental Agriculture, 47(2), 179-184.https://doi.org/10.1017/S0014479711000019

Corbeels, M., Scopel, E., Cardoso, A., Bernoux, M., Douzet, J. M., & Neto, M. S. (2006). Soil carbon storage potential of direct seeding mulch-based cropping systems in the Cerrados of Brazil. Global Change Biology, 12(9), 1773-1787. https://doi.org/10.1111/j.1365-2486.2006.01233.x

Coulibaly, J. Y., Chiputwa, B., Nakelse, T., & Kundhlande, G. (2017). Adoption of agroforestry and the impact on household food security among farmers in Malawi. Agricultural systems, 155, 52-69. http://dx.doi.org/10.1016/j.agsy.2017.03.017

County Government of Siaya. (2019). Siaya County Spatial Plan 2018 – 2028. https://siaya.go.ke/wp-content/uploads/2019/04/DRAFT-SIAYA-County-Spatial-Plan-REVISED-MARCH-2019.pdf

Coxe, S., West, S. G., & Aiken, L. S. (2009). The analysis of count data: A gentle introduction to Poisson regression and its alternatives. Journal of personality assessment, 91(2), 121-136.https://doi.org/10.1080/00223890802634175

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. psychometrika, 16(3), 297-334.

Dalal, R.C. & Allen, D.E. (2008). Greenhouse gas fluxes from natural ecosystems. Australian Journal of Botany, 56(5), pp.369-407. https://doi.org/10.1071/BT07128

Dapilah, F., Nielsen, J. Ø., Lebek, K., & D'haen, S. A. L. (2021). He who pays the piper calls the tune: Understanding collaborative governance and climate change adaptation in Northern Ghana. Climate Risk Management, 32, 100306.https://doi.org/10.1016/j.crm.2021.100306

Darkwah, K. A., Kwawu, J. D., Agyire-Tettey, F., & Sarpong, D. B. (2019). Assessment of the determinants that influence the adoption of sustainable soil and water conservation practices in Techiman Municipality of Ghana. International soil and water conservation research, 7(3), 248-257. https://doi.org/10.1016/j.iswcr.2019.04.003

Desbiez, A., Matthews, R., Tripathi, B., & Ellis-Jones, J. (2004). Perceptions and assessment of soil fertility by farmers in the mid-hills of Nepal. Agriculture, ecosystems & environment, 103, 191-206. https://doi.org/10.1016/j.agee.2003.10.003

Devendra, C. (2012). Climate change threats and effects: challenges for agriculture and food security. Kuala Lumpur: Academy of Sciences Malaysia.

Di Falco, S., Veronesi, M., & Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. American Journal of Agricultural Economics, 93, 829-846. https://doi.org/10.1093/ajae/aar006

Diiro, G. M., Seymour, G., Kassie, M., Muricho, G., & Muriithi, B. W. (2018). Women's empowerment in agriculture and agricultural productivity: Evidence from rural maize farmer households in western Kenya. PloS one, 13(5), e0197995. https://doi.org/10.1371/journal.pone.0197995

Doggart, N., Morgan-Brown, T., Lyimo, E., Mbilinyi, B., Meshack, C. K., Sallu, S. M., & Spracklen, D. V. (2020). Agriculture is the main driver of deforestation in Tanzania. Environmental Research Letters, 15(3), 034028.https://doi.org/10.1088/1748-9326/ab6b35

Donkor, E., Onakuse, S., Bogue, J., & De Los Rios-Carmenado, I. (2019). Fertilizer adoption and sustainable rural livelihood improvement in Nigeria. Land Use Policy, 88, 104193. https://doi.org/10.1016/j.landusepol.2019.104193

Ehiakpor, D. S., Danso-Abbeam, G., & Mubashiru, Y. (2021). Adoption of interrelated sustainable agricultural practices among smallholder farmers in Ghana. Land Use Policy, 101, 105142.https://doi.org/10.1016/j.landusepol.2020.105142

El-Shater, T., Yigezu, Y.A., Mugera, A., Piggin, C., Haddad, A., Khalil, Y., Loss, S. & Aw-Hassan, A. (2016). Does zero tillage improve the livelihoods of smallholder cropping farmers?. Journal of Agricultural Economics, 67(1), 154-172. https://doi.org/10.1111/1477-9552.12133

Emmanuel, D., Owusu-Sekyere, E., Owusu, V., & Jordaan, H. (2016). Impact of agricultural extension service on adoption of chemical fertilizer: Implications for rice productivity and development in Ghana. NJAS-Wageningen Journal of Life Sciences, 79, 41-49.http://dx.doi.org/10.1016/j.njas.2016.10.002

Esfandiari, M., Khalilabad, H. R. M., Boshrabadi, H. M., & Mehrjerdi, M. R. Z. (2020). Factors influencing the use of adaptation strategies to climate change in paddy lands of Kamfiruz, Iran. Land Use Policy, 95, 104628. https://doi.org/10.1016/j.landusepol.2020.104628

Essougong, U.P.K., Slingerland, M., Mathé, S., Vanhove, W., Ngome, P.I.T., Boudes, P., Giller, K.E., Woittiez, L.S. & Leeuwis, C. (2020). Farmers' Perceptions as a

Driver of Agricultural Practices: Understanding Soil Fertility Management Practices in Cocoa Agroforestry Systems in Cameroon. Human Ecology, 48, 709-720. https://doi.org/10.1007/s10745-020-00190-0

Fahey, D., Doherty, S., Hibbard, K. A., Romanou, A., & Taylor, P. (2017). Physical drivers of climate change.

FAO, (2009). Global agriculture towards 2050: How to feed the world 2050. https://www.fao.org/fileadmin/templates/wsfs/docs/Issues_papers/HLEF2050_Global_Agriculture.pdf

FAO, F. (2012). Conservation Agriculture: Conserving resources above-and below-the ground.

FAO. (2014). FAO success stories on climate-smart agriculture.

Field, A. (2009). Discovering statistics using SPSS: Book plus code for E version of text (p. 896). London, UK: SAGE Publications Limited.

Findlater, K. M., Kandlikar, M., & Satterfield, T. (2019). Misunderstanding conservation agriculture: Challenges in promoting, monitoring and evaluating sustainable farming. Environmental Science & Policy, 100, 47-54. https://doi.org/10.1016/j.envsci.2019.05.027

Fosu-Mensah, B. Y., Vlek, P. L., & MacCarthy, D. S. (2012). Farmers' perception and adaptation to climate change: a case study of Sekyedumase district in Ghana. Environment, Development and Sustainability, 14(4), 495-505.https://doi.org/10.1007/s10668-012-9339-7

Fredenburg, P. (2015). Conservation agriculture: Opportunities for intensified farming and environmental conservation in dry areas. Aleppo, Syria: International Center for Agricultural Research in the Dry Areas (ICARDA). https://hdl.handle.net/20.500.11766/5073

Fuglie, K.O. & Bosch, D.J. (1995). Economic and environmental implications of soil nitrogen testing: A switching-regression analysis. American Journal of Agricultural Economics, 77(4), 891-900. https://doi.org/10.2307/1243812

Kibue, G. W., Liu, X., Zheng, J., Pan, G., Li, L., & Han, X. (2016). Farmers' perceptions of climate variability and factors influencing adaptation: Evidence from Anhui and Jiangsu, China. *Environmental management*, *57*(5), 976-986.https://doi.org/10.1007/s00267-016-0661-y

García de Jalón, S., Silvestri, S., Granados, A., & Iglesias, A. (2015). Behavioural barriers in response to climate change in agricultural communities: an example from Kenya. Regional Environmental Change, 15(5), 851-865.https://doi.org/10.1007/s10113-014-0676-y

Gatzweiler, F. W., & Von Braun, J. (2016). Technological and institutional innovations for marginalized smallholders in agricultural development (p. 435). Springer Nature.

Gbetibouo, G.A. (2009). Understanding farmers' perceptions and adaptations to climate change and variability: The case of the Limpopo Basin, South Africa (Vol. 849). Intl Food Policy Res Inst.

