

Pan African University

Institute of Water and Energy Science including Climate Change

**Adoption of Climate-smart agriculture practices among farmers and its effect
on crop revenue in Adea Berga District, Ethiopia.**

Department of Climate Change

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April,2024

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on crop revenue in Adea Berga District, Ethiopia.**

**A thesis submitted to Pan African University in partial fulfillment of the requirements for
the degree of Master of Science**

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DEDICATION

I dedicate this thesis manuscript to my beloved parents, Ato Chaka Gameda and W/ro Sara Guluma, whose unwavering love, support, and encouragement have been my guiding lights throughout this journey. To my brothers, Tekle Chaka, Firaol Chaka, and Naol Chaka, your constant encouragement and belief in my abilities have been a source of strength and inspiration. To my cousins Aster Tadele and Yeabsira Demessa, your friendship and encouragement have been a constant source of motivation, reminding me of the importance of perseverance and determination. Finally, I dedicate this thesis to the St. Gebriel Sunday School in Hawassa, where I learned the values of compassion, service, and faith, shaping me into the person I am today.

STATEMENT OF THE AUTHOR

I, hereby declare that this thesis entitled “ADOPTION OF CLIMATE-SMART AGRICULTURE PRACTICES AMONG FARMERS AND ITS EFFECT ON CROP REVENUE IN ADEA BERGA DISTRICT, ETHIOPIA” is a Bonafede record of research done by me during the allocated period for the research at the Pan African University, Institute of Water and Energy Science including climate change and the thesis has not previously formed the basis for the award to me of any educational institute’s degree, diploma, associateship, fellowship or other similar titles, of any other University or Scientific Society. I submit this document in partial fulfillment of the requirement for a degree from Pan African University. This document is available from the PAU Library to borrowers under the rules of the library.

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BIOGRAPHICAL SKETCH

The author was born in Hawassa, Sidama Region of Ethiopia, on October 10, 1998. She attended her elementary and secondary schools at Hawassa Nigste Fura Primary School from 2006 to 2013 and Alamura Secondary and Preparatory School from 2014 to 2015, and Preparatory school from 2016 to 2017 at Hawassa Tabor Senior Secondary & Preparatory School.

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In May 2022, she joined the Pan African University of Water and Energy Science as a scholarship award of PAU for a Master of Science Degree in Climate Change.

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ABBREVIATIONS AND ACRONYMS

ABW-ARDO	Animal and Biosystems Workforce – Agricultural Research and Development Outreach
ATT	Average Treatment Effect on the Treated
BFS/USAID	Bureau for Food Security/U.S. Agency for International Development
CIAT	International Center for Tropical Agriculture
CSA	Climate Smart Agriculture
CSAPs	Climate Smart Agricultural Practices
ENMA	Ethiopian National Metrology Agency
ETB	Ethiopian Birr
ESR	Endogenous Switching Regression
FAO	Food and Agricultural Organization
GDP	Gross Domestic Product
GHGs	Green House Gases
IPCC	Intergovernmental Panel on Climate Change
MESR	Multinomial Endogenous Switching Regression
PSM	Propensity Score Matching
SSA	Sub-Saharan African
TLU	Total Livestock Unit
UN SDG	United Nations’ Sustainable Development Goals

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ABSTRACT

Climate change presents a major challenge to the productivity of agriculture worldwide, necessitating the development of environmentally sustainable agricultural systems capable of withstanding its challenges. This study investigates the determinants influencing the adoption of climate-smart agriculture (CSA) practices among smallholder farmers, aiming to understand the factors guiding adoption decisions and evaluate the impact of CSA on smallholder farmer income. Data was collected through structured household surveys from 230 households by using a mixed method of purposive and simple three-stage stratified random sampling. Meteorological data spanning 30 years (1994 to 2023) were obtained from the Ethiopian National Meteorological Agency (ENMA). The Mann–Kendall and Sen’s slope tests, revealed no significant trend in total maximum annual rainfall but indicated a significant upward trend in total annual maximum temperature. The descriptive analysis showed that the sampled households had a mean livestock holding of 30.58 TLU, and an average annual farm income of 61,117.39 ETB. Approximately 50.87% of respondents received climate information, while 20.43% had access to credit services. Transitioning from non-adoption to adoption increased farm income from 52,584.07 to 69,358.97 ETB, accompanied by an increase in total land owned from 2.35 to 3.45 hectares. The multinomial logit model (MNL) demonstrated that education level, household size, land ownership, off-farm income, climate information, and contact with extension agents positively influenced adoption decisions, with erosion showing a negative influence across all practices. Additionally, education level significantly influenced the adoption of soil and water conservation practices and the joint adoption of CSA practices. Household size positively influenced the adoption of crop rotation, while off-farm income significantly affected the adoption of joint climate-smart practices. Livestock ownership negatively affected the adoption of soil and water conservation practices but positively influenced crop rotation adoption. Contact with extension agents was significant across all adoption types. The multinomial endogenous switching regression model (MESR) revealed that joint adoption of crop rotation and soil and water conservation practices significantly increased farm income by 1,107,245 ETB. Overall, these findings contribute valuable insights toward achieving sustainable economic growth, combating climate change, and enhancing resilience in agricultural systems.

Keywords: CSAPs, Multinomial Endogenous Switching Regression Model

1. INTRODUCTION

Climate change is a critical global barrier to agricultural outputs. It significantly influences the entire agricultural industry, potentially leading to positive outcomes like the expansion of agricultural production zones or negative consequences such as increased occurrences of natural disasters like heat stress. Developing nations, with a larger portion of their national gross domestic product derived from agriculture, bear a heightened impact. Moreover, these countries tend to be more susceptible to such variations compared to their developed counterparts (Long et al., 2016).

Developing countries like Sub-Saharan Africa (SSA), whose agriculture depends on rain, bear the brunt of climate change impacts on agriculture (Van *et al.*, 2016). Dry periods, meteorological droughts, flooding, unpredictable rainfall, farming calendar changes, and rising temperatures in the atmosphere are indicative of climate change (Bryan *et al.*, 2013). Climate change triggers crop failures and livestock declines, leading to food insecurity and posing significant risks to societal welfare (Thornton & Herrero, 2015). Climate change has the potential to affect food security through various pathways. A significant channel involves its influence on the quantity of food, stemming from direct effects on crop yields and indirect consequences related to changes in water availability and quality, as well as the prevalence of pests and diseases (FAO, 2015). Although the agricultural sector is affected by climate change, there is a growing need to increase food production to meet the demands of the rising population in Sub-Saharan African nations, including Ethiopia. Hence, interventions like the adoption of Climate-Smart Agricultural Practices (CSAPs) among smallholder farmers are crucial.

Ethiopia's agricultural sector is susceptible to climate change due to its reliance on traditional methods, dependence on rainfall, and the predominant involvement of smallholder farmers who lack sufficient resources to adapt to evolving environmental circumstances and unforeseen disasters (Skambraks, 2014). Climate change makes the ecosystem less capable of providing its services, as demonstrated by the inability to supply enough food to feed the smallholder farmers focused on agriculture. Accordingly, climate change is expected to elevate the risks associated with production as well, leading agricultural product producers to act irrationally. Research by Abebe & Bekele, (2017) suggests that by 2050, climate change might decrease Ethiopia's GDP by 8-10%, although implementing agricultural adaptation strategies could potentially halve losses

due to climate-related shocks. Ethiopian smallholder farmers are notably impacted by climate change, leading to fluctuations in their production and earnings, thereby heightening their vulnerability to food insecurity and poverty (Aragi, 2013).

The embrace of CSA practices is widely acknowledged as a promising and effective strategy to mitigate the negative effects of climate change (Lipper *et al.*, 2014). Climate-smart agriculture (CSA) is a strategy designed to direct the administration of agriculture amidst the challenges posed by climate change. CSA aims to establish principles applicable across regions to sustainably manage agriculture, ensuring food security amid the challenges posed by climate change. These principles could form the basis for policy advice and suggestions provided by the global organization (FAO) of the United Nations. The fundamental components of the CSA strategy were developed to address deficiencies in comprehending agriculture's contribution to food security within the global climate policy realm and its potential to leverage benefits from both adaptation and mitigation endeavors (Lipper & Zilberman, 2018).

CSA represents a holistic strategy aiming to achieve three objectives concurrently: increased productivity and income, enhanced resilience (adaptation), and reduced emissions (Totin *et al.*, 2018). In Ethiopia, various CSA practices have been implemented to enhance livelihoods and food security (Eshete *et al.*, 2020). These practices include integrated watershed management, integrated soil fertility management, sustainable land management, conservation agriculture, agroforestry, crop residue management, composting, improved livestock feed promotion, and rangeland management (Eshete *et al.*, 2020).

Research conducted by Jirata *et al.*, (2016) on a national scale in Ethiopia indicates that the adoption of Climate-Smart Agriculture (CSA) practices is not widespread. In theory, farmers must maximize profits to adopt either individual or combined CSA practices. The adoption of CSA practices needs to be higher in developing countries, including Ethiopia (Mazhar *et al.*, 2021). Despite their potential benefits, CSA practices and technologies like conservation agriculture and agroforestry remain under-adopted among Ethiopian smallholder farmers due to limited financial resources for initial investments and challenges with the insecure land tenure system (Gelaw, 2017).

1.2. Statement of problem

A wealth of literature explores the adoption effects of individual climate-smart practices, yielding diverse findings (Di Falco & Chavas, 2009); (Abdulai & Huffman, 2014); (Campbell *et al.*, 2014). Commonly cited pathways include the potential of climate-smart agriculture to enhance crop yields, ensure food and nutrition security, and mitigate crop failure (Di Falco & Chavas, 2009); (Abdulai & Huffman, 2014). Conversely, certain studies indicate reduced farm returns from plots treated with specific soil conservation practices, such as stone bunds, in Burkina Faso (Zougmore *et al.*, 2014), while others like (Nkala, 2011) found no significant impact of minimum tillage on household incomes in Mozambique.

Moreover, (Di Falco & Chavas, 2009) observed a beneficial impact of biodiversity on risk mitigation among barley farms in Ethiopia. Similarly, the research conducted by (Di Falco and Veronesi, 2014) suggests that adapting to climate change by implementing soil conservation methods, altering crop varieties, transitioning from early to late planting, and employing other strategies resulted in heightened maize yields among agricultural households in Ethiopia. Further research has shown that crop selection, soil conservation, and others can improve farmers' technical efficiency while reducing environmental harm (Mishra *et al.*, 2017). Although these studies help us understand the factors that influence the adoption of climate-smart practices and their effects on productivity and risk exposure, more research is required to determine whether individual climate-smart practices and combinations of those practices can complement or replace one another. An additional empirical investigation into the potential advantages of specific climate-smart agricultural practices on crop income and vulnerability to production risks within agroecology is prompted by the contradictory findings from these studies regarding the adoption's impact on farm productivity.

A few studies, typically from the perspective of monocropping (e.g., maize, rice, or wheat), have assessed the adoption and effects of several climate innovation practices on smallholder farmers' production and risk exposure (Di Falco & Veronesi, 2013); (Kassie *et al.*, 2014); (Kalinda *et al.*, 2017). However, for several reasons, this method of analyzing farm output and risk from the standpoint of monocropping may underestimate or overestimate the actual effects of adoption. First, adopting CSAPs in a mixed-cropping environment, such as soil and water conservation, may help other crops, such as wheat or sorghum, that would not be evident if the researcher focused solely on wheat production and ignored other crops. In a mixed-crop environment, there may also

be unfavorable crop interactions where just one crop performs better at the expense of others. Tessema (2019) found that some crops increase the productivity of others when analyzing the effects of conservation agriculture on farm productivity in a diverse crop setting. For instance, maize-cowpea mixed crop yields may be boosted because cowpeas fix nitrogen from the atmosphere. As a result, it is wise to examine production using data from all crops rather than just one.

1.3. Significance of the study

The study's goal aligns with global, continental, and regional development goals and agendas. It helps to achieve the United Nations' Sustainable Development Goals (Goal 8 and Goal 13) and supports the Africa We Want Agenda 2063 goals (Goal 5 and Goal 7). The UN SDG 8 promoting sustainable economic growth goes with the study's specific objective of investigating factors influencing smallholder farmers' adoption of climate-smart agriculture (CSA). Understanding these factors contributes to building the resilience of smallholder farmers, allowing them to continue their agricultural activities in the face of challenging climate conditions. Assessing the impact of CSA adoption on crop revenue is also crucial, as it directly relates to the economic well-being of smallholder farmers. The study's findings can shed light on how CSA practices contribute to increased crop revenue, thus supporting the goal of economic growth (Akter *et al.*, 2022).

Adopting climate-smart agriculture practices is a proactive approach to mitigating the effects of climate change. By understanding the factors influencing adoption choices, the study helps to address Goal 13(Climate action) of the UN SDG by encouraging actions that reduce the vulnerability of the agricultural sector to climate-related risks. The study's focus on the impact of CSA practices on income aligns with this goal's objective to enhance resilience and adapt to climate change impacts.

In addition to that, the study directly contributes to Agenda 2063's Goal 5 of Modern Agriculture and Productivity by investigating modern agricultural practices that increase productivity and production. Environmental Sustainability and Climate Resilience Goal 7 of this agenda emphasizes environmentally sustainable and climate-resilient economies and communities. The studies align with this goal by promoting agricultural systems that are environmentally sustainable and capable of withstanding the challenges posed by a changing climate.

1.4. Scope and objective of the study

This research seeks to address the critical global challenge of climate change's impact on agricultural productivity, focusing on its consequences in developing countries, particularly in Adea Berga district, Ethiopia. The study aims to understand the dynamics of climate change and assess its effects on the traditional, rain-fed agriculture practiced by smallholder farmers in Adea Berga district, Ethiopia. The vulnerability of Ethiopia's agriculture to climate change is exacerbated by limited adaptive capacity among smallholder farmers, leading to increased production risks and potential economic losses.

The primary objective of this study is to investigate the adoption and impact of Climate-Smart Agriculture (CSA) practices among smallholder farmers in Adea Berga district, Ethiopia. CSA, as an integrated approach, aims to enhance productivity, income, and resilience while reducing emissions. The study will specifically focus on identifying the determinants influencing the adoption of CSA practices in the study areas, understanding the factors guiding farmers' decisions to choose adoption, and evaluating the impact of CSA on smallholder farmer income and food security.

To achieve these objectives, the research will analyze the current state of CSA adoption in Ethiopia, considering the challenges faced by smallholder farmers, such as financial constraints and insecure land tenure systems. The study will draw upon existing literature on the impacts of individual climate-smart practices, recognizing the divergent findings in previous research. By investigating the effects of CSA practices on crop revenues and production risk exposure, the study aims to contribute valuable insights into building the resilience of smallholder farmers and fostering sustainable economic growth.

Furthermore, the research aligns with global and regional development goals, including the United Nations' Sustainable Development Goals (SDG 8 and SDG 13) and the Africa We Want Agenda 2063 goals (Goal 5 and Goal 7). The study's findings are expected to provide practical recommendations for policymakers and international organizations, facilitating the promotion of environmentally sustainable and climate-resilient agricultural practices in Ethiopia and similar contexts. Overall, the research aspires to contribute to the broader goals of achieving sustainable economic growth, combating climate change, and enhancing resilience in agricultural systems.

This document adheres to academic writing standards and is structured into five parts. The initial chapter serves as an Introduction, offering an overview of the research work, outlining its main topics, and providing detailed explanations of its scope and objectives. The second chapter is dedicated to the Literature Review, delving into the existing body of knowledge related to the paper's topic. This encompasses historical records, spanning from the commencement of recording climate datasets in the country to recent publications. Moving on to Chapter Three, the Methodology section explicitly outlines how the entire study was conducted to achieve its objectives in a scientifically rigorous manner. This involves a discussion on descriptive and statistical analysis, the selected econometric models, analytical methods, and other techniques utilized, along with the corresponding steps taken for the intended purpose. Chapter Four, titled Result and Discussion, follows, presenting the outcomes of the analysis and providing interpretations and discussion of the results. Finally, Chapter Five, titled Reference, compiles and presents the citations used throughout the document to substantiate facts, facilitate comparisons, and serve other relevant purposes.

