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Climate-Smart Agriculture Practices and their Impact on Smallholder Farmers' Resilience to Climate Change: The case of Gubalafto Woreda, Ethiopia

By

Melkamu Sete Wereta

June 2026

Bahir Dar, Ethiopia

Bahir Dar University

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Climate-Smart Agriculture Practices and their Impact on Smallholder Farmers' Resilience to Climate Change: The case of Gubalafto Woreda, Ethiopia

By

Melkamu Sete Wereta

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Doctor of Philosophy (PhD) in Disaster Risk Science

Principal advisor: Dr. Zemen Ayalew Ayele (Asso. Prof, Bahir Dar University)

Co-advisor: Dr. Yilebes Addisu (Asso. Prof, Bahir Dar University)

June 2026

Bahir Dar, Ethiopia

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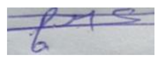
DECLARATION

This is to certify that the dissertation entitled *"***Climate-Smart Agriculture Practices and their Impact on Smallholder Farmers' Resilience to Climate Change: The case of Gubalafto Woreda, Ethiopia***"*, submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Disaster Risk Science in the Department of Disaster Risk Management & Sustainable Development, Bahir Dar University, is a record of original work carried out by me and has not been submitted to this or any other institution for the award of any other degree or certificate. The assistance and support I received during the course of this investigation have been duly acknowledged.

Melkamu Sete Wereta	 21/06/2026	Bahir Dar
Name of the Student	**Signature & Date**	**Place**

Bahir Dar University

Institute of Disaster Risk Management and Food Security Studies

Department of Disaster Risk Management & Sustainable Development

Approval of Dissertation for Defense

I hereby certify that I have supervised, read, and evaluated this dissertation titled "**Climate-Smart Agriculture Practices and their Impact on Smallholder Farmers' Resilience to Climate Change: The case of Gubalafto Woreda, Ethiopia"** by Melkamu Sete Wereta prepared under my guidance. I recommend that the dissertation be submitted for oral defense.

Dr. Zemen Ayalew Ayele		21/06/2026
Name of principal advisor	Signature	Date
Dr. Yilebes Addisu Damtie		21/06/2026
Name of Co-advisor	Signature	Date

Bahir Dar University

Institute of Disaster Risk Management and Food Security Studies

Department of Disaster Risk Management & Sustainable Development

Approval of the Dissertation for Defense Results

As members of the board of examiners, we examined this dissertation entitled **"Climate-Smart Agriculture Practices and their Impact on Smallholder Farmers' Resilience to Climate Change: The case of Gubalafto Woreda, Ethiopia**" by Melkamu Sete Wereta. We hereby certify that the dissertation is accepted for fulfilling the requirements for the award of the degree of **"Doctor of Philosophy in Disaster Risk Science".**

Board of Examiners

External examiner name	Signature	Date
Abayineh Amare (PhD)		21/06/2026

Internal examiner name	Signature	Date
Zewdu Berhanie Ayele (PhD)		21/06/2026

Chair person's name	Signature	Date
Shifaraw Abebe (PhD)		21/06/2026

DEDICATION

This PhD work is dedicated to the memory of my beloved father, **Sete Wereta**, whom I lost in May 2009, in recognition of his unconditional love, moral support, and encouragement throughout my educational journey.

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ABBREVIATIONS AND ACRONYMS

ATE	Average Treatment Effect
ATT	Average Treatment Effect on Treated
ATU	Average Treatment Effect on the Untreated
CRGE	Climate-Resilient Green Economy
CSA	Climate-Smart Agriculture
CSI	Coping Strategies Index
DEEP	Data & Evidence to End Extreme Poverty
DRMFSS	Disaster Risk Management and Food Security Study
EOA	Ethiopia Minster of Agriculture
GHGs	Green House Gas
KII	Key Informant Interviews
FA	Factor Analysis
FAO	Food and Agricultural Organization of the United Nations
FCS	Food Consumption Score
FDRE	Federal Democracy Republic of Ethiopia
FGD	Focused Group Discussions
HDDS	Household Dietary Diversity Score
HFIAS	Household Food Insecurity and Access Scale
HHS	Household Hunger Scale
IPCC	Intergovernmental Panel on Climate Change
MDFS	Multidimensional Food Security
MESR	Endogenous Switching Regression
MOEFCC	Ministry of Environment, Forest and Climate Change
PCA	Principal Component Analysis
PSM	Propensity Score Matching
RCI	Resilience Capacity Index
rCSI	Reduced Coping strategy Index
RIMA	Resilience Measurement Analysis
SAFS	Self-assessment of Food Security
TLU	Tropical Livestock Unit

UNDP	United Nations Development Programme
UNFCCC	United Nations Framework Convention on Climate Change
UoND	University of Notre Dame
WHO	World Health Organization
WFP	World Food Programme

ABSTRACT

Ethiopia, including the study area, is highly affected by drought, floods, erratic rainfall, and land degradation, which reduce agricultural productivity, threaten food security, and weaken rural livelihoods. As a result, many households continue to experience low resilience capacity and food insecurity. However, previous studies have provided limited evidence on resilience dimensions, the intensity of climate-smart agriculture adoption, and the synergies and trade-offs among different climate-smart agriculture practices. Thus, this study aims to assess climate-smart agriculture practices and their impacts on smallholder farmers' resilience and food security in Gubalafto Woreda, Ethiopia. The study employed a quasi-experimental research design using a mixed-methods approach. Primary data were collected from 355 farm households and supplemented by 3 focus group discussions and 10 key informant interviews. The data were analyzed using principal component analysis, the food consumption score, the multidimensional food security index, the multivariate probit model, and the multinomial endogenous switching regression model. The top 5 climate-smart agriculture practices adopted by households were chemical fertilizers (50%), improved crop varieties (33%), small-scale irrigation systems (27%), agrochemicals (23%), and compost (22%). Conversely, about 30% of households did not adopt any top climate-smart agriculture practice. About 44% of the households were found to have a low resilience capacity index. Lowland households demonstrated a higher average resilience score than did midland and highland households, with p values of $P<0.01$. About 10.42% of households were classified as food secure, 60.28% as mildly food insecure, 23.1% as moderately food insecure, and 6.2% as severely food insecure. The partial, multiple, and full climate-smart agriculture adopters improved their resilience capacity by 7.4%, 12%, and 17%, respectively. Multiple- and full-package climate-smart agriculture practices were associated with 12.3% and 34.7% greater food consumption scores (food secure), respectively, while partial, multiple, and full adopters were achieving higher quality scores of 9.7%, 16.9%, and 13.2%, respectively. In contrast, households adopting multiple and full practices had 7.3% and 10% lower quantity scores. Small-scale irrigation shows a strong synergistic effect on both food security and resilience (0.99). Compost also has strong synergy, contributing to both food security (0.72) and resilience (0.74). In contrast, agrochemicals show a moderate positive effect on food security (0.38) but create a trade-off by reducing resilience (0.19).

In conclusion, despite the high levels of food insecurity and low resilience in the study area, the adoption of diverse combinations of climate-smart agriculture practices was found to improve the food security and resilience of rural households. Therefore, relevant institutions should prioritize investments in communication infrastructure, institutional support services, and social safety nets. Particular emphasis should be placed on highland and midland agroecological zones, where household resilience capacities are relatively low. In addition, stakeholders should promote the adoption of diverse climate-smart agriculture practices to strengthen household food security and resilience capacity.

Keywords: Agroecology**,** adoption intensity, climate change, climate smart agriculture, food security, resilience**,** synergies, trade-offs

CHAPTER ONE: INTRODUCTION

1.1 Background of the Study

Climate change is a major global challenge that threatens populations and food security in both developed and developing countries. It increases the frequency and intensity of extreme weather events such as rising temperatures and irregular rainfall, which negatively affect rural livelihoods and agricultural production (Fadairo et al., 2023; Hatfield et al., 2020; Raza et al., 2019). Global temperatures have already risen by about 0.8°C and are projected to increase by 1.5–4.8°C in the coming century. This warming trend is expected to intensify climatic disruptions including droughts, floods, and El Niño/La Niña events (Arora, 2019). These changes contribute to resource scarcity, reduced crop yields, lower incomes, and social instability, especially in vulnerable regions (Gitz et al., 2016; Ray et al., 2019). In addition, climate-related hazards such as land degradation, sea-level rise, heat waves, and droughts threaten biodiversity, agricultural systems, and nutritional health (Abebe & Amare, 2025; IPCC, 2021). Therefore, urgent global action is required to address climate change.

In Africa, climate change poses significant and uneven risks to sustainable livelihoods and strongly affects food security (UNICEF, 2020). The continent is the most vulnerable to climate change due to institutional weaknesses, high poverty levels, and limited adoption of modern farming practices, which hinder farmers' ability to adapt (Tol, 2018). Research by Aryal et al. (2021), Gebre (2021), and Kabubo-Mariara and Mulwa (2019) highlighted similar issues, showing that the adverse effects of climate change in African nations are exacerbated by a combination of factors, such as rapid population growth, severe poverty, insufficient infrastructure, and overreliance on rainfall. This exposure to climate risks, combined with communities' low capacity to adapt, makes Africa particularly susceptible to climate impacts (Pereira, 2017).

Food insecurity remains a major global concern, with rates considerably higher in developing nations than in advanced nations (Adeyanju et al., 2023; Gadiso et al., 2023). Africa has the most severe hunger rates, impacting 20% of its population (World Health Organization, 2024). Similarly, in Ethiopia, 8.6 million people experienced severe food insecurity in 2020, with approximately 7.2 million classified as being in crisis (IPC, 2021). As of May 2023, 22.8 million people in Ethiopia were undernourished (WHO, 2024). In 2022, more than 3 million individuals in the Amhara region required emergency food assistance due to food insecurity (DRMFSS, 2022). Ongoing natural and man-made hazards have led many Ethiopians to face livelihood failures and food insecurity, such as a lack of safe and nutritious food for all, low dietary diversity, and poor building resilience to shock and stress (limited climate adaptation and resiliency) (UNFCCC, 2022).

In in Ethiopia, the agricultural sector is the primary income source for the economy (Belay et al., 2017; Eshete et al., 2020), with smallholder farming accounting for approximately 90% of the cropland area. It accounts for 33.3% of the GDP and provides employment for approximately 80% of the population (Tesso, 2020). Agriculture is a critical component of the Ethiopian government's development strategy, which is aimed at fostering industrialization (UNFCCC, 2022). Despite its importance, the agricultural sector in Ethiopia remains fragile and vulnerable to climate-induced shocks due to limited infrastructure, technology, and adaptive capacity (Serdeczny et al., 2017). As noted by Gezie (2019), key constraints of agriculture include reliance on traditional practices, climate extremes, deforestation, weak market access, and inadequate infrastructure. These challenges adversely impact agricultural productivity, negatively affect income and livelihoods, and further exacerbate poverty and food insecurity (Ouko, 2021; WFP, 2019). Thus, critical intervention is needed to make how the agricultural system can become more resilient to climate change and increase productivity, thereby improving food security.

Climate adaptation is essential for reducing the negative impacts of climate change on agricultural productivity, food systems, and resilience capacity. One widely recognized approach is CSA, which has gained strong attention across African countries. CSA was formally introduced in 2010 and has since been widely promoted by governments and development partners in Africa and globally to enhance agricultural resilience, productivity, and sustainability (Lipper et al., 2014; Lipper & Zilberman, 2018). According to Lipper and Zilberman (2018), CSA is defined as a strategic approach designed to transform and reorient agricultural development in response to climate change challenges. In theory, CSA aims to achieve three goals: (i) increasing agricultural productivity and food security, (ii) adapting and increasing the resilience of people to climate change, and (iii) mitigating GHG emissions (Lipper et al., 2014; Thornton et al., 2018). In line with its commitment to adaptation strategies, the Ethiopian government's response to climate change impacts is demonstrated through climate-related policies and initiatives, such as the Climate Resilience Green Economy (CRGE), the 10-Year Perspective Development Plan (2021--2030) aimed at reducing reliance on rain-fed agriculture by enhancing irrigation capacity, the Ethiopia National Adaptation Plan (NAP-ETH2019), and the Ethiopia Programme of Adaptation to Climate Change (EPACC2010) (FDRE, 2011; Ouko, 2021; UNFCCC, 2022). However, the implementation of CSA practices often involves trade-offs. In practice, achieving all three objectives simultaneously may not be possible, requiring policymakers and practitioners to prioritize one or two goals over others.

Synergies and trade-offs are inherent features of CSA interventions (Girardello et al., 2019). Many farm-level management practices and technologies simultaneously deliver two or more climate-smart benefits synergistic effects or trade-offs across productivity, adaptation, and mitigation outcomes (Ogola & Ouko, 2021). While various CSA practices can increase farm productivity and household income, they may also increase labor requirements or environmental emissions, thereby creating trade-offs (Girardello et al., 2019). The terms **s**ynergy and trade-off are widely used in reports and scientific literature to explore the links between CSA practices and adaptation, agricultural productivity, and mitigation. Synergy refers to a positive relationship between measurable objectives, where CSA practices simultaneously improve productivity, adaptation, and mitigation. For example, irrigation can increase yields (productivity) while also strengthening adaptive capacity through higher household income (Bryan et al., 2013). In contrast, Trade-off describes negative outcomes, where progress in one objective undermines another. For example, irrigation may increase productivity (synergy) but also contribute to increased greenhouse gas emissions (trade-offs) (Antwi-Agyei et al., 2023). Trade-offs occur when a CSA intervention advances one goal but constrains others (Ogunyiola et al., 2022). Therefore, a holistic approach is critical to maximize the benefits of CSA practices and minimize adverse impacts across productivity, adaptation, and mitigation.

Gubalafto Woreda has a semiarid climate with erratic rainfall, frequent dry spells, and high inter-annual rainfall variability that strongly affects crop production. Rainfall is mainly concentrated between June and September, but its onset and cessation are unpredictable, increasing agricultural risk (Abegaz et al., 2020; Wassie et al., 2022). The area also faces recurrent drought, land degradation, soil erosion, declining soil fertility, and water scarcity, all of which reduce crop and livestock productivity and threaten household food security (Gebre et al., 2017; OCHA, 2024). These In response, smallholder farmers have adopted various CSA practices such as improved crop varieties, irrigation, crop diversification, soil and water conservation, adjusting planting dates, and livestock management (Temesgen, 2018). These practices support

Ethiopia's broader CSA goals of improving productivity, resilience, and adaptation (Kanter et al., 2018)., thus making their scaling-up essential for strengthening food security and resilience in the area.

1.2 Statement of the Problem

Intensifying extreme weather events such as droughts, floods, heatwaves, and erratic rainfall, which undermine ecosystems, agricultural productivity, and food security worldwide (FAO, 2022; IPCC, 2021). In developing regions, particularly Africa, the impacts are more severe due to high dependence on rain-fed agriculture, widespread poverty, and limited adaptive capacity, making rural livelihoods highly vulnerable to climate variability and change (Pereira, 2017; Serdeczny et al., 2017). In Ethiopia, recurrent droughts, floods, and rainfall unpredictability have increasingly constrained agricultural production and worsened rural food insecurity, with smallholder farmers experiencing substantial yield losses and livelihood instability climate change and limited access to adaptation technologies (Mersha & van Laerhoven, 2018; World Bank, 2023). Despite the severity of these challenges, food security and resilience among rural households remain fragile, highlighting the urgent need for effective and context-specific climate adaptation strategies.

Low adaptive and resilience capacity remains a major challenge to effective climate change response, particularly in economically vulnerable communities where livelihoods are highly dependent on climate-sensitive sectors such as agriculture (IPCC, 2023; Zhu et al., 2026). Limited access to infrastructure, modern technologies, climate information services, and financial resources, together with persistent poverty and weak institutional support, significantly constrains households' ability to anticipate, cope with, and recover from climate-related shocks and stresses. These challenges are more severe in developing regions, where weak institutional systems and limited adaptive resources further increase vulnerability and undermine long-term resilience (Mersha & van Laerhoven, 2018; G Zerssa et al., 2021). As a result, many communities remain trapped in repeated cycles of climate risk, livelihood disruption, and slow recovery, highlighting the urgent need for strengthened adaptive capacity through improved infrastructure, technology access, financial support, and institutional interventions to promote sustainable resilience building.

Food insecurity remains a major development challenge in Sub-Saharan Africa, where inadequate infrastructure, limited technological advancement, and weak adaptive capacity increase the vulnerability of smallholder farmers who rely heavily on rain-fed agriculture (Serdeczny et al., 2017).