Gil, R., Bojacá, C.R. & Schrevens, E., (2019). Understanding the heterogeneity of smallholder production systems in the Andean tropics–The case of Colombian tomato growers. NJAS-Wageningen Journal of Life Sciences, 88, pp.1-9. https://doi.org/10.1016/j.njas.2019.02.002

Giller, K.E., Witter, E., Corbeels, M. & Tittonell, P. (2009). Conservation agriculture and smallholder farming in Africa: the heretics' view. Field crops research, 114(1), pp.23-34. https://doi.org/10.1016/j.fcr.2009.06.017

Giltrap, D.L., Li, C. and Saggar, S., 2010. DNDC: A process-based model of greenhouse gas fluxes from agricultural soils. Agriculture, ecosystems & environment, 136(3-4), pp.292-300. https://doi.org/10.1016/j.agee.2009.06.014

Githongo, M. W., Kiboi, M. N., Ngetich, F. K., Musafiri, C. M., Muriuki, A., & Fliessbach, A. (2021). The effect of minimum tillage and animal manure on maize yields and soil organic carbon in sub-Saharan Africa. Environmental Challenges, 100340. https://doi.org/10.1016/j.envc.2021.100340

Githongo, M.W., Musafiri, C.M., Macharia, J.M., Kiboi, M.N., Fliessbach, A., Muriuki, A. & Ngetich, F.K. (2022). Greenhouse Gas Fluxes from Selected Soil Fertility Management Practices in Humic Nitisols of Upper Eastern Kenya. Sustainability, 14(3), p.1938. https://doi.org/10.3390/su14031938

Government of Kenya. (2010). National Climate Change Response Strategy. Government Printer. Nairobi, Kenya.

Government of the Republic of Kenya. (2007). Kenyan Vison 2030. The popular version. Nairobi, KenyaGrabowski, P.P., Kerr, J.M., Haggblade, S. and Kabwe, S., 2016. Determinants of adoption and disadoption of minimum tillage by cotton farmers in eastern Zambia. Agriculture, Ecosystems & Environment, 231, 54-67. https://doi.org/10.1016/j.agee.2016.06.027

Greene, W. H. (1997). FIML estimation of sample selection models for count data.

Habtewold, T. M. (2021). Impact of climate-smart agricultural technology on multidimensional poverty in rural Ethiopia. Journal of Integrative Agriculture, 20(4), 1021-1041. https://doi.org/10.1016/S2095-3119(21)63637-7

Hair, J. F. , Black, W. C. , Babin, B. J. & Anderson, R. E. (2010). Multivariate data analysis (7th ed.). New Jersey, NJ: Pearson Prentice Hall.

Hammond, J., Rosenblum, N., Breseman, D., Gorman, L., Manners, R., van Wijk, M.T., Sibomana, M., Remans, R., Vanlauwe, B. & Schut, M. (2020). Towards actionable farm typologies: Scaling adoption of agricultural inputs in Rwanda. Agricultural Systems, 183, p.102857. https://doi.org/10.1016/j.agsy.2020.102857

Haq, S. M., & Ahmed, K. J. (2017). Does the perception of climate change vary with the socio-demographic dimensions? A study on vulnerable populations in Bangladesh. Natural Hazards, 85(3), 1759-1785.https://doi.org/10.1007/s11069-016-2664-7

Herrero, M. T., Ringler, C., Steeg, J. V. D., Thornton, P. K., Zhu, T., Bryan, E., & Notenbaert, A. M. O. (2010). Climate variability and climate change and their impacts on Kenya's agricultural sector. https://cgspace.cgiar.org/bitstream/handle/10568/3840/climateVariability.pdf

Hillier, J., Walter, C., Malin, D., Garcia-Suarez, T., Mila-i-Canals, L. & Smith, P., (2011). A farm-focused calculator for emissions from crop and livestock production. Environmental Modelling & Software, 26(9), pp.1070-1078. https://doi.org/10.1016/j.envsoft.2011.03.014

Huang, X., Chen, C., Qian, H., Chen, M., Deng, A., Zhang, J. & Zhang, W. (2017). Quantification for carbon footprint of agricultural inputs of grains cultivation in China since 1978. Journal of Cleaner Production, 142, pp.1629-1637. https://doi.org/10.1016/j.jclepro.2016.11.131

ICRISAT. (2017) Farmers in East Africa on the move beyond subsistence farming. http://www.icrisat.org/wp-content/uploads/2017/10/27-October_3d-news-letter-2.pdf

ICRISAT. (2019). Breaking barriers for climate-smart crop adoption in Kenya – ICRISAT. [online] Available at: <https://www.icrisat.org/breaking-barriers-for-climate-smart-crop-adoption-in-kenya/> [Accessed 18 December 2021].

IPCC. (2007). Summary for policymakers. Climate change 2007: the physical science basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. In: Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K.B., Tignor, M., Miller, H.L. (Eds.). Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

IPCC. (2014). Climate change 2014: synthesis report, in Contri- bution ofWorking Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, R. K. Pachauri and L. A. Meyer, Eds., IPCC, Geneva, Swit- zerland, 2014.

Irianti, M., Nasrul, B., & Syahza, A. (2020). Erosion control in sustainable plantation development efforts in Siak watershed region, Riau province, Indonesia. Asian Journal of Scientific Research, 13(4), 259-269.http://doi.org/10.3923/ajsr.2020.259.269

Jaetzold R., Schmidt H., Hornetz B. & Shisanya C. (2010). Farm Management Handbook of Kenya. Gesellschaft für Internationale Zusammenarbeit, vol. 2. Brookpak Printing & Supplies, Nairobi, Kenya.

Jahnke, H.E. (1982). Livestock production systems and livestock development in tropical Africa (Vol. 35). Kiel: Kieler Wissenschaftsverlag Vauk.

Jaleta, M., Kassie, M., Tesfaye, K., Teklewold, T., Jena, P.R., Marenya, P. & Erenstein, O. (2016). Resource saving and productivity enhancing impacts of crop management innovation packages in Ethiopia. Agricultural Economics, 47(5), 513-522. https://doi.org/10.1111/agec.12251

Jawid, A., & Khadjavi, M. (2019). Adaptation to climate change in Afghanistan: Evidence on the impact of external interventions. Economic Analysis and Policy, 64, 64–82. https://doi.org/10.1016/j.eap.2019.07.010

Jena, P. R. (2019). Can minimum tillage enhance productivity? Evidence from smallholder farmers in Kenya. Journal of Cleaner Production, 218, 465-475. https://doi.org/10.1016/j.jclepro.2019.01.278

Johnston, A. M., & Bruulsema, T. W. (2014). 4R nutrient stewardship for improved nutrient use efficiency. Procedia Engineering, 83, 365-370. https://doi.org/10.1016/j.proeng.2014.09.029

Joshi, B., Ji, W., & Joshi, N. B. (2017). Farm households' perception on climate change and adaptation practices: A case from mountain district of Nepal. International Journal of Climate Change Strategies and Management.http://www.emeraldinsight.com/1756-8692.htm

Kamau, J.W., Stellmacher, T., Biber-Freudenberger, L. & Borgemeister, C. (2018). Organic and conventional agriculture in Kenya: A typology of smallholder farms in Kajiado and Murang'a counties. Journal of rural studies, 57, pp.171-185. https://doi.org/10.1016/j.jrurstud.2017.12.014

Kanyenji, G. M., Oluoch-Kosura, W., Onyango, C. M., & Karanja Ng'ang'a, S. (2022). Does the adoption of soil carbon enhancing practices translate to increased farm yields? A case of maize yield from Western Kenya. Heliyon, e09500. https://doi.org/10.1016/j.heliyon.2022.e09500

Kanyenji, G. M., Oluoch-Kosura, W., Onyango, C. M., & Karanja Ng'ang'a, S. (2020). Prospects and constraints in smallholder farmers' adoption of multiple soil carbon enhancing practices in Western Kenya. Heliyon, 6(3), e03226. https://doi.org/10.1016/j.heliyon.2020.e03226

Kanyenji, G. M., Oluoch-Kosura, W., Onyango, C. M., & Karanja Ng'ang'a, S. (2020). Prospects and constraints in smallholder farmers' adoption of multiple soil carbon enhancing practices in Western Kenya. Heliyon, 6(3), e03226.https://doi.org/10.1016/j.heliyon.2020.e03226

Karanja, A. N. (2020). Quantifying greenhouse gas emissions and carbon stocks in maize-soybean cropping systems in Siaya County, Kenya (Theis, Kenyatta University).

Karanja, D.R., Kisilu, R.K., Kathuli, P., Mutisya, D.L., Njaimwe, A.N., Keya, G., Ouda, J., & Ayemba, J. (2014). Enhancing sorghum production and marketing in semi-arid Kenya: Manual. Kenya Agricultural and Livestock Research Organization, Nairobi, Kenya.