2. LITERATURE REVIEW

2.1. Definition, concept and terms

This section offers a comprehensive understanding of theoretical, empirical, and methodological aspects, along with defining and discussing conceptual terms relevant to the research. It familiarizes the reader with concepts such as climate change, climate-smart agricultural practices, factors affecting adoption decisions, and their impact on smallholder farmers' income in Ethiopia and globally.

2.1.1. Concepts and terms

As outlined by the Intergovernmental Panel on Climate Change (IPCC), climate change denotes the variations in average weather conditions and their characteristics observed over varying temporal scales, spanning from months to millennia. These variations are discerned through prolonged assessments of temperature and precipitation trends, alongside other environmental parameters such as pressure and humidity levels. Moreover, the most well-known local and worldwide repercussions of climate change include the erratic weather patterns, melting of the world's ice sheets, and resulting rise in sea level (Lipczynska-Kochany, 2018).

2.1.2. Concepts of climate smart agriculture practice

Based on the definition of FAO climate-smart agriculture is “that sustainably increases productivity, resilience (adaptation), reduces/removes GHGs (mitigation), and enhances achievement of national food security and development goals” (FAO, 2010). It is additionally characterized as the integration of diverse agricultural methodologies and systems, alongside enhancements in input utilization encompassing seeds, pesticides, water, among others (Khatri-Chhetri *et al.*, 2019; Lipper *et al.*, 2014).

Technologies for CSA are tailored to specific contexts and locations, involving a range of biophysical and agronomic practices. Instances comprise enhanced seed types, crop sequencing, mixed cropping, and soil cover in agricultural practices. Integrated soil fertility management encompasses the use of both natural and synthetic fertilizers. Additionally, tillage, residue handling, water control methods (like irrigation, bunding, terracing, contouring, and water collection), integrated pest management (employing cultural, biological, and chemical controls), and

agroforestry (the coordinated cultivation of trees alongside crop and/or animal husbandry) are integral components of this holistic strategy (Branca *et al.*, 2021; Saguye, 2017). Climate-smart agriculture (CSA) holds promise in mitigating the intertwined effects of climate change and soil deterioration. CSA has the potential to alleviate the interlinked impacts of climate change and land degradation. It aims to boost agricultural production while preserving the functionality of ecosystem services (Kifle *et al.*, 2022).

While the advantages of CSA have been thoroughly examined and are apparent, it is crucial to acknowledge the associated disadvantages. Doshi *et al.*, (2019) have underscored key issues that farmers need to be mindful of, including potential challenges like unreliable and sluggish internet connectivity, sensor malfunctions impacting overall production processes, and a deficiency in expertise and understanding for smooth operations. It's also important to consider potential conflicts among various CSA elements; for instance, increased productivity may lead to higher greenhouse gas emissions (Pivoto *et al.*, 2018). Obtaining inputs like seeds and fertilizer promptly can present challenges (Lipper *et al.*, 2014), and implementing CSA technologies like sensors and smart devices may be hindered by a lack of financial resources.

Technology providers could pose challenges for CSA adopters (Long *et al.*, 2016), particularly in less developed nations. Nevertheless, it's worth noting that some CSA elements, such as alterations in intercropping, planting dates, and the use of resilient crop varieties, are cost-effective or even free (FAO, 2010). Additionally, Payments for Environmental Services (PES) offer an alternative solution by covering initial implementation costs (Engel & Muller, 2016), which is particularly beneficial for impoverished farmers facing significant economic impacts from climate change (Fernández, 2019). Beyond financial concerns, the availability of labor can also be a hurdle, given that many CSA practices demand higher labor intensity, including various irrigation systems (Mango *et al.*, 2018; Murray *et al.*, 2016), elements of conservation agriculture (Hellin & Fisher, 2019; Branca *et al.*, 2021), and bench terracing (Nyasimi *et al.*, 2017).

2.2. Impacts of climate change on agriculture and food security in Ethiopia

Climate change has helped researchers understand how crop yield sensitivity and agricultural productivity are affected by climate change, which is of great importance to the global economy.

In the present times, agriculture stands out as a highly vulnerable sector in the face of climate change. Fluctuations in climatic conditions from one year to another play a significant role in influencing variations in crop yields on a global scale. Studies affirm that without implementing measures to address the escalating trends of global warming, there could be a 16% reduction in agricultural productivity globally, with developing countries experiencing a more substantial decline of 21.3% (FAO, 2012; IPCC, 2014). The substantial poverty rates, food insecurity, and diminished productivity in Sub-Saharan Africa, including Ethiopia, predominantly stem from the limited adoption of agricultural technology and the impacts associated with climate change (Stuch *et al.*, 2021).

According to Kassaye *et al.*, (2021) climate change poses the pressing threat to various cereal crops, including teff, maize, wheat, barley, and sorghum. Agricultural technologies are not being invested in or adopted by farmers, field operations are uncertain, and extreme weather events are occurring more often, contributing to the vulnerability of these crops. To address concerns about current and future food security, and to communicate the implications of these impacts, the study emphasizes the importance of analyzing the projected impacts of climate change on agricultural productivity. According to the research findings, the mean monthly temperature rose significantly between 1988 and 2018, and rainfall increased as well. Crop yields were positively affected by increased maximum temperatures, but adversely affected by rising minimum temperatures. Notably, the total production witnessed a considerable increase since 2000, primarily attributed to expansions in the cultivated area. Despite this, the study's projections indicate that the yield of sorghum and wheat will decline by 18.1% and 13.2%, respectively, at the end of the 21st century due to a significant increase in temperatures as well as a decrease in rainfall. Conversely, teff and maize are expected to experience yield increases of 20.2% and 17.9%, respectively. These results underscore the intricate and diverse effects of climate change on various cereal crops, underscoring the necessity for tailored strategies to mitigate and adapt agricultural practices accordingly.

The impact of climate change, coupled with associated droughts, is inflicting harm upon Ethiopia's agricultural sector. The susceptibility of Ethiopian agriculture to climate change is exacerbated by its predominantly traditional, rain-fed nature, primarily carried out by smallholder farmers with limited adaptive capacities to cope with climate-related challenges and disasters (Skambraks, 2014; Hirpha *et al.*, 2020). The repercussions of climate change on Ethiopia's agricultural sector

reverberate through the country's economy, as emphasized by Thornton *et al.*, (2014). Gelaw (2017) predicts an 8–10% reduction in Ethiopia's GDP by 2050 due to climate change, but highlights that implementing agricultural adaptation measures could potentially cut losses related to climate shocks by half. The formidable challenge of climate change presents a significant threat to Ethiopian smallholder farmers, causing fluctuations in their agricultural output and earnings (Abebe & Bekele, 2017). This heightened vulnerability to food insecurity and poverty among smallholder farmers is increasingly alarming (Aragie, 2013; Alemu & Mengistu, 2019; Fekad & Bekalu, 2020) (Negera *et al.*, 2022).

Forecasts from models suggest that Sub-Saharan Africa will experience warming exceeding the global average, leading to extreme occurrences such as droughts and floods. This situation significantly affects smallholder farmers heavily dependent on rain-fed agriculture for sustenance. Additionally, there is an increased occurrence of pests and diseases, adversely affecting both livestock and crop productivity (Belay *et al.*, 2017).

2.3. Determinant factors of adopting climate-smart agricultural practices

The modest adoption of CSA among small-scale farmers sparks investigations into the factors influencing its uptake within this farming system. The research revealed that elements like educational background, income from farming and other sources, proximity of residence to the farm, interactions with agricultural extension agents, media exposure, engagement in agricultural production, affiliation with agricultural associations or groups, perception of climate change impact, and marital status are determinant factors. These factors were found to be influential and exhibited a favorable relationship with the adoption rate of CSA among small-scale farmers. (Abegunde *et al.*, 2019).

The implementation of CSA practices is discovered to be complementary. Additionally, factors such as the age and education level of the household head, land size, asset value, frequency of extension services, awareness of climate change, experience with climatic shocks, soil fertility, slope, and severity of soil erosion significantly influence both the adoption rate and intensity of CSA practices among farmers. In theory, farmers aim to maximize profits when adopting individual or combinations of CSA practices (Gelaw, 2017). However, the adoption of CSA

practices remains limited in developing nations like Ethiopia due to challenges such as financial constraints for initial investments and an insecure land tenure system, leading to the underutilization of practices like conservation agriculture and agroforestry among Ethiopian smallholder farmers (Mazhar *et al.*, 2021).

While there is agreement that the potential of CSA technologies to enhance natural resource management and ecosystem resilience for sustainable food security, Ethiopia's adoption rate remains low (CIAT, BFS/USAID, 2017). Factors affecting the adoption of CSA practices in the country include resource scarcity and ownership, policy formulation and implementation, inadequate infrastructure, and demographic, economic, and socio-cultural factors (Zerssa *et al.*, 2021; Kifle *et al.*, 2022).

According to Jirata *et al.*, (2016), the adoption of conservation agriculture in Ethiopia was influenced by shared perceptions among stakeholders, as well as socio-economic and environmental factors. Furthermore, they emphasized that the adoption of conservation agriculture technology was determined by factors such as the policy implementation manual and the existing farming practices.

As per the findings of Kifle *et al.*, (2022), the application of Binary logistic regression revealed that several factors influencing the adoption of CSA practices, including variables such as the type of farming system, farm size, availability of irrigated land, access to extension services, proximity to markets, and access to weather information.

Research, such as the study conducted by Brandt *et al.*, (2017), suggests that the adoption of CSA practices is influenced by socioeconomic factors, institutional assistance, and financial resources, including resource availability, access to extension services, and knowledge about technology utilization. These variables are crucial in explaining variations in adoption within agriculture, especially when considering CSA practices for sustainable agriculture.

2.4. Determinant factors of farmers' decision to choose adoption of climate-smart practices

Variations in climate and socioeconomic factors across the region influence the adoption of CSA practices, with farmers predominantly opting for measures like adjusting cropping schedules in response to climate change. The primary CSA practices adopted include altering cropping schedules, implementing zero or minimum tillage, managing water resources, utilizing improved crop varieties, and adopting nutrient management techniques.

Utilizing multinomial logistic regression, the investigation conducted by Sardar *et al.*, in 2021 uncovers compelling insights. It indicates that the decision to adopt CSA practices, ranging from single measures to a comprehensive package, is predominantly influenced by institutional factors (specifically weather information), financial resources, subsidies for CSA technologies, landholding size, farm household characteristics (including farming experience), and the farmers' educational attainment. These factors emerge as the primary determinants shaping farmers' choices regarding the adoption of CSA practices, encompassing those who decide to adopt at least one CSA measure.

The motivation for farmers to embrace CSA practices may be attributed to increasing temperatures during sowing periods and the availability of water in specific regions, which ultimately impacts sowing dates in irrigated areas. Furthermore, farmers who have experienced greater impacts from climatic shocks show a higher inclination to adopt CSA practices. The study's findings affirm that farmers who adopt a complete set of CSA practices achieve significantly higher yields—32% and 44% more kilograms per hectare—and increased farm income—45% and 48% more US dollars per hectare compared to non-adopting farmers, particularly in the context of cotton–wheat and rice–wheat crops.

The research conducted in Northern Togo employed Zero-inflated Poisson regression and multivariate analysis to identify the factors influencing households' selection of adaptation strategies. Primary determinants encompass gender, household location, education level, minimum consumption needs, land ownership, family size, and allocated labor. Institutional factors, such as market access, credit availability, and extension services, play a pivotal role in encouraging the adoption of environmentally friendly climate-smart practices. Additionally, farmers' choices regarding adaptation strategies may be influenced by their perceptions of climate

change. The most commonly adopted farming practices include the use of resistant and high-yielding varieties, integration of crops and livestock, soil and water conservation, organic fertilizer application, and adjustments to sowing times. The study highlights a strong complementarity among the various adopted practices, contributing to agricultural development (Ali, 2021).

Hence, a farmer's decision to employ multiple adaptation practices is contingent upon their perception of climatic risks. The selection of adaptation strategies is influenced by farmers' anticipated benefits in addressing climate change (CC) and their socio-economic circumstances. For example, the findings indicate that access to extension services contributes to an increased adoption of adaptation strategies, a trend consistent with the results reported by Deressa *et al.*, (2009) for Ethiopia and Di Falco (2014) for Sub-Saharan Africa. The socio-economic and regional characteristics of farm households have played a role in shaping farmers' choices. This outcome may be explained by traditional beliefs, such as praying to living gods and engaging in ceremonies, which previous studies, including those by Ali (2019) and Amegnalo *et al.*, (2017), have suggested could influence the selection of adaptation strategies.

These factors comprise individual household attributes (such as gender, age, education level, number of family members involved in farming, and experience in rice cultivation) (Lavison, 2013; Teklewold *et al.*, 2017); economic considerations (including income from rice farming, off-farm earnings, tropical livestock units, and rice farm size) (Maguza-Tembo *et al.*, 2017; Parvathi & Waibel, 2015); market-related factors (distance to input and output markets) (Wollni *et al.*, 2010); institutional aspects (access to agricultural extension services and credit, availability of climate information, trust in extension workers' expertise, and membership in social or agricultural groups) (Maguza-Tembo *et al.*, 2017; Mwangi & Kariuki, 2015; Teklewold *et al.*, 2017); climate-related shocks (including measures like rainfall satisfaction index, waterlogging, drought stress, and pest and disease pressure) (Kassie *et al.*, 2013; Teklewold *et al.*, 2013); farm characteristics (such as land tenure, slope of land, and soil fertility); and attitudes (including self-assessment of willingness to adopt new technologies and risk attitude) (Arslan *et al.*, 2017; Kassie *et al.*, 2013; Teklewold *et al.*, 2013, 2017; Tran *et al.*, 2020). The study investigated the influencing factors behind farm households' inclination toward adopting climate-smart agriculture, utilizing a logistic model.

The findings revealed that fundamental factors influencing the ability to adapt, including the human, physical, natural, financial, and social capacities of farm households, substantially influenced the likelihood of adopting climate-smart agriculture practices. Additionally, the research identified a lack of institutional support and inadequate information as significant barriers to the adoption of these innovative measures, as highlighted in the work by Sardar *et al.*, in 2019.

Ndiritu *et al.*, (2014) utilized multivariate and ordered probit models to examine the factors contributing the simultaneous adoption of CSAPs in Western Kenya. The analysis revealed both complementary and substitutive relationships between different CSAPs. The multivariate probit analysis identified several determinants influencing the adoption of CSAPs, including gender, education, age, family size, contact with extension agents, access to weather information, arable land, livestock ownership, perception of climate change, infertile soil, and persistent soil erosion. The ordered probit model highlighted the significance of gender, arable land, livestock ownership, soil fertility, and constant soil erosion in determining the adoption of CSAPs. Smallholder farmers opt for CSAPs as a strategy to cope with climate change-related challenges.

Small-scale farmers encounter complex choices regarding the adoption, non-adoption, or selection of individual or combined CSAPs for mitigating and adapting to climate change.

The decision to adopt CSAPs is primarily influenced by expected satisfaction, as proposed by Rabin (2013), wherein farmers opt for adoption if the anticipated benefits outweigh non-adoption. Nevertheless, smallholder farmers also grapple with the decision of whether to adopt a combination of CSAPs, as indicated in studies by Kpadonou *et al.*, (2017), Mulwa *et al.*, (2017), and Musafiri *et al.*, (2022).