In Ethiopia, recurrent climate shocks, including the 2008/2009 food crisis, the 2011 Horn of Africa drought, and the 2015 El Niño event, caused severe crop failure, livestock losses, and widespread food shortages (Kosmowski, 2018; Kourouma et al., 2022). Despite agriculture being the backbone of the Ethiopian economy, smallholder farmers continue to experience low productivity, food insecurity, and poverty (Wondimagegnhu et al., 2019). In Ethiopia, the continued reliance on traditional farming practices, combined with increasing environmental degradation, has contributed to stagnant agricultural productivity and persistent food system instability (Gebeyanesh Zerssa et al., 2021). Crop yield losses ranging from 50% to 90% are frequently reported due to climate shocks and soil degradation, further intensifying household food insecurity and poverty (AKLDP, 2017; Tsegaye et al., 2018). Moreover, low adaptive capacity, limited access to finance and climate information, and weak institutional support continue to threaten sustainable livelihoods and national food security in Ethiopia (Lewis, 2017; Tofu et al., 2022). Consequently, persistent climate-induced food insecurity remains a major obstacle to sustainable livelihoods, rural resilience, and national food security in Ethiopia.

Despite climate change adaptation is essential for protecting economic productivity, livelihoods, and human well-being, adaptation efforts remain fragmented, poorly coordinated, and constrained by limited financial, institutional, and technical capacities (IPCC, 2022). CSA practices have been identified as essential pathways to sustainably increasing productivity and food security, yet adoption remains low and uneven (Abegaz et al., 2023). In Ethiopia, although CSA is considered a critical strategy for addressing climate-related agricultural challenges and improving food security (Tariku & Kebede, 2025), a substantial gap persists between its theoretical potential and practical implementation. Studies show that inadequate institutional support, low access to resources and technologies, and weak coordination mechanisms continue to hinder widespread adoption of CSA practices (Abegaz et al., 2023; Dabesa et al., 2022). As a result, the agricultural sector remains highly vulnerable to recurrent climate shocks, threatening rural livelihoods and long-term food security.

While studies in Ethiopia have assessed CSA and its determinants (Bekele, 2025; Belay et al., 2023; Negera et al., 2022a; Teklewold et al., 2019), important research gaps still remain. Existing literature typically evaluates a narrow range of CSA practices (limited CSA practices) and focuses primarily on the binary adoption of single or multiple techniques. Consequently, there remains a lack of focus on adoption intensity the degree or scale to which these practices are implemented. Therefore, this study was tackle adaptation puzzles and providing localized evidence on the determinants of CSA adoption intensity.

Teklu et al. (2023) and Ali et al. (2023b) examined household resilience capacity; however, their studies provided limited disaggregation of resilience outcomes across different agroecological settings and gave insufficient attention to how absorptive, adaptive, and transformative capacities contribute to overall household resilience. As noted by Antwi-Agyei et al. (2013) community-level resilience assessments are essential because household characteristics vary considerably. Similarly, Jayadas and Ambujam (2021) developed a farmer resilience index, but their study was constrained by a limited sample size and a greater emphasis on physical and economic indicators, with less consideration given to institutional and social dimensions. Therefore, the current study incorporates social and institutional factors while also identifying agroecological settings with stronger resilience capacity to provide location-specific interventions that enhance the resilience of rural households.

Although studies on CSA and its impact have evolved (Abonesh et al., 2021b; Ali et al., 2023b; Jamil et al., 2021; Teklewold et al., 2017; Teklu et al., 2022, 2023), limited attention has been given to the effects of adoption intensity such as single, partial, multiple, and full adoption on household resilience and food security. Most previous studies, including Teklu et al. (2023), predominantly examined single technologies in isolation. However, Aseres et al. (2019) argued that evaluating a single technology may produce incomplete estimates of outcomes. Similarly, although studies have linked CSA adoption to improved livelihoods, they have focused on individual technologies rather than the intensity of multiple CSA practices (Abonesh et al., 2021b; Zeleke & Demeke, 2025).

Despite smallholder farmers adopt multiple CSA practices simultaneously to address climate-related production challenges (Asante et al., 2024), empirical evidence on the extent of CSA adoption and its effects on household resilience and food security remains scarce, particularly in

Ethiopia. This implies that existing studies provide insufficient understanding of how different levels of CSA adoption enhance resilience and food security among smallholder farmers. Moreover, because resilience and food security are dynamic and context-specific, there is a need for updated and location-specific evidence to inform policymakers and development practitioners.

Despite the growing body of literature on CSA (Ethiopia Report, 2022; Tilahun et al., 2023b) there remains a gap in prioritizing specific CSA practices and understanding their associated synergies and trade-offs with respect to food security and resilience. As noted by Shikuku et al. (2015) and Lopez-Ridaura et al. (2018), trade-off analysis is essential for evaluating sustainability of agricultural innovations. Studies in Ghana and Kenya by Antwi et al. (2023) and Ogola and Ouko (2021) examine the trade-offs of CSA practices, but the study mainly relied on qualitative methods, which may limit the robustness of the findings and does not adequately explore how these practices can simultaneously enhance both food security and resilience.

This study strives to fill the abovementioned gaps and adaptation puzzles. As a result, this study adds to existing knowledge regarding the intensity of CSA practices and how rural communities cope with, adapt to, and transform in response to climate-related risks. Understanding these capacities is critical for identifying vulnerable households and designing interventions that reduce food insecurity and enhance resilience. Ultimately, this study provides valuable evidence for the development of effective plans and strategies for climate change adaptation.

1.3 Objectives of the Study

1.3.1 General Objective

The general objective of this study was to assess climate-smart agriculture practices and their impact on the resilience of smallholder farmers in the case of Gubalafto Woreda, northeastern Amhara Region, Ethiopia.

1.3.2 Specific Objectives

Specific objectives of the study are:

- To assess the climate-smart agricultural practices adopted by smallholder farmers in the study area;
- To estimate the resilience capacity of smallholder farmers in the study area;

- To estimate the impacts of the adoption intensity of climate-smart agriculture practices on smallholder farmers' food security in the study area;
- To estimate the impacts of the adoption intensity of climate-smart agriculture practices on resilience among smallholder farmers;
- Analyze the synergies and trade-offs of climate-smart agriculture practices with respect to food security and resilience.

1.4 Research Questions

On the basis of the above-formulated objectives, the main research questions were as follows:

- What climate-smart agriculture practices have been adopted by smallholder farmers in the study area?
- What was the adoption intensity of climate-smart agriculture practices among the smallholder farmers in the study area?
- What is the status of the resilience capacity of the smallholder farmers in the study area?
- What factors determine the adoption of climate-smart agriculture practices?
- Does the adoption intensity of CSA practices significantly impact the resilience of smallholder farmers?
- What was the status of the food security of the smallholder farmers in the study area?
- Does the adoption intensity of CSA practices significantly impact smallholder farmers' food security?
- Which trade-offs and synergies were experienced upon the implementation of the CSA practices?

1.5 Significance of the Study

This study provides important insight into the impacts of CSA practices on stallholder farmers' food security and resilience. Specifically, the results of the study have some contributions and benefits from practical and academic perspectives. Practically, this study provides evidence-based insights that can inform community-based development initiatives; thereby enhance resilience and improving food security. In particular, this study provides crucial empirical evidence regarding the food security and resilience of smallholder farmers to climate change. This evidence is expected to inform decision-makers in the development of effective agricultural policies, guiding strategies that enhance resilience and support food security among vulnerable communities. Moreover, this study is essential for providing valuable policy insights that support the achievement of CSA goals. It also offers an opportunity to evaluate the effectiveness of current practices and identify priority practices for future implementation.

This study offers valuable insight that benefits a diverse array of stakeholders. These findings underscore the importance of implementing CSA practices to increase climate resilience and address food security challenges at the local level. Consequently, the findings serve as vital information for various stakeholders, including government officials, policymakers, ministries and their agencies, institutions, individuals, and local communities.

Academically, this study significantly enriches the growing body of research on CSA by deepening our understanding of its applications and impacts. This study improves current knowledge on how to quantify resilience on the basis of indicators and household characteristics. Moreover, the findings establish a foundation for future research on related topics, facilitating ongoing investigations and developments in this important field.

1.6 Scope and Limitations of the Study

The priorities of the problem, time frame, financial resource availability, and manageability are considered when determining the scope of this study. This study was conducted in Gubalafto Woreda, which is located in the northern part of the Amhara regional state in Ethiopia. Due to resource and time constraints, along with local conflict, limited data collection to only three *kebeles*, namely: Dengolla, Gedo-ber, and Doro-gibr. The study site was selected due to its vulnerability to climate change, recurrent droughts, erratic rainfall, and food insecurity (Gebre et al., 2017; OCHA, 2024; Tsegaye et al., 2018).

This study employed a quasi-experimental research design with a mixed-methods data analysis approach. Both quantitative and qualitative data were collected, but the latter was used to triangulate, complement and supplement the former. Data were collected through household surveys covering socioeconomic and biophysical factors, alongside focus group discussions and key informant interviews.

Quantifying resilience and developing relevant indicators are critical for this study. To achieve this, the resilience capacity of smallholder farmers was measured on the basis of the 3-D resilience framework (Bene et al., 2012). Three dimensions of resilience: absorptive, adaptive, and transformative capacity was considered. Additionally, the study examined the intensity of adoption of the top five out of 18 CSA practices and their impact on resilience and food security via multinomial endogenous switching regression. Although mitigation is a core pillar of CSA, it was excluded from this study due to high costs and the require laboratory testing.

Data were collected between September and November 2024. While this study provides empirical evidence on the benefits of CSA, it is subject to certain limitations regarding its scope. Although CSA encompasses a wide array of both farm-level and non-farm-level interventions, this study was constrained by the practical challenges of evaluating every possible practice within a single study. Consequently, the analysis is restricted to the intensity of five specific CSA practices, potentially excluding other practices. Furthermore, while CSA is a multidimensional concept with far-reaching environmental, social, and economic effects, this study specifically isolates food security and resilience as the primary outcome variables. Other critical goals such as carbon sequestration and biodiversity conservation were beyond the immediate scope of this research and remain areas for further investigation.

1.7 Operational Definition of Terms

Climate-smart agriculture**:** A set of agricultural practices and technologies designed to simultaneously increase crop yields, improve food security, and enhance resilience to climate change.

Climate change: Climate change is the change in weather in a statistical manner over periods of time. This change in weather may be due to natural variability or human activities.

Resilience: The ability of socioecological systems to respond to and adapt to changing conditions, especially in the context of climate change, includes the capacity for transformation when necessary.

Food security: is commonly defined as a state in which all individuals have regular access to sufficient, safe, and nutritious food to maintain a healthy and active life.

Smallholder farmers: Smallholder farmers are producers who rear livestock or cultivate crops on a limited scale; they typically produce their main source of food on their own and rely on rainfall.

Control group: Respondents who did not adopt any of the five major CSA practices during the 2023 production year.

Top five CSA practices: The first five most widely adopted CSA practices by households during the 2023 *Mehir* growing year, selected from a total of eighteen practices.

Treatment Group**:** The group of respondents who have adopted at least one of the top five climate-smart agriculture practices. These respondents are categorized into one of four groups: single adopters (one practice), partial adopters (two practices), multiple adopters (three-four practices), and full adopters (all practices).

1.8 Ethical Consideration

In this study, ethical considerations were prioritized at every stage. First, ethical clearance was obtained from the Bahir Dar University IDRMFSS Institute of Review Board (IRB), and permission was obtained from district agricultural offices. Researchers ensured that the participants fully understood the purpose, procedures, and benefits of the study and voluntarily agreed to participate. Oral consent was obtained from respondents involved in household surveys, key informant interviews (KIIs), and focus group discussions (FGDs). The participants were assured of their anonymity and informed that the data collected would be used solely for academic purposes.

The identity of the respondents was protected by assigning a code to each interviewee and respondent. Additionally, the study respected and safeguarded respondents' private information, as well as their local values and norms, ensuring confidentiality throughout the research process.

1.9 Organization of the Study

This dissertation is structured into five chapters. Chapter one introduces the study by outlining the background, problem statement, objectives, research questions, significance, scope, and limitations. Chapter two synthesizes the relevant theoretical, empirical, and conceptual literature while developing the conceptual framework for the study. Chapter three details the research methodology and describes the study area, research design, approach, sampling techniques, data collection methods, and data analysis procedures. Chapter four presents, interprets, and discusses the study’s findings, which are organized into subsections for clarity. The final chapter concludes the dissertation by summarizing the key findings and offering recommendations.

CHAPTER TWO: REVIEW LITERATURE

This chapter reviews the literature relevant to the present study, highlighting theoretical and empirical aspects related to CSA practices and their impacts. The necessary information was gathered by searching for relevant studies, books, and conference papers. Additionally, the chapter presents the conceptual framework of the study, emphasizing key variables to provide a comprehensive understanding of the topic.

2.1 Concepts and Theoretical Framework

2.1.1 Concepts and Definitions

Climate change refers to long-term patterns of weather, including temperature, precipitation, and storm events. Contemporary climate change involves both shifts in long-term averages and increased variation around them, with extreme events becoming more common (US Natl. Res, 2016). The IPCC defines climate change broadly as any change in climate over time, whether due to natural conditions or as a result of humans (Pielke, 2004). Climate change has led to recurrent droughts, famines, flooding, desertification, loss of wetlands, reduced biodiversity, and water shortages, all of which have contributed to a decline in agricultural production (Zegeye, 2018).

CSA practices were formally introduced in 2010 and have since been actively promoted by governments and development partners in Africa and globally to strengthen agricultural resilience, productivity, and sustainability (Lipper et al., 2014; Lipper & Zilberman, 2018). Lipper and Zilberman (2018), define CSA as a strategic approach designed to transform and reorient agricultural development in response to climate change challenges. It serves as a guiding framework for managing agriculture under a changing climate.

According to Lipper et al. (2014) and Thornton et al. (2018), CSA aims to achieve three goals: (i) increasing agricultural productivity and food security, (ii) adapting and increasing the resilience of people to climate change, and (iii) mitigating GHG emissions. However, the implementation of CSA practices often involves trade-offs. In practice, achieving all three objectives simultaneously may not be possible, requiring policymakers and practitioners to prioritize one or two goals over others (Andrieu et al., 2017).

CSA practices lessen the negative effects of climate change by increasing crop yields and making production systems more adaptive and resilient (Palombi & Sessa, 2013); achieve climate resilience (Gori et al., 2022); facilitate a transition to agriculture and food systems that are more sustainable, productive, and climate friendly (Siminyu et al., 2020); and build resilience and adapt to climate change (Wekesa et al., 2018).

Food security exists when "all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life" (FAO, 2008). This definition emphasizes that food security involves not only food production but also people's ability to obtain, utilize, and sustain adequate food. Accordingly, food security is a multidimensional concept that encompasses food availability, access, utilization, and stability over time. Food availability refers to the physical presence of sufficient quantities of food within a given area. Food access, in contrast, concerns the ability of individuals and households to obtain adequate food through purchase, own production, exchange, or transfers. In this regard, economic access depends on factors such as income levels, food prices, employment opportunities, and access to credit (Sen, 1982). Food utilization relates to the proper biological use of food, which requires adequate dietary energy and nutrients, safe drinking water, proper sanitation, and appropriate health care services. It also includes knowledge of food preparation, storage, and feeding practices. Furthermore, food stability denotes the ability of individuals or households to maintain adequate food security over time. It highlights that food must remain available, accessible, and properly utilized at all times (FAO, 2015).

In the literature, there is no formal definition of resilience that is commonly accepted and that, in fact, some definitions of the term even overlap with other concepts (Hosseini et al., 2016). While resilience has received a good deal of attention, it would be fair to say that the field has not reached consensus on a definition. Recognizing the importance of resilience, many definitions in multiple domains have been offered, including physical resilience (Bodin & Wiman, 2004), social resilience (Kofinas, 2003), ecological resilience (Longstaff, 2005), economic resilience (Rose, 2007), and community resilience (Coles & Buckle, 2004). The word resilience originally stems from the Latin term "resiliere", which means jumping back or bouncing back. Resilience focuses on enhancing a system's ability to withstand a variety of threats rather than eliminating or minimizing the loss of assets due to specific events.

Resilience was originally introduced by Holling (1973), as the concept of resilience is a measure of the persistence of systems and of their ability to absorb change and disturbance (Nadu et al., 2021). The latest definition of resilience, according to the United Nations Office for Disaster Risk Reduction (UNDRR), is "the ability of a system, community, or society exposed to hazards to resist, absorb, accommodate, adapt, transform, and recover from the effects of a hazard in a timely and efficient manner" (Nguyen & Akerkar, 2020). From a social-ecological perspective, resilience has been theorized as the capacity of socioeconomic systems, such as households, to withstand shocks through processes of absorption, adaptation, and transformation (Walker et al., 2004).