Karienye, D., & Macharia, J. (2020). Adaptive Capacity to Mitigate Climate Variability and Food Insecurity of Rural Communities Along River Tana Basin, Kenya. African Handbook of Climate Change Adaptation, 1-12.https://doi.org/10.1007/978-3-030-42091-8_57-1

Kassam, A., Friedrich, T., & Derpsch, R. (2019). Global spread of conservation agriculture. International Journal of Environmental Studies, 76(1), 29-51. https://doi.org/10.1080/00207233.2018.1494927

Kassie, M., Ndiritu, S. W., & Stage, J. (2014). What determines gender inequality in household food security in Kenya? Application of exogenous switching treatment regression. World development, 56, 153-171.https://doi.org/10.1016/j.worlddev.2013.10.025

Kassie, M., Teklewold, H., Jaleta, M., Marenya, P., & Erenstein, O. (2015). Understanding the adoption of a portfolio of sustainable intensification practices in eastern and southern Africa. Land use policy, 42, 400-411. http://dx.doi.org/10.1016/j.landusepol.2014.08.016

Kassie, M., Teklewold, H., Marenya, P., Jaleta, M. & Erenstein, O. (2015). Production risks and food security under alternative technology choices in Malawi: Application of a multinomial endogenous switching regression. Journal of Agricultural Economics, 66(3), 640-659. https://doi.org/10.1111/1477-9552.12099

Kavoi, J. M., Mwangi, J. G., & Kamau, G. M. (2014). Factors related to the low uptake of technologies and innovations in semi-arid areas of lower Eastern Kenya. Agriculture and Soil Sciences, 1(2), 12-21. http://www.landmarkresearchjournals.org/lrjass/index.php

Kebede, B., 2007. Community wealth-ranking and household surveys: An integrative approach. Q- Squared Working paper No. 38, Centre for International Studies, University of Toronto, Canada.

Kebeney, S. J., Msanya, B. M., Semoka, J. M., Ngetich, W. K., & Kipkoech, A. K. (2015). Socioeconomic factors and soil fertility management practices affecting sorghum production in Western Kenya: a case study of Busia county. Journal of Experimental Agriculture International, 1-11. http://www.suaire.sua.ac.tz/handle/123456789/757

Kenya Ministry of Agriculture, Livestock and Fisheries (MoALF). (2016). Climate Risk Profile for Siaya. Kenya County Climate Risk Profile Series., Nairobi, Kenya.

Kenya National Bureau of Statistics (KNBS). (2019). Kenya Population and Housing Census. Population by County and sub-county. Government printers, Nairobi, Kenya.

Kenya News Agency. (2019). Sorghum no longer a poor man's crop for Siaya farmers – Kenya News Agency. [online] Available at: <https://www.kenyanews.go.ke/sorghum-no-longer-a-poor-mans-crop-for-siaya-farmers/> [Accessed 18 December 2021].

Khan, I., Lei, H., Shah, I. A., Ali, I., Khan, I., Muhammad, I., & Javed, T. (2020). Farm households' risk perception, attitude and adaptation strategies in dealing with climate change: promise and perils from rural Pakistan. Land use policy, 91, 104395.https://doi.org/ 10.1016/j.landusepol.2019.104395

Khonje, M. G., Manda, J., Mkandawire, P., Tufa, A. H., & Alene, A. D. (2018). Adoption and welfare impacts of multiple agricultural technologies: evidence from eastern Zambia. Agricultural Economics, 49, 599-609. https://doi.org/10.1111/agec.12445

Khonje, M., Manda, J., Alene, A. D., & Kassie, M. (2015). Analysis of adoption and impacts of improved maize varieties in eastern Zambia. World Development, 66, 695-706. https://doi.org/10.1016/j.worlddev.2014.09.008

Kiboi, M. N., Ngetich, K. F., Fliessbach, A., Muriuki, A., & Mugendi, D. N. (2019). Soil fertility inputs and tillage influence on maize crop performance and soil water content in the Central Highlands of Kenya. Agricultural Water Management, 217, 316–331. https://doi.org/10.1016/j.agwat.2019.03.014

Kiboi, M.N., Ngetich, K.F., Diels, J., Mucheru-Muna, M., Mugwe, J. & Mugendi, D.N., (2017). Minimum tillage, tied ridging and mulching for better maize yield and yield stability in the Central Highlands of Kenya. Soil and Tillage Research, 170, pp.157-166. https://doi.org/10.1016/j.still.2017.04.001

Kibunja, C. N., Ndungu-Magiroi, K. W., Wamae, D. K., Mwangi, T. J., Nafuma, L., Koech, M.N., Ademba, J. & Kitonyo, E. M. (2017). Optimizing fertilizer use within the context of integrated soil fertility management in Kenya. Fertilizer use optimization in sub-Saharan Africa, 82-99. http://dx.doi.org/10.1079/9781786392046.0082

Kim, C.G. (2008). The Impact of Climate Change on the Agricultural Sector: Implications of the Agro-Industry for Low Carbon, Green Growth Strategy and Roadmap for the East Asian Region. Korea Rural Economic Institute.

Kimaru-Muchai, S. W., Ngetich, F. K., Baaru, M., & Mucheru-Muna, M. W. (2020). Adoption and utilisation of Zai pits for improved farm productivity in drier upper Eastern Kenya. Journal of Agriculture and Rural Development in the Tropics and Subtropics (JARTS), 121(1), 13-22.https://doi.org/ 10.17170/kobra-202002281030

Kimaru-Muchai, S. W., Ngetich, F. K., Mucheru-Muna, M. W., & Baaru, M. (2021). Zai pits for heightened sorghum production in drier parts of Upper Eastern Kenya. Heliyon, 7(9), e08005. https://doi.org/10.1016/j.heliyon.2021.e08005

Kimathi, S. M., Ayuya, O. I., & Mutai, B. (2021). Adoption of climate-resilient potato varieties under partial population exposure and its determinants: case of smallholder farmers in Meru County, Kenya. Cogent Food & Agriculture, 7(1), 1860185.https://doi.org/10.1080/23311932.2020.1860185

Kiptot, E., & Franzel, S. (2012). Gender and agroforestry in Africa: a review of women's participation. Agroforestry systems, 84(1), 35-58.https://doi.org/10.1007/s10457-011-9419-y

Komissarov, M.A. & Klik, A. (2020). The impact of no-till, conservation, and conventional tillage systems on erosion and soil properties in Lower Austria. Eurasian soil science, 53, 503-511. https://link.springer.com/article/10.1134/S1064229320040079

Kpadonou, R. A. B., Owiyo, T., Barbier, B., Denton, F., Rutabingwa, F., & Kiema, A. (2017). Advancing climate-smart-agriculture in developing drylands: Joint analysis of the adoption of multiple on-farm soil and water conservation technologies in West African Sahel. Land use policy, 61, 196-207.https://doi.org/10.1016/j.landusepol.2016.10.050

Kumar, U., Werners, S., Roy, S., Ashraf, S., Hoang, L.P., Kumar Datta, D. and Ludwig, F., 2020. Role of Information in Farmers' Response to Weather and Water Related Stresses in the Lower Bengal Delta, Bangladesh. Sustainability, 12(16), 1-24. https://doi.org/10.3390/su12166598

Landais, E. (1998). Modelling farm diversity: new approaches to typology building in France. Agricultural Systems 58, 505-527. https://doi.org/10.1016/S0308-521X(98)00065-1

Lata, S., Kohli, A., Singh, Y.K., Shambhavi, S., Ghosh, M. & Gupta, S.K., 2020. Estimation of greenhouse gas emissions in rice based cropping systems under fertigation using cool farm tool. Journal of Soil and Water Conservation, 19(1), pp.26-31. DOI:10.5958/2455-7145.2020.00004.1

Leahy, S., Clark, H. & Reisinger, A. (2020). Challenges and prospects for agricultural greenhouse gas mitigation pathways consistent with the Paris agreement. Frontiers in Sustainable Food Systems, 4, p.69. https://doi.org/10.3389/fsufs.2020.00069

Lee, L. F., & Trost, R. P. (1978). Estimation of some limited dependent variable models with application to housing demand. Journal of Econometrics, 8(3), 357-382. https://doi.org/ 10.1016/0304-4076(78)90052-0

Lokshin, M. & Sajaia, Z. (2004). Maximum likelihood estimation of endogenous switching regression models. The Stata Journal, 4(3), 282-289. https://journals.sagepub.com/doi/pdf/10.1177/1536867X0400400306

Mabhaudhi, T., Chimonyo, V. G. P., Hlahla, S., Massawe, F., Mayes, S., Nhamo, L., & Modi, A. T. (2019). Prospects of orphan crops in climate change. Planta, 250, 695-708. https://doi.org/10.1007/s00425-019-03129-y

Macharia, J., Mugwe, J., Mucheru-Muna, M. & Mugendi, D. (2014). Socioeconomic factors influencing levels of knowledge in soil fertility management in the central highlands of Kenya. Journal of Agricultural Science and Technology B, 4(9), 701-711. https://doi.org/10.17265/2161-6264/2014.09.003

Macharia, J.M., Pelster, D.E., Ngetich, F.K., Shisanya, C.A., Mucheru-Muna, M. & Mugendi, D.N. (2020). Soil greenhouse gas fluxes from maize production under different soil fertility management practices in East Africa. Journal of Geophysical Research: Biogeosciences, 125(7), p.e2019JG005427.