2.5. Impacts of CSA on smallholder farmer income

The adoption of CSA represents a crucial pathway for enhancing the livelihoods of smallholder farming communities in developing nations facing climate change challenges and limited agricultural land availability (Zougmore *et al.*, 2016). CSA plays a vital role in helping farmers meet the escalating rising food demand, contributing to overall food security, economic progress, and poverty alleviation (Ouédraogo *et al.*, 2019). Existing research suggests that heightened agricultural productivity can positively impact household welfare by well-being by augmenting

income and enhancing food security through the production of their own food (Sani & Kemaw, 2019).

Multiple research endeavors have examined the impacts of CSA, uncovering various outcomes including direct benefits such as improved crop and livestock yields and decreased overall variable expenses. Additionally, indirect effects like enhanced food security have been observed, stemming from greater access to staple crops both within households and in markets, increased individual consumption, boosted household earnings, and a heightened demand for agricultural labor, resulting in improved wage rates (Fentie & Beyene, 2019).

A study by Mujeyi *et al.*, (2021) investigated the impact of climate-smart agriculture on household well-being within integrated crop-livestock farming systems among smallholders in Zimbabwe. Their findings revealed that factors such as soil fertility levels, access to input markets, total land use (TLU), and ownership of communication assets significantly shape farmers' decisions to adopt CSA practices. Moreover, the Average Treatment Effect on the Treated (ATT) was found to be positive and statistically significant, suggesting that CSA adoption has had a notably beneficial effect on farmers' welfare.

The study utilizes endogenous switching regression (ESR) to address endogeneity concerns and selection bias related to the adoption of Climate-Smart Agriculture (CSA). Propensity score matching (PSM) is also employed for a robustness check. The consistent findings from both models reveal that the adoption of CSA has positive effects on both yield and income for smallholder farms. Notably, if households that have not adopted CSA are mindful of soil salinity and decide to adopt it, their crop yield could increase by 7.55%. Furthermore, non-adopting households would experience significant income gains due to the adoption of CSA. The results underscore the substantial impact of CSA adoption on both crop yield and household income (Akter *et al.*, 2022).

Employing a propensity score matching approach, the study investigated the impact of Climate-Smart Agriculture (CSA) practices on income of farm household and food security. The finding of the analysis indicate that the adoption of CSA practices has positively influenced household food security and has led to an improvement in the average annual income of households.

Specifically, beneficiaries who adopted improved breeding and soil and water conservation practices experienced a significant increase in their average annual income.

In communities facing food insecurity, the selection of CSA practices should prioritize those that contribute more significantly to enhancing household food security. Conversely, in food-secure communities, the emphasis should be on promoting CSA practices that are related to income generation. Identifying suitable CSA options tailored to specific locations can assist decision-makers and funding organizations in prioritizing the expansion of CSA practices.

Climate-Smart Agriculture (CSA) stands out as a sustainable solution among various development options, offering opportunities to boost agricultural productivity and income through adaptation strategies, resilience building against climate change, and mitigation of greenhouse gas emissions (FAO, 2013; Engel & Muller, 2016; Tesfaye *et al.*, 2021). Aggarwal *et al.*, (2018) found that adopting CSA practices leads to heightened agricultural productivity, thereby enhancing household income and ensuring food and nutrition security.

Farmers' adoption of Climate-Smart Agriculture (CSA) practices serves as a dual solution, mitigating climatic risks while simultaneously boosting crop productivity and farm income through enhanced production. This adoption not only directly contributes to income growth but also acts as a strategy to mitigate the negative effects of climate change and variability, as emphasized by Hussain *et al.*, (2022). Additionally, findings by Ogunyiola *et al.*, (2022) indicate that farmers adopting CSA practices experience reduced climatic risks, increased crop productivity, improved household income, and the fulfillment of food consumption requirements.

On the contrary, farmers' choice to refrain from adopting Climate-Smart Agriculture (CSA) or to continue with traditional farming methods can exacerbate risks, making them more susceptible to the effects of climate change and diminishing farm income through decreased crop yields per hectare (ha), as noted by Sardar *et al.*, (2021). Embracing CSA practices provides smallholder farmers with a means to augment crop income, bolster food security, and alleviate losses and damages stemming from climate change, as indicated by Musafri *et al.*, (2022) and Sedebo *et al.*, (2022).

The significant findings of the study underscore that smallholder farmers implementing CSA measures have achieved notably higher farm income and improved food security compared to those who have not adopted these practices (Belay *et al.*, 2023).

3. MATERIALS AND METHODS

3.1. Description of the study area

3.1.1 Location and size

The present study was conducted in the Adea Berga districts located in the West Shewa Zone of the Oromia Regional State, Ethiopia. Situated approximately 65 km west of Addis Ababa, the district shares boundaries with Walmara to the south, Ejere to the southwest, Meta Robi to the west, and the Muger River to the north and east. Geographically, Adea Berga lies between 9° 14' 60" N latitude and 38° 24' 60" E longitude, with elevations ranging from 1,166 to 3,238 meters above sea level. Covering a total area of 798.35 km², the district comprises 34 rural kebeles and three urban towns: Enchini, Muger, and Reji (Adea Berge Woreda- Agricultural and Rural Development Office, ABW-ARDO, 2022).

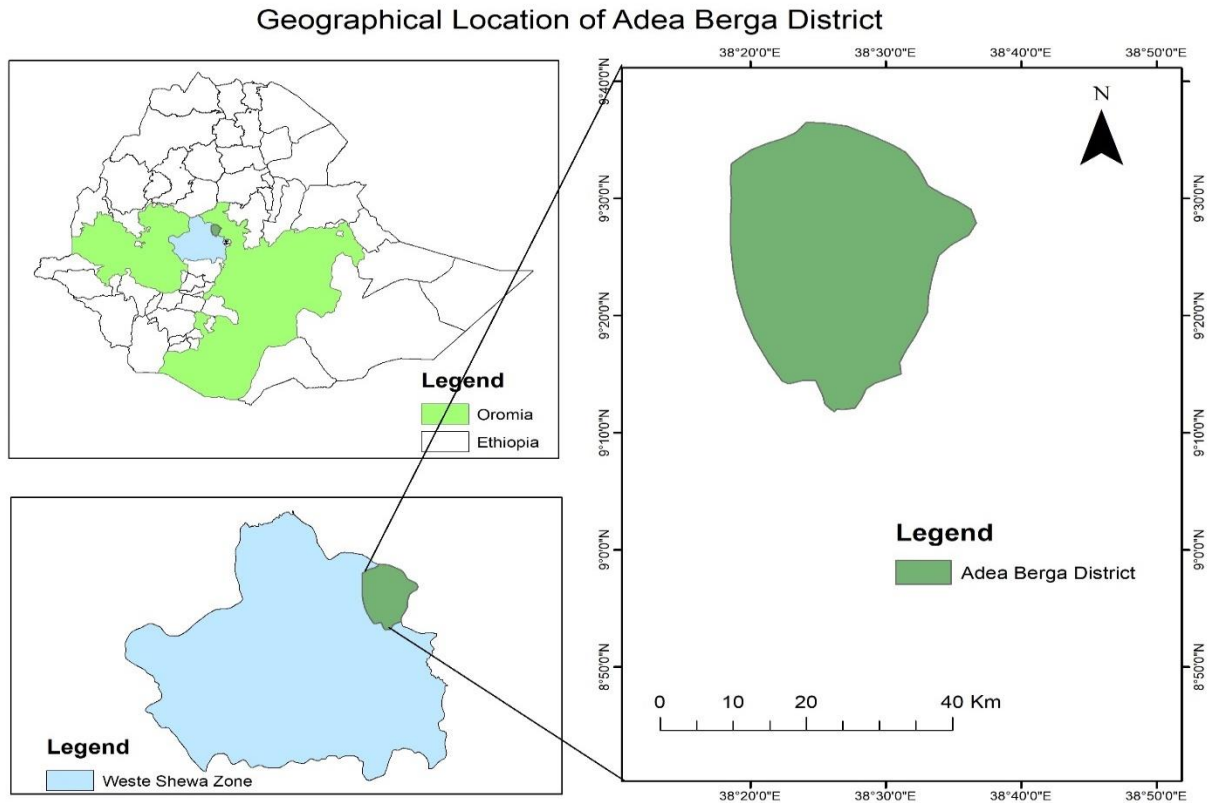


Figure 3.1| Map of Adea Berga District

3.1.2. Topography and soil

The district's topography encompasses a variety of landforms, including elevated areas, undulating lands, river-cut valleys, and plateaus. The altitude ranges from 3,169 masl at Bilacha to 1,371 masl at Ebisa Agasa. The elevated regions, primarily in the Dega and Woina Dega agro-climatic zones, mostly feature plateaus. These elevated areas act as watersheds between the tributaries of the Abay and Awash Rivers. Conversely, the Qolla section of the district is characterized by river-cut valleys, particularly along the Muger River and its tributaries, as well as undulating stony terrain. This region has relatively sparse human settlement (ABW-ARDO, 2022).

According to data compiled by the Adea Berga woreda agricultural office, the district's land surface is predominantly covered by three main soil types. Vertisols make up 44 percent of the land surface and are commonly found in the Qolla and Woina-dega agro-climatic zones. Nithosols, covering the Dega agro-climatic zone, account for 39 percent. The remaining 17 percent consists of Luvisols and is found in the Woina-dega and Qolla parts of the district (ABW-ARDO, 2022).

3.1.3. Climate and drainage

The variation in altitude within Adea Berga district results in the presence of three distinct agro-climatic zones: Dega, Woina-Dega, and Qolla, constituting 29%, 34%, and 37% respectively. The district experiences an average annual rainfall ranging from 918 to 1450 millimeters and temperatures between 11 to 21 degrees Celsius (ABW-ARDO, 2022). The southern, eastern, and western parts of the woreda are primarily dominated by the Dega and Woina-Dega agro-climates, while the Qolla agro-climate is confined to the northern part. Rainfall is distributed throughout most months of the year, with varying amounts and magnitudes across seasons. The highest concentration of rainfall occurs in June, July, August, and September, with a significant amount also observed during the Belg season (March, April, and May).

Adea Berga woreda is rich in both permanent and seasonal rivers. Major rivers that flow through the woreda include Muger, Shobore/Warke, Birate, Rushe, and Berga. These rivers, along with smaller streams, contribute water to the Abay and Awash Rivers. Rivers like Shobore/Warke, Birate, and Rushe drain into the Abay via the Muger River, while Berga drains into the Awash River (ABW-ARDO, 2022).

3.1.4. Demography

According to the population projections from 2017, the total population of the district is currently estimated at 183,599, with 91,120 males and 92,479 females. The sex ratio in the woreda is nearly balanced between males and females. Approximately 30,556 households are located in Adea Berga, with an average family size of 6 individuals per household (CSA population projection, 2023).

3.1.5. Major livelihood

Adea Berga district is primarily characterized by rural areas, and the sustenance of the local population relies significantly on a combination of crop cultivation and animal husbandry. In the Dega and Woina Dega agro-climatic zones, there is concentrated cultivation of wheat, barley, and pulses, with high-density settlements. Urban centers within the district are marked by common activities such as hotels, shopping, and cement production. (ABW-ARDO, 2022).

3.2. Sample size and sampling procedure

The sampling approach utilized in this study combined purposive and simple random sampling methods, employing a three-stage stratified random sampling procedure to enhance the reliability and validity of the data. Initially, Adea Berga District was purposively selected due to its susceptibility to frequent droughts, climate-related risks, and the researcher's interest. Subsequently, three kebeles—Ula Gora, Getira Nabe, and Bishan Disnu—were chosen at the second stage based on factors such as agricultural production systems, potential for CSA practices, climatic conditions, soil quality, latitude, and socio-physical context. Furthermore, households were divided into two strata: adopters of CSA practices and non-adopters. Finally, households were randomly sampled from each stratum using a simple random sampling technique, with selection probabilities proportional to the population size of each kebele.

The sample size was calculated using Yamane's (1967) formula, ensuring a 95% confidence level, a degree of variability of 0.05, and an estimated margin of error of 8.5%.

$$n = \frac{N}{1 + N(e)^2}$$

Where:

n = the required sample size

N = population size

e = is the level of precision

Hence, the sample size was established as follows:

$$n = \frac{542}{1 + 542(0.05)^2}$$
$$= 230 \text{ households}$$

The sample size for each kebele was determined as:

$$n_i = n \left(\frac{N_i}{N} \right)$$

In this equation, "ni" represents the sample size from each selected kebele, "n" is the total sample size of the study (the sum of the sample sizes of the three kebeles), "Ni" is the total number of farm households in each respective kebele, and "N" represents the total household size in the selected three kebeles, which is the total population. Table 3.1 illustrates the proportional sample size of the three kebeles.

Table 3.1 Distribution of sample households in each kebele

Sample Kebeles	Household size	Adopters		Non-adopters		Total Sample
		Total	Sample	Total	Sample	
Ula Gora	456	235	41	221	39	80
Getira Nabe	435	223	39	212	38	77
Bishan Disnu	416	215	38	201	35	73
Total	1307	673	118	634	112	230

Source: Adea Berga district agriculture office and own computation (2024).

3.3. Method of data collection

For this research, primary data was acquired through a structured questionnaire survey conducted during household visits. Secondary data were sourced from reports of agricultural and development offices at the woreda and kebele levels, along with various documents including published journal articles, research reports from organizations, books, and related proceedings. Additionally, temperature and rainfall data spanning 30 years (1994 to 2023) were obtained from the Ethiopian National Meteorological Agency (ENMA), derived from meteorological stations situated in Enchini (for rainfall) and neighboring districts Addis Alem (for temperature).

3.4. Data analysis

3.4.1. Mann-Kendal test

The MK test is utilized to identify statistically meaningful trends of decrease or increase within long-term temporal data, as outlined by Aditya *et al.*, 2021. The MK trend test is grounded on two hypotheses: one being the null hypothesis (H0), and the other the alternative hypothesis (H1) (Lebeza *et al.*, 2023). H0 posits the absence of any trend, whereas H1 suggests a significant upward or downward trend in precipitation data (Agbo *et al.*, 2021). At a significance level of 5%, if the p-value is less than 0.05, the alternative hypothesis is upheld, indicating the presence of a trend in the data. Conversely, if the p-value is equal to or greater than 0.05, H0 is accepted, indicating no trend in the data (Baig *et al.*, 2021). The formula for this test is represented by the following equation:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sign}(X_j - X_i) \quad (1)$$

Here, n represents the total number of data points, X_j and X_i denote the annual values in years j and i , $j > i$ and $\text{Sign}(X_j - X_i)$ determined using the following equation:

$$\text{Sign}(X_j - X_i) = \begin{cases} -1 & \text{for } (X_j - X_i) < 0 \\ 0 & \text{for } (X_j - X_i) = 0 \\ +1 & \text{for } (X_j - X_i) > 0 \end{cases} \quad (2)$$

3.4.2. Test of Sen's slope estimator

This test initially devised by Sen to assess statistical linear relationships, and it is employed to gauge the extent of trends within long-term temporal data (Garba & Udokpoh, 2023).

Sen's slope is favored for its ability to detect linear relationships without being influenced by outliers in the dataset, as emphasized by Ray *et al.*, (2021). In this research, Sen's slope method is utilized to determine the trend magnitude for temperature and rainfall data. The subsequent equation is employed to calculate each individual slope (Q_i):

$$Q_i = \frac{Y_j - Y_i}{j - i} \quad (3)$$

In this equation, i ranges from 1 to $n-1$, j ranges from 2 to n . Y_j and Y_i represent data values at time j and i respectively, where ($j > i$). If there are n values of Y_j in the time series, the estimate of the slope will be $N = n(n-1)/2$. The slope of the Sen estimator is the mean slope among these N values. The formula for Sen's slope is as follows:

$$Q_{ij} = \begin{cases} \frac{Y_j - Y_i}{j - i} & \text{if } n \text{ is odd} \\ \frac{1}{2} (Q_{\frac{N}{2}} + Q_{[\frac{N+2}{2}]}) & \text{if } n \text{ is even} \end{cases} \quad (4)$$

A positive (Q_i) signifies a trend of increasing, whereas negative Q_i values indicate a decreasing trend in the temporal data. Sen's slope (Q_i) is expressed in units of slope magnitude per year.