Absorptive capacity refers to the ability of a socioecological system, such as a smallholder agricultural system, to withstand the adverse effects of climate change by using available skills and resources. As noted by Oxfam (2017), absorptive capacity denotes the ability to take deliberate protective measures and cope with known shocks and stresses. In contrast, adaptive capacity reflects the actions undertaken by households to respond to shocks and stresses effectively. It encompasses the ability to implement appropriate adaptation strategies that reduce both the likelihood of climate-related hazards and the severity of their impacts (Schipper et al., 2014). Furthermore, transformative capacity refers to the ability of a socioecological system to sustain itself when shocks and stresses exceed its adaptive capacity. It involves not only recovering from adverse conditions but also achieving positive and structural changes during periods of crisis (Bene et al., 2014).

2.1.2 Political-economy Theories

Climate-Smart Agriculture (CSA) is widely promoted as a “triple-win” approach that aims to increase agricultural productivity, enhance climate resilience, and reduce greenhouse gas emissions (Hellin et al., 2023). However, political-economy perspectives, particularly Political Ecology, challenge this optimistic narrative by emphasizing that the benefits of CSA are shaped by power relations, resource control, and socio-economic inequalities. From this perspective, CSA outcomes are not equally distributed, as access to resources, technologies, and adaptation opportunities is often influenced by existing social and economic structures.

Political ecologists argue that CSA is frequently presented as a technical solution to climate change while overlooking the political and social factors that drive vulnerability. Mainstream CSA approaches tend to prioritize technological innovations, market integration, and productivity enhancement, often paying limited attention to issues of equity, land access, and social justice. Consequently, wealthier farmers and agribusiness actors are often better positioned to benefit from CSA interventions, while resource-poor smallholders may face barriers due to limited capital, knowledge, and institutional support (Budiman, 2022).

Furthermore, political ecologists warn that CSA interventions can result in maladaptation if local socio-economic conditions and power dynamics are ignored. Success is often measured through adoption rates and productivity gains, which may conceal inequalities within communities. As a result, CSA practices that require substantial investments in land, technology, or finance may disproportionately benefit wealthier households while excluding poorer farmers, thereby reinforcing existing vulnerabilities and inequalities (Hellin et al., 2023).

In addition, the implementation of CSA in many developing countries, particularly in Sub-Saharan Africa, is strongly influenced by international donors, development agencies, and external experts. These actors often shape policy priorities, knowledge production, and evaluation criteria, limiting the participation of local governments and smallholder farmers in decision-making processes. Consequently, externally driven CSA agendas may undermine local policy autonomy and fail to adequately address the needs and experiences of vulnerable farming communities (Newell et al., 2019).

While Political Ecology provides a macro-level critique of the political and economic forces shaping agricultural development, the Theory of Access offers a micro-level framework for understanding that actually benefits from CSA. Ribot and Peluso (2003), define access as the ability to derive benefits from things, distinguishing it from property, which refers only to *the* right to benefit from things. They argue that access is better understood as a "bundle of powers" rather than a "bundle of rights" because people may possess legal rights to resources but still lack the means to benefit from them.

This distinction is particularly important in assessing the impacts of CSA on food security and climate resilience. Although farmers may have secure land tenure, their ability to benefit from

CSA depends on access to multiple enabling mechanisms, including capital, knowledge, technology, markets, and institutional support. Many CSA technologies, such as drought-tolerant seeds, solar-powered irrigation systems, and improved farm inputs, require significant financial investment. Farmers with limited access to credit or savings may be unable to adopt these technologies despite having legal access to land. Consequently, resource-poor households often face barriers to participation in CSA initiatives, which may reinforce existing inequalities and undermine food security outcomes (Budiman, 2022). On the other hands, effective implementation of CSA practices requires technical knowledge, extension services, and access to climate information. According to Ribot and Peluso (2003), knowledge and information are important mechanisms through which access is gained and maintained. When extension services and climate information systems primarily reach wealthier, more educated, or male farmers, marginalized groups are excluded from the benefits of CSA, thereby widening social and economic disparities (Peluso & Ribot, 2020).

Conventional CSA frameworks often portray the adoption of sustainable practices such as agroforestry, conservation agriculture, and soil fertility management as rational technical decisions made by farmers. However, a political ecology perspective reveals that such choices are deeply embedded within broader socio-political contexts. In conflict-affected regions of Northern Ethiopia, particularly during and after the Tigray conflict, armed violence disrupted livelihood systems through displacement, destruction of productive assets, and market fragmentation, thereby undermining farmers' adaptive capacity (Gebrihet & Gebresilassie, 2025). Drawing on Sen's entitlement framework, conflict generates entitlement failures by limiting access to food, land, labor, and markets, forcing households to prioritize immediate survival over long-term adaptation investments. Consequently, farmers often resort to distress coping mechanisms such as selling productive livestock, reducing food consumption, or depleting savings, which may enhance short-term survival but erode future resilience and agricultural productivity (Gebrihet & Gebresilassie, 2025). This suggests that climate resilience cannot be understood independently of political stability and security conditions.

Ethiopia's Climate-Resilient Green Economy (CRGE) strategy demonstrates a strong national commitment to climate adaptation and low-carbon development. Nevertheless, the gap between policy ambitions and local implementation remains substantial. Mainstream explanations frequently attribute low CSA adoption to inadequate farmer awareness or technical knowledge. In contrast, institutional governance theory highlights structural constraints embedded within state institutions. Climate governance requires effective coordination among multiple sectors and administrative levels, yet institutional fragmentation, overlapping mandates, and weak inter-agency collaboration continue to hinder policy implementation (Simane et al., 2016). Moreover, while climate finance mechanisms such as the CRGE Facility operate at the federal level, limited administrative capacity, bureaucratic inefficiencies, and insufficient decentralization constrain implementation at regional and Woreda levels (Amsalu et al., 2014). These governance challenges often leave local extension services underfunded and poorly equipped to support farmers, revealing that CSA adoption is influenced not only by technology availability but also by institutional effectiveness and political commitment.

Increased agricultural production through CSA does not automatically improve household food security or income. Farmers must also have access to markets, transportation, and decision-making institutions. In many rural areas, market access is controlled by traders, brokers, or local authorities, limiting smallholders' ability to obtain fair prices for their produce. As a result, the economic gains generated by CSA may be captured by intermediaries rather than the farming households themselves (Ribot & Peluso, 2003). Studies evaluate CSA using agronomic indicators such as crop productivity, soil health, and carbon sequestration, limited attention has been given to how unequal access to resources, services, and decision-making processes influences farmers' ability to benefit from CSA interventions. Moreover, climate resilience cannot be achieved solely through the adoption of improved agricultural technologies. Sustainable resilience requires transformative adaptation that addresses the underlying social, economic, and institutional constraints affecting livelihood opportunities and food security outcomes (Hellin et al., 2023). Existing literature shows limited integration of political-economic perspectives with quantitative assessments of food security and climate resilience. In particular, insufficient evidence exists on how factors such as gender relations, institutional support, credit access, and resource ownership shape the effectiveness of CSA practices. This study addresses this gap by applying Political Ecology and the Theory of Access to examine how socio-economic and institutional factors influence farmers' capacity to adopt and benefit from CSA practices.

2.1.3 Theoretical Framework of Measuring Impact of CSA Practices

In literature, there are different impact model analysis including Propensity Score Matching (PSM), Generalized Propensity Score Matching (GPSM) and Endogenous Switching Regression (ESR) model. The last decade has seen a broad surge of interest in PSM to estimate average treatment based on real-world data. However, PSM may be affected by unmeasured confounding variables, leading to biased results (Nuttall & Houle, 2008), and it is also unsuitable for scenarios with more than two treatment groups. While, GPSM is evaluating certain treatment programs, more complex framework may be necessary since the actual choice set of individuals contains more than just two options. For example, when analyzing more than two treatment options or dosage level, conventional form of PSM is inadequate and extensions are necessary (Baser, 2013). In this case, adopt GPSM, which estimates average treatment effect of more than two treatments. GPSM technique is applied to commercial claims data to estimate the multiple treatment effect (Baser, 2013), which is more applied in experimental research design.

The Multinomial Endogenous Switching Regression (MESR) model is employed to account for multilevel treatment effects. The MESR model is a modified version of the classical Heckman Selection Model and consists of two simultaneously estimated equations: the selection equation and the outcome equation. In nonexperimental studies, individuals are not randomly assigned to treatment and control groups, which may introduce systematic selection bias (Greene, 2006; Ojoko et al., 2017). This bias makes it difficult to establish clear causal relationships. In addition, farmers' decisions to adopt specific practices may be influenced by the expected benefits, leading to endogeneity problems. Unobserved household characteristics may simultaneously affect both the adoption decision and the outcome variables, resulting in inconsistent and biased estimates. To address these issues, the MESR model is applied because it effectively corrects selection bias arising from both observed and unobserved heterogeneity (Khanal & Mishra, 2018). Therefore, the MESR model provides a robust framework for analyzing multiple treatment choices and handling endogeneity in the selection process.

The estimation of the MESR model follows a two-step procedure. In the first step, a selection equation is computed to assess the likelihood that households adopt different levels of CSA practices. This step helps identify the key factors that influence the extent of CSA adoption. To conduct this analysis, a multinomial logit model is employed. The probability of being in a specific regime is modeled via this multinomial logit, which is typically a function of observable covariates.

The adoption decisions model is based on McFadden (1972) random utility maximization theory, which speculates that farmers' decisions to use adaptations are random and that the farmers choose these strategies if the probability of a specific option's utility being greater than that of other alternative measures. Utility maximization theory assumes that all farmers behave in a manner that maximizes their utility. Hence, farmer i' decides to use 'j' adaptation options if the probability of perceived utility from option 'j' is greater than the utility from other strategies (say, 'k').

In the second stage of the analysis, outcome equations are computed to derive the Average Treatment Effect for the Treated (ATT) and the Average Treatment Effect for the Untreated (ATU). The ATT quantifies the actual impact of intervention by measuring the change in food security and resilience specifically for those who adopted CSA practices. In contrast, the ATU represents the average potential impact or the expected gain in food security and resilience that would have occurred had the non-adopters chosen to participate in the intervention. Together, these metrics allow for a comprehensive evaluation of both the realized benefits for participants and the missed opportunities for those currently non participants (White & Raitzer, 2017).

As food security serves as a primary outcome variable, MESR utilized two indicators to assess food security: the Food Consumption Score (FCS) and the Multidimensional Food Security Score (MDFS). Specifically, the FCS is calculated following WFP (2008) guidelines through a 7-day dietary recall, where food items are categorized into specific groups and their weekly frequencies are summed. Subsequently, these totals are multiplied by standard weights and aggregated into a final score representing overall dietary diversity. In addition, the MDFS index provides evaluation by incorporating 24 questions across four key dimensions: availability, quality, preference, and stability. To compute this index, respondents report the frequency of specific conditions over a four-week period, and the scores for each dimension are ultimately determined by summing the coded responses within each category.

In this framework, $S_{\mathbf{Qn}}$= represents the household score of quantity; S_{Ql}= represents the household score of quality; $S_{\mathbf{Acc}}$= represents the household score of acceptability; S_{St}= represents the household score of stability. The Q_{ni} denotes the quantity score derived i^{th}

questions, which include NOEAT, NOFOOD, SKIPEAT, SENDBEG, SENDEAT, EATSEED, WILD, FDCRED, BORROW, RMEAL, and LMTPOR. The $S_{\mathbf{QI}i}$ indicates the quality score i^{th} questions: PULSES, GRAIN, VARFOOD, DAIRY, EGGS, MEAT, FRUIT, and VEGET. Additionally, SAcci refers to the acceptability score of i^{th} questions: NOTWNT and PREFER, while S_{Ati} represents the stability score i^{th} questions: SLPHUN, WORRY, and SAFS (see Appendix G).

The dependent variable in this study is adoption intensity of the top five CSA practices, measured by the number of CSA practices adopted by each household. For the causal analysis, households that adopted the top five CSA practices during the 2023 crop growing year were considered the treatment group and were further categorized into discrete groups based on their level of adoption intensity: single adoption (one practice), partial adoption (two practices), multiple adoption (three to four practices), and full adoption (all five practices). In contrast, the control group consisted of households that did not adopt any of the top CSA practices.

2.1.4 Analytical Framework of Resilience

Resilience is not directly observable per se but must be placed in relation to a given outcome, e.g., resilience to conflict or climate change and identifiable shocks. Resilience is necessarily specific to context time, space, livelihood and shocks (resilience of who/what? to what?), but this precludes generic indicators of resilience and therefore makes comparisons difficult (Sturgess, 2016). Furthermore, many common survey instruments are unsuitable for measuring resilience holistically because of their multiscale, dynamic, and multidimensional nature (Bene et al., 2016).

As outlined by Sturgess (2016), measuring resilience faces both conceptual and methodological challenges. Conceptually, accurately measuring resilience requires a clear understanding of what aspects need to be assessed, but varying definitions of resilience complicate this process. Most quantification efforts focus on the household level; the links between the resilience of individuals, households, communities, infrastructure and countries are not straightforward. Methodologically, obtaining data that are both reliable and meaningful can be difficult. While it may be easier to quantify formal aspects of life, such as membership in an organization, these formal dimensions often provide less insightful information about resilience than informal aspects do.

Despite the challenges outlined above, progress has been made in forming general principles to underpin attempts to measure/quantify resilience and in constructing relevant indicators for use in programs. These include (i) the 3-D resilience framework proposed by Bene et al. (2012), which suggests that resilience arises from three key capacities: absorptive, adaptive, and transformative capacities. Each of these capacities results in different outcomes: persistence (the ability to maintain function), incremental adjustment (small, gradual changes), or transformational responses (significant changes in response to challenges). This framework seeks to quantify resilience by categorizing it on the basis of various indicators and characteristics. (ii) Food security information network principles and the common analytical model proposed by Constas et al. (2014), which measures resilience with a focus on food security by viewing resilience in terms of absorptive, adaptive and transformative capacity; this model includes subjective assessments and qualitative data as well as quantitative data. Furthermore, this model builds a common analytical model for measuring resilience according to three components: ex ante: component data describing the initial state before a shock; disturbance data describing the effects of shocks and stresses; and ex post data on the subsequent states/trajectories after the shock. (iii) Costs of resilience: Bene (2013) proposed the idea that ‘costs of resilience’ (costs to go through a shock) provide an independent metric to quantify resilience across scales and dimensions. ‘Costs’ refer not only to financial costs but also to ecological, social, psychological, and nutritional costs. The resilience costs can be calculated by adding together the anticipation (the ex-ante investments for disaster/shock preparedness), impact (the costs of destruction following the impact of the shock) and recovery costs (including adaptation and aid). This means that the lower the resilience costs are, the more resilient a system is.

One of the most common ways of measuring resilience to date has been to use a framework that considers different dimensions of resilience and proposes related variables to gauge levels of resilience. Essentially, the idea of livelihood resilience in particular is becoming increasingly well-known owing to international development and humanitarian organizations that aim to measure and build resilience to specific disturbances such as floods or droughts. However, measuring livelihood resilience is a difficult task, and practical methods for measuring livelihood resilience, as well as analyzing and visualizing data, are needed.

As outlined in Quandt (2018), one method used to measure resilience is the household livelihood resilience approach (HLRA), which draws from the sustainable livelihoods approach and its five capital assets (financial, human, social, physical and natural). However, each variable was given equal weight to aid interpretation and reduce ambiguity, as was done by (Erenstein, 2007). As outlined in Smith et al. (2008), the Brief Resilience Scale is designed as an outcome measure to assess the ability to bounce back or recover from stress (illness). The majority of resilience measures have concentrated on analyzing the protective factors and resources that could enable a resilient outcome. This scale was developed with a specific focus on bouncing back from stress. This scale was developed to have a specific focus on bouncing back from stress. In relation to our definition, this scale could be a useful outcome measure in the context of stress. Furthermore, Windle et al. (2008) outlined psychological resilience measurements through assessments (self-esteem, personal competence and interpersonal control) that act as protective factors against risks and adversities.

As outlined by Sturgess (2016), several resilience measurement frameworks have been proposed since 2008 (Table 2.1).