Maddala, G. S. (1983). Methods of estimation for models of markets with bounded price variation. International Economic Review, 361-378. https://doi.org/10.2307/2648751

Mahama, A., Awuni, J. A., Mabe, F. N., & Azumah, S. B. (2020). Modelling adoption intensity of improved soybean production technologies in Ghana-a Generalized Poisson approach. Heliyon, 6(3), e03543.https://doi.org/10.1016/j.heliyon.2020.e03543

Mahmood, N., Arshad, M., Mehmood, Y., Shahzad, M. F., & Kächele, H. (2021). Farmers' perceptions and role of institutional arrangements in climate change adaptation: Insights from rainfed Pakistan. Climate Risk Management, 32, 100288.. https://doi.org/10.1016/j.crm.2021.100288

Maina, K. W., Ritho, C. N., Lukuyu, B. A., & Rao, E. J. O. (2020). Socioeconomic determinants and impact of adopting climate-smart Brachiaria grass among dairy farmers in Eastern and Western regions of Kenya. Heliyon, 6, e04335. https://doi.org/10.1016/j.heliyon.2020.e04335

Mairura, F.S., Musafiri, C.M., Kiboi, M.N., Macharia, J.M., Ng'etich, O.K., Shisanya, C.A., Okeyo, J.M., Okwuosa, E.A. & Ngetich, F.K. (2022b). Homogeneous land-use sequences in heterogeneous small-scale systems of Central Kenya: Land-use categorization for enhanced greenhouse gas emission estimation. Ecological Indicators, 136, p.108677.

Mairura, F.S., Musafiri, C.M., Kiboi, M.N., Macharia, J.M., Ng'etich, O.K., Shisanya, C.A., Okeyo, J.M., Mugendi, D.N., Okwuosa, E.A & Ngetich, F.K. (2021). Determinants of farmers' perceptions of climate variability, mitigation, and adaptation strategies in the central highlands of Kenya. Weather and Climate Extremes, 34, p.100374. https://doi.org/10.1016/j.wace.2021.100374

Mairura, F.S., Musafiri, C.M., Kiboi, M.N., Macharia, J.M., Ng'etich, O.K., Shisanya, C.A., Okeyo, J.M., Okwuosa, E.A. & Ngetich, F.K. (2022a). Farm factors influencing soil fertility management patterns in Upper Eastern Kenya. Environmental Challenges, 6, p.100409. https://doi.org/10.1016/j.envc.2021.100409

Manda, J., Alene, A. D., Tufa, A. H., Abdoulaye, T., Wossen, T., Chikoye, D., & Manyong, V. (2019). The poverty impacts of improved cowpea varieties in Nigeria: A counterfactual analysis. World Development, 122, 261-271. https://doi.org/10.1016/j.worlddev.2019.05.027

Mangin, B., Siberchicot, A., Nicolas, S., Doligez, A., This, P., & Cierco-Ayrolles, C., (2012). Novel measures of linkage disequilibrium that correct the bias due to population structure and relatedness. Heredity 108, 285–291. http://dx.doi.org/10.1038/hdy.2011.73

Mango, N., Makate, C., Tamene, L., Mponela, P., & Ndengu, G. (2017). Awareness and adoption of land, soil and water conservation practices in the Chinyanja Triangle, Southern Africa. International Soil and Water Conservation Research, 5(2), 122-129. https://doi.org/10.1016/j.iswcr.2017.04.003

Marenya, P. P., Gebremariam, G., & Jaleta, M. (2020). Sustainable intensification among smallholder maize farmers in Ethiopia: Adoption and impacts under rainfall and unobserved heterogeneity. Food Policy, 95, 101941. https://doi.org/10.1016/j.foodpol.2020.101941

Marenya, P.P., Kassie, M., Jaleta, M. & Erenstein, O. (2017). Predicting minimum tillage adoption among smallholder farmers using micro-level and policy variables. Agricultural and Food Economics, 5(1), pp.1-22. https://doi.org/10.1186/s40100-017-0081-1

Martey, E., Etwire, P. M., & Mockshell, J. (2021). Climate-smart cowpea adoption and welfare effects of comprehensive agricultural training programs. Technology in society, 64, 101468. https://doi.org/10.1016/j.techsoc.2020.101468

Martey, E., Kuwornu, J. K., & Adjebeng-Danquah, J. (2019). Estimating the effect of mineral fertilizer use on Land productivity and income: Evidence from Ghana. Land Use Policy, 85, 463-475. https://doi.org/10.1016/j.landusepol.2019.04.027

Masud, M. M., Azam, M. N., Mohiuddin, M., Banna, H., Akhtar, R., Alam, A. F., & Begum, H. (2017). Adaptation barriers and strategies towards climate change: Challenges in the agricultural sector. Journal of cleaner production, 156, 698-706. https://doi.org/10.1016/j.jclepro.2017.04.060

Mbanda-Obura, S. A., Tabu, I. M., Amudavi, D. M., & Obura, R. K. (2017). Determinants of choice of agricultural information sources and pathways among sorghum farmers in Ndhiwa Sub-County, Western Kenya. International Journal of Agricultural Extension, 5(, 39-49. https://www.journals.esciencepress.net/index.php/IJAE/article/view/2012

McCord, P. F., Cox, M., Schmitt-Harsh, M., & Evans, T. (2015). Crop diversification as a smallholder livelihood strategy within semi-arid agricultural systems near Mount Kenya. Land Use Policy, 42, 738-750.https://doi.org/10.1016/j.landusepol.2014.10.012

Meyer, J. (2002). Expected utility as a paradigm for decision making in agriculture. In A comprehensive assessment of the role of risk in US Agriculture (pp. 3-19). Springer, Boston. https://link.springer.com/chapter/10.1007/978-1-4757-3583-3_1

Mihretie, F.A., Tsunekawa, A., Haregeweyn, N., Adgo, E., Tsubo, M., Ebabu, K., Masunaga, T., Kebede, B., Meshesha, D.T., Tsuji, W. & Bayable, M. (2021). Tillage and crop management impacts on soil loss and crop yields in northwestern Ethiopia. International Soil and Water Conservation Research.(in press). https://doi.org/10.1016/j.iswcr.2021.04.006

Mitaru, B. N., Mgonja, M. A., Rwomushana, I., & Opio, F. (2006). Integrated sorghum and millet sector for increased economic growth and improved livelihoods in Eastern and Central Africa. In Proceedings of the ECARSAM Stakeholders Conference. https://www.asareca.org/sites/default/files/publications/Integrated%20sorghum%20and%20millet%20(website%20version).pdf

Mogaka, B. O., Bett, H. K., & Karanja Ng'ang'a, S. (2021). Socioeconomic factors influencing the choice of climate-smart soil practices among farmers in western Kenya. Journal of Agriculture and Food Research, 5, 100168.https://doi.org/10.1016/j.jafr.2021.100168

Moges, A. & Holden, N.M. (2007). Farmers' perceptions of soil erosion and soil fertility loss in Southern Ethiopia. Land Degradation & Development, 18(5), 543-554. https://doi.org/10.1002/ldr.795

Mojo, D., Fischer, C., & Degefa, T. (2017). The determinants and economic impacts of membership in coffee farmer cooperatives: recent evidence from rural Ethiopia. Journal of Rural studies, 50, 84-94. https://doi.org/10.1016/j.jrurstud.2016.12.010