3.4.3. Econometrics model analysis

3.4.3.1. Modelling choice of climate-smart agricultural practice

Suppose the farmer aims to maximize anticipated benefits by employing a combination of CSAP. The anticipated benefits for the i^{th} plot resulting from the implementation of a combination of practices (denoted as U^*_{it}) are expressed. However, these expected benefits, encapsulated in the latent variable U^*_{it} , are not directly observable. They can be articulated as a function of both observed characteristics (X_i) and unobserved factors (ε_{it}), presented as follows:

$$U^*_{it} = X_{it}\beta_t + \theta_t\bar{X}_{it} + \varepsilon_{it} \quad (1)$$

In the decision-making process for adoption, let U_i represent an index signifying the farmer's observed selection of a combination of practices, as follows:

$$U_i = \begin{cases} 1 & \text{if } U_{i1}^* > \max_{k \neq 1} (U_{ik}^*) \text{ or } \varepsilon_{i1} < 0 \\ M & \text{if } U_{iM}^* > \max_{k \neq t} (U_{it}^*) \text{ or } \varepsilon_{iM} < 0 \end{cases} \quad (2)$$

where $\max_{k \neq t} (U_{it}^* - U_{ik}^*) < 0$. Equation 2 suggests that a farmer will employ CSAP t on plot i with the aim of maximizing expected benefits, given that the selected practice offers higher expected benefits than any other available alternative $k \neq t$, that is if $\varepsilon_{it} = \max_{k \neq t} (U_{it} - U_{ik}^*) < 0, \forall t, k \in M$. In this research, the incorporation of two CSAPs, crop rotation and soil and water conservation, yields four potential options for farmers to select from (specifically: adopting crop rotation only, adopting soil and water conservation only, joint adoption, or non-adoption). Assuming that ε_{it} in Equation 1 adheres to an independent and identically distributed Gumbel distribution, the probability of opting for practice t can be delineated through a multinomial logit (MNL) model, as proposed by McFadden (1972).

$$P_{it} = P(\varepsilon_{it} < 0 | X_i) = \frac{\exp(X_{it}\beta_t + \bar{X}_{it}\delta_t)}{\sum_{k=1}^M \exp(X_{it}\beta_k + \bar{X}_{it}\delta_k)} \quad (3)$$

Here, \bar{X}_{it} represents a set of average plot-specific variables, and δ_t represents the corresponding parameters subject to estimation. The parameters of the latent model in Equation 3 are estimated using a maximum-likelihood approach. Following this, we utilize the Multinomial Endogenous Switching Regression framework (MESR) to analyze the chosen strategies, establishing the link between Climate-Smart Agricultural Practices (CSAP) and the focal outcomes, notably crop revenues and the distribution of revenue skewness.

3.4.3.2. Multinomial endogenous switching regression model

The multinomial endogenous switching regression (MESR) model, introduced by Bourguignon *et al.*, (2007) and applied in various empirical studies (e.g., Oparinde 2021; Zegeye *et al.*, 2022; Mabe, 2023), is employed in this research. In this methodology, the base category is non-adoption, denoted as $t = 0$. For the other practices ($t = 1$ for crop rotation only, $t = 2$ for soil and water conservation only, $t = 3$ for joint adoption), at least one combination of CSAP is implemented on a plot. The outcome equation for each potential regime t is expressed as follows:

$$\begin{cases} \text{Regime 1 : } y_{i1} = Z_{i1}\alpha_1 + \bar{Z}_{i1}\theta_t + j_{i1} \text{ if } U_i = 1 \\ \text{Regime } M : y_{it} = Z_{it}\alpha_t + \bar{Z}_{it}\theta_t + j_{it} \text{ if } U_i = 1 \end{cases} \quad (4)$$

In the equation, y_{it} refers to the outcome variable (crop revenue) of the i^{th} farm plot in regime M , Z_i represents a vector of farm and household characteristics, and the j 's indicate error terms with anticipated mean values of zero and constant variance, denoted as $Var(j_{it}|X_i, Z_i) = \sigma_t^2$, while α_t signifies a vector of parameters subject to be estimated.

The variable \bar{Z}_i represents the average of specific plot characteristics such as soil fertility, slope, and drainage. Meanwhile, θ_t signifies the parameters to be calculated for these characteristics. This is crucial to address unobserved variations arising from the correlation between plot-specific traits and household-level variables when a household is involved in cultivating multiple plots. The variable \bar{Z}_i refers to mean plot-specific characteristics (e.g. soil fertility, plot slope and drainage), and θ_t denotes the corresponding parameters to be estimated (Mundlak 1978). A Wald test is performed to assess the significance of plot-specific heterogeneity by testing the null hypothesis that the vector θ_t is collectively equal to zero (Issahaku & Abdulai, 2020).

To ensure the unbiased and consistent estimation of α_t in Equation 4, it is necessary to incorporate selection correction terms derived from the multinomial selection process. Following the approach of Bourguignon *et al.*, (2007), we assume a linear correlation between the error terms (ε_{it}) and j_{it} for each option t . The expected value of j_{it} is expressed as $E[u_1|\varepsilon_1, \dots, \varepsilon_t] = \sigma \sum_{t=1 \dots M} \rho_t \varepsilon_t$, where ρ_t represents the correlation between j_{it} and ε_{it} , and σ is the standard deviation of the error term j_{it} . Thus, the modified outcome equation (Equation 4), accounting for the bias correction associated with the choices made, can be reformulated as described in Issahaku & Abdulai, (2020):

$$\begin{cases} \text{Regime 1 : } y_{i1} = Z_{i1}\alpha_1 + \sigma_1\hat{k}_{i1} + \bar{Z}_i\theta_t + \omega_{i1} \text{ if } U_i = 1 \\ \text{Regime M : } y_{it} = Z_{it}\alpha_t + \sigma_t\hat{k}_{it} + \bar{Z}_i\theta_M + \omega_{it} \text{ if } U_i = T \end{cases} \quad (5)$$

Where $k_{it} = \sum_{k \neq t}^M \rho_t \left[\frac{\hat{P}_{ik} \ln(\hat{P}_{ik})}{1 - \hat{P}_{ik}} + \ln \hat{P}_{it} \right]$ refers to the inverse Mills ratios computed from the estimated probabilities in MNL model in Equation 3, ρ_t is the correlation coefficient between the error terms ε_{it} and u_{it} , with the error terms ω_{it} assumed to have a zero mean, and \hat{P}_{it} denotes the estimated probability that plot i is treated with practice t .

3.4.3.3. Estimation of counterfactual and treatment effects

We calculate anticipated results in both actual and counterfactual scenarios based on the methodology outlined in Issahaku & Abdulai, (2020). To begin with, we compute the expected

outcomes for plots subjected to treatment, where treatment corresponds to $t = 2, \dots, M$ (with $t = 1$ serving as the reference category, signifying non-adoption). Utilizing Equation 5, the conditional expectations for each outcome variable associated with the adoption practice are determined as follows:

For adopters with observed adoption (actual adoption observed in the sample):

$$\begin{aligned} E(y_{i2}|U_i = 2) &= Z_{i2}\alpha_2 + \sigma_2\hat{k}_{i2} + \bar{Z}_i\theta_2 \\ E(y_{it}|U_i = T) &= Z_{it}\alpha_t + \sigma_t\hat{k}_{it} + \bar{Z}_i\theta_t \end{aligned}$$

The counterfactual case that adopters did not adopt is also stated as:

$$\begin{aligned} E(y_{i1}|U_i = 2) &= Z_{i2}\alpha_1 + \sigma_1\hat{k}_{it} + \bar{Z}_i\theta_t \\ E(y_{i1}|U_i = t) &= Z_{ij}\alpha_1 + \sigma_1\hat{k}_{it} + \bar{Z}_i\theta_t \end{aligned}$$

The effect of adopting practice t is represented as the average treatment effect on the treated (ATT), which is determined by subtracting Equation 6 from 7, resulting in Equation 8 as follows:

$$\begin{aligned} ATT &= E(y_{2i}|U_i = 2) - E(y_{i1}|U_i = 2) \\ &= Z_{i2}(\alpha_2 - \alpha_1) + \bar{Z}_{i2}(\theta_2 - \theta_1) + \hat{k}_{i2}(\sigma_2 - \sigma_1) \end{aligned}$$

The term $\hat{k}_{it}(\cdot)$, along with the Mundlak device (\bar{Z}_{i2}), addresses selection bias and endogeneity arising from unobserved heterogeneity. The MESR approach facilitates the reliable and efficient estimation of α_2 offering a sensible correction for bias in the outcome equations, even when the assumption of independence of irrelevant alternatives (IIA) is not satisfied (Bourguignon *et al.*, 2007).

Another benefit of employing this approach is its capability to assess the impact of both individual climate-smart agricultural practices and their combinations, as demonstrated by Issahaku & Abdulai, (2020). Additionally, it alleviates the restrictive assumptions inherent in Lee's (1983) selectivity model and provides a comprehensive understanding of the selectivity effects on all options considered by farmers. To ensure proper identification of the MESR model, it is recommended to incorporate some variables in the vector X_i that are not present in the vector Z_i (Bourguignon *et al.*, 2007). In this study, we utilize farmers' perceptions of the impact of adopting CSAP on income and their access to climate information as identifying instruments.

These variables naturally impact farmers' choices to adopt CSAP but may not have a direct influence on farm revenues, as indicated by Issahaku & Abdulai, (2020). The researcher verifies the credibility of these instruments through a falsification test, in which a variable is deemed a valid instrument if it influences farmers' decisions to adopt a practice but does not affect the outcome variables for non-adopters, according to Issahaku & Abdulai, (2020).

The study conducted a robustness check on our findings by employing an alternative approach using multivariate treatment effects. This approach considers unobservable factors within a framework of multinomial choice and impact analysis, as outlined by Khonje *et al.*, (2018). To address potential endogeneity in our model, particularly with regard to having off-farm income and extension contact, we control for these variables. The presence of off-farm income might be used to purchase inputs or invested in CSAP this is the income effect. On the other hand, participation in off-farm work is potentially endogenous since the adoption of certain CSAP is labor-intensive, and households engaged in off-farm work may face challenges in adopting such practices, leading to a labor-loss effect. Regarding extension contact, there's a possibility that farmers adopting practices may attract more contact from extension staff compared to non-adopters. To handle the potential endogeneity of the variables, the study employed the control function approach, as outlined by Woldeyohanes *et al.*, (2017). This approach entails specifying the potentially endogenous variable (e.g., off-farm work participation or extension contact) as a function of explanatory variables influencing the adoption of each practice. This specification is combined with a set of instruments in a first-stage probit regression (for extension contact, a Poisson specification was used in the first stage). Rather than employing predicted values of variables like off-farm income or extension contact, as in two-stage-least-squares, the MESR model incorporates observed values of the endogenous variables and the generalized residuals derived from the initial regression as covariates. This incorporation of residuals acts as a control mechanism, ensuring the reliable estimation of potentially endogenous variables in the MESR model, as outlined by Woldeyohanes *et al.*, (2017).

3.5. Definition of variables and hypothesis

Dependent Variable

Adoption choice of CSA practice: In the analysis, it is measured by the likelihood of smallholder farmers opting for crop rotation only, soil and water conservation only, joint adoption, or none of these practices.

Outcome Variables

Annual farm cash income: A continuous variable represents the annual farm cash income accrued by households through livestock sales, crop production, and off/non-farm activities. This variable, measured in Ethiopian Birr (ETB), denotes the outcome and is logarithmically transformed.

Crop revenue: This is a continuous variable that signifies the total income households generate from the sale of various types of crops. It is the second outcome variable measured in terms of ETB.

Table 3.2 | Independent variables or Predictors

N/S	Variables	Type	Measurement	Expected Sign
1	Age of the household head	Continuous	Year	+
2	Sex of the household head	Dummy	1=Male, 0 otherwise	+
3	Education status of the household head	Categorical	0=No formal education, 1=Primary school, 2=Junior high school, 3=Senior secondary school, 4=Tertiary education, 5=Postgraduate	+
4	Landholding size	Continuous	Hectare	+/-
5	Frequency of extension contact	Continuous	Amount of contact per year	+/-

6	Distance between the farm and the homestead	Continuous	Hours	+/-
7	Credit access	Dummy	1 = yes, 0 otherwise	+
8	Agronomic Practices	Dummy	1 = yes, 0 otherwise	+/-
9	Soil and water conservation practices	Dummy	1 = yes, 0 otherwise	+
10	Cultivating different crops	Dummy	1 = yes, 0 otherwise	+
11	Off/non-farm income	Dummy	1 = yes, 0 otherwise	+/-
12	Number of livestock owned	Continuous	No. of livestock	+
13	Changing planting dates	Dummy	1 = yes, 0 otherwise	+/-
14	Distance from the nearest market	Continuous	Hours	-
15	Fertiliser	Continuous	Kilograms	+/-
16	Herbicide	Continuous	Liters	+/-
17	Hired labour	Continuous	ETB	-
18	Household size	Continuous	No. of people	+
19	Climate information	Dummy	1=receives CI, 0 otherwise	+
20	Slope	Dummy	1= steep slop, 0 otherwise	-
21	Erosion	Categorical	0=moderate 1=severe, 2=otherwise	-
22	Drainage	Dummy	1=drained, 0=otherwise	+

23	Fertility	Dummy	0=Extremely fertile, 1=Moderately fertile, 2=Slightly fertile, 3=Marginally fertile, 4=Infertile, 5=Depleted, 6=Unknown/Not sure	+/-
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4. RESULTS AND DISCUSSION

4.1. Descriptive statistics result

4.1.1. Demographic and socio-economic characteristics of the sample households

In the study area, the maximum landholding was 9 hectares, while the minimum was 1 hectare (as shown in Table 4.1). The survey findings indicated that the average livestock holding, measured in tropical livestock units (TLU), among the households surveyed was 30.58 TLU, with the range spanning from 12 to 76 TLU.

The average age of the household head was 49.42 years, ranging from a minimum of 30 to a maximum of 65 years. An average farm income of the surveyed households was 61,117.39 ETB per annum. The descriptive result in Table 4.2 showed that 11% of households was female headed while 89% is male headed. The survey result showed that 50.87 and 20.43% of respondents were getting climate information and credit services respectively. Moreover, 53.48% of household heads have an access to off/non-farm income. 95.22% of households have drainage system in their farm land. Out of the total sample households surveyed, 53.48% reported that they attend primary school, 42.61% of the were attended junior high school, the other 3.87% were attended senior secondary school and 0.87% of the total household heads were attended tertiary education.