Table 2.0.1: Examples of resilience measurement frameworks and indicators

Dimension/characteristics of Resilience	Indicators/examples of Indicators	Applied in Practice
3A's – anticipatory capacity, adaptive capacity, absorptive capacity and transformation	assets, access to services, adaptive capacity, income and food access, safety nets	Yes, as part of monitoring and evaluation framework for projects
FAO Resilience Index Measurement and Analysis Model (RIMA) (earlier version) (next version – RIMA II)	Physical dimensions » Income and Food Access »Access to Basic Services »Assets » Social Safety Nets (Model was later updated to include: » Enabling institutional environment »Natural environment	»Average per person daily income »Access to school, markets, health facilities »Amount of cash and in-kind assistance »Housing number of rooms owned) »Diversity of income sources » Expenditure change

	»Agricultural practice/technology) Capacity dimensions »Adaptive capacity » Sensitivity	
Oxfam GB Multi-Dimensional Approach to Measuring Resilience	»Livelihood viability » Innovation potential »Contingency resources & support access » Integrity of natural & built environment » Social and institutional capability	Examples of social capability indicators: »Participation in drought preparedness meetings »Awareness of local action on adaptation
USAID Measurement Framework for Community Resilience	»Income and food access »Assets »Adaptive capacity » Social capital and safety nets »Governance »Nutrition and health	»Per capita expenditure (income proxy) »Change in household asset ownership »Access to credit » % of households with access to positive coping strategies »Prevalence of stunted children under 5

Source: Author review (2024)

2.2 Empirical Literature Review

2.2.1 Food Security Status in Ethiopia

Ethiopia is facing a severe food security crisis, with millions of people struggling to access sufficient and nutritious food. Recent reports show that about 5.3 million people were acutely food insecure in 2025 (Welthungerhilfe, 2026), highlighting the ongoing challenges in the country. Food insecurity remains one of the most persistent development challenges in Ethiopia, shaped by the interaction of climate variability, armed conflict, economic instability, rapid population growth, and structural agricultural constraints. Food insecurity remains one of the country's major development challenges, driven by the combined effects of climate variability, armed conflict, economic instability, rapid population growth, and structural agricultural limitations. A recent systematic review and meta-analysis estimated that the pooled prevalence of household food insecurity in Ethiopia reached 51.46% in 2026, indicating that more than half of households lack adequate access to food. Significant regional disparities also exist, reflecting differences in climate conditions, livelihood systems, conflict exposure, infrastructure, and institutional support. The Amhara region recorded the highest prevalence of food insecurity at 61.14%, while Oromia reported a relatively lower prevalence of 41.52% (Yayeh et al., 2025). These findings suggest that food insecurity in Ethiopia is both widespread and unevenly distributed, requiring targeted and context-specific policy interventions.

Conflict and political instability have further aggravated the food security situation, particularly in northern Ethiopia. The recent armed conflict in Tigray severely disrupted agricultural production, market systems, humanitarian assistance, and livelihood activities, leading to alarming levels of food insecurity. Evidence from post-conflict in Tigray revealed that 57% of households experienced food insecurity, with 21.86% exhibiting severe levels (Gebrihet & Gebresilassie, 2025). Similar northern conflict in Ethiopia has severely worsened food insecurity and livelihood conditions. More than 5.5 million people were affected by acute food insecurity (Muhyie et al., 2025).

As of early 2026, Ethiopia remains in the grip of a severe humanitarian crisis, with the Tigray, Afar, Amhara, Somali, and Oromia regions identified as the most critically food-insecure areas (FEWS NET, 2025). Approximately 13 to 16 million people currently require urgent food assistance, with the highest concentrations of need found in Tigray (where nearly 90% of the population is aid-dependent) and the Somali and Oromia regions, which together account for over 50% of the national assistance requirement (IPC, 2014; WFP, 2025).

2.2.2 Empirical Findings of Impact of CSA Practices

Households adopting CSA practices achieve better food consumption, dietary diversity, and economic well-being than nonadopters. Kebeda (2019) found that CSA adopters had higher food consumption scores and more diverse diets, while Okumu et al. (2022) and Wekesa et al. (2018) confirmed that CSA practices improve food security and reduce vulnerability among smallholder farmers. Studies consistently show that CSA practices improve household food security, income, and farmers' well-being. For example, Abonesh et al. (2021a) found that CSA practices reduce hunger and food insecurity among smallholder farmers in Ethiopia. Comparable findings were also reported in Pakistan by Jamil et al. (2021) and in Zimbabwe by Okumu et al. (2022), indicating that CSA technologies contribute to improved food security and support the achievement of SDG 2. Although those studies generally agree on the positive effects of CSA practices, most focus mainly on overall adoption impacts, with limited attention to comparing the effects of different CSA practice combinations, adoption intensity, and context-specific trade-offs.

Improved seeds, chemical fertilizers, and organic fertilizers enhance agricultural productivity and food security (Paul et al., 2023; Teklu et al., 2023; Tilahun et al., 2023a). While chemical fertilizers mainly increase yields, organic fertilizers improve dietary diversity and climate resilience. Conservation agriculture practices, including reduced tillage, crop residue management, crop rotation, intercropping, compost, and manure application, improve household food consumption and food security (Kebeda, 2019). Similarly, (Davide et al., 2021)and Okumu et al. (2022) reported that crop residue management, cover crops, and zero tillage positively enhance dietary diversity and household food security by increasing agricultural productivity and food stability. However, those studies provide limited evidence on the comparative effectiveness, trade-offs synergies, and long-term sustainability of combining different CSA practices.

crop rotation and row planting enhance food security and reduce farmers' vulnerability to climate change by increasing yields and improving food self-sufficiency (Teklu et al., 2022; Tilahun et al., 2023a). Similarly, agroforestry, border tree planting, and small-scale irrigation positively affect household food consumption, dietary diversity, and farmers' welfare by helping households manage climate-related risks (Okumu et al., 2022; Teklu et al., 2022; Wekesa et al., 2018). However, most existing studies focus on the impacts of individual CSA practices, with limited attention to comparing the effectiveness, synergies, and trade-offs of multiple CSA practices on food security and climate resilience in the Ethiopian context.

Individuals who adopted crop management, field management, risk reduction, and specific soil management practices achieved higher levels of food security than those who did not adopt these practices. Haq et al. (2021), reported that the combined adoption of CSA practices, such as crop diversification, mixed farming, modern inputs, soil conservation, and water conservation, improved dietary diversity more effectively than the adoption of a single strategy. Similarly, Paul et al. (2023), found that combining improved seeds with intercropping positively influences household food consumption scores.

Crop diversification, irrigation, conservation agriculture, soil fertility management, improved seed use, and intercropping enhances household food consumption and food security (Kebeda, 2019; Paul et al., 2023). Similarly, Wekesa et al. (2018) and Abegunde et al. (2022) indicate that using diverse crop packages and multiple CSA practices improves farmer welfare and increases the likelihood of achieving food security, particularly among smallholder farmers. However, while these studies agree on the positive impacts of CSA adoption, most of them primarily focus on either single effects of practices rather than interaction effects of different CSA combinations.

With respect to adaptation and resilience building, the literature shows that CSA technologies enhance household resilience, reduce vulnerability to climate shocks, and improve productivity. Practices such as improved crop varieties, crop rotation, compost application, row planting, irrigation, agroforestry, intercropping, and manure use strengthen farmers' adaptive capacity and resilience (Paul et al., 2023; Tilahun et al., 2023a). Similarly, evidence from Ethiopia indicates that small-scale irrigation, compost, manure management, chemical fertilizers, conservation agriculture, and crop diversification significantly increase the resilience index of rural households (Ali et al., 2023b). Evidence from Kenya and Tanzania also confirms that maize-legume intercropping, manure application, and broader CSA adoption improve productivity and resilience while contributing to climate change mitigation (Kurgat et al., 2020; Siminyu, 2021). Consistent findings from Teklu et al. (2022) and Jamil et al. (2021) further support that soil and water management, crop management, and modern inputs enhance resilience, food security, and climate change adaptation in line with Sustainable Development Goal 13. Despite this, limited empirical attention has been given to impacts of CSA adoption intensity and the associated trade-offs between benefits and costs.

2.2.3 Factors Influencing CSA Adoption

Studies across Sub-Saharan Africa show that the adoption or dis-adoption of agricultural technologies is influenced by multiple factors (Kassie et al., 2013; Knowler & Bradshaw, 2007; Kurgat et al., 2018; Teklewold et al., 2013). With this in mind, the adoption of CSA practices is shaped by household characteristics (such as education, household size, and sex), economic factors (farm size and off-farm income), institutional factors (extension services, input-output markets, and social networks), as well as environmental conditions and access to information.

However, the influence of these factors is often context-specific; varying across locations and technologies, suggesting that no single set of determinants universally explains CSA adoption.

Sex of the household head: The sex of the household head shows a consistent and comparable influence on the adoption of CSA technologies. Evidence indicates that male-headed households are more likely to adopt agroforestry (Ahmed et al., 2023a; Sisay et al., 2023). Similarly, studies in Kenya, Ghana, and Pakistan report that male-headed households have a higher likelihood of adopting integrated CSA packages, including soil management, crop diversification, and water conservation practices (Haq et al., 2021; Issahaku & Abdulai, 2020; Wekesa et al., 2018). In contrast, female-headed households are generally less likely to adopt these technologies due to limited access to land, labor, credit, education, and extension services, as well as higher domestic responsibilities. Comparatively, evidences highlights a clear gender-based disparity in adoption behavior, suggesting that sex of household head is a consistently significant.

Age of the household head: The effect of the age of the household head on CSA adoption shows mixed and context-specific results when compared across studies. On one hand, evidence from Ethiopia and Kenya indicates a positive relationship, where older farmers are more likely to adopt practices such as crop diversification, field management, and soil management (Sisay et al., 2023; Wekesa et al., 2018), due to greater experience and may have accumulated assets. On the other hand, studies from Pakistan, Ethiopia, and Tanzania report a negative relationship between age and the adoption of more modern or capital-intensive CSA practices, including improved inputs, water conservation, irrigation, and integrated pest management (Asrat & Simane, 2017; Haq et al., 2021; Kurgat et al., 2020). This suggests that younger farmers are more likely to adopt innovative technologies, possibly due to higher risk tolerance and better access to new information.

Comparatively, these contrasting findings highlight an important interrelationship: while age may enhance adoption of traditional or experience-based practices, it can limit the uptake of modern, labor- and capital-intensive technologies. This indicates that the influence of age is not uniform but depends on the type of CSA practice, with older farmers favoring low-risk strategies and younger farmers more inclined toward innovation-driven technologies.

Education of the household head: In most cases, education is positively associated with the adoption of climate-smart practices; evidence from Ethiopia, Ghana, and Pakistan indicates that more educated household heads are more likely to adopt conservation agriculture, integrated soil fertility management, modern inputs, and water conservation practices due to better access to information, improved understanding of climate risks, and stronger decision-making capacity (Ahmed et al., 2023a; Haq et al., 2021; Issahaku & Abdulai, 2020; Sisay et al., 2023). In contrast, a study in Kenya reports a negative relationship between education and the use of certain traditional practices such as crop and field management techniques (Wekesa et al., 2018), suggesting that more educated farmers may shift away from labor-intensive or conventional practices toward alternative strategies. Comparatively, these findings highlight that education generally increases the likelihood of adopting knowledge-intensive and modern CSA technologies, but its effect varies depending on the type of practice considered. This indicates an important interrelationship where education enhances information processing and innovation capacity, but may also reduce reliance on traditional farm management practices, leading to differentiated adoption patterns across CSA technologies.

Family size: Family size has consistent positive relationship with the adoption of CSA practices across studies. Evidence from Ethiopia and other SSA countries indicates that larger households are more likely to adopt conservation agriculture, mixed farming systems, improved agricultural practices, farm financial management, and diversification strategies (Issahaku & Abdulai, 2020; Kifle, Yayeh, et al., 2022; Onyeneke et al., 2018). This is largely because larger households tend to may have greater available family labor, which reduces the cost of labor-intensive CSA practices. These evidences highlight that family size is an enabling factor that primarily influences labor-demanding CSA technologies rather than capital- or knowledge-intensive practices. Thus, its effect is strongly interrelated with the labor requirements of specific CSA options, suggesting that household labor availability plays a key role in shaping adoption intensity and the type of technologies implemented.

Livestock ownership: Livestock ownership emerges as a critical driver for the adoption of diverse CSA technologies, with its influence extending across various regional contexts. According to Sisay et al. (2023), increased livestock holdings significantly bolster the uptake of small-scale irrigation, integrated soil fertility management, and agroforestry, primarily because animals provide the essential manure necessary for enhancing soil health and offer a financial buffer for investing in specialized equipment. This positive correlation is mirrored in southern Nigeria, where Onyeneke et al. (2018) found that larger herds similarly increased the likelihood of farmers diversifying their systems and refining financial management. Suggesting livestock act as a foundational asset that enhances both the biological capacity and the economic resilience required to transition toward sustainable farming practices.

Family size: Evidence from Ethiopia and other SSA countries indicates that larger households are more likely to adopt conservation agriculture, mixed farming systems, improved agricultural practices, farm financial management, and diversification strategies (Issahaku & Abdulai, 2020; Onyeneke et al., 2018) This is largely because larger households tend to may have greater available family labor, which reduces the cost of labor-intensive CSA practices. These findings highlight that family size is an enabling factor that primarily influences labor-demanding CSA technologies rather than capital- or knowledge-intensive practices.

Off-farm income: According to a study conducted in Ethiopia by Kifle, Ayal, et al. (2022), households with higher incomes both on and off farm were more likely to adopt conservational agriculture. In contrast, findings in Pakistan by Haq et al. (2021) indicate that off-farm income sources are negatively associated with the adoption of crop diversification at farms. The reason may be the involvement of households in other occupations and doing agriculture just as a part-time or a second profession to fulfill their needs. The growth of more crops on farms will require more time for farm activities, and it may not be possible for a part-time farmer. The other reason may be that they have enough off-farm income resources to fulfill their needs, and they do not need to diversify their crops. This finding is in line with the other study conducted by Taylor et al. (2003).

Access to credit**:** According Sisay et al. (2023), access to credit had a positive effect on the adoption of crop diversification and integrated soil fertility management. On the other hand, Haq et al. (2021) reported that credit unavailability is negatively associated with the adoption of crop diversification and modern inputs. This result is in line with study findings in Nigeria on the adoption of agricultural technologies, which indicate that farmers' access to credit increases the probability of the uptake of all climate-smart agricultural practices (Onyeneke et al., 2018).

Furthermore, Wekesa et al. (2018), confirmed that access to credit had a positive influence on the use of crops, fields, and risk management. This is because credit availability increases farmers' financial resources and their ability to pay for any transaction fees associated with any CSA technologies they may choose to adopt. The availability of credit eases cash constraints and allows farmers to buy inputs. This finding indicates that farmers can meet the costs of CSA technology implementation by having access to credit. Farmers with credit availability are more likely to diversify their crops by buying modern seeds and other farm inputs.

Distance to marketplace: According to Wekesa et al. (2018), input and output market distance had a negative effect on the adoption of CSA practices. Sisay et al. (2023), also reported that market distance adversely impacted crop diversification. This finding is also corroborated by Haq et al. (2021), who revealed that market distance was negatively associated with crop diversification, modern inputs, and soil conservation strategies. As suggested, longer distances to the market increase the transaction costs associated with buying inputs and selling outputs. The markets are not only a sale point for agricultural inputs and output but also a source of information through farmer to farmer extension, where farmers sit together and share their ideas. Therefore, farmers benefit from each other's experience. A farmer near the market can visit easily and regularly; therefore, it can increase the likelihood of adopting climate-smart agricultural practices.

Membership: According to Wekesa et al. (2018), membership has a positive effect on the usage of packages. A study in the Nile Basin of Ethiopia by H. Teklewold et al. (2019b) argues that membership in various groups has a positive and significant effect on increasing the number of adaptation practices but with varying degrees of marginal probability. With membership in local institutions, a household increases the marginal probability of adopting more than two adaptation practices. This result is consistent with the findings of Ahmed et al. (2023a). Social capital can assist farmers in mitigating the effects of climate change, preparing for increased climate variability, and providing backup plans to handle rising risks. Again, group networks allow participants to manage farm demonstrations, share ideas, and obtain connections to disseminate important research findings.

Extension contacts: The outcome suggests that frequent visits by extension workers had a positive and significant effect on integrated soil fertility management (Sisay et al., 2023). This might be because extension services provide access to information on CSA technologies, climate change, and agronomic techniques. Farmers who have access to technology information are more aware of and capable of using the technology. This result is in line with the report of Haq et al. (2021), who reported that these variables positively contribute to the adoption of water conservation and mixed farming strategies; they work as catalysts to increase adoption at the farm level. This finding is consistent with the findings of a study in Ghana, Issahaku & Abdulai (2020). Moreover, Wekesa et al. (2018), indicated that the number of contacts with extension service providers positively influences the use of crops, fields and risk management. This further suggests that extension contact is a means by which farmers obtain relevant information about climate-smart practices.

While, the existing literature highlights various demographic, economic, and institutional determinants of CSA adoption, there remains a lack regarding how these factors specifically influence the intensity of adoption. Consequently, study is needed to move beyond binary adoption models and explain context-specific drivers that determine the scale and depth of technological integration at the farm level.

2.3 Conceptual Framework of the Study

The conceptual framework of this study comprises four components: i) climate-related risks, ii) adoption of climate-smart practices, iii) farmers' characteristics, and iv) the resilience capacity and food security of smallholder farmers. Climate-related risks, such as drought, flooding, and irregular rainfall, have repeatedly affected the area. In response to these climate risks, farmers have adopted climate-smart agricultural practices. The adoption of these practices is also influenced by various factors, including socioeconomic, institutional and biophysical factors (see Figure 2.1).