Montes de Oca Munguia, O., Pannell, D. J., & Llewellyn, R. (2021). Understanding the Adoption of Innovations in Agriculture: A Review of Selected Conceptual Models. Agronomy, 11, 139. https://doi.org/10.3390/agronomy11010139

Moroda, G. T., Tolossa, D., & Semie, N. (2018). Perception and adaptation strategies of rural people against the adverse effects of climate variability: a case study of Boset district, East Shewa, Ethiopia. Environmental development, 27, 2-13. https://doi.org/10.1016/j.envdev.2018.07.005

Morton, J. F. (2007). The impact of climate change on smallholder and subsistence agriculture. Proceedings of the national academy of sciences, 104(50), 19680-19685. https://doi.org/10.1073/pnas.0701855104

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

Mucheru-Muna, M. W., Ada, M. A., Mugwe, J. N., Mairura, F. S., Mugi-Ngenga, E., Zingore, S., & Mutegi, J. K. (2021). Socioeconomic predictors, soil fertility knowledge domains and strategies for sustainable maize intensification in Embu County, Kenya. Heliyon, 7, e06345. https://doi.org/10.1016/j.heliyon.2021.e06345

Mugi-Ngenga, E. W., Mucheru-Muna, M. W., Mugwe, J. N., Ngetich, F. K., Mairura, F. S., & Mugendi, D. N. (2016). Household's socioeconomic factors influencing the level of adaptation to climate variability in the dry zones of Eastern Kenya. Journal of Rural Studies, 43, 49-60. https://doi.org/10.1016/j.jrurstud.2015.11.004

Mugi-Ngenga, E. W., Mucheru-Muna, M. W., Mugwe, J. N., Ngetich, F. K., Mairura, F. S., & Mugendi, D. N. (2016). Household's socio-economic factors influencing the level of adaptation to climate variability in the dry zones of Eastern Kenya. Journal of Rural Studies, 43, 49-60. https://doi.org/10.1016/j.jrurstud.2015.11.004

Mugwe, J., Mugendi, D., Mucheru-Muna, M., Merckx, R., Chianu, J., & Vanlauwe, B. (2009). Determinants of the decision to adopt integrated soil fertility management practices by smallholder farmers in the central highlands of Kenya. Experimental agriculture, 45(1), 61-75. https://doi.org/10.1017/S0014479708007072

Mulwa, C., Marenya, P., & Kassie, M. (2017). Response to climate risks among smallholder farmers in Malawi: A multivariate probit assessment of the role of information, household demographics, and farm characteristics. Climate Risk Management, 16, 208-221. https://doi.org/10.1016/j.crm.2017.01.002

Musafiri, C. M., Macharia, J. M., Ng'etich, O. K., Kiboi, M. N., Okeyo, J., Shisanya, C. A., Okwuosa, E.A., Mugendi, D.N., & Ngetich, F. K. (2020a). Farming systems' typologies analysis to inform agricultural greenhouse gas emissions potential from smallholder rain-fed farms in Kenya. Scientific African, 8, e00458. https://doi.org/10.1016/j.sciaf.2020.e00458

Musafiri, C.M., Kiboi, M., Macharia, J., Ng'etich, O.K., Kosgei, D.K., Mulianga, B., Okoti, M. & Ngetich, F.K. (2022a). Adoption of climate-smart agricultural practices among smallholder farmers in Western Kenya: do socioeconomic, institutional, and biophysical factors matter?. Heliyon, 8(1), p.e08677. https://doi.org/10.1016/j.heliyon.2021.e08677

Musafiri, C.M., Kiboi, M., Macharia, J., Ng'etich, O.K., Kosgei, D.K., Mulianga, B., Okoti, M. and Ngetich, F.K. (2022b). Smallholders' adaptation to climate change in Western Kenya: Considering socioeconomic, institutional and biophysical determinants. Environmental Challenges, 7, p.100489. https://doi.org/10.1016/j.envc.2022.100489

Musafiri, C.M., Macharia, J.M., Kiboi, M.N., Ng'etich, O.K., Shisanya, C.A., Okeyo, J.M., Okwuosa, E.A. & Ngetich, F.K. (2021). Comparison between observed and DeNitrification-DeComposition model-based nitrous oxide fluxes and maize yields under selected soil fertility management technologies in Kenya. Plant and soil, 463(1), pp.395-413. https://link.springer.com/article/10.1007/s11104-021-04924-x

Musafiri, C.M., Macharia, J.M., Kiboi, M.N., Ng'etich, O.K., Shisanya, C.A., Okeyo, J.M., Mugendi, D.N., Okwuosa, E.A. & Ngetich, F.K. (2020b). Soil greenhouse gas fluxes from maize cropping system under different soil fertility management technologies in Kenya. Agriculture, Ecosystems & Environment, 301, p.107064. https://doi.org/10.1016/j.agee.2020.107064

Musyoki, M. E., Busienei, J. R., Gathiaka, J. K., & Karuku, G. N. (2022). Linking farmers' risk attitudes, livelihood diversification and adoption of climate smart agriculture technologies in the Nyando basin, South-Western Kenya. Heliyon, 8(4), e09305. https://doi.org/10.1016/j.heliyon.2022.e09305

Mutenje, M. J., Farnworth, C. R., Stirling, C., Thierfelder, C., Mupangwa, W., & Nyagumbo, I. (2019). A cost-benefit analysis of climate-smart agriculture options in Southern Africa: Balancing gender and technology. Ecological Economics, 163, 126-137. https://doi.org/10.1016/j.ecolecon.2019.05.013

Mutisya, M., Ngware, M. W., Kabiru, C. W., & Kandala, N. B. (2016). The effect of education on household food security in two informal urban settlements in Kenya: a longitudinal analysis. Food Security, 8(4), 743-756. https://link.springer.com/article/10.1007/s12571-016-0589-3

Mutoko, M. C., Hein, L., & Shisanya, C. A. (2014). Farm diversity, resource use efficiency and sustainable land management in the western highlands of Kenya. Journal of rural studies, 36, 108-120. http://dx.doi.org/10.1016/j.jrurstud.2014.07.006

Muui, C. W., Muasya, R. M., & Kirubi, D. T. (2013). Baseline survey on factors affecting sorghum production and use in eastern Kenya. African journal of food, agriculture, nutrition and development, 13, 7339-7353. http://repository.seku.ac.ke/handle/123456789/387

Mwadalu, R. & Mwangi, M., (2013). The potential role of sorghum in enhancing food security in semi-arid eastern Kenya: A review. Journal of Applied Biosciences, 71, pp.5786-5799. https://doi.org/10.4314/jab.v71i1.98826

Mwaura, G. G., Kiboi, M. N., Bett, E. K., Mugwe, J. N., Muriuki, A., Nicolay, G., & Ngetich, F. K. (2021). Adoption intensity of selected organic-based soil fertility management technologies in the Central Highlands of Kenya. Front. Sustain. Food Syst. 4: 570190. doi: 10.3389/fsufs.

Ndeke, A.M., Mugwe, J.N., Mogaka, H., Nyabuga, G., Kiboi, M., Ngetich, F., Mucheru-Muna, M., Sijali, I. & Mugendi, D. (2021). Gender-specific determinants of Zai technology use intensity for improved soil water management in the drylands of Upper Eastern Kenya. Heliyon, 7(6), p.e07217.https://doi.org/10.1016/j.heliyon.2021.e07217

Ndiritu, S. W., Kassie, M., & Shiferaw, B. (2014). Are there systematic gender differences in the adoption of sustainable agricultural intensification practices? Evidence from Kenya. Food Policy, 49, 117-127. https://doi.org/10.1016/j.foodpol.2014.06.010

Ngetich, K. F., Diels, J., Shisanya, C. A., Mugwe, J. N., Mucheru-Muna, M., & Mugendi, D. N. (2014). Effects of selected soil and water conservation techniques on runoff, sediment yield and maize productivity under sub-humid and semi-arid conditions in Kenya. Catena, 121, 288-296.https://doi.org/10.1016/j.catena.2014.05.026

Ngoma, H. (2018). Does minimum tillage improve the livelihood outcomes of smallholder farmers in Zambia?. Food security, 10(2), 381-396. https://doi.org/10.1007/s12571-018-0777-4

Ng'ombe, J., Kalinda, T., Tembo, G. and Kuntashula, E., 2014. Econometric analysis of the factors that affect adoption of conservation farming practices by smallholder farmers in Zambia. Journal of Sustainable Development, 7(4), 124-138 http://dx.doi.org/10.5539/jsd.v7n4p124

Niza-Ribeiro, J. (2022). Food and water security and safety for an ever-expanding human population. In One Health (pp. 155-204). Academic Press. https://doi.org/10.1016/B978-0-12-822794-7.00003-4

Njagi, T., Onyango, K., Kirimi, L., & Makau, J. (2019). Sorghum Production in Kenya: Farm-level Characteristics, Constraints and Opportunities. Tegemeo Institute.