Table 4.1 | Summery for continues variables only

Variable	Obs.	Mean	Std. Dev.	Min	Max
Farm income (ETB)	230	61117.391	51622.743	10000	500000
Age (years)	230	49.417	7.748	30	65
Household size (number)	230	6.196	1.922	2	11
Total land owned in Ha	230	2.905	1.35	1	9
Livestock owned TLU	230	30.583	14.421	12	76
Extension contacts	230	4.543	3.612	1	20

Sources: survey data 2024

Table 4.2 | Frequency and percentage table for categorical variable

Variable		Frequency	percentage
Household head	Female	26	11.30
	Male	204	88.70
HHH have access to information		117	50.87
HHH have access to Credit		47	20.43
HHH have access to off/non-farm income		124	53.91
Having drainage systems		219	95.22
Highest education level	Primary school	123	53.48
	Junior high school	98	42.61
	Senior secondary school	7	3.87
	Tertiary education	2	0.87
Degree of observed erosion	Low	128	55.65
	Moderate	70	30.43
	Severe	32	13.91
Soil fertility of your farm lands	Extremely fertile	34	14.78
	Moderately fertile	31	13.48
	Slightly fertile	100	43.48
	Marginally fertile	6	2.61
	Infertile	59	25.65

Sources: survey data 2024

4.1.2. Inferential statistics based on whether the farmer adopts any of CSAP or not

Table 4.3 presents the average variances of continuous variables based on adoption status. The final column in Table 4.3 displays the t-value and its associated statistical significance, which assesses whether there are significant differences in the means of the variables between non-adopters and adopters. The findings indicate that transitioning from non-adoption to adoption of agricultural practices leads to an increase in farm income from 52,584.07 to 69,358.97 ETB. The finding shows that in the shift in agricultural practice from non-adoption to adoption, the household family size increases from around 6 to 7 and the group difference is significantly different at the 1% level. Compared with non-adopters, the adopters total land owned increases from 2.35 to 3.45

hectare at 1% significance difference. In shifting agricultural practice from non-adopters to adopters, number of livestock increases from around 23 to 38 and the group difference is significantly different at the 1% level. Generally, the results in Table 4.3 show that non-adopters and adopters are notably different in observed characteristics.

Table 4.3 | Inferential statistics for continuous variable

Variable	Non adopters	Adopters	mean-diff	t
Farm income	52584.07	69358.97	-1.68e+04	-2.492
Age	49.95	48.91	1.041	1.019
Household size	5.69	6.68	-0.993***	-4.048
Total own land	2.35	3.45	-1.101***	-6.763
Livestock	22.50	38.39	-15.89***	-10.004
Extension contacts	4.06	5.01	-0.947	-2.000

Sources: own competition

Note: Standard errors in parentheses. ***, **, * represent 1%, 5% and 10% significance level, respectively.

Table 4.4 displays the mean differences of categorical variables by adaptation status. The final column of Table 4.4 illustrates the Chi-square (χ^2) value and the corresponding statistical significance, assessing whether a significant association exists between the adoption of CSAPs and the variables. A significant chi-square test indicates that the adoption of CSAPs significantly varies across different categories of the variables. The chi-square results indicate a significant difference in CSAP adoption between male-headed and female-headed households ($\chi^2 = 9.06$). Furthermore, there is a significant association between access to information and CSAP adoption ($\chi^2 = 82.77$), suggesting that households with access to information are more likely to adopt CSAPs.

The conducted chi-square test to determine whether a significant difference exists in CSAP adoption between households with and without access to off-farm income suggests that access to off-farm income influences CSAP adoption ($\chi^2 = 62.69$). Similarly, a significant p-value indicates that having drainage influences CSAP adoption ($\chi^2 = 8.07$). Lastly, a significant association between the degree of observed erosion and CSAP adoption concludes that the degree of observed erosion affects CSAP adoption ($\chi^2 = 97.58$).

Table 4.4 | Inferential statistics for categorical variable

Variable	Values	Percentage	Percentage	Chi 2
		Non adopter	adopter	
Household head	Male	45.59	54.41	9.06***
	Female	76.92	23.08	
Access to information	Have access	19.66	80.34	82.77***
	No access	79.65	20.35	
Access to Credit	Have access	25.53	74.47	13.16
	No access	55.19	44.81	
Access to off/non-farm income	Have access	25.00	75.00	62.69***
	No access	77.36	22.64	
Highest education level	Primary school	65.85	34.15	15.35
	Junior high school	32.65	67.35	
	Senior secondary school	0	100	
	Tertiary education	0	100	
Having drainage	Have	47.03	52.97	8.07***
	Have not	90.91	9.09	
Degree of observed erosion	Low	71.88	28.13	97.58***
	Moderate	0.00	100.00	
	Severe	65.63	34.38	
Soil fertility of farm lands	Extremely fertile	35.29	64.71	17.64
	Moderately fertile	32.26	67.74	
	Slightly fertile	61.00	39.00	
	Marginally fertile	0.00	100.00	
	Infertile	50.85	49.15	

Sources: own competition

Note: Standard errors in parentheses. ***, **, * represent 1%, 5% and 10% significance level, respectively.

4.2. Metrological variables result

4.2.1. Mann-Kendal trend test (total maximum annual rainfall and temperature)

The findings from the Mann–Kendall and Sen’s slope test for the overall maximum annual rainfall reveal a P-value of 0.592, indicating the absence of a trend in the series or variability of rainfall. Moreover, the negative Qi values (-0.042) suggest a decrease in the rainfall data over time. Additionally, the trend analysis of rainfall indicates a negative trend in the rainfall graph for the Enchini station, with a slope of $-0.0323x + 105.61$, consistent with findings from a previous study.

According to Gelaw (2017) implementing agricultural adaptation measures could potentially cut losses related to climate shocks by half. This decreasing and varying value of rainfall indicates farmers vulnerability to climate change and this may encourage them to adopt CSAPs in order to mitigate and adopt the impact.

Table 4.5 | Summary statistics for total maximum annual rainfall:

Variable	Observations	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
Total Maximum Annual Rainfall	30	0	30	31.130	50.516	40.743	5.461

Table 4.6 | Sen's slope for total maximum annual rainfall:

	Value	Lower bound (95%)	Upper bound (95%)
Slope	-0.042	-0.274	0.206
Intercept	123.055	-125.631	356.761

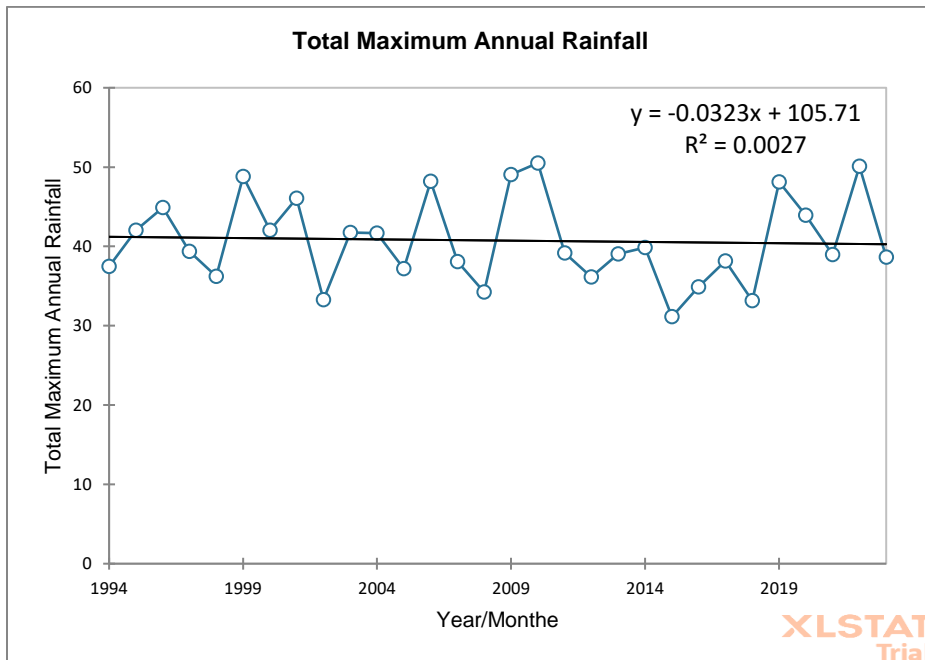


Figure 4.1 | Total maximum annual rainfall

The total annual maximum temperature exhibits a P-value of 0.0001, indicating the presence of a trend in the series, suggesting a continued increase in temperature. Additionally, the positive Qi values (1.176) signify an upward trend in temperature. It is in line with Mekasha *et al.*, (2014) result, in Ethiopia it was recorded that a general tendency of increasing temperature, extreme variability and inconsistent precipitation trends. Farmers in the study area have rain-fed agricultural practices and this variability can cause crop losses, if they increase their adoption level the impact may decrease. Knowing and understanding of this variability helps to adopt CSAPs, reduction in crop failure and it shows climate change impact on agricultural productivity.

Table 4.7 | Summary statistics for total maximum annual temperature

Variable	Observations	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
Total Annual Maximum Temperature	30	0	30	281.985	331.732	296.994	13.615

Table 4.8 |Sen's slope for total maximum annual temperature:

	Value	Lower bound (95%)	Upper bound (95%)
Slope	1.176	0.830	1.566
Intercept	-2062.643	-2452.886	-1715.887

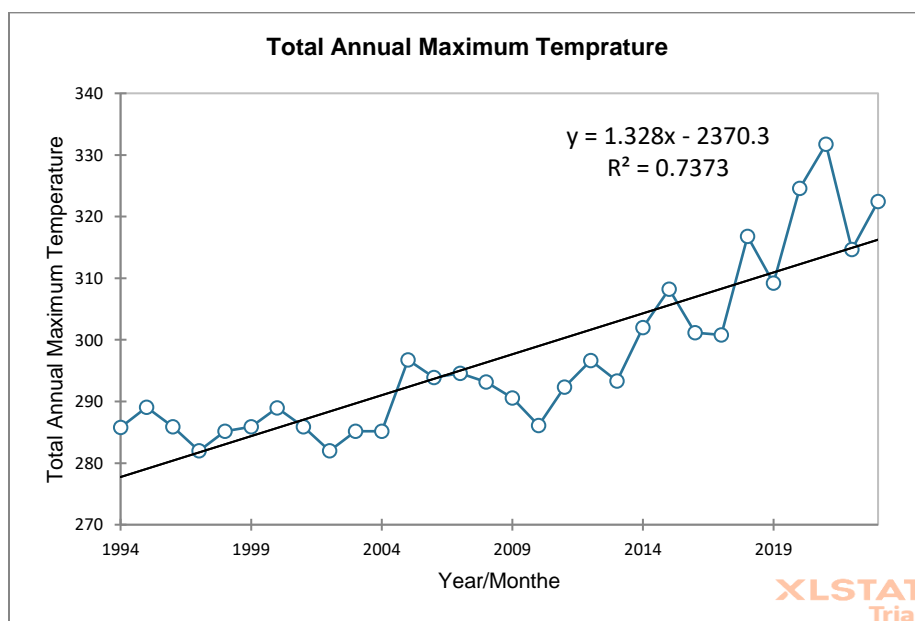


Figure 4.2 | Total maximum annual temperature.

4.3. Econometric results

The figures displayed in Figure 4.3 illustrate the distributions of farm income based on the chosen agricultural practices. These distributions suggest a trend of negative skewness and higher variability for non-adoption scenarios compared to instances where practices have been adopted.

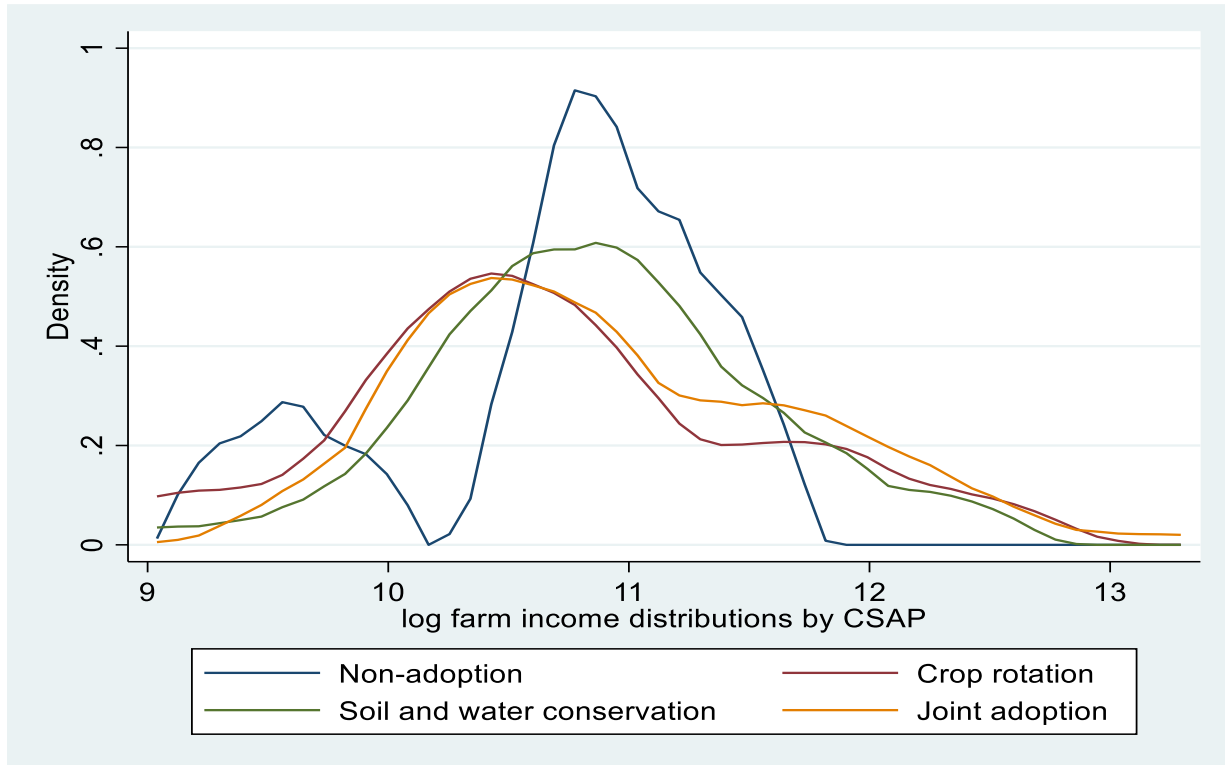


Figure 4.3 | Kernel density distributions of farm income by CSAP type

4.3.1. Determinant factors of adopting climate-smart agricultural practices

The results of the determinants of adoption of climate smart agricultural practices are presented in Table 4.9.

The findings suggest that various factors related to the household head, supplementary income sources, and climate information play a significant role in determining the adoption choices regarding individual practices like crop rotation, soil and water conservation, as well as joint adoption. Specifically, variables such as education level, household size, total land ownership,

access to off-farm income, availability of climate information, and contact with extension agents have a positive and noteworthy impact on the adoption of individual practices (crop rotation and soil and water conservation) as well as joint adoption. Farmers with higher educational attainment are more inclined to adopt crop rotation (10.39), soil and water conservation (10.29), and joint (11.23) CSAPs, as they have better understanding and awareness of modern farming techniques, environmental sustainability, and the benefits of adopting innovative practices, making them more receptive to change and adaptation.

Larger household sizes positively influence the adoption of crop rotation (1.71), soil and water conservation (1.48) and joint (1.53) CSAPs because they often entail more labor resources available for implementing new techniques, diversifying production, and managing agricultural risks, thus facilitating the adoption process and increasing the likelihood of success. Farmers with larger landholdings are more inclined to adopt crop rotation (1.82), soil and water conservation (1.94), and joint (1.93) CSAPs as they have more resources to invest in technology, infrastructure, and inputs necessary for implementation. Additionally, larger landholdings provide opportunities for diversification and experimentation, reducing risk aversion and encouraging adoption.

Access to off-farm income positively influences the adoption of crop rotation (8.34), soil and water conservation (8.84), and joint (9.5) CSAPs by providing additional financial resources that can be invested in new technologies, training, and infrastructure. Off-farm income acts as a financial cushion, reducing the perceived risks associated with adopting innovative practices and enabling farmers to make long-term investments in sustainable agriculture. Access to timely and accurate climate information empowers farmers to make informed decisions about when to plant, irrigate, and harvest crops, as well as how to manage pests and diseases in response to changing weather patterns. This information boosts farmers' capacity to foresee and adjust to climate fluctuations and severe occurrences, thereby elevating the probability of embracing crop rotation (12.09), soil and water conservation (11.76), and joint (12.16) CSAPs. Regular contact with extension agents provides farmers with technical advice, training, and support regarding climate-smart agricultural practices, increasing their knowledge, skills, and confidence in adopting crop rotation (3.25), soil and water conservation (3.24), and joint (3.26) practices. Extension workers also facilitate access to resources, networks, and markets, fostering a supportive environment for adoption and implementation. The outcome aligns with the discovery of Abegunde *et al.*, 2019, and Negera *et*

al., 2022, indicating that educational attainment, farm size, interaction with agricultural extension services, and media exposure were identified as statistically significant and positively associated with the degree of CSA adoption.