Climate change affects agricultural output by increasing crop pests and diseases while also decreasing soil fertility. This ultimately threatens food security by disrupting food systems and reducing food availability. In response, rural farmers have adopted climate-smart agricultural practices aimed at enhancing agricultural productivity and food security. In this study, farmers utilized chemical fertilizers, improved crop varieties, small-scale irrigation, agrochemicals, and compost on their farms to increase food security.

Moreover, climate risks undermine household adaptive capacity by affecting key components such as human capital, physical assets, social networks, and access to essential services. The conceptual framework illustrates that the adoption of CSA practices can increase households' resilience through increasing their absorptive, adaptive, and transformative capacities. Resilience and its associated dimensions are considered latent variables, meaning that they are not directly observable. According to TANGO (2018), key indicators of a household's absorptive capacity include asset ownership, access to savings, and preparedness for shocks. Similarly, Bahadur et al. (2015), emphasize that access to safety nets and savings accounts, the ability to exchange assets, and access to support and advisory services significantly influence a household's ability to absorb climate-related shocks. Therefore, in this study, the selection of indicators for absorptive capacity is guided by these studies.

Adaptive capacity refers to the strategies households use to sustain their livelihoods under climate stress (Bene et al., 2012). This capacity is influenced by various factors, including literacy, income diversification, agricultural experience, and demographic structure (RIMA-II, 2016). As noted by Asmamaw et al. (2019), important factors for building adaptive capacity include access to credit, disaster management experience, farming practices, and technological inputs. Similarly, institutional factors such as access to essential public services are considered part of transformative capacity (Asmamaw et al., 2019).

Overall, this study employs an integrated social–ecological approach to resilience as the analytical framework for climate-resilient agriculture (Adger et al., 2005; Bene & Doyen, 2018). According to this framework, the adoption of climate-smart agriculture (CSA) innovations impacts several areas, including risk management, informal safety nets, disaster mitigation and early warning systems (DMEWSs), adaptation strategies, wealth and income, food security, information and training, social networking, and infrastructure. These indicators contribute to three dimensions of resilience capacity: absorptive, adaptive, and transformative. These capacities influence the overall resilience of smallholder agricultural households (Figure 2.1).

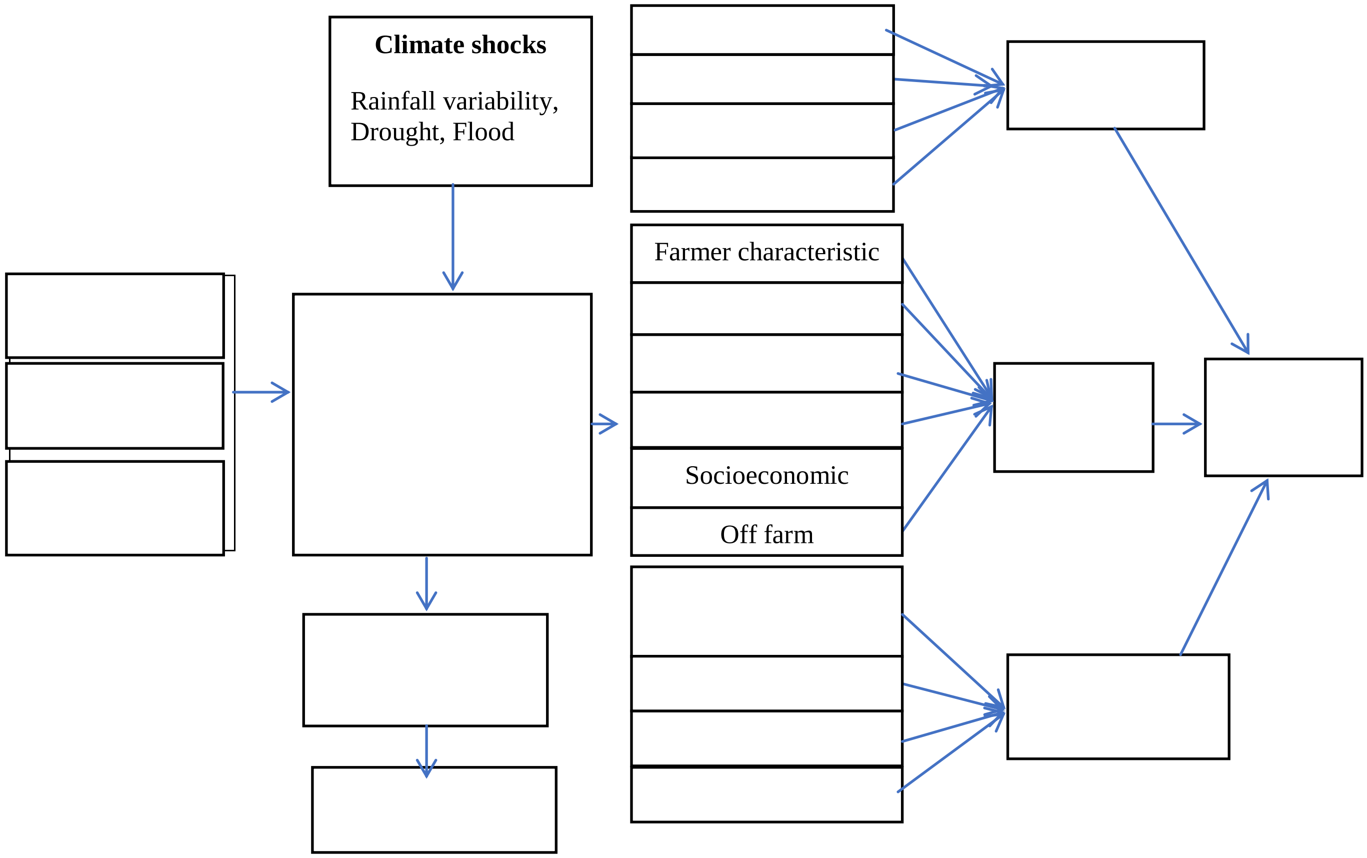

Figure 2.1: Resilient agriculture framework
Source: adopted from (Bene et al., 2015)

CHAPTE THREE: RESEARCH METHODOLOGY

This chapter outlines the research methodologies employed throughout the study. First, the physical features of the study area are described to provide context. Next, the research design is outlined, and the process of sample size determination is explained, along with the rationale for selecting a representative sample. Additionally, the techniques and tools for data collection, such as surveys and interviews, are detailed. Finally, the methods of data analysis used to interpret the collected data are described.

3.1 Physical Features of the Study Area

3.1.1 Descriptive of Study Area

Gubalafto Woreda is found in the Amhara region of northern Ethiopia, specifically between latitudes 11°34'54" N and 11°58'59" N and longitudes 39°06'09" E and 39°45'58" E (Figure 3.1). Gubalafto Woreda[1] is located in the southern part of the north Wollo Zone of Ethiopia. The administrative Woreda of Gubalafto covers approximately 900.49 km^2 making it the fifth largest Woreda in the north Wollo zone (Asnake & Elias, 2017).

Gubalafto Woreda is one of the 18 Woredas in the North Wollo Zone of the Amhara Region in Ethiopia. It bordered north by Gidan, southeast by Habru Woreda, west by Delanta Woreda and Wadla Woreda, and northeast by the Logiya River. The Woreda comprises 34 administrative *Kebeles*. Among these *Kebeles*[2], 10 are classified as Kolla (lowland), 13 as Woina-dega (midland), and 11 as Dega (highland). Woldia, the capital of Gubalafto Woreda, is located approximately 521 kilometers from Addis Ababa, the capital city of Ethiopia (GWAO, 2024).

Agricultural livelihoods in northern Ethiopia, including Gubalafto Woreda, are highly vulnerable due to climate variability, recurrent droughts, and land degradation (Gebre et al., 2017; OCHA, 2024; Tsegaye et al., 2018). In response, smallholder farmers have implemented diverse CSA practices to enhance resilience, including the use of manure, mixed cropping, crop rotation, organic and chemical fertilizers, agroforestry, and structural soil conservation measures like stone bunds and check dams Eshete et al. (2020). Adaptation practices further include shifting planting dates, adopting drought-resistant crop varieties, irrigation and managing

[1] Woreda is the lowest (4th) level administrative structure of the Ethiopian government

[2] Kebele implies a grass-root level administrative unit equivalent to local community, which is the fifth-order administrative division in Ethiopia

livestock numbers, all of which align with national efforts to balance agricultural productivity with climate mitigation and adaptive capacity (Kanter et al., 2018; Temesgen, 2018).

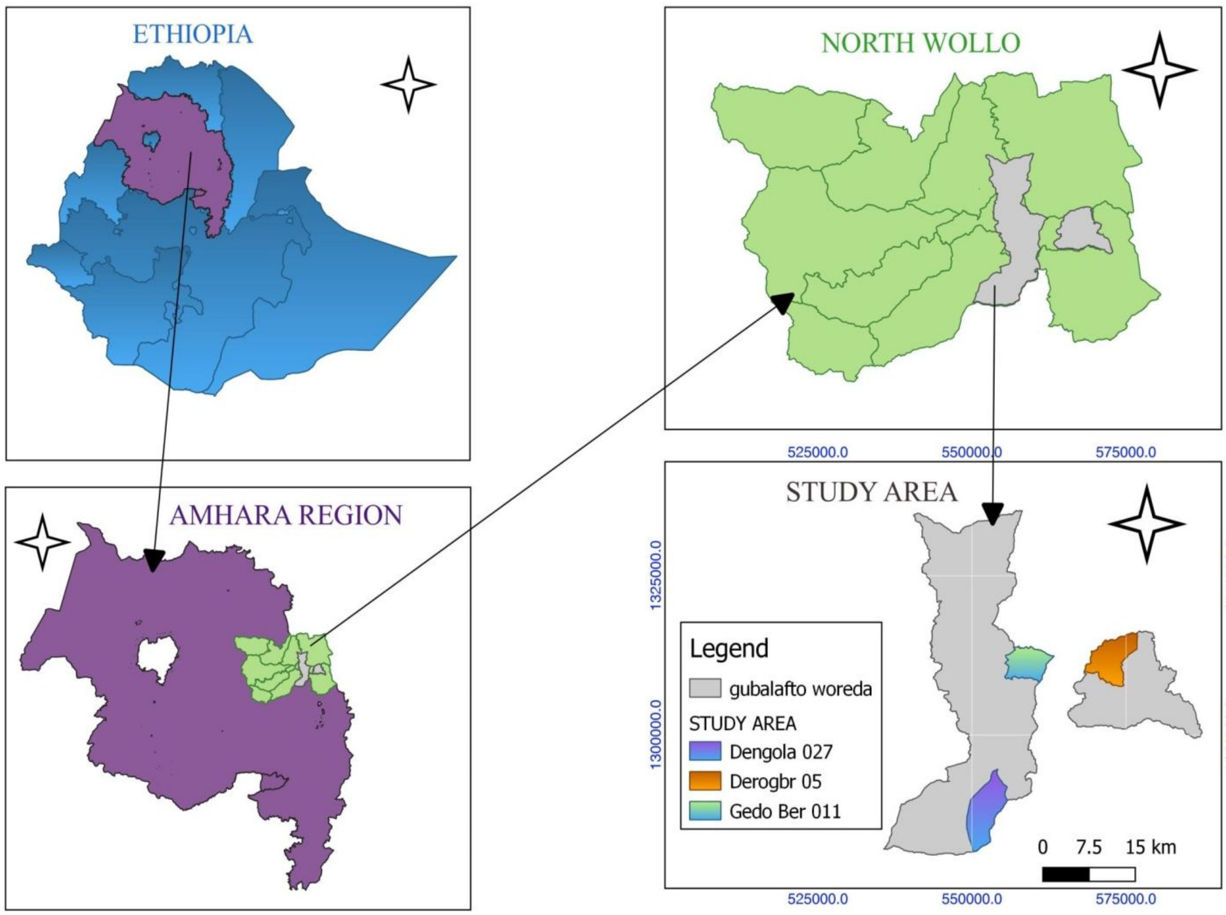

Figure 3.1: Study area map

Source: Author visualization (2024)

3.1.2 Topography and Drainage Patterns

A significant part of Gubalafto Woreda's landscape consists of a series of mountains, hills, and valleys; with elevations ranging from 1,379 to 3,809 m a.s.l. Gubalafto Woreda's terrain is largely sloping and mountainous**.** Accordingly, the topography consists of approximately 35% mountains, 30% undulating terrain (hills), 20% flat areas, and 15% gorges or valleys (Ale et al., 2025; Ebabu et al., 2021).

The presence of multiple streams and rivers in a mountainous and valley-rich topography contributes to drainage and, in certain areas, a risk of flooding, especially where runoff from uplands flows down into valleys (Ebabu et al., 2021). The major rivers in Gubalafto Woreda include the Alewuha, Beshilo (also referred to as 'Beshitta'), and Gimborra Rivers. Beshilo flows into the Abay/Blue Nile River, which in turn becomes part of the Nile Basin, and at least a portion of the Gubalafto Woreda River drains into the Nile Basin through the Beshilo–Abay drainage system (Nile Basin Initiative, 2007). In addition, the Woreda contains several smaller streams and seasonal waterways, such as Cherti, Shellea, Abakolsha, and Abakalu. Many watercourses in Gubalafto are likely seasonal or small streams; during heavy rains, they may contribute runoff to larger downstream basins.

3.1.3 Agroecology and Climate

Agroecology is defined as the division of a landscape into geographic areas that share similar agricultural and ecological characteristics (Hurni, 1998). In Ethiopia, these zones are primarily classified according to altitude, mean daily temperature, and the crop growing period. Consequently, Gubalafto Woreda is categorized into three distinct agroecological zones based on their respective growing seasons: the lowlands, which feature over 210 days suitable for drought-tolerant crops; the midlands, which provide 150–210 days for diverse cereal and legume growth; and the highlands, where the growing period is limited to less than 150 days, thereby favoring cool-climate crops such as barley and highland pulses (Akkaraboyina & Tareke, 2018). This classification aligns with (Ethiopian Ministry of Agriculture (MoA), 2022). Furthermore, based on its dominant agro-ecological characteristics, the kebeles of Gubalafto Woreda are distributed as follows: 32% are classified as Dega (highland), 38% as Woina-Dega (midland), and 30% as Kolla (lowland) (Gubalafto Woreda Agricultural Office, 2024b).

A regional climate analysis covering the broader Wollo area, which includes Gubalafto Woreda, revealed that the mean annual rainfall across the region ranges from about 531 mm to 1,005 mm, depending on location (Adane & Asmerom, 2025). The study area faces erratic rainfall, droughts, and land degradation, all of which undermine agricultural productivity and food security. Despite local resilience efforts, limited access to climate-smart adaptation and weak institutional support hinder progress (DEEP, 2025). The area is characterized by two rainy seasons: the long rainy season from June to September (*kiremt*) and the short rainy season from February to May (*belg*). In this context, rainfall during *the Belg season* is highly erratic and unstable relative to that during the main growing season. Overall, the district's rainfall has bimodal characteristics. According to Sirinka Agricultural Research meteorological data, the annual mean minimum and maximum temperatures range from 13.5 to 25.40°C. December is the coldest month, whereas May and June are the hottest months (Goshu, 2016).

3.1.4 Population Distribution and Density

According to the Ethiopian Statistical Service (2022), the projected population of the Woreda is approximately 172,818, with 87,027 males, 85,791 females, and a density of 191.9 persons/km^2. Among the total population of Gubalafto Woreda, 75% of the people followed Ethiopian Orthodox Christianity, whereas 25% followed the Islamic religion. The Amhara ethnic group constitutes 99.3% of the population in this study area (CSA, 2007).

The settlement pattern in Gubalafto Woreda is widely dispersed, with many people residing on hillsides, highlands, and plateaus. The settlement distribution in the area is strongly shaped by kinship-based clustering, in which relatives establish homes near one another. In addition, the availability of essential natural resources, particularly potable water, as well as access to basic infrastructure such as roads significantly influences where households choose to settle (Ale et al., 2025; Zewdu & Hibu, 2026)

3.1.5 Soils, Farming, and Livelihood System

The most prevalent soil types in the study area are Lithic Leptosols (92.2%), Eutric Cambisols (3.9%), and Eutric Leptosols (3.5%) (Alemayehu, 2011). Lithic Leptosols are shallow, brown or yellowish brown, and clay to clay loam (Antwi et al., 2023). In practice, Leptosols are shallow sandy soils and are often found in mountainous or hilly areas where the topography is steep and rocky. The shallow depth of leptosols is due primarily to the limited soil formation processes in these areas. Hence, leptosols are agriculturally less critical due to their shallow rooting depth, stoniness, and steep slopes. However, many farmers in the study area cultivate cereals from these soil types.