Nkegbe, P. K., & Shankar, B. (2014). Adoption intensity of soil and water conservation practices by smallholders: evidence from Northern Ghana. Bio-based and Applied

Economics Journal, 3(1050-2016-85757), 159-174.https://doi.org/10.13128/BAE-13246

Ntinyari, W. & Gweyi-Onyango, J.P. (2021). Greenhouse Gases Emissions in Agricultural Systems and Climate Change Effects in Sub-Saharan Africa. In African Handbook of Climate Change Adaptation (pp. 1081-1105). Springer, Cham. https://link.springer.com/chapter/10.1007/978-3-030-45106-6_43

Ntshangase, N. L., Muroyiwa, B., & Sibanda, M. (2018). Farmers' perceptions and factors influencing the adoption of no-till conservation agriculture by small-scale farmers in Zashuke, KwaZulu-Natal Province. Sustainability, 10(2), 555. https://doi.org/10.3390/su10020555

Ochieng, J., Kirimi, L., & Makau, J. (2017). Adapting to climate variability and change in rural K enya: f armer perceptions, strategies and climate trends. In Natural resources forum (Vol. 41, No. 4, pp. 195-208). Oxford, UK: Blackwell Publishing Ltd. https://doi.org/10.1111/1477-8947.12111

Odendo, M., Obare, G., & Salasya, B. (2010). Farmers' perceptions and knowledge of soil fertility degradation in two contrasting sites in western Kenya. Land Degradation & Development, 21, 557-564. https://doi.org/10.1002/ldr.996

OECD & FAO (2016) Agriculture in Sub-Saharan Africa: Prospects and challenges for the next decade. OECD-FAO Agricultural Outlook 2016-2025.

Ogada, M. J., Mwabu, G., & Muchai, D. (2014). Farm technology adoption in Kenya: a simultaneous estimation of inorganic fertilizer and improved maize variety adoption decisions. Agricultural and food economics, 2(1), 1-18.http://www.agrifoodecon.com/content/2/1/12

Ogada, M. J., Rao, E. J., Radeny, M., Recha, J. W., & Solomon, D. (2020). Climate-smart agriculture, household income and asset accumulation among smallholder farmers in the Nyando basin of Kenya. World Development Perspectives, 18, 100203. https://doi.org/10.1016/j.wdp.2020.100203

Ogeto, R.M., Cheruiyot, E., Mshenga, P. & Onyari, C.N. (2013). Sorghum production for food security: A socioeconomic analysis of sorghum production in Nakuru County, Kenya.

http://repository.embuni.ac.ke/bitstream/handle/123456789/343/Onyari-%20Sorgham%20production%20for%20food%20security.pdf?sequence=1

Ogle, S.M., Olander, L., Wollenberg, L., Rosenstock, T., Tubiello, F., Paustian, K., Buendia, L., Nihart, A. & Smith, P. (2014). Reducing greenhouse gas emissions and adapting agricultural management for climate change in developing countries: providing the basis for action. Global change biology, 20(1), pp.1-6. https://doi.org/10.1111/gcb.12361

Ojo, T. O., & Baiyegunhi, L. J. S. (2020). Determinants of climate change adaptation strategies and its impact on the net farm income of rice farmers in south-west Nigeria. Land Use Policy, 95, 103946.

Ojo, T. O., Baiyegunhi, L. J. S., & Salami, A. O. (2019). Impact of credit demand on the productivity of rice farmers in South West Nigeria. Journal of Economics and Behavioral Studies, 11, 166-180. https://doi.org/10.22610/jebs.v11i1(J).2757

Okalebo, J. R., Gathua, K. W., & Woomer, P. L. (2002). Laboratory methods of soil and plant analysis: a working manual second edition. *Sacred Africa*, *Nairobi*, *21*, 25-26.

Okeyo, A.I., Mucheru-Muna, M., Mugwe, J., Ngetich, K.F., Mugendi, D.N., Diels, J. & Shisanya, C.A. (2014). Effects of selected soil and water conservation technologies on nutrient losses and maize yields in the central highlands of Kenya. Agricultural Water Management, 137, 52-58. http://dx.doi.org/10.1016/j.agwat.2014.01.014

Okeyo, S. O., Ndirangu, S. N., Isaboke, H. N., & Njeru, L. K. (2020a). Determinants of sorghum productivity among small-scale farmers in Siaya County, Kenya. African Journal of Agricultural Research, 16, 722-731. DOI:10.5897/AJAR2020.14850

Okeyo, S. O., Ndirangu, S. N., Isaboke, H. N., Njeru, L. K., & Omenda, J. A. (2020b). Analysis of the determinants of farmer participation in sorghum farming among small-scale farmers in Siaya County, Kenya. Scientific African, 10, e00559. https://doi.org/10.1016/j.sciaf.2020.e00559

Ortiz-Gonzalo, D., Vaast, P., Oelofse, M., de Neergaard, A., Albrecht, A. & Rosenstock, T.S. (2017). Farm-scale greenhouse gas balances, hotspots and uncertainties in smallholder crop-livestock systems in Central Kenya. Agriculture, Ecosystems & Environment, 248, pp.58-70. https://doi.org/10.1016/j.agee.2017.06.002

Osewe, M., Miyinzi Mwungu, C., & Liu, A. (2020). Does Minimum Tillage Improve Smallholder Farmers' Welfare? Evidence from Southern Tanzania. Land, 9(12), 513. https://doi.org/10.3390/land9120513

Oyetunde-Usman, Z., Olagunju, K. O., & Ogunpaimo, O. R. (2021). Determinants of adoption of multiple sustainable agricultural practices among smallholder farmers in Nigeria. International Soil and Water Conservation Research, 9(2), 241-248.https://doi.org/10.1016/j.iswcr.2020.10.007

Pacini, G.C., Colucci, D., Baudron, F., Righi, E., Corbeels, M., Tittonell, P. and Stefanini, F.M., 2014. Combining multi-dimensional scaling and cluster analysis to describe the diversity of rural households. Experimental Agriculture, 50(3), pp.376-397. https://doi.org/10.1017/S0014479713000495

Parry, J. E., Echeverria, D., Dekens, J., & Maitima, J. (2012). Climate risks, vulnerability and governance in Kenya: A review. Commissioned by: climate risk management technical assistance support project (CRM TASP), joint initiative of bureau for crisis prevention and recovery and bureau for development policy of UNDP. https://www.iisd.org/system/files/publications/climate_risks_kenya.pdf

Pasley, H. R., Cairns, J. E., Camberato, J. J., & Vyn, T. J. (2019). Nitrogen fertilizer rate increases plant uptake and soil availability of essential nutrients in continuous maize production in Kenya and Zimbabwe. Nutrient cycling in agroecosystems, 115(3), 373-389. https://link.springer.com/article/10.1007/s10705-019-10016-1

Paudel, G. P., Kc, D. B., Justice, S. E., & McDonald, A. J. (2019). Scale-appropriate mechanization impacts on productivity among smallholders: Evidence from rice systems in the mid-hills of Nepal. Land Use Policy, 85, 104-113. https://doi.org/10.1016/j.landusepol.2019.03.030

Paul, B., Frelat, R., Birnholz, C., Ebong, C., Gahigi, A., Groot, J.C.J., Herrero, M., Kagabo, D.M., Notenbaert, A., Vanlauwe, B., & van Wijk, M.T. (2017). Agricultural intensification scenarios, household food availability and greenhouse gas emissions in Rwanda: Ex-ante impacts and trade-offs. Agric. Syst. https://doi.org/10.1016/j.agsy.2017.02.007

Pelster, D., Rufino, M., Rosenstock, T., Mango, J., Saiz, G., Diaz-Pines, E., Baldi, G. & Butterbach-Bahl, K. (2017). Smallholder farms in eastern African tropical highlands have low soil greenhouse gas fluxes. Biogeosciences, 14(1), pp.187-202. https://bg.copernicus.org/articles/14/187/2017/