The outcome regarding access to credit demonstrates a positive and noteworthy impact on the adoption of combined practices. This finding is consistent with the research by Nyang'au *et al.*, 2021, which indicated that access to credit significantly and positively influenced the adoption of various practices like mixed cropping, adjustments in planting schedules, and the use of animal manure in Kenya. Hence, providing financial assistance to farmers would help alleviate their financial constraints, thereby encouraging them to adopt CSA practices.

The findings reveal that the coefficient of the erosion variable is negative and statistically significant in crop rotation (-2.68), soil and water conservation (-3), and joint (-2.74) at significance levels of 10%, 5%, and 10%, respectively. This implies that an escalation in erosion on farmland results in a reduction in the probability of adopting climate-smart agricultural practices. This outcome contrasts with the conclusion drawn by Musafiri *et al.*, 2022, where persistent soil erosion was found to positively and significantly influence the adoption of agroforestry and soil water conservation practices. This is maybe Farmers facing erosion-related challenges may prioritize immediate interventions to address soil erosion and land degradation over adopting climate-smart agricultural practices. They may lack the necessary resources, such as labor, capital, and technical know-how, to simultaneously implement erosion control measures and climate-smart practices, leading to a trade-off between addressing immediate threats and adopting long-term sustainable practices.

Table 4.9 | Parameter estimates of adoption of climate-smart practices: multinomial logit selection model

VARIABLES	Crop rotation	Soil and water conservation	Joint adoption
Age	0.268(0.172)	0.226(0.174)	0.273(0.172)
Gender	-5.399(4.067)	-5.741(4.008)	-7.637*(3.916)
Education	10.39***(2.975)	10.29***(2.968)	11.23***(2.970)
Household size	1.709***(0.491)	1.480***(0.487)	1.532***(0.484)
Total own land	1.815**(0.835)	1.935**(0.831)	1.925**(0.833)
Access to off-farm	8.340***(2.987)	8.838***(2.967)	9.499***(2.946)
Livestock	-0.0448(0.0625)	-0.0934(0.0621)	-0.0839(0.0618)
Climate information	12.09***(3.381)	11.76***(3.315)	12.16***(3.368)
Extension contacts	3.249***(1.076)	3.235***(1.075)	3.261***(1.075)
Erosion	-2.680*(1.455)	-2.998**(1.445)	-2.738*(1.443)
Drainage	26.11(1,230)	28.17(1,873)	13.43(195.8)
Soil fertility	-0.0491(0.517)	-0.166(0.507)	-0.236(0.507)
Credit	1.811(1.341)	1.776(1.346)	2.202*(1.317)
Constant	-85.40(1,230)	-81.42(1,873)	-70.06(196.7)
Observations	230	230	230

Source: own competition

Note: Preliminary estimates with multivariate probit showed a positive significant correlation between crop rotation and soil and water conservation with ρ 0.5283 and Likelihood Ratio LR 300.71. Standard errors in parentheses. ***, **, * represent 1%, 5% and 10% significance level, respectively.

4.3.2. Determinants of farmers' decision to choose adoption of climate-smart practices

The result of Table 4.10 shows the Marginal effect of adoption of CSAPs by using multinomial logit selection model. The predictors are age, gender, education level, household size, total owned land, access to off-farm income, number of livestock, climate information, contact with extension agent, erosion, drainage, soil fertility and access to credit.

Education level of the farm household positively and significantly influences farmers decision to choose adoption of soil and water conservation practice only and joint adoption of climate smart agricultural practices at 10% and 1% significance level. Educated farmers possess the ability to comprehend and assess both the benefits and drawbacks of new technologies, unlike their less educated counterparts. They can conduct cost-benefit analyses and are more open to accepting innovations that they perceive as advantageous. This finding in line with finding (Sardar *et al.*, 2021; Ali *et al.*, 2021) more educated farmers are more likely to access advice from extension agents and information which influence their adoption.

Household size positively and significantly influence farmers decision on adoption of crop rotation. As family size increase by one, the probability of applying crop rotation increase by 3.19% holding other variables constant. This is, might be due to that the large family helps to buy and cultivate different crop types easily. This result is also in line with the finding of Ndiritu *et al.*, (2014), large household size affects adoption of CSAPs.

Access to off-farm income positively and significantly affects the adoption of joint climate smart practices. As off-farm income increases by one percent, the probability of adopting joint climate smart agricultural practices increases by 17.7%. This is because having additional source of income encourage farmers to invest and adopt both climate smart agricultures at the same time. This result consistent with finding of (Maguza-Tembo *et al.*, 2017) based on economic consideration having access to off-farm income increases adoption of CSAPs.

Number of livestock owned by farmers are significant explanatory variable and it is negatively affecting an adoption of soil and water conservation practice, whereas positively affect for the

farmers who prefer crop rotation. One unit increases in TLU, the probability of adopting soil and water conservation practice decreases by 0.374% and the probability of adopting crop rotation practice increases by 0.3%. This is because TLU is main source of income in rural area and they purchase different crop types than investing in soil and water conservation. This result is in line with the finding of (Parvathi & Waibel, 2015) livestock has a positive impact on crop rotation adaptation.

Contact with extension agents are one of the most important sources of climate and agricultural information and the variable is significant in all crop rotation only, soil and water conservation only and joint adoption at 5% significance level. This result is in line with the findings of Deressa *et al.*, (2009) for Ethiopia and Di Falco (2014) for Sub-Saharan Africa, the findings indicate that access to extension services contributes to an increased adoption of adaptation strategies.

Table 4.10 | Marginal effect adoption of CSAP: multinomial logit selection model

VARIABLES	No adoption	Crop rotation	Soil and water conservation	Joint adoption
Age	-0.00831 (0.00556)	0.00350 (0.00440)	-0.000248 (0.00499)	0.00506 (0.00485)
Gender	0.204* (0.123)	0.0730 (0.122)	-0.00163 (0.130)	-0.276** (0.115)
Education	-0.351*** (0.0902)	0.0583 (0.0468)	0.102* (0.0581)	0.191*** (0.0493)
Household size	-0.0517*** (0.0140)	0.0319** (0.0136)	0.0124 (0.0145)	0.00735 (0.0137)
Total own land	-0.0629** (0.0261)	0.00798 (0.0205)	0.0325 (0.0223)	0.0225 (0.0206)
Access to off-farm	-0.294*** (0.0872)	0.00498 (0.0707)	0.112 (0.0766)	0.177** (0.0749)
Livestock	0.00255 (0.00198)	0.00300* (0.00164)	-0.00327* (0.00191)	-0.00228 (0.00187)
Climate information	-0.397*** (0.0992)	0.120 (0.0790)	0.144* (0.0871)	0.133 (0.0884)
Extension contacts	-0.108*** (0.0339)	0.0304** (0.0133)	0.0459** (0.0186)	0.0313** (0.0128)
Erosion	0.0940** (0.0447)	-0.0129 (0.0415)	-0.0662 (0.0446)	-0.0149 (0.0446)
Drainage	-0.781 (30.38)	0.831 (122.1)	1.197 (177.3)	-1.246 (110.2)
Soil fertility	0.00504 (0.0165)	0.0125 (0.0166)	-0.00250 (0.0172)	-0.0151 (0.0175)
Credit	-0.0631 (0.0405)	-0.00177 (0.0500)	0.00418 (0.0535)	0.0606 (0.0527)
Observations	230	230	230	230

Source: own competition

Note: Standard errors in parentheses. ***, **, * represent 1%, 5% and 10% significance level, respectively.

4.3.2.1. Determinants of farm income: second-stage MESR model

Table 4.11 illustrates the factors influencing farm income based on the selection of climate-smart agricultural practices. The selectivity correction terms, labeled as m_0 , m_1 , m_2 , and m_3 , account for selectivity effects stemming from unobserved variables. The result show that m_3 are significant in crop rotation only, indicating the presence of unobservable selectivity bias. Thus, the MESR approach is preferred to estimate the impacts of adoption of climate smart agricultural practice on income since, it enables to solve selectivity bias effect arising from the observed and unobserved characteristics.

The result of other variables effect shows in Table 4.11 further demonstrate that contact with extension agent significantly influences on farm income among adopters of crop rotation only and joint adopters, but not soil and water conservation only. This implies that having contact with extension agents could influence the adoption of crop rotation and result in high farm income. Crop rotation practices can contribute to improved market access and income stability by diversifying farmers' crop portfolios and spreading production risks. Extension agents may play a crucial role in helping farmers identify profitable crop rotations, market opportunities, and value-added activities that enhance farm income. In contrast, the impact of soil and water conservation practices on farm income may be more indirect and long-term, primarily focused on preserving soil fertility, reducing erosion, and mitigating environmental risks, rather than immediate income generation. This discovery aligns with the outcome of Ogunwande *et al.*, (2018), indicating that farmers who received extension visits gained additional skills and access to new technologies through extension education, consequently leading to comparatively higher income levels.

Table 4.11 | Determinants of log farm income by climate-smart practices: second-stage MESR estimation

VARIABLES	Farm income	Crop rotation	Soil and water conservation	Joint adoption
Age	-0.0664 (0.0409)	0.0741 (0.0654)	-0.0275 (0.0388)	0.0461 (0.0563)
Gender	-0.892** (0.418)	-2.144 (2.172)	-0.0165 (1.457)	-0.341 (0.586)
Household size	0.0631 (0.263)	0.0746 (0.128)	-0.0933 (0.132)	0.0896 (0.182)
Access to off-farm	-0.599**	0.665	-0.400	-0.600

	(0.286)	(0.874)	(0.714)	(0.486)
Extension contacts	-0.565***	0.146**	0.0505	0.0485**
	(0.150)	(0.0611)	(0.0376)	(0.0224)
Erosion	-0.0984	0.281	-0.317	0.0263
	(0.368)	(0.429)	(0.390)	(0.347)
Soil fertility	-0.0193	-0.0855	-0.110	0.0313
	(0.142)	(0.164)	(0.105)	(0.107)
Market distance	-3.107***			
	(0.867)			
Education		1.353	0.125	0.393
		(0.984)	(0.806)	(0.247)
Total own land		0.0295	0.269	-0.0112
		(0.220)	(0.265)	(0.160)
Livestock		0.0182	-0.0483	0.0192
		(0.0309)	(0.0304)	(0.0425)
Credit		0.833	-0.279	0.162
		(0.559)	(0.401)	(0.260)
_m0		-0.0857	0.639	-0.0229
		(2.178)	(1.092)	(0.752)
_m1	-15.09		-2.024	1.950
	(13.24)		(1.668)	(3.426)
_m2	7.616	-6.207		-2.021
	(9.256)	(4.249)		(3.656)
_m3	0	6.017*	0.261	
	(0)	(3.339)	(2.134)	
Constant	19.38***	4.511	11.85***	6.999
	(3.186)	(5.451)	(2.437)	(5.661)

Source: own competition

Note: Standard errors in parentheses. ***, **, * represent 1%, 5% and 10% significance level, respectively.

4.3.3. Impact of adopting CSAP on smallholder farmer income

The impacts of adoption of individual and joint climate-smart agricultural practices on farm income are presented in Table 4.12. In this table, the anticipated (Log) farm income is presented both scenarios: one where the farmer implements the strategies, and another where they do not are indicated. The findings indicate that adopting only crop rotation or solely soil and water conservation practices significantly reduces farm income in the study area. However, the joint

adoption of both crop rotation and soil and water conservation strategies yields the highest positive effect on log income (1,107,245 ETB), suggesting the synergistic benefits of combining these two climate-smart agricultural practices. These results are in line with those of Musafiri *et al.*, (2022) in Western Kenya, which demonstrate that the simultaneous adoption of CSAPs can decrease soil erosion rates, thereby enhancing agricultural productivity and income.

The results also show that in all the counterfactual cases, adopters had lower farm income when they adopt only one climate-smart agricultural practice. Joint adoption of multiple CSAPs often leads to synergistic effects that amplify the benefits of each practice, resulting in greater improvements in productivity, resilience, and income. For instance, combining crop rotation with soil and water conservation measures can enhance soil fertility, moisture retention, and pest management, leading to higher crop yields and income compared to implementing each practice individually. Studies conducted by Zougmore *et al.*, 2014 in West Africa also shows the same results on income.

Table 4.12 | MESR based average treatment effects of adoption of MATs on household welfare

Outcome variables	CSA choice	Adoption status		Average treatment Effects
		Adopting	Non-adopting	
	(j)	(j=1,2,3)	(j=0)	
		(1)	(2)	(3) = (1) – (2)
Log farm income	Crop rotation	55870 (4366)	1658898(1595635)	-1603028*** (1593457)
	Soil and Water conservation	62160 (7045)	80498 (15811)	-18338*** (13289)
	Joint adoption	1159139 (1073618)	51893 (8350)	1107245*** (1072230)

Source: own competition

Note: Standard errors in parentheses. ***, **, * represent 1%, 5% and 10% significance level, respectively.

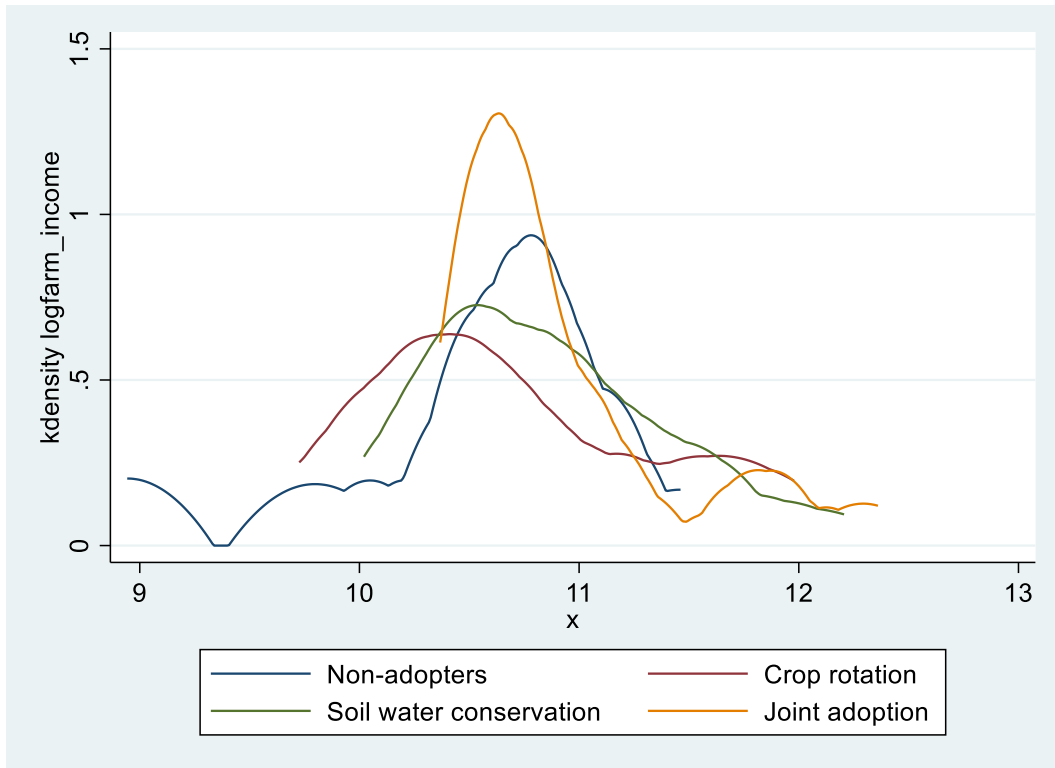


Figure 4.4 | Kernel density distributions of MESR based average treatment effects of adoption of MATs on farm income by CSAP type

5. SUMMARY, CONCLUSION AND RECOMMENDATION

5.1. Summary

Agricultural productivity is negatively affected by climate change globally, especially in developing countries like Sub-Saharan Africa (SSA), where agriculture contributes significantly to the economy. Smallholder farmers in Ethiopia, in particular, are vulnerable due to their reliance on rain-fed agriculture. The concept of climate-smart agriculture (CSA) emerges as a strategic response to these challenges, aiming at enhancing productivity, resilience, and emissions reduction simultaneously. CSA encompasses a range of practices, including improved seeds, crop rotation, and soil conservation, aimed at enhancing productivity while preserving ecosystem services. Ethiopians have made efforts to implement CSA practices, but land tenure insecurity and financial constraints prevent widespread adoption.