According to Temesgen (2018), Gubalafto Woreda's land use is dominated by cultivated land, which accounts for approximately 34-35% of the land use in Gubalafto Woreda is dominated by cultivated land, which accounts for approximately 34-35% of the total area. Forest or woody vegetation cover ranges from 16% to 27%, with variations depending on the year and the land-cover classification used. As reported by Abebe et al. (2021), grazing and rangeland areas constitute about 6-18% of Woreda's land. Rocky, bare, and other non-vegetated lands, including settlements, make up approximately 9-12% of the total area (Mengistie & Asmamaw, 2016).

Gubalafto Woreda livelihoods are based on small-scale and rain-fed agriculture centered on crop growth and livestock rearing **(**Abebe et al., 2022**)**. Agriculture has been practiced for a long time and is the main economic activity and source of income in the study area. As reported by Andualem (2016), the agricultural production system is dominated by smallholder mixed crop–livestock production practiced within the same management unit.

Five cereals are widely recognized as the core crops in Ethiopia's cereal-based farming systems, and these cereals, on average, occupy approximately three-quarters of the total cultivated area at the national scale **(**Alemayehu, 2011**)**, which is true for Gubalafto Woreda. The crop distribution in Gubalafto Woreda can be described via local evidence. According to the *Mehir* season postharvest crop production survey results in 2023/24, cereals dominate cultivation, covering approximately 86.5% of the total farmland. Within this category, teff accounts for roughly 26.3%, reflecting its widespread use. Sorghum covers a 33.5%, whereas barley, a major crop in the highland and midland zones, represents approximately 6.4% of the cultivated area. Wheat contributes an estimated 20.9%, and the other 3.1% (Gubalafto Woreda Agricultural Office, 2024a). These ranges offer a reliable approximation of crop distribution in Gubalafto Woreda on the basis of the best available local information.

Livestock are a significant source of animal protein, crop cultivation power, transportation, export commodities, manure for farmland and household energy, crop failure security, and wealth accumulation (FAO, 2018). The Ethiopian livestock population is almost entirely composed of indigenous animals. The livestock population in Ethiopia is overwhelmingly dominated by local breeds, with estimates showing that 97.8% of cattle are indigenous, 1.9% are hybrids, and only 0.3% are exotic breeds (Mekuriaw & Harris-Coble, 2021). This national pattern is closely reflected in Gubalafto Woreda, where cattle production similarly relies predominantly on indigenous breeds.

Gubalafto Woreda's livestock sector is dominated by ruminants, primarily cattle, sheep, and goats, which constitute the core of household production systems and are supported by notable numbers of equines and backyard poultry. According to the 2024 annual report of the Gubalafto Woreda Livestock and Fishery Office, the Woreda possessed an estimated livestock population of 140,284 cattle, 42,887 sheep, 38,895 goats, and 28,529 equines, including horses, mules, and donkeys (Gubalafto Woreda Livestock and Fishery Office, 2024). Furthermore, indigenous chicken breeds are widely reared at the household level in Habru and Gubalafto districts, indicating the presence of well-adapted local chicken populations that contribute to both household food security and income generation (Tadesse et al., 2023). Beekeeping is actively practiced, whereas camels are uncommon or absent in the highland areas of the Woreda (Yigrem & Shiferaw, 2024).

3.2 Research Paradigm and Design

Once a research topic has been identified, the researcher's first step is often to become familiar with the relevant research paradigms, the overall strategy to be used, and the appropriate data collection instruments. According to Creswell (2008), in the field of research philosophy, two key areas are concerned with truth and knowledge: ontology, which examines the nature of reality or what truth is, and epistemology, which explores how knowledge is acquired. By combining such concepts, research paradigms can be specified as follow.

One is the positivism paradigm, which is frequently associated with quantitative approaches; again, objective reality exists apart from the research process. The positivist paradigm assumes that reality is single, tangible, and objective, which implies that knowledge can be accurately observed and measured through standardized scientific methods (Park et al., 2019). In contrast, constructivism is typically associated with qualitative approaches and an interpretivist lens. Within social constructivism, knowledge is viewed as socially constructed through human interaction and experience rather than as a universal scientific truth. This perspective suggests that realities are multiple and subjective, meaning knowledge is interpreted or explained contextually rather than measured against a fixed standard (Rahi, 2017).

While, pragmatism is commonly associated with mixed-methods approaches; it posits a flexible sense of truth that may be singular or plural, allowing knowledge to be measured or interpreted depending on the specific research situation or problem (Kaushik & Walsh, 2019). The pragmatic view was therefore followed for this study, since the use of a mixed approach is guaranteed to understand the effects of CSA practices on rural household food security and resilience. Pragmatism is widely associated with mixed-methods research, as it embraces a flexible understanding of reality and truth, which may be singular or multiple depending on the research context. This paradigm allows knowledge to be both quantitatively measured and qualitatively interpreted in addressing specific research problems (Kaushik & Walsh, 2019).

The study employed a mixed research approach, integrating both quantitative and qualitative data (Salmons, 2020), outlined mixed methods studies as research approaches that use both qualitative and quantitative approaches within a single study. In this study, greater emphasis was placed on quantitative data, while qualitative data were used to supplement and clarify the quantitative findings. Statistical results are compared with qualitative insights, allowing a more comprehensive understanding of the research problem to be achieved. Consequently, the overall strength of the study is enhanced, as mixed methods offer advantages beyond what either qualitative or quantitative research can provide alone (Creswell & Clark, 2017).

The primary rationale for employing a mixed research approach is fourfold. First, it allows the researcher to collect both quantitative and qualitative data within a single data collection phase. Second, it enhances the reliability and validity of the findings by enabling data triangulation, and it is well suited for explaining relationships among variables and predicting outcomes. Third, it provides the opportunity to gain insights from different types and levels of data, offering a broader perspective on the research problem. Finally, using both approaches together results in a more comprehensive and robust study.

In the literature, various research designs are available, each of which is suited to specific research contexts. For this study, a quasi-experimental research design was employed. This design is used to examine cause-effect relationships without fully randomizing participants into treatment and control groups. The main reason for using this approach is that participants are not randomly allocated to different conditions or groups (e.g., farmers who adopted CSA vs. those who did not). Quasi-experimental designs are useful when true random assignment is not feasible, implying that they do not involve random assignment of participants to different conditions or groups (Campbell & Stanley, 2015). Despite this limitation, the design still aims to determine whether an intervention or condition has caused a particular outcome, allowing for cause-effect inference**.** Quasi-experimental designs are especially useful in real-world settings where full environmental control is impossible, allowing for the study of impacts in natural contexts.

For this study, the natures of data were cross-sectional because socioeconomic and other relevant information was collected at a single point in time. This approach was chosen for its cost-effectiveness and efficiency in gathering both quantitative and qualitative data within a limited timeframe through a one-time household survey. It is relatively inexpensive and time-efficient (Gubalafto Woreda Agricultural Office, 2024a). Moreover, the cross-sectional design allows for a focused examination of the role of CSA in enhancing climate resilience and food security among smallholder farmers, even under constraints of time and resources.

3.3 Sampling Techniques and Sample Size Determination

This study focused on Gubalafto Woreda as the study area representing the target population. The Woreda is characterized by climate variability, irregular hydro-meteorological patterns, and low adaptive capacity (DEEP, 2025), conditions that make it highly vulnerable to food insecurity and related risks. These challenges make the area particularly relevant for this study. In addition, Gubalafto Woreda has a notable presence of actively implemented CSA practices, providing a suitable context for examining adoption patterns and their associated outcomes.

A multistage random sampling technique was employed in this study. Specifically, multistage cluster sampling was used to ensure adequate representation of households across different agroecological zones. As a probability-based sampling approach, the population was first divided into clusters based on agroecological categories (lowland, midland, and highland), with kebeles serving as the primary sampling units. Respondents were then selected proportionally from each agroecological category.

In the first stage, Gubalafto Woreda is classified into three agro-ecological zones based on altitude and length of crop-growing period. These include the lowland areas (below 1,500 m.a.s.l.), which have a short growing period of less than 150 days and are mainly suitable for drought-tolerant crops; the midland areas (1,500–2,300 m.a.s.l.), with a moderate growing period of 150–210 days supporting diverse cereal and legume production; and the highland areas (above 2,300 m.a.s.l.), which experience more than 210 days of growing season and are favorable for cool-climate crops such as barley and highland pulses. This classification is consistent with the Ethiopian Ministry of Agriculture (Ethiopian Ministry of Agriculture (MoA), 2022). In addition, it aligns with the existing administrative structure, where the *kebeles* of Gubalafto Woreda are categorized into Dega, Woina-Dega, and Kolla.

In the second stage, since the *kebeles* are relatively evenly distributed across the agro-ecological zones, one *kebele* was randomly selected from each zone using a lottery-based sampling technique. This approach ensured adequate representation of all agro-ecological zones while maintaining feasibility. The number of sample *kebeles* was limited to three due to practical constraints, including resource limitations, time constraints, and local security challenges. Accordingly, one *kebele* was selected from each agroecological zone: Masso-Dengolla from the highland, Gedo-Ber from the midland, and Doro-Gibr from the lowland area.

In the third stage, sample households were selected from the chosen *kebeles* via systematic sampling, accounting for the number of households allocated proportionally to each sampled *kebele*. Systematic random sampling was chosen because (i) it enhances the representativeness of the sample and (ii) complete household lists were available at the *kebele* administration offices, providing an appropriate sampling frame. A similar sampling procedure was also used (Haq et al., 2021).

In the literature, various methods are available for determining sample size, each suited to specific research contexts: the Cochran (1963) formula is used when the population is large or infinite and the estimated proportion is known. It is widely used in surveys involving categorical data. The Kothari (2004) formula applies to finite populations with a known estimated proportion. The Yamane (1967) formula is applied when the population size is finite and known, but the estimated proportion is unknown. It is particularly useful in development studies where detailed population parameters may not be available.

In the study area, the estimated proportion of the population was unknown, and the population was assumed to be relatively uniform in characteristics relevant to the study. Therefore, the Yamane (1967) sample size formula was employed, as shown in (Equ 1).

$$\mathrm{n} = \frac{N}{1+N*e^2.} \qquad (1)$$

$$\mathrm{n} = \frac{3163}{1+3163*0.05^2.} = 355$$

Where: n = sample size, N= total number of households in all *Kebeles* e=level of precision or Sampling of Error, which is +_5%

In the simple determination method, the sample size was calculated using Yamane (1967) formula. An additional 10% was initially considered to account for possible non-response. However, due to budget limitations, security concerns, and no more significant non-response, respondents, the final sample size was determined solely based on the formula without applying the non-response adjustment. According to Naing et al. (2006), when missing data is not a major concern, such adjustment may not be necessary. Based on these considerations, the researcher attempted to collect survey data from 355 sampled households as much as possible.

After determining the total sample size, each *Kebele* sample size was proportionally distributed based on their population sizes as follows (Hoyle et al., 2002).

$$ni = \frac{n*N}{\sum Ni} \tag{2}$$

Where n is the sample size, n_i is the required sample size in the i^{th} *Kebele*, and N_i is the total number of households in the i^{th} *Kebele*.

Table 3.1: Number of sampled households

Woreda	Agroecological zone	*Kebeles*	Total household	Sampled household
	Highland	Masso-dengolla	1093	123
Gubalafto	Midland	Gedo-ber	908	102
	Lowland	Doro-gibr	1162	130
Total			3163	**355**

Source: Gubalafto Woreda Agricultural office (2024)

3.4 Data Sources and Collection Techniques

Comprehensive and realistic numerical data, ideas, viewpoints, concepts, arguments and suggestions were collected to enhance the analytical frameworks and develop profound study outputs and thoughtful recommendations. While ethical considerations were considered to guarantee confidentiality, honesty, consents, and other human aspects of the informants.

The data required for this study were obtained from both primary and secondary sources. Primary data were specifically collected using household surveys, key informant interviews, and focus group discussions, each of which is detailed in the following sections.

Household survey questionnaires: Household survey questionnaires were designed to generate quantitative data at the household level. The questionnaires had both close- and open-ended questions designed to answer the study objectives. The questionnaire includes information regarding socioeconomic, institutional, biophysical, and climate-smart agriculture practices; food consumption patterns; and other attributes. Before the main survey, it is critical to pretest the data collection instruments (questionnaires). In the literature, 10% of the sample size should be sufficient for a pilot survey (Moore et al., 2011). Hence, the data collection instruments were pretested with 35 non-sample households to assess data reliability and validity. The researcher then revised and refined the tools on the basis of feedback from this pilot exercise to improve clarity, relevance, and effectiveness. To ensure accurate and contextually appropriate communication, all questionnaires were translated into Amharic, the local language spoken by the target population.

Six enumerators were recruited for data collection on the basis of their prior experience in field surveys and their fluency in the local language, which ensured effective communication and data accuracy. Those enumerators trained for 2 days on Kobo Toolbox, ethical standards data collection, and proper administration of the questionnaires. Data collection was conducted via the Kobo Collect mobile application, with completed surveys Daily uploads to centralized Open Networked Analysis (ONA) server for secure and timely oversight. Before conducting the structured interviews, the enumerators provided households with appropriate information about the study and obtained informed consent. The data were collected through interviews that took approximately 25 minutes to complete. Since farmers in the study area practice both *Belg* (including small-scale irrigation) and *Mehir* cropping systems, data were collected from late September 2024 to early November 2024 to capture *Belg* harvest outcomes and the pre-harvest conditions of the main *Mehir* season. This period was considered appropriate for assessing household food security and resilience. Throughout the data collection process, the researcher provided continuous support and guidance to the enumerators, addressing any challenges that arose from start to finish.

Focus group discussions (FGDs): One of the principal advantages of FGDs is their effectiveness in capturing how groups of individuals think and feel about a particular issue, as well as providing deeper insight into the reasons underlying certain beliefs (Almutrafi, 2019). Accordingly, one focus group discussion was conducted in each *kebele* via a predesigned checklist. Each FGDs involved 6 to 12 participants with similar interests (Basnet, 2018). Accordingly, a total of 18 participants from three *kebeles* (each FGDs involving six representative members), including model farmers, women, and community leaders, participated in the discussions. This finding suggests that model farmers and local leaders have practical experience with CSA practices and could therefore provide valuable insights for the study. By developing discussion checklists focusing on issues of climate-smart agriculture practices, including their synergies and trade-offs in relation to food security and resilience. For each selected *kebele*, focus group discussions were conducted via open-ended guiding questions. The participants were encouraged to interact with one another by sharing, comparing, and contrasting their experiences and perspectives. The researcher facilitated the discussions and made deliberate efforts to ensure that the views of all the participants were heard.

Key informant interview (KIIs): key informants were selected on the basis of their experience and background knowledge of CSA practices. Actually, in qualitative data collection methods such as KIIs, sampling typically continues until no new information or ideas emerge, a point known as data saturation (Elmusharaf, 2012). Thus, KIIs continued until data saturation (no new ideas emerging). On the other hands, as recommended by Muellmann et al. (2021), 4-6 key informants are generally sufficient. Considering time and resource constraints, six key informant farmers and four agricultural experts were interviewed with all of them.

Key informant participation was intended to strengthen the validity of the study findings by incorporating informed opinions, perceptions, and attitudes. As noted by ACF (2010), key informant interviews were employed as a qualitative data collection method via semi structured interviews. Accordingly, KIIs were conducted with community leaders, agricultural experts, and model farmers, as these individuals possess substantial experience with CSA practices. The informants were asked about synergies and trade-offs of CSA practices, and other related issues.

In addition to primary data, secondary data were collected through a desk review of national, regional, and zonal government reports. These documents were utilized to characterize the study area's socioeconomic features. Rather than being analyzed in isolation, these secondary sources were used to contextualize, compare, and contrast the empirical findings of this study.

3.5 Data Analytical Tools and Methods

The collected data were carefully checked and edited for completeness, consistency, accuracy, and clarity and then coded (data transcribe from a questionnaire to a coding sheet) before the analysis was performed. The data collected in this study were subsequently analyzed via both descriptive and inferential statistics. Specifically, principal component analysis, food consumption score, multidimensional food security score, and multinomial endogenous switching regression (MESR) were used to analyze the quantitative data of the study. Data obtained from focus group discussions and KIIs were analyzed and presented qualitatively via thematic analyses.

The qualitative data were grouped into themes via thematic analysis, and the data were combined in the most logical way possible. The thematic analysis works best in cases where data about household views, opinions, experiences, and knowledge on the above themes are gathered. Thus, themes such as the impact of CSA practices on food security, the synergistic effects of CSA practices on food security and resilience, and the trade-offs of CSA practices on food security and resilience were identified. The analyses of the study were managed via STATA 17.0 software, and Microsoft excel. The major data analysis techniques used in this study are discussed below.

3.5.1 Rates and Indices of CSA Practices

The literature that suggests the adoption of a combination of five practices is considered a full package (Ahmed et al., 2023b; Haq et al., 2021). Accordingly, this study limited the analysis to five CSA practices. To identify these practices, all 18 identified CSA practices were included in a scoring exercise to determine the top five practices currently implemented by farmers. The average score of each practice was computed as the score (frequency) divided by the number of respondents.