Qazlbash, S. K., Zubair, M., Manzoor, S. A., ul Haq, A., & Baloch, M. S. (2021). Socioeconomic determinants of climate change adaptations in the flood-prone rural community of Indus Basin, Pakistan. Environmental Development, 37, 100603.https://doi.org/10.1016/j.envdev.2020.100603

Rabin, M. (2013). Risk aversion and expected-utility theory: A calibration theorem. In Handbook of the fundamentals of financial decision making: Part I (pp. 241-252).https://doi.org/10.1142/9789814417358_0013

Raimi, A., Adeleke, R., & Roopnarain, A. (2017). Soil fertility challenges and Biofertiliser as a viable alternative for increasing smallholder farmer crop productivity in sub-Saharan Africa. Cogent Food & Agriculture, 3, 1400933. https://doi.org/10.1080/23311932.2017.1400933

Rakotovao, N.H., Razafimbelo, T.M., Rakotosamimanana, S., Randrianasolo, Z., Randriamalala, J.R. & Albrecht, A. (2017). Carbon footprint of smallholder farms in Central Madagascar: The integration of agroecological practices. Journal of Cleaner Production, 140, pp.1165-1175. https://doi.org/10.1016/j.jclepro.2016.10.045

Rapsomanikis, G. (2015). The economic lives of smallholder farmers: An analysis based on household data from nine countries. Food and Agriculture Organization of the United Nations, Rome.

Reppin, S., Kuyah, S., de Neergaard, A., Oelofse, M., & Rosenstock, T. S. (2020). Contribution of agroforestry to climate change mitigation and livelihoods in Western Kenya. Agroforestry Systems, 94(1), 203-220.https://doi.org/10.1007/s10457-019-00383-7

Ricker-Gilbert, J. (2020). Inorganic Fertiliser Use Among Smallholder Farmers in Sub-Saharan Africa: Implications for Input Subsidy Policies. In The Role of Smallholder Farms in Food and Nutrition Security (pp. 81-98). Springer, Cham.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. Biometrika, 70, 41-55. https://doi.org/10.1093/biomet/70.1.41

Rosenbaum, P. R., & Rubin, D. B., (1983). The central role of the propensity score in observational studies for causal effects. Biometrika, 70, 41-55. https://doi.org/10.1093/biomet/70.1.41

Rosenbaum, P. R., & Rubin, D. B. (1985). The bias due to incomplete matching. Biometrics, 103-116.

Rosenstock, T.S., Mpanda, M., Pelster, D.E., Butterbach-Bahl, K., Rufino, M.C., Thiong'o, M., Mutuo, P., Abwanda, S., Rioux, J., Kimaro, A.A. & Neufeldt, H. (2016). Greenhouse gas fluxes from agricultural soils of Kenya and Tanzania. Journal of Geophysical Research: Biogeosciences, 121(6), pp.1568-1580.

Rudel, T. K., Meyfroidt, P., Chazdon, R., Bongers, F., Sloan, S., Grau, H. R., & Schneider, L. (2020). Whither the forest transition? Climate change, policy responses, and redistributed forests in the twenty-first century. Ambio, 49(1), 74-84. https://doi.org/10.1007/s13280-018-01143-0

Saguye, T. S. (2017). Analysis of farmers perception on the impact of land degradation hazard on agricultural land productivity in Jeldu district in West Shewa Zone, Oromia, Ethiopia. Journal of Agricultural Extension and Rural Development, 9, 111-123. DOI: 10.5897/JAERD2017.0854

Salami, A., Kamara, A. B., & Brixiova, Z. (2010). Smallholder agriculture in East Africa: Trends, constraints and opportunities. Tunis, Tunisia: African Development Bank. https://docs.igihe.com/IMG/pdf/working_105_pdf_d.pdf

Sapkota, T.B., Khanam, F., Mathivanan, G.P., Vetter, S., Hussain, S.G., Pilat, A.L., Shahrin, S., Hossain, M.K., Sarker, NR and Krupnik, T.J., 2021. Quantifying opportunities for greenhouse gas emissions mitigation using big data from smallholder crop and livestock farmers across Bangladesh. Science of the Total Environment, 786, p.147344.

Seebauer, M. (2014). Whole farm quantification of GHG emissions within smallholder farms in developing countries. Environmental Research Letters, 9(3), p.035006. https://iopscience.iop.org/article/10.1088/1748-9326/9/3/035006/meta

Seitz, S., Goebes, P., Puerta, V.L., Pereira, E.I.P., Wittwer, R., Six, J., van der Heijden, M.G. & Scholten, T., (2019). Conservation tillage and organic farming reduce soil erosion. Agronomy for Sustainable Development, 39(1), pp.1-10. Agronomy for Sustainable Development https://doi.org/10.1007/s13593-018-0545-z

SGS North America (2015) Agricultural Market Research the Carbon Footprint of Sorghum for sorghum.

Shiferaw, B., Kassie, M., Jaleta, M., & Yirga, C. (2014a). Adoption of improved wheat varieties and impacts on household food security in Ethiopia. Food policy, 44, 272-284. http://dx.doi.org/10.1016/j.foodpol.2013.09.012

Shiferaw, B., Tesfaye, K., Kassie, M., Abate, T., Prasanna, B. M., & Menkir, A. (2014b). Managing vulnerability to drought and enhancing livelihood resilience in sub-Saharan Africa: Technological, institutional and policy options. Weather and Climate Extremes, 3, 67-79. https://doi.org/10.1016/j.wace.2014.04.004

Sileshi, M., Kadigi, R., Mutabazi, K., & Sieber, S. (2019). Determinants for adoption of physical soil and water conservation measures by smallholder farmers in Ethiopia. International soil and water conservation research, 7(4), 354-361.https://doi.org/10.1016/j.iswcr.2019.08.002

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

Sommer, R., Thierfelder, C., Tittonell, P., Hove, L., Mureithi, J. and Mkomwa, S., 2014. Fertilizer use should not be a fourth principle to define conservation agriculture: response to the opinion paper of Vanlauwe et al.(2014) 'A fourth principle is required to define conservation agriculture in sub-Saharan Africa: the appropriate use of fertilizer to enhance crop productivity'. Field Crops Research, 169, 145-148. http://dx.doi.org/10.1016/j.fcr.2014.05.012

Sova, C. (2017) Assessing climate change adaptation needs in the agricultural sector: Experiences from the CGIAR Research Program on Climate Change, Agriculture and Food Security. https://cgspace.cgiar.org/handle/10568/80014

Streletskaya, Nadia A., Samuel D. Bell, Maik Kecinski, Tongzhe Li, Simanti Banerjee, Leah H. Palm-Forster, and David Pannell. (2020). "Agricultural adoption and behavioral economics: Bridging the gap." Applied Economic Perspectives and Policy 42, no. 1 54-66.

Svubure, O., Struik, P.C., Haverkort, A.J. & Steyn, J.M. (2018). Carbon footprinting of potato (Solanum tuberosum L.) production systems in Zimbabwe. Outlook on Agriculture, 47(1), pp.3-10. https://doi.org/10.1177%2F0030727018757546

Syahza, A., & Irianti, M. (2021). Formulation of control strategy on the environmental impact potential as a result of the development of palm oil plantation. Journal of Science and Technology Policy Management. https://doi.org/10.1108/JSTPM-06-2019-0059

Talanow, K., Topp, E. N., Loos, J., & Martín-López, B. (2021). Farmers' perceptions of climate change and adaptation strategies in South Africa's Western Cape. Journal of Rural Studies, 81, 203-219.https://doi.org/10.1016/j.jrurstud.2020.10.026

Tegemeo Institute. (2021). Unfavourable Tax Policies Constrain Post-Pandemic Recovery and Long-term success for the Sorghum Value chain. Tegemeo Institute Technical Report.