Several studies have explored the adoption and impact of various CSAPs on smallholder farmers' productivity and risk exposure, particularly focusing on monocropping of staple crops like maize, rice, or wheat. However, analyzing farm outcomes solely based on monocropping may overlook or exaggerate the true effects of CSAP adoption for several reasons. Therefore, a comprehensive analysis of production should consider data from all crops rather than focusing solely on one crop to better understand the true impacts of CSAP adoption.

CSA practices have been shown to increase crop yields, improve food security, and reduce crop failure when implemented individually, and together. However, more research is needed to understand how these practices interact and complement each other. Studies suggest that factors such as education level, household size, off-farm income, and access to extension services influence adoption decisions. Yet, gaps remain in assessing the combined impact of CSA practices on production and risk exposure.

This study in the Adea Berga district of Ethiopia aims to address these gaps by examining the adoption and impact of CSA practices among smallholder farmers. Using mixed methods, including surveys and secondary data analysis, the study identifies determinants of CSA adoption, factors guiding farmers' decisions to choose adoption and evaluates its impact on farmer income. The findings align with global and regional development goals, providing valuable insights for policymakers and international organizations to promote sustainable agriculture.

The study employs statistical techniques like the Mann-Kendall test and Sen's slope to analyze climate data trends and assess the magnitude of changes. Additionally, econometric models like the multinomial logit and multinomial endogenous switching regression models are used to identify factors influencing adoption decisions and estimate the impact of CSA practices on farm income.

This study contributes to our understanding of the dynamics of climate change and its effects on traditional agriculture in Ethiopia. By examining the adoption and impact of CSA practices, it offers insights into how smallholder farmers can enhance their resilience and improve their livelihoods in the face of climate change. The findings underscore the importance of promoting sustainable agricultural practices to achieve long-term economic growth and food security in Ethiopia and beyond.

5.2. Conclusion

Prior research has explored the adoption and outcomes of climate innovation practices on smallholder farmers' production and risk exposure, primarily focusing on monocropping perspectives. However, this approach overlooks the broader benefits of implementing climate-smart practices in mixed-cropping contexts, where practices like crop rotation, and soil and water conservation can positively impact multiple crops. Additionally, there is insufficient research to comprehend the interplay and synergy among these practices, leaving gaps in evaluating the collective influence of CSA practices on both production and risk exposure. In this study, metrological data from Ethiopian Metrological stations for three Kebeles in Adea Berga District were analyzed to identify trends in climate variables. The Mann–Kendall and Sen's slope tests revealed crucial insights: while there is no discernible trend in total maximum annual rainfall, there is a significant upward trend in total annual maximum temperature, indicating a likely continuation of temperature increase. Based on the results of descriptive analysis, it can be concluded that the sampled households generally had moderate livestock holdings and farm incomes. A considerable portion of respondents received climate information, while access to credit services was relatively low in the study area. Transitioning from non-adoption to adoption of climate-smart agricultural practices was associated with an increase in farm income and total land ownership.

Additionally, econometric analysis employing the Multinomial logit model and the Multinomial endogenous switching regression model shed light on determinants of adoption of climate-smart agricultural practices, on understanding of determinant factors of farmers' decision to choose adoption of CSAPs and its impact on the income of smallholder farmers. The Multinomial logit model findings underscore the pivotal roles of education level, household size, total size of land owned, access to off-farm income, climate information, and contact with extension agents positively and significantly influenced adoption decisions. The result also shows a negative influence of land erosion.

Moreover, education level significantly influenced the adoption of soil and water conservation practices and the joint adoption of CSA practices. Household size positively influenced the adoption of crop rotation, while off-farm income significantly affected the adoption of joint climate-smart practices. Livestock ownership negatively affected the adoption of soil and water conservation practices but positively influenced crop rotation adoption. Contact with extension agents was significant across all adoption types.

Furthermore, the study elucidates the income impacts of joint adaptation of CSA practices, revealing both challenges and opportunities for farmers. Overall, this research contributes valuable insights for achieving sustainable economic growth, combating climate change, and enhancing agricultural resilience, emphasizing the importance of informed policy interventions and support mechanisms to promote CSA adoption and improve livelihoods in the study areas.

5.3. Recommendation

Based on the findings of the study, the author recommends that efforts from government institutions are crucial in supporting farmers with accurate and timely weather forecasts in local languages, addressing concerns about the reliability of existing forecasts among some farmers. By ensuring that farmers have access to reliable weather information, they can better exploit seasonal rainfall distribution to enhance and stabilize crop yields. Alongside this, policymakers should prioritize providing financial support and policy interventions to promote the adoption of climate-smart agriculture (CSA) practices. This includes addressing land tenure insecurity and offering subsidies for CSA inputs and technologies. Capacity-building initiatives should also be prioritized

to empower smallholder farmers with the knowledge and skills needed to implement CSA practices effectively.

Furthermore, promoting synergies between different CSA practices and facilitating research and knowledge-sharing platforms will contribute to maximizing the benefits of CSA adoption. Through these concerted efforts, stakeholders can collectively enhance agricultural resilience, foster sustainable economic growth, and mitigate the adverse impacts of climate change in the Adea Berga district and beyond. Additionally, fostering partnerships between government agencies, non-governmental organizations, research institutions, and local communities can create a collaborative ecosystem conducive to the widespread adoption of CSA practices. These partnerships can facilitate the development of tailored CSA solutions that address the specific needs and challenges faced by smallholder farmers in the region. By leveraging the collective expertise and resources of various stakeholders, policymakers can ensure the successful implementation and scaling up of CSA initiatives, ultimately leading to improved livelihoods and food security for rural communities.

Further research should explore long-term trends in climate data beyond the scope of this thesis to gain a deeper understanding of climate variability and change in the study area. Analyzing historical climate data spanning several decades can help identify patterns and trends that may impact agricultural production. Additionally, conducting a more comprehensive assessment of the combined impact of climate-smart agricultural (CSA) practices on both production and risk exposure is essential. This should involve analyzing data from all crops rather than focusing solely on one crop to better understand the true effects of CSA adoption. Investigating the interplay and synergy among different CSA practices, particularly in mixed-cropping contexts, is also recommended. Research should explore how practices such as crop rotation, soil conservation, and water management interact and complement each other to enhance overall productivity and resilience.

Furthermore, it is crucial to further investigate the determinants of farmers' decisions to adopt CSA practices, focusing on understanding the role of education level, household size, access to off-farm income, and other socio-economic factors. Additionally, expanding econometric analysis to include additional models and techniques for assessing the impact of CSA adoption on farm income is necessary. This could involve exploring alternative regression models or incorporating

additional control variables to better understand the relationship between CSA adoption and income generation. Comparative studies should be conducted to compare the effectiveness of different CSA practices and strategies in improving agricultural productivity and resilience. Exploring the role of innovation and technology in advancing CSA practices and addressing the specific needs and challenges faced by smallholder farmers is also recommended. By addressing these unanswered questions through further research, policymakers, researchers, and development practitioners can gain valuable insights into the dynamics of CSA adoption and its impact on smallholder farmers' livelihoods, informing more effective strategies and interventions for promoting sustainable agriculture and resilience to climate change.

6. REFERENCES

- Abdulai, A. & W. Huffman (2014). "The adoption and impact of soil and water conservation technology: An endogenous switching regression application." *Land Economics* **90**(1): 26–43.
- Abebe, Y. and A. Bekele (2017). "Vulnerability of smallholder farmers to climate change in the central rift valley of Ethiopia: a gender disaggregated approach." *Ethiopian Journal of Agricultural Sciences* **27**(2): 85-97.
- Abegunde, V. O., Sibanda, M., & Obi, A. (2019). Determinants of the adoption of climate-smart agricultural practices by small-scale farming households in King Cetshwayo District Municipality, South Africa. *Sustainability*, *12*(1), 195.
- Adea Berge Woreda- Agricultural and Rural Development Office, ABW-ARDO, (2022).
- Aditya, F., Gusmayanti, E., & Sudrajat, J. (2021, November). Rainfall trend analysis using Mann-Kendall and Sen's slope estimator test in West Kalimantan. In *IOP Conference Series: Earth and Environmental Science* (Vol. 893, No. 1, p. 012006). IOP Publishing.
- Agbo, E. P., Ekpo, C. M. & Edet, C. O. (2021). Analysis of the effects of meteorological parameters on radio refractivity, equivalent potential temperature and field strength via Mann-Kendall test. *Theoretical and Applied Climatology* *143*, 1437–1456.
- Akter, A., Geng, X., Mwalupaso, G. E., Lu, H., Hoque, F., Ndungu, M. K., & Abbas, Q. (2022). Income and yield effects of climate-smart agriculture (CSA) adoption in flood prone areas of Bangladesh: Farm level evidence. *Climate Risk Management*, *37*, 100455.
- Alemu, T., & Mengistu, A. (2019). Impacts of climate change on food security in Ethiopia: adaptation and mitigation options: a review. *Climate change-resilient agriculture and agroforestry: Ecosystem services and sustainability*, 397-412.
- Ali E (2019). Perception of climate change, traditional beliefs and determinants of farm households' adaptation decisions in Northern Togo. In: JKM Kuwornu (ed) *Climate change and SubSaharan Africa: the vulnerability and adaptation of food `y chain actors*. Vernon Press, Thailand, p 83–106.
- Ali, E. (2021). Farm households' adoption of climate-smart practices in subsistence agriculture: Evidence from Northern Togo. *Environmental Management*, *67*(5), 949-962.
- Amegnalo CJ, Anaman KA, Mensah-Bonsu A, Onumah EE, Amoussouga AFG (2017). Contingent valuation study of the benefits of seasonal climate forecasts for maize farmers in the Republic of Benin, West Africa. *Clim Serv* *6*:1–11.
- Aragie, E. A. (2013). "Climate change, growth, and poverty in Ethiopia." *The Robert S. Strauss Center for International Security and Law working paper*(3).
- Arslan, A., Belotti, F. and Lipper, L. (2017). "Smallholder productivity and weather shocks: adoption and impact of widely promoted agricultural practices in Tanzania", *Food Policy*, Vol. 69, pp. 68-81.

- Baig, M. R. I., Naikoo, M. W., Ansari, A. H., Ahmad, S. & Rahman, A. (2021). Spatio-temporal analysis of precipitation pattern and trend using standardized precipitation index and Mann–Kendall test in coastal Andhra Pradesh. *Modeling Earth Systems and Environment* 8, 2733–2752.
- Belay, A., Recha, J. W., Woldeamanuel, T., & Morton, J. F. (2017). Smallholder farmers’ adaptation to climate change and determinants of their adaptation decisions in the Central Rift Valley of Ethiopia. *Agriculture & Food Security*, 6(1), 1-13.
- Belay, A., Mirzabaev, A., Recha, J. W., Oludhe, C., Osano, P. M., Berhane, Z., ... & Solomon, D. (2023). Does climate-smart agriculture improve household income and food security? Evidence from Southern Ethiopia. *Environment, Development and Sustainability*, 1-28.
- Bourguignon, F., Fournier, M., & Gurgand, M. (2007). Selection bias corrections based on the multinomial logit model: Monte Carlo comparisons. *Journal of Economic surveys*, 21(1), 174-205.
- Branca, G., Arslan, A., Paolantonio, A., Grever, U., Cattaneo, A., Cavatassi, R., ... & Vetter, S. (2021). Assessing the economic and mitigation benefits of climate-smart agriculture and its implications for political economy: A case study in Southern Africa. *Journal of Cleaner Production*, 285, 125161.
- Brandt, P., Kvakić, M., Butterbach-Bahl, K., & Rufno, M. C. (2017). How to target climate-smart agriculture? Concept and application of the consensus-driven decision support framework “targetCSA”. *Agricultural Systems*, 151, 234–245. <https://doi.org/10.1016/J.AGSY.2015.12.011>.
- 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.
- Campbell, B. M., Thornton, P., Zougmore, R., Van Asten, P., & Lipper, L. (2014). Sustainable intensification: What is its role in climate smart agriculture?. *Current Opinion in Environmental Sustainability*, 8, 39-43.
- CIAT, BFS/USAID. (2017). Climate-Smart Agriculture in Ethiopia. CSA Country Profiles for Africa Series. International Center for Tropical Agriculture (CIAT); Bureau for Food Security, United States Agency for International Development (BFS/USAID), Washington, D.C. 26 p.
- Deressa, T. T., Hassan, R. M., Ringler, C., Alemu, T., & Yesuf, M. (2009). Determinants of farmers’ choice of adaptation methods to climate change in the Nile Basin of Ethiopia. *Global environmental change*, 19(2), 248-255.
- Di Falco, S. and J. P. Chavas (2009). "On crop biodiversity, risk exposure, and food security in the highlands of Ethiopia." *American journal of agricultural economics* 91(3): 599-611.
- Di Falco, S. and M. Veronesi (2013). "How can African agriculture adapt to climate change? A counterfactual analysis from Ethiopia." *Land Economics* 89(4): 743-766.

- Di Falco, S. and M. Veronesi (2014). "Managing environmental risk in the presence of climate change: the role of adaptation in the Nile Basin of Ethiopia." *Environmental and Resource Economics* **57**: 553-577.
- Doshi, J., Patel, T., & kumar Bharti, S. (2019). Smart Farming using IoT, a solution for optimally monitoring farming conditions. *Procedia Computer Science*, *160*, 746-751.
- Engel, S., & Muller, A. (2016). Payments for environmental services to promote "climate-smart agriculture"? Potential and challenges. *Agricultural Economics*, *47*(S1), 173-184.
- Eshete, G., Assefa, B., Lemma, E., Kibret, G., Ambaw, G., Samuel, S., ... & Solomon, D. (2020). Ethiopia climate-smart agriculture roadmap.
- FAO (2012). The state of food insecurity in the world: economic growth is necessary but not sufficient to accelerate reduction of hunger and malnutrition. FAO, Rome <http://www.fao.org/docrep/016/i3027e/i3027e.pdf>.
- FAO (2013). Climate smart agriculture: Sourcebook. Rome, Italy: Food and Agriculture Organization of the United Nations.
- FAO (2010). "Climate-Smart" Agriculture: Policies, Practices and Financing for Food Security, Adaption and Mitigation. Rome, Italy: Food and Agriculture Organization of the United Nations.
- FAO (2015). Climate changes and food security: risks and responses. Rome, Italy: Food and Agriculture Organization of the United Nations.
- Fekad, M., & Bekalu, Y. (2020). Climate change impacts on household food security and its adaptation options in rural Ethiopia: a systematic review. *EPRA Int. J. Res. Develop*, 2455-7838.
- Fentie, A., & Beyene, A. D. (2019). Climate-smart agricultural practices and welfare of rural smallholders in Ethiopia: Does planting method matter?. *Land use policy*, *85*, 387-396.
- Fernández, F. J., Blanco, M., Ponce, R. D., Vásquez-Lavín, F., & Roco, L. (2019). Implications of climate change for semi-arid dualistic agriculture: A case study in Central Chile. *Regional Environmental Change*, *19*, 89-100.
- Garba, H., & Udokpoh, U. U. (2023). Analysis of Trend in Meteorological and Hydrological Time-series using Mann-Kendall and Sen's Slope Estimator Statistical Test in Akwa Ibom State, Nigeria. *International Journal of Environment and Climate Change*, *13*(10), 1017-1035.
- Gelaw, A. (2017). "Climate-Smart agriculture in Ethiopia." *International Center for Tropical Agriculture* **26**.
- Hellin, J., & Fisher, E. (2019). Climate-smart agriculture and non-agricultural livelihood transformation. *Climate*, *7*(4), 48.