The practice with the highest average score was ranked first, while the practice with the lowest average score was ranked last, following the approach of Ogola and Ouko (2021). Subsequently, ranking points were assigned such that the practice ranked first received five points, whereas the practice ranked fifth received one point, in descending order. The total score for each of the top five CSA practices was calculated by multiplying the frequency of responses by the corresponding ranking points. Finally, the practices were ranked on the basis of their total scores; with the highest score assigned a rank of one and the lowest score assigned the last rank (Appendix A).

Accordingly, the following five CSA practices were selected: efficient application of chemical fertilizers, use of improved crop varieties (pest-resistant and high-yielding), small-scale irrigation, efficient use of agrochemicals, and composting. The number of adopted climate-smart practices was subsequently indexed on the basis of the extent to which these top practices were adopted. On the basis of the extent of adoption, households were categorized into distinct groups according to the number of top CSA practices implemented on their farmland.

The indexed variable is measured as follows:

Y1=0 (none-adopter), if a farmer does not adopts any of top CSA practices

Y1= 1 (single adopter), if a farmer adopts one practice

Y1=2 (partial adopter), if a farmer adopts a combination of two CSA practices

Y1=3 (multiple adopters): if a farmer adopts a combination of three to four CSA practices

Y1=4 (full adopter): if a farmer adopts a combination of five CSA practices.

3.5.2 Estimating Resilience Capacity

Measuring resilience capacity: Measuring resilience is inherently challenging because it is not directly observable. Accordingly, this study treats resilience as a latent variable. Bene et al. (2014), conceptualize resilience as emerging from three interrelated capacities: absorptive, adaptive, and transformative. Quantifying resilience and developing relevant indicators are critical to this study. Accordingly, the resilience capacity of smallholder farmers was computed using the three-dimensional (3-D) resilience framework proposed by (Bene et al., 2012). Within this framework, resilience is defined as households' capacity to absorb, adapt, and transform in response to climate change. In the literature, farmers' resilience capacity is operationalized in three dimensions, each measured via a set of indicators and corresponding observed variables. Following this framework, the present study identifies three major dimensions of household resilience: absorptive capacity (ABPC), adaptive capacity (ADPC), and transformative capacity (TRNC). Each of these dimensions was further disaggregated into specific subcomponents or indicators, as illustrated in Table 5.2. Using these indicators, the dimensional resilience capacities of households were estimated. Accordingly, dimensional resilience indices and the overall composite resilience index were calculated separately. This methodological approach is consistent with that of (Ali et al., 2023a; Nadu et al., 2021; Teklu et al., 2022).

$$ABP_j = f\,(FSSN_j, ISSN_j, DMEWS_j, RM_j),$$

$$ADP_j = f\,(FC_j, ADPS_j, W_j, FS_j, SE_j, OFF_j), \text{ and}$$

$$TRN_j = f\,(ITSN_j, INFRA_j, SN_j, SS_j) \quad (3)$$

Where ABP_j is the absorptive capacity of household j, FSSN: formal social safety net, ISSN: informal formal social safety net, DMEWS: disaster mitigation and early warning system RM: risk management, FC: farmer characteristic, ADPS: adaptation strategies, W: wealth, FS: food security, SE: socioeconomic, OFF: off-farm IT: information and training, INFRA: use of infrastructure of household, SN: social network, and SS: social service of household j for j = 1. . n

The composite household resilience capacity (RCi) was also derived from the set of resilience dimensions, as outlined below.

$$CRi_j = f\ (ABP_j\ ADP_j,\ TRN_j) \quad (4)$$

Where CRi_j is the resilience capacity index of household j, ABP_j is absorptive capacity, ADP_j is adaptive capacity, and TRN_j is the transformative capacity of household j for j = 1. . n

However, resilience is not directly observable, and the resilience cannot be directly estimated. To overcome such challenges, principal component analysis (PCA) was chosen over factor analysis (FA) to estimate resilience capacity, primarily because of its suitability for data reduction and its minimal reliance on strong statistical assumptions (Alinovi et al., 2008). This study focuses on variance and dimensionality reduction, i.e., simplifying data for further analysis and running with PCA, whereas factor analysis is more suitable for exploring underlying relationships, i.e., the underlying factors influencing resilience capacity. PCA is designed to extract the maximum variance from observed variables and summarize them into a smaller set of uncorrelated components. This aligns well with resilience measurement, which often involves diverse indicators that need to be synthesized into a composite index. FA assumes that observed variables are influenced by unobserved latent factors and includes error terms, which may not be appropriate or identifiable in resilience studies with limited sample sizes, whereas FA often requires larger samples and strong assumptions about error structures and latent variables (Jolliffe & Cadima, 2016).

The necessary statistical criteria for a robust PCA model were checked. For example, the Bartlett test of sphericity was conducted via a factor test to assure that variables significantly correlated with the components. Subsequently, KMO was conducted to measure the sampling adequacy of the individual variables used in the model. Rather, continuous variables were standardized, and categorical variables were normalized, whereas variables with negative implications for resilience were reverse-coded.

The resilience estimation was conducted hierarchically. First, resilience blocks (indicators) were derived from observable household-level variables via PCA. As proposed by Kaiser (1960), an eigenvalue greater than 1 criterion was applied to select components. In addition, components can also be "rotated" to simplify the structure of the loading matrix. A varimax rotation technique was used to produce a more interpretable component. Varimax rotation is an orthogonal rotation technique applied after PCA to achieve a simpler and more interpretable component structure. It allows each variable to load strongly on only one principal component, making it easier to identify and label the underlying dimensions. Thus, the heaviest loading of the principal component is expressed in terms of the variables as an index for each household that captures the largest amount of information.

Subsequently the dimensional resilience index for each household was estimated separately via the derived indicators. The indices for each dimension were calculated as the product of the component scores and their corresponding weights (explained variance) (Adane, 2018). Accordingly, the model specified in Equation (3) was transformed into Equation (5). Hence, the dimensional resilience scores (CI_i) for each household was computed as follows:

$$CI\mathrm{i} = \mathrm{w1} \times \mathrm{CS1} + \cdots + \mathrm{wj} \times \mathrm{CSij} \qquad (5)$$

Where CI_i is the score of a dimension (absorptive, adaptive, and transformative), w_j is the percentage of variance explained by the i^{th} component (weight), and CS_{ij} is the component score of the i^{th} household on the j^{th} component.

Following the above argument, this study employed 14 variables to measure households' absorptive capacity, 16 variables to measure their adaptive capacity, and 13 variables to measure their transformative capacity (Table 3.2).

In the second stage, PCA was applied to the resilience dimension, which was derived from the first-stage exercise. Finally, the resilience capacity index (RCi) was estimated for each household as a product of the component score and weight (explained variation) of a component via (Equ 6).

$$\mathrm{RCi} = \frac{\sum_{i=1}^{3} wjCIj}{\sum_{i=1}^{3} wj} \qquad (6)$$

Where RC_i is the composite resilience score, CI_j is the component score of the j^{th} component, and w_j is the weight of the j^{th} component.

The estimated continuous-dimensional and composite resilience scores were normalized to a 0–1 scale. These normalized values were then rescaled into three categories. According to the cutoff points proposed by Jayadas and Ambujam (2021) and Siminyu et al. (2020), households' resilience levels were classified as follows: scores between 0.00 and 0.33 indicate low resilience, scores from 0.34 to 0.66 indicate medium resilience**,** and scores from 0.67 to 1.00 indicate high resilience.

Table 3.2: Overview of the resilience capacity dimensions and indicators

Dimension	Indicators/components	Variables	Literature	Measurement
Absorptive capacity index	Formal and Informal social safety net	Income from PSNP	-	Annual getting in Birr
		Friend support	(Teklu et al., 2022)	Annual getting in Birr
		Informal social insurance	(Teklu et al., 2022)	1 if yes 0=otherwise
		Formal aid, NGO & Gov.)	-	Annual getting in Birr
	Disaster mitigation and early warning system (DMEWS)	Access to weather information	(Teklu et al., 2022)	1 if yes 0=otherwise
		Mobile phone communication	(Teklu et al., 2022)	1 if yes 0=otherwise
		Possession of communication Radios and televisions	(Ali et al., 2023)	1 if yes 0=otherwise
		Remittances	(Ali et al., 2023)	Annual getting in Birr
	Risk management	Decrease th quantity of meal	(Teklu et al., 2022)	1 if yes 0=otherwise
		Decrease diversity of meal	(Teklu et al., 2022)	1 if yes 0=otherwise
		Decrease the number of meal	-	1 if yes 0=otherwise
		Borrow grain from neighbors	(Teklu et al., 2022)	1 if yes 0=otherwise
		Sales of livestock	(Teklu et al., 2022)	Amount in Birr
		Provision of farm Labor	(Siminyu, 2021)	1 if yes 0=otherwise
Adaptive capacity index	Farmer characteristics	Sex of household head	(Ali et al., 2023)	1 if male 0 female
		Marital status	(Ali et al., 2023)	0 = single, 1 = married, 2 =divorced, 3= widowed
		Education level measured in years	(Siminyu, 2021)	0 if uneducated, 1 if informal educated, 2 if primarily educated, 3 secondary

		Age	(Ali et al., 2023)	Age in years of HH
		Farming experience	(Ali et al., 2023)	experience in year
		Labor availability	(Quandt, 2018)	Number of HH members b/n 18 – 55
	Adaptive strategies	Different crops planted	(Quandt, 2018)	1 if yes 0=otherwise
		Use of improved verities	(Ali et al., 2023)	1 if yes 0=otherwise
		Use of water-harvesting technologies	(Teklu et al., 2022)	1 if yes 0=otherwise
	Wealth and income	Working on-farm	(Siminyu, 2021)	1 if yes 0=otherwise
		Working off-farm	(Siminyu, 2021)	1 if yes 0=otherwise
		Total farm size	(Ali et al., 2023b; Teklu et al., 2023)	Farm size in hectare
		Income source/average annual income	(Siminyu, 2021; Teklu et al., 2022)	Average annual income in Birr
		Livestock holding	(Ali et al., 2023)	TLU
		Deposit in bank	(Siminyu, 2021)	Total amount on Birr
		Physical asset	-	Value in Birr
		Food consumption score	(Getaneh et al., 2022)	poor <=21, borderline if 21.5-35, Acceptable if >35
	Food security	Multidimensional food security	(Kini, 2022)	food security=1, mildly FI =2, moderately =3, severe = 4
Transformative capacity index	Information, Training, and Social Networks	Access to extension service	(Teklu et al., 2022)	1 if yes 0=otherwise
		Access to agricultural training	(Teklu et al., 2022)	1 if yes 0=otherwise
		Membership in iqub	(Ali et al., 2023)	1 if yes 0=otherwise
	Infrastructure	Access to credit	(Quandt, 2018))	1 if yes 0=otherwise
		Access to irrigation	(Ali et al., 2023)	1 if yes 0=otherwise
		Distance to school	(Ali et al., 2023)	Take in hours
		Distance to health institution	(Quandt, 2018)	Take in hours
		Distance to market	-	Take in hours
		Distance to dirk water	(Ali et al., 2023)	Take in hours
		Reliable all-weather road	(Ali et al., 2023)	1 if yes 0=otherwise
		water and sanitation facilities	(Siminyu, 2021; Teklu et al., 2022)	1 if yes 0=otherwise
		Electricity	(Siminyu, 2021; Teklu et al., 2022)	1 if yes 0=otherwise

Source: Author literature review (2024)

3.5.3 Measuring Food Security

Given the multidimensional nature of food security, practitioners and policymakers have long recognized the need for multiple measurement approaches. In the literature, there is no single universally accepted method for measuring food security (Kahsay, 2017). The food consumption score (FCS) and multidimensional food security factor (MDFS) were utilized to assess the food security status of households for this study. To reduce recall bias, the study used relatively short and standardized recall periods (7 days for the Food Consumption Score and 4 weeks for the Multidimensional Food Security Index). In addition, trained enumerators administered structured questionnaires and used local event references to help respondents accurately recall and report their food consumption and food security experiences.

The FCS is a standardized and more transparent methodology. It is also able to capture both dietary diversity and food frequency. Thus, it was used since it is used as a composite measure that considers dietary diversity, food frequency, and the nutritional value of various food groups. The FCS encompasses nine questions and adapts food items to local contexts. Following the guidelines of WFP (2008), a 7-day recall of consumed food items was used to calculate the FCS. The process began by grouping all the food items into specific food groups on the basis of standard 7-day food frequency data (see Table 3.3). Next, the consumption frequencies for each food group were summed. These summed values were then multiplied by their respective weights to create weighted food group scores. Finally, the weighted scores were summed to obtain the final FCS.

Table 3.3: Food groups and its weights

No	Food Group	Food items (examples)	Weight
1	Main staples and	cereals, tubers	2
2	Pulses	beans, lentils, peas	3
3	Vegetables	carrot, cabbage, onion	1
4	Fruits	Banana, orange, mango	1
5	Meat and fish	meat, poultry, fish, eggs	4
6	Milk	Milk and dairy products	4
7	Oil	Oils, fats	0.5
8	Sugar	Sugar and sugar products, honey	0.5
9	Condiments	condiments, coffee, tea	0

Note: $FCS = (Staples \times 2) + (Pulses \times 3) + (Vegetables \times 1) + (Fruits \times 1) + (Meat \times 4) + (Milk \times 4) + (Sugar \times 0.5) + (Oil \times 0.5)$

The FCS was then recoded from a continuous variable into a categorical variable via the following thresholds: a score of 0-21 indicate poor consumption, a score of 21.5-35 indicate borderline consumption, and a score above 35 indicates acceptable consumption.

FCS and the indicators do not fully encompass all four dimensions of food security: access, availability, utilization, and stability. To address this gap, this study employed a multidimensional food security (MDFS) index, which integrates all four dimensions of food security. The MDFS index, developed by Maxwell et al. (2013), is a composite measure of food security that integrates different existing indicators. These include Household Food Consumption Score, Household Dietary Diversity Score, Household Food Insecurity Access Scale, Household Hunger Scale, Coping Strategies Index, Reduced Coping Strategies Index, and the Self-Assessment Food Security Scale.

The MDFS was used for two main reasons. First, food security is now widely recognized as multidimensional, with these four dimensions as pillars (Makombe, 2023). Although no universally accepted method for measuring food security exists (Kahsay, 2017), previous studies have often employed these dimensions in their analyses, for example, in Tanzania by (Magrini & Vigani, 2016b) and in Ethiopia by (Kassie et al., 2024). Second, it comprises a comprehensive multidimensional food security indicator code (Gadiso et al., 2023). This implies that the indicator is data rich in that it captures multiple dimensions of food security. Unlike stand-alone indicators, the MDFS is advantageous because it effectively measures all four dimensions of food security, namely, daily food consumption patterns, food consumption-increasing behaviors, dietary change preferences and value food consumption behaviors, rationing strategies, rare behaviors in severe conditions, and stability. Furthermore, the MDFSI is intended to measure the severity and prevalence of household food security.

The MDFS questionnaire comprises a set of 24 composite questions categorized by dimensions such as quantity or availability, quality or diversity, acceptance or choice or preference, and stability. Each question, the self-assessed food security indicator, can be answered from a set of four frequency of occurrence responses borrowed from the HFIAS. The respondents were asked how often the reported condition occurred during the preceding four weeks in each question. Except for the SAFS, the remaining questions have four choices: "1 = never," "2 = rarely," "3 =

sometimes," and "4 = often.” The response option ‘Never’ refers to the nonoccurrence of the condition reported; ‘Rarely’ implies that the condition has happened 1 or 2 times in the past four weeks; Sometimes implies that the condition has occurred 3 to 10 times in the past four weeks; and the response option ‘Often’ refers to more than ten occurrences of the condition in the past four weeks, as suggested by (Kassie & Alemu, 2021).

In this study, the method of summing coded responses and interpreting scores is based on (Maxwell et al., 2013). The score of each dimension was computed by summing the code responses of each question under each dimension. These scores served as outcome variables. Moreover, studies by Willits et al. (2016) and Harpe (2015) demonstrate that summing coded responses from a Likert scale can produce meaningful composite scores. On the basis of this evidence, the current study used this technique to assess the food security status of rural households. The following formula illustrates how the score summation is performed for each dimension of food security:

$$SQn = \sum_{i=1}^{11} Qni$$

$$SQl = \sum_{i=1}^{8} Qli \qquad (7) \qquad SAcc = \sum_{i=1}^{2} Acci$$

$$SSt = \sum_{i=1}^{3} Sti$$

In this framework, S_{Qn} represents the household score of quantity; S_{Ql} represents the household score of quality; S_{Acc} represents the household score of acceptability; and S_{St} represents the household score of stability. Q_{ni} denotes the quantity score derived for the i^{th} question, which includes NOEAT, NOFOOD, SKIPEAT, SENDBEG, SENDEAT, EATSEED, WILD, FDCRED, BORROW, RMEAL, and LMTPOR. The $S_{\mathbf{Qli}}$ indicates the quality score i^{th} questions: PULSES, GRAIN, VARFOOD, DAIRY, EGGS, MEAT, FRUIT, and VEGET. In this dimension, a higher score indicates better food security status. Additionally, SAcci refers to the acceptability score of the i^{th} questions NOTWNT and PREFER, whereas S_{Ati} represents the stability score of the i^{th} questions SLPHUN, WORRY, and SAFS. Except for the quality dimension, a lower score indicates better food security status.

As shown in (Eq. 7), the quantity dimension includes 11 questions, with scores ranging from a minimum of 11 (if a respondent answers "1" or "never" to all questions) to a maximum of 44 (if a respondent answers "4" or "often" to all questions). The quality dimension includes 8 questions, with scores ranging from a minimum of 8 to a maximum of 32. Similarly, the accessibility dimension includes 2 questions, with scores ranging from a minimum of 2 to a maximum of 8. The stability dimension includes 3 questions, with scores ranging from a minimum of 3 to a maximum of 12. However, each dimension lacks cutoff points to classify households into specific food security levels. For this reason, the scores are less easily interpreted on their own. In this context, each dimensional score for a household only becomes meaningful compared to other groups (e.g., CSA adopters vs. nonadopters) or within its minimum and maximum value).

Previous researchers, such as Coates et al. (2007) and Kahsay (2017), have interpreted food security results by focusing on what higher or lower scores imply about food security status rather than attempting to interpret individual scores directly. Following this approach, the results are discussed by interpreting how higher or lower score values in each dimension indicate food security differences between adopters and non-adopters. Second, a multidimensional food security score (outcome variable) was estimated on the basis of household responses to questions, which were computed as indicated in Appendix B, and then, households were classified into four distinct food security levels: food secure, mildly food insecure, moderately food insecure, and severely food insecure (Table 3.4).

Table 3.4: Thresholds for categorizing multidimensional food security

	Responses	**MDFS category**
1	If NOEAT, SLPHUN, NOFOOD, SKIPEAT, SENDBEG, SENDEAT=never, PULSES, GRAIN=Often, EATSEED, WILD, FDCRED, BORROW, NOTWNT=never, VARFOOD, PREFER, RMEAL, LMTPORT, WORRY=never or rarely, SAFS=foo secure or mildly food insecure, DAIRY, EGGS, MEAT, FRUIT, and VEGET=rarely, or sometimes, or often	1=Food security
2	If PULSES and GRAIN=sometimes, EATSEED WILD, FDCRED, BORROW, and NOTWNT==rarely, VARFOOD, PREFER, RMEAL, LMTPORT,WORRY, and SAFS=sometimes, DAIRY, EGGS, MEAT, FRUIT, and VEGET=never	2=Mildly food insecurity

3	If NOEAT, SLPHUN, NOFOOD, SKIPEAT, SENDBEG, SENDEAT, PULSES, and GRAIN=rarely, EATSEED, WILD, FDCRED, BORROW, and NOTWNT=sometimes, VARFOOD, PREFER, RMEAL, LMTPORT, and WORRY=often SAFS=severely food insecurity,	3=Moderately food insecurity
4	If NOEAT, SLPHUN, NOFOOD, SKIPEAT, SENDBEG, and SENDEAT=sometimes or often, PULSES and GRAIN= never, EATSEED, WILD, FDCRED, BORROW, and NOTWNT=often	4=Severely food security

Source: Adapted from (Gidelew et al., 2025; Maxwell et al., 2013)

3.5.4 Multivariate Probit (MVP) Model

In this study, a multivariate probit (MVP) model was employed to analyze the determinants of farmers' adoption of CSA practices. The MVP model is well suited for multiple technology adoption studies because it allows for the joint analysis of interrelated binary choices (Hausman & Wise, 1977). A key advantage of the MVP model is its ability to accommodate a flexible correlation structure among unobservable factors, allowing the error terms across adoption equations to be freely correlated (Huguenin *et al*., 2009). This feature enables the model to efficiently capture the simultaneous effects of explanatory variables on farmers' multiple adaptation decisions (Xiaoping Chen et al., 2018). Furthermore, by explicitly accounting for potential correlations among CSA practices, the MVP model provides more accurate and reliable estimates of the relationships between each CSA practice and its determinants (Huguenin *et al*., 2009).

This research model is based on McFadden (1972) random utility maximization theory, which speculates that farmers' decisions to use adaptations are random and that the farmers choose these strategies if the probability of a specific option's utility being greater than that of other alternative measures. Utility maximization theory assumes that all farmers behave in a manner that maximizes their utility. Hence, farmer i' decides to use 'j' adaptation options if the probability of perceived utility from option 'j' is greater than the utility from other strategies (say, 'k'), stated as:

$$U_{ij}(\beta_j{}' X_i + \varepsilon_j) > U_{ik}(\beta_K{}' X_i + \varepsilon_K), k \neq j \qquad (8)$$

Where U_{ik} the benefits are gained by farmer i from the adoption of CSA practices options j and k, respectively; Xi is a vector of independent variables that influence the choice of adoptions;

β_j and β_k are the model parameters to be calculated; and ε_i and ε_k are the random terms captured used to capture unobserved factors.

The specification of the MVP regression model is based on multiple dependent and latent variables. Following Huguenin *et al*. (2009), the MVP model in the present study consists of five binary choice equations (Y_{ij}) and a matrix of covariates that can be any mixture of discrete and continuous variables; such that:

$$Y^*_{ij} = X'_{ij} B_j + \varepsilon_{ij} \qquad \text{where} \quad j = 1,2,3 \ldots N$$

$$Y_{ij} = \begin{cases} 1 \; if \; Y^*_{ij} > 0 \\ 0 \; otherwises. \end{cases} \tag{9}$$

Where Y^*_{ij} is the latent variable that expresses the unobserved preference associated with j^{th} (in this case, five CSA practices chosen by smallholder farmers: chemical fertilizer, improved crop variety, small-scale irrigation, agrochemical, and compost); Y_{ij} is the dependent variable that is affected by the independent variables (X_{ij}) and unforeseen factors captured by the error term (ε_{ij})); and β_j is a vector of parameters to be estimated.

In this study, the interpretation of the MVP model results depends on marginal effects instead of the direct coefficient parameter estimated. Therefore, the marginal effects of the independent variables, which quantify the expected change in the probability of adopting an adaptation option for a one-unit change in a given variable, were calculated via Eq.(10) as follows:

$$\delta_{ij} = \frac{\partial P_i}{\partial x_i} = \Phi(x^* \beta)\beta_i, i = 1,2,3,\ldots n \tag{10}$$

Where δ_{ij} represents the marginal effects of the covariates on the probability of the j alternative adaptation methods.

3.5.5 Multinomial Endogenous Switching Regression

Multinomial endogenous switching regression (MESR) model was used to estimate the impacts of different adoption levels of CSA practices on the resilience and food security of smallholder farmers. MESR is a statistical model designed to analyze the choices made by individuals when confronted with multiple alternatives (more than two treatments) while considering the potential endogeneity between the selection of alternatives and the outcomes associated with those choices.

Recent studies indicate the growing use of various impact models for impact analysis. For example, (Ali et al., 2022; Issahaku & Abdulai, 2020; Paul et al., 2023; Teklu et al., 2024; Wekesa et al., 2018) applied endogenous switching regression (ESR) to estimate the effects of climate-smart agriculture on food security. Similarly, (Abonesh et al., 2021b; Haq et al., 2021) employed PSM models to estimate the effects of CSA practices on access to adequate and nutritious food in Kenya and Pakistan. However, PSM may be affected by unmeasured confounding variables, leading to biased results (Nuttall & Houle, 2008), and it is also unsuitable for scenarios with more than two treatment groups. To address these limitations, this study employed the multinomial MESR model, which is recommended in the literature (Abdulai & Huffman, 2014; Aseres et al., 2019; Biru et al., 2020; Jaleta et al., 2016; Kassie et al., 2017). The MESR model can offer advantages over other impact evaluation models in specific situations. Notably, the MESR addresses endogeneity in the selection process, which can lead to biased estimates if unobserved factors influence both the treatment choice and the outcome. It can correct selection bias arising from both unobserved and observed heterogeneity (Khanal & Mishra, 2018). In summary, the MESR is well suited for handling endogeneity in the selection process and offers a robust framework for analyzing scenarios involving multiple treatment options.

In nonexperimental research, the assignment of individuals to treatment and control groups is not random, which can introduce systematic bias (Greene, 2006; Ojoko et al., 2017). Such selection bias complicates the ability to establish clear cause–and–effect relationships. On the other hand, farmers' decision to adopt may have been influenced by the expected outcomes they anticipated, resulting in selection bias. Unobservable characteristics of farmers may affect both the adoption decision and its outcome, resulting in inconsistent estimates. For example, if only skilled or motivated farmers choose to adopt and the analysis fails to control for these factors, then upward bias will be incurred. The MESR estimation model assumes that farmers who adopt CSA practices may systematically differ in characteristics from those who do not adopt these practices. This systematic difference can arise from observable and unobservable characteristics, leading to variations in outcomes based on the treatment (adoption of CSA practices).

Previous studies suggest that MESR model can account for selection bias arising from both observable and hidden variables (Abdulai & Huffman, 2014; Aseres et al., 2019; Biru et al., 2020; Jaleta et al., 2016; Kassie et al., 2017). Thus, the study takes into account the endogeneity of the adoption decision by controlling for the effects of various factors on both the decision to adopt CSA practices and their outcomes. This is achieved through the estimation of a simultaneous equation model via MESR. This enables a more accurate evaluation of the impacts of CSA practices on various outcomes, such as food security and resilience.

The estimation of the MESR model follows a two-step procedure. In the first step, a selection equation is computed to assess the likelihood that households adopt different levels of CSA practices. This step helps identify the key factors that influence the extent of CSA adoption. To conduct this analysis, a multinomial logit model is employed. The probability of being in a specific regime is modeled via this multinomial logit, which is typically a function of observable covariates, specified as follows:

$$P\ (Y = j/X) = Y = \frac{e^{BjX}}{\sum_{k=1}^{J} 1 e^{BkX}} \quad (11)$$

where P(Y=j|X) is the probability that the outcome is category j given the predictor variables X, βj is the vector of coefficients associated with category j, and X represents different household socioeconomic characteristics. Thus, in this study, the variable Y is a multinomial choice variable, measured as the number of CSA practices adopted by a given household on its farmland, which is categorized as follows: none-adoption, single adoption, partial adoption, and multiple adoptions.

In the case of the adoption of CSA practices, farmers freely choose the particular CSA practices they want to adopt with their own consent. Hence, there is the problem of self-selection, which leads to selection bias. Selection bias is addressed through model identification, where outcome equations vary by treatment status to account for unobserved heterogeneity. On the other hand, the decision to adopt a given practice is likely to be affected by unobservable characteristics that may be correlated with the outcome variables (food security and resilience capacity). To account for this, an MESR model was used for the outcome variables, in which farmers face two regimes: Regime 1, to adopt, and Regime 2, not to adopt. Markedly, endogeneity bias was addressed by incorporating a selectivity correction term, commonly known as the inverse Mills ratio (λ). The inverse Mills ratio was calculated after conducting a multinomial logistic regression. Assuming that no adoption of a particular CSA practice ($Z = 0$) is a reference category. Following Ayenew et al. (2020) and Aseres et al. (2019), the outcome equation adjusted for the selectivity correction term is specified as follows:

Regime 1: $Y_{0i} = \Gamma_0 X_{0i} + \Theta_0 \hat{\lambda}_{0i} + U_{0i}$ if $Z = 0$

Regime j: $Y_{ji} = \Gamma_j X_{ji} + \Theta_j \hat{\lambda}_{ji} + U_{ji}$ if $Z = j$ (12)

Where $Y_{0i\ldots}$ Y_{ji} is the expected outcome variable of the study (climate resilience). $U_{0\ldots}U_{ji}$ are independently and identically distributed random disturbance terms with a mean of zero and constant variance. X_{ji} is a vector of explanatory variables indicating the socioeconomic characteristics of households. Γ_0 and Θ_0 are parameters to be estimated, whereas $\hat{\lambda}_{0i}$ is the inverse Mills ratio, which is derived from the first stage of the selection equation.

Di Falco et al. (2011), emphasize the importance of using selection instruments that are not only derived from the nonlinearity of the selection model for adoption but also include other variables that directly influence the adoption of CSA practices without directly affecting the outcome variable (except through their impact on the dependent variables). Instrumental variables are utilized to reduce bias that may occur when independent variables are correlated with the error term of the model. Following the foundational study of Hussein (2024), market distance was used as an instrumental variable in this study to predict variations in the adoption of CSA practices. Accordingly, the researcher run falsification test whether this instruments are valid instruments.

Outcome equations with inverse Mills ratios were computed to derive the average treatment effect for the treated (ATT) and the average treatment effect for the untreated (ATU). The ATT measures the actual impact of intervention on the expected outcome of interest, considering only those who received these interventions; it measures the impact of CSA practices on the food security and resilience of adopters. While ATU measures the impact of CSA practices on the food security and resilience of nonadopters. ATU is the average potential impact on those who do not participate in the intervention (White & Raitzer, 2017).

The actual expected value of the outcome variables for adopters of a particular level of CSA practice (single, partial, multiple and full adoption) is given by:

$Y_j = E(Y_{ji}|Z = j; X_{ji}, \hat{\lambda}_{ji})$ for j 1, 2, 3, and 4 (13)

The actual expected value of the outcome variables for nonadopters is given by:

$Y_0 = E(Y_{0i}|Z = 0; X_{0i}, \hat{\lambda}_{0i})$ (14)

The counterfactual expected value of the outcome variables for CSA adopters is given by:

$Y_{0j} = E(Y_{0i}|Z = 0; X_{ji}, \hat{\lambda}_{ji})$ (15)

The counterfactual expected value of the outcome variables for CSA nonadopters is given by:

$Y_{j0} = E(Y_{ji}| Z = j; X_{0i}, \hat{\lambda}_{0i})$ for j = 1, 2, 3, and 4 (16)

The ATT is computed from the expected outcome variable of the farm households that adopt a particular level of CSA practices (Equ 13) with respect to counterfactual hypothetical cases (Equ 15) if the adopted farm households do not adopt such practices. ATU is computed from the expected outcome variable of the farm households that did not adopt any practices (Equ 14) with respect to counterfactual hypothetical cases (Equ 16) that the nonadopted farm household adopted (see Table 3.5).

Table 3.5: Conditional expectations, treatment, and heterogeneity effects

Adopter category	Adoption Decision		Treatment Effect
	To adopt	Not to Adopt	
Adopter	$Y_j = E(Y_{ji}\| Z = j; X_{ji}, \hat{\lambda}_{ji})$	$Y_{0j} = E(Y_{0i}\|Z = j; X_{ji}, \hat{\lambda}_{ji})$	$ATT=Y_j-Y_{0j}$
None-adopter	$Y_{j0} = E(Y_{ji}\| Z = 0; X_{0i}, \hat{\lambda}_{0i})$	$Y_0 = E(Y_{0i}\|Z = 0; X_{0i}, \hat{\lambda}_{0i})$	$ATU=Y_{j0}-Y_0$
Heterogeneity effects	$H_{1j}=Y_j-Y_{j0}$	$H_{2j}=Y_{0j}-Y_0$	TH=ATT-ATU

Note: In this framework, (Y_j) and (Y_0) denote actual outcome values for adopters and nonadopters, respectively; (Y_{0j}) and (Y_{j0}) denote counterfactual outcome values for adopters and nonadopters, respectively. Z = j (adopter) if farm households adopted CSA practices, i.e., single, partial, multiple and fully adopted; Z = 0 (no adopter) if households did not adopt any CSA practices; ATT refers to the difference between the actual outcomes observed for households that adopted CSA practices and the hypothetical outcomes they would have experienced if they had not adopted. ATU: difference between the actual outcomes observed for households that did not adopt any CSA practices and the hypothetical outcomes they would have experienced if they had adopted them. H_{ij}: the effect of base heterogeneity for farm households that adopted practices (i = 1, 2, 3, 4) and did not adopt the practices (i = 0); TH (transitional heterogeneity): the difference between the treatment effect for adopters and the potential effect for nonadopters.

To ensure the validity and robustness of the multinomial endogenous switching regression model, key assumptions were rigorously tested for model fitness. These included (i) tested normality, often assumed to be normally distributed data, which is checked by histogram and Kernel density (Appendix C); (ii) checked outliers and multicollinearity, i.e., covariates had no perfect correlation with each other to ensure reliable estimation, which was checked by pwcorr and vif (Appendix D); and (iii) the presence of