Teklewold, H., Kassie, M., & Shiferaw, B. (2013). Adoption of multiple sustainable agricultural practices in rural Ethiopia. Journal of agricultural economics, 64(3), 597-623.https://doi.org/ 10.1111/1477-9552.12011

Tesfahunegn, G. B., Ayuk, E. T., & Adiku, S. G. K. (2021). Farmers' perception on soil erosion in Ghana: Implication for developing sustainable soil management strategy. Plos one, 16, e0242444. https://doi.org/10.1371/journal.pone.0242444

Tesfahunegn, G. B., Mekonen, K., & Tekle, A. (2016). Farmers’ perception on causes, indicators and determinants of climate change in northern Ethiopia: Implication for developing adaptation strategies. Applied Geography, 73, 1-12.https://doi.org/10.1016/j.apgeog.2016.05.009

Tessema, Y. A., Joerin, J., & Patt, A. (2018). Factors affecting smallholder farmers' adaptation to climate change through non-technological adjustments. Environmental development, 25, 33-42. https://doi.org/10.1016/j.envdev.2017.11.001

Thierfelder, C., Matemba-Mutasa, R. & Rusinamhodzi, L., (2015). Yield response of maize (Zea mays L.) to conservation agriculture cropping system in Southern Africa. Soil and Tillage Research, 146, pp.230-242. https://doi.org/10.1016/j.still.2014.10.015

Thierfelder, C., Paterson, E., Mwafulirwa, L., Daniell, T. J., Cairns, J. E., Mhlanga, B., & Baggs, E. M. (2022). Toward greater sustainability: how investing in soil health may enhance maize productivity in Southern Africa. Renewable Agriculture and Food Systems, 37(2), 166-177. https://doi.org/10.1017/S1742170521000442

Thinda, K. T., Ogundeji, A. A., Belle, J. A., & Ojo, T. O. (2020). Understanding the adoption of climate change adaptation strategies among smallholder farmers: evidence from land reform beneficiaries in South Africa. Land Use Policy, 99, 104858. https://doi.org/10.1016/j.landusepol.2020.104858

Thornton, P.K., & Herrero, M. (2015). Adapting to climate change in the mixed crop and livestock farming systems in sub-Saharan Africa, Nat Clim Chang. 5 830-836. 10.1038/NCLIMATE2754 https://doi.org/10.1038/NCLIMATE2754

Tittonell, P., Corbeels, M., Van Wijk, M.T., Vanlauwe, B. & Giller, K.E. (2008). Combining organic and mineral fertilizers for integrated soil fertility management in smallholder farming systems of Kenya: Explorations using the crop-soil model FIELD. Agronomy journal, 100(5), pp.1511-1526. https://acsess.onlinelibrary.wiley.com/journal/14350645

Toan, D. T. T., Kien, V. D., Giang, K. B., Minh, H. V., & Wright, P. (2014). Perceptions of climate change and its impact on human health: an integrated quantitative and qualitative approach. Global health action, 7(1), 23025.https://doi.org/10.3402/gha.v7.23025

Udimal, T. B., Jincai, Z., Mensah, O. S., & Caesar, A. E. (2017). Factors influencing the agricultural technology adoption: The case of improved rice varieties (Nerica) in the Northern Region, Ghana. Journal of Economics and Sustainable Development, 8, 137-148.

United Nations Environment Programme (UNEP). (2015). Green Economy Sector Study on Agriculture in Kenya. https://wedocs.unep.org/handle/20.500.11822/32300

United Nations. (2016). Transforming our world: The 2030 agenda for sustainable development.

United Nations. (2019). World population prospects: The 2019 revision, New York, United Nations Population Division. 2019.

van der Burgt, F., van Pelt, S. & Lobbrecht, A. (2018). Mobile weather services for small-scale farmers. Success factors from African case studies. Weather Impact.

Van Ittersum, M. K., Van Bussel, L. G., Wolf, J., Grassini, P., Van Wart, J., Guilpart, N., & Cassman, K. G. (2016). Can sub-Saharan Africa feed itself?. Proceedings of the National Academy of Sciences, 113(52), 14964-14969. https://doi.org/10.1073/pnas.1610359113

Vanlauwe, B., Six, J., Sanginga, N., & Adesina, A. A. (2015). Soil fertility decline at the base of rural poverty in sub-Saharan Africa. Nature plants, 1(7), 1-1. https://doi.org/10.1038/NPLANTS.2015.101

Vanlauwe, B., Wendt, J., Giller, K.E., Corbeels, M., Gerard, B. and Nolte, C., 2014. A fourth principle is required to define conservation agriculture in sub-Saharan Africa: the appropriate use of fertilizer to enhance crop productivity. Field Crops Research, 155, 10-13. https://doi.org/10.1016/j.fcr.2013.10.002

Vervuurt, W., Slingerland, M.A., Pronk, A.A. & Van Bussel, L.G.J., (2022). Modelling greenhouse gas emissions of cacao production in the Republic of Côte d'Ivoire. Agroforestry Systems, 96(2), pp.417-434. https://link.springer.com/article/10.1007/s10457-022-00729-8

Waithaka, M.M., Thornton, P.K., Shepherd, K.D. & Ndiwa, N.N. (2007). Factors affecting the use of fertilizers and manure by smallholders: the case of Vihiga, western Kenya. Nutrient Cycling in Agroecosystems, 78(3), pp.211-224. https://link.springer.com/article/10.1007/s10705-006-9087-x

Wetende, E., Olago, D., & Ogara, W. (2018). Perceptions of climate change variability and adaptation strategies on smallholder dairy farming systems: Insights from Siaya Sub-County of Western Kenya. Environmental development, 27, 14-25. https://doi.org/10.1016/j.envdev.2018.08.001

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

World Bank & International Center for Tropical Agriculture (CIAT), (2015). Climate-smart agriculture in Kenya. CSA Country Profile. Washington DC: The World Bank Group. Retrieved from: https://cgspace.cgiar.org/handle/10568/69545

World Bank Group. (2018). Kenya Economic Update, April 2018, No. 17: Policy options to advance the Big 4. World Bank, Nairobi. Retrieved from: https://openknowledge.worldbank.org/handle/10986/29676

Wossen, T., Abdoulaye, T., Alene, A., Haile, M. G., Feleke, S., Olanrewaju, A., & Manyong, V. (2017). Impacts of extension access and cooperative membership on technology adoption and household welfare. Journal of rural studies, 54, 223-233. https://doi.org/10.1016/j.jrurstud.2017.06.022

Yamba, S., Appiah, D. O., & Siaw, L. P. (2019). Smallholder farmers' perceptions and adaptive response to climate variability and climate change in southern rural Ghana. Cogent Social Sciences, 5(1), 1646626.https://doi.org/10.1080/23311886.2019.1646626

Yigezu, Y.A., El-Shater, T., Boughlala, M., Devkota, M., Mrabet, R. & Moussadek, R., (2021). Can an incremental approach be a better option in the dissemination of conservation agriculture? Some socioeconomic justifications from the drylands of Morocco. Soil and Tillage Research, 212, 105067. https://doi.org/10.1016/j.still.2021.105067

Zeweld, W., Van Huylenbroeck, G., Tesfay, G., Azadi, H., & Speelman, S. (2020). Sustainable agricultural practices, environmental risk mitigation and livelihood improvements: Empirical evidence from Northern Ethiopia. Land use policy, 95, 103799. https://doi.org/10.1016/j.landusepol.2019.01.002

Zhang, D., Shen, J., Zhang, F., Li, YE & Zhang, W. (2017). Carbon footprint of grain production in China. Scientific Reports, 7(1), pp.1-11. https://www.nature.com/articles/s41598-017-04182-x

Zulfiqar, F., & Thapa, G. B. (2018). Determinants and intensity of adoption of "better cotton" as an innovative cleaner production alternative. Journal of cleaner production, 172, 3468-3478.https://doi.org/10.1016/j.jclepro.2017.09.024

APPENDICES

Appendix 1 Variance inflation factor (VIF) of the independent variables

Variable	VIF	1/VIF
Household and farm characteristics		
Gender	2.03	0.49
Literacy	1.81	0.55
Age	1.68	0.59
Occupation	1.62	0.62
Experience	1.46	0.68
Household size	1.45	0.69
Remittance	1.42	0.70
Acreage	1.34	0.74
Seed type	1.32	0.76
Seed quantity	1.23	0.81
Perceptions of soil status		
Fertility poor	1.21	0.83
Erosion high	1.21	0.83
Institutional factors		
Agricultural association	1.19	0.84
Farm credits	1.16	0.86
Extension	1.13	0.89
Weather information	1.10	0.91
Geographical location		
Site	1.09	0.92
Mean VIF	1.38	

Appendix 2 Test for validity of instrumental variable

Variable	Inorganic fertilizer adoption		Log sorghum yields (kg ha^{-1})	
	Coefficient	Robust std. error	Coefficient	Robust std. error
Weather information receipt	-0.678***	0.173	0.189	0.127
Constant	2.329***	0.851	3.296**	0.923
	LR Chi 2 (1) = 4.76		F Value = 0.19	

***P<0.001