- Hirpha, H. H., Mpandeli, S., & Bantider, A. (2020). Determinants of adaptation strategies to climate change among the smallholder farmers in Adama District, Ethiopia. *International Journal of Climate Change Strategies and Management*, 12(4), 463-476.
- Hussain, S., Amin, A., Mubeen, M., Khaliq, T., Shahid, M., Hammad, H. M., Sultana, S. R., Awais, M., Murtaza, B., & Amjad, M. (2022). Climate smart agriculture (CSA) technologies. In *Building Climate Resilience in Agriculture* (pp. 319–338).
- IPCC (2014). Summary for policymakers, In: *Climate change 2014: impacts, adaptation, and vulnerability. Part A: global and sectoral aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Field, CB; Barros, VR; Dokken, DJ; Mach, KJ; Mastrandrea, MD; Bilir, TE; Chatterjee, M; Ebi, KL Estrada, YO; Genova, RC; Girma, B; Kissel, ES; Levy, AN; MacCracken, S; Mastrandrea, PR; White, LL (eds.)]. Cambridge University Press, Cambridge, United Kingdom, pp. 1-32.
- Issahaku, G., & Abdulai, A. (2020). Adoption of climate-smart practices and its impact on farm performance and risk exposure among smallholder farmers in Ghana. *Australian Journal of Agricultural and Resource Economics*, 64(2), 396-420.
- Jirata, M., Grey, S., & Kilawe, E. (2016). Ethiopia climate-smart agriculture scoping study. *FAO: Addis Ababa, Ethiopia*.
- Kalinda, T. H., Tembo, G., & Ng'ombe, J. N. (2017). Does adoption of conservation farming practices result in increased crop revenue? Evidence from Zambia. *Agrekon*, 56(2), 205-221.
- Kassaye, A. Y., Shao, G., Wang, X., Shifaw, E., & Wu, S. (2021). Impact of climate change on the staple food crops yield in Ethiopia: implications for food security. *Theoretical and Applied Climatology*, 145(1-2), 327-343.
- Kassie, B. T., Rötter, R. P., Hengsdijk, H., Asseng, S., Van Ittersum, M. K., Kahiluoto, H., & Van Keulen, H. (2014). Climate variability and change in the Central Rift Valley of Ethiopia: challenges for rainfed crop production. *The Journal of Agricultural Science*, 152(1), 58-74.
- Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F. and Mekuria, M. (2013), “Adoption of interrelated sustainable agricultural practices in smallholder systems: evidence from rural Tanzania”, *Technological Forecasting and Social Change*, Vol. 80 No. 3, pp. 525-540.
- Khatri-Chhetri, A., Pant, A., Aggarwal, P. K., Vasireddy, V. V., & Yadav, A. (2019). Stakeholders prioritization of climate-smart agriculture interventions: Evaluation of a framework. *Agricultural systems*, 174, 23-31.
- 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(5), 599-609.

- Kifle, T., Ayal, D. Y., & Mulugeta, M. (2022). Factors influencing farmers adoption of climate smart agriculture to respond climate variability in Siyadebrina Wayu District, Central highland of Ethiopia. *Climate Services*, 26, 100290.
- 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.
- Lavison, R.K. (2013). "Factors influencing the adoption of organic fertilizers in vegetable production in Accra", Master thesis, University of Ghana, Legon.
- Lebeza, T. M., Gashaw, T., Tefera, G. W., & Mohammed, J. A. (2023). Trend analysis of hydro-climate variables in the Jemma sub-basin of Upper Blue Nile (Abbay) Basin, Ethiopia. *SN Applied Sciences*, 5(5), 129.
- Lee, L.F. (1983). Notes and comments generalized econometric models with selectivity, *Econometrica* 51, 507–515.
- Lipper, L., Thornton, P., Campbell, B. M., Baedeker, T., Braimoh, A., Bwalya, M., ... & Torquebiau, E. F. (2014). Climate-smart agriculture for food security. *Nature climate change*, 4(12), 1068-1072.
- Lipper, L., & Zilberman, D. (2018). A short history of the evolution of the climate smart agriculture approach and its links to climate change and sustainable agriculture debates. *Climate smart agriculture: Building resilience to climate change*, 13-30.
- Lipczynska-Kochany, E. (2018). Effect of climate change on humic substances and associated impacts on the quality of surface water and groundwater: A review. *Science of the total environment*, 640, 1548-1565.
- Long, T. B., Blok, V., & Coninx, I. (2016). Barriers to the adoption and diffusion of technological innovations for climate-smart agriculture in Europe: evidence from the Netherlands, France, Switzerland and Italy. *Journal of cleaner production*, 112, 9-21.
- Mabe, F. N. (2023). Impacts of Farmer Innovation Systems and Improved Agricultural Technologies on Rice Yield in Ghana. *Ghana Journal of Science, Technology and Development*, 9(1), 25-41.
- Maguza-Tembo, F., Edriss, A.K. and Mangisoni, J. (2017). "Determinants of climate smart agriculture technology adoption in the drought prone districts of Malawi using a multivariate probit analysis", *Asian Journal of Agricultural Extension, Economics and Sociology*, Vol. 16 No. 3, pp. 1-12.
- Mango, N., Makate, C., Tamene, L., Mponela, P., & Ndengu, G. (2018). Adoption of small-scale irrigation farming as a climate-smart agriculture practice and its influence on household income in the Chinyanja Triangle, Southern Africa. *Land*, 7(2), 49.
- Mazhar, R., Ghafoor, A., Xuehao, B., & Wei, Z. (2021). Fostering sustainable agriculture: Do institutional factors impact the adoption of multiple climate-smart agricultural practices among new entry organic farmers in Pakistan?. *Journal of Cleaner Production*, 283, 124620.

- McFadden, D. (1972). Conditional logit analysis of qualitative choice behavior.
- Mekasha, A., Tesfaye, K., & Duncan, A. J. (2014). Trends in daily observed temperature and precipitation extremes over three Ethiopian eco-environments. *International Journal of Climatology*, 34(6), 1990-1999.
- Mishra, A., Vu, T., Veettil, A. V., & Entekhabi, D. (2017). Drought monitoring with soil moisture active passive (SMAP) measurements. *Journal of Hydrology*, 552, 620-632.
- Mujeyi, A., Mudhara, M., & Mutenje, M. (2021). The impact of climate smart agriculture on household welfare in smallholder integrated crop–livestock farming systems: evidence from Zimbabwe. *Agriculture & Food Security*, 10(1), 1-15.
- Mulwa, C., Marenja, 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.
- Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica: journal of the Econometric Society*, 69-85.
- Murray, U., Gebremedhin, Z., Brychkova, G., & Spillane, C. (2016). Smallholder farmers and climate smart agriculture: Technology and labor-productivity constraints amongst women smallholders in Malawi. *Gender, Technology and Development*, 20(2), 117-148.
- Musafiri, C. M., Kiboi, M., Macharia, J., Ng'etich, O. K., Kosgei, D. K., Mulianga, B., ... & 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).
- Mwangi, M. and Kariuki, S. (2015). “Factors determining adoption of new agricultural technology by smallholder farmers in developing countries”, *Journal of Economics and Sustainable Development*, Vol. 6 No. 5.
- 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.
- Negera, M., Alemu, T., Hagos, F., & Hailelassie, A. (2022). Determinants of adoption of climate smart agricultural practices among farmers in Bale-Eco region, Ethiopia. *Heliyon*, 8(7).
- Nkala, P. (2011). Assessing the impacts of conservation agriculture on farmer livelihoods in three selected communities in central Mozambique, University of Natural Resources and Life Sciences.
- Nyang'au, J. O., Mohamed, J. H., Mango, N., Makate, C., & Wangeci, A. N. (2021). Smallholder farmers' perception of climate change and adoption of climate smart agriculture practices in Masaba South Sub-county, Kisii, Kenya. *Heliyon*, 7(4).

- Nyasimi, M., Kimeli, P., Sayula, G., Radeny, M., Kinyangi, J., & Mungai, C. (2017). Adoption and dissemination pathways for climate-smart agriculture technologies and practices for climate-resilient livelihoods in Lushoto, Northeast Tanzania. *Climate*, 5(3), 63.
- Ogunwande, I. O., Odefadehan, O. O., & Akinrinola, O. O. (2018). Analysis of Agricultural Extension Contact Effects on Rural Farming Households' Productivity in Oyo State, Nigeria. *Journal of Sustainable Technology*, 9(2), 1-11.
- Ogunyiola, A., Gardezi, M., & Vij, S. (2022). Smallholder farmers' engagement with climate smart agriculture in Africa: Role of local knowledge and upscaling. *Climate Policy*, 22, 1–16.
- Oparinde, L. O. (2021). Fish farmers' welfare and climate change adaptation strategies in southwest, Nigeria: Application of multinomial endogenous switching regression model. *Aquaculture Economics & Management*, 25(4), 450-471.
- Ouédraogo, M., Houessionon, P., Zougmore, R. B., & Partey, S. T. (2019). Uptake of climate-smart agricultural technologies and practices: Actual and potential adoption rates in the climate-smart village site of Mali. *Sustainability*, 11(17), 4710.
- Parvathi, P. and Waibel, H. (2015), "Is organic agriculture and fair trade certification a way out of crisis? Evidence from black pepper farmers in India", Paper Presented at the 55th Annual Conference of Association of Agricultural Economists (GEWISOLA), 23-25 September, Giessen.
- Pivoto, D., Waquil, P. D., Talamini, E., Finocchio, C. P. S., Dalla Corte, V. F., & de Vargas Mores, G. (2018). Scientific development of smart farming technologies and their application in Brazil. *Information processing in agriculture*, 5(1), 21-32.
- 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).
- Ray, S., Das, S. S., Mishra, P. & Al Khatib, A. M. G. (2021). Time series SARIMA modelling and forecasting of monthly rainfall and temperature in the south Asian countries. *Earth Systems and Environment* 5, 531–546.
- Saguye, T. S. (2017). Determinants of the Adoption of Sustainable Land Management Practices among Smallholder Farmers' in Jeldu District, West Shewa Zone, Oromia Region, Ethiopia. *Glob. J. Econ. Sustain. Dev.*, 8, 96-116.
- Sani, S., & Kemaw, B. (2019). Analysis of households food insecurity and its coping mechanisms in Western Ethiopia. *Agricultural and food economics*, 7(1), 1-20.
- Sardar, A., Kiani, A. K., & Kuslu, Y. (2021). Does adoption of climate-smart agriculture (CSA) practices improve farmers' crop income? Assessing the determinants and its impacts in Punjab province, Pakistan. *Environment, Development and Sustainability*, 23, 10119-10140.
- Sardar, A., Kiani, A. K., & Kuslu, Y. (2019). An assessment of willingness for adoption of climate-smart agriculture (Csa) practices through the farmers' adaptive capacity determinants. *Yuzuncu Yil University Journal of Agricultural Sciences*, 29(4), 781-791.

- Sedebo, D. A., Li, G., Etea, B. G., Abebe, K. A., Ahiakpa, J. K., Arega, Y., & Anran, Z. (2022). Impact of smallholder farmers' climate-smart adaptation practices on wheat yield in southern Ethiopia. *Climate and Development*, 14, 1–15.
- Skambraks, A. (2014). "Smallholder farmers' adaptation to climate change in Zenzelima, Ethiopia." Aarhus University, pp. 1–84.
- Stuch, B., Alcamo, J., & Schaldach, R. (2021). Projected climate change impacts on mean and year-to-year variability of yield of key smallholder crops in Sub-Saharan Africa. *Climate and Development*, 13(3), 268–282.
- Teklewold, H., Kassie, M. and Shiferaw, B. (2013). "Adoption of multiple sustainable agricultural practices in rural Ethiopia", *Journal of Agricultural Economics*, Vol. 64 No. 3, pp. 597-623.
- Teklewold, H., Mekonnen, A., Kohlin, G. and Di Falco, S. (2017). "Does adoption of multiple Climate smart practices improve farmers' climate resilience? Empirical evidence from the Nile basin of Ethiopia", *Climate Change Economics*, Vol. 8 No. 1, p. 1750001.
- Tesfaye, A., Hammond, J., Radeny, M., Recha, J. W., Nigussie, A., Ambaw, G., ... & Solomon, D. (2021). The impacts of climate-smart agricultural practices on household income and food security: evidence from Doyogena and Basona climate-smart landscapes.
- Tessema, A. K. (2019). "Smallholder farmers' perception and adaptation strategies to climate change and variability in Ankesha Guagusa District of Awi Zone, North Western Ethiopia." *Journal of Resources Development and Management* 58: 15-24.
- Thornton, P. K., Ericksen, P. J., Herrero, M., & Challinor, A. J. (2014). Climate variability and vulnerability to climate change: a review. *Global change biology*, 20(11), 3313-3328.
- Thornton, P. K. & M. Herrero (2015). "Adapting to climate change in the mixed crop and livestock farming systems in sub-Saharan Africa." *Nature Climate Change* 5(9): 830–836.
- Totin, E., Segnon, A. C., Schut, M., Affognon, H., Zougmore, R. B., Rosenstock, T., & Thornton, P. K. (2018). Institutional perspectives of climate-smart agriculture: A systematic literature review. *Sustainability*, 10(6), 1990.
- Tran, N. L. D., Rañola Jr, R. F., Ole Sander, B., Reiner, W., Nguyen, D. T., & Nong, N. K. N. (2020). Determinants of adoption of climate-smart agriculture technologies in rice production in Vietnam. *International journal of climate change strategies and management*, 12(2), 238-256.
- 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.

- Woldeyohanes, T., Heckelei, T., & Surry, Y. (2017). Effect of off-farm income on smallholder commercialization: panel evidence from rural households in Ethiopia. *Agricultural Economics*, 48(2), 207-218.
- Wollni, M., Lee, D.R. and Thies, J.E. (2010). “Conservation agriculture, organic marketing, and collective action in the Honduran hillsides”, *Agricultural Economics*, Vol. 41 Nos 3/4, pp. 373-384.
- Yamane, T. (1973). *Statistics: An introductory analysis*.
- Zegeye, M. B., Meshesha, G. B., & Shah, M. I. (2022). Measuring the poverty reduction effects of adopting agricultural technologies in rural Ethiopia: findings from an endogenous switching regression approach. *Heliyon*, 8(5).
- Zerssa, G., Feysa, D., Kim, D.G., Eichler-Lobermann, B. 2021. Challenges of smallholder farming in ethiopia and opportunities by adopting climate-smart agriculture. *Agriculture* 2021, 11(3), 192. 10.3390/agriculture11030192.
- Zougmoré, R., Jalloh, A., & Tioro, A. (2014). Climate-smart soil water and nutrient management options in semiarid West Africa: a review of evidence and analysis of stone bunds and zaï techniques. *Agriculture & Food Security*, 3, 1-8.
- Zougmoré, R., Partey, S., Ouédraogo, M., Omitoyin, B., Thomas, T., Ayantunde, A., ... & Jalloh, A. (2016). Toward climate-smart agriculture in West Africa: a review of climate change impacts, adaptation strategies and policy developments for the livestock, fishery and crop production sectors. *Agriculture & Food Security*, 5(1), 1-16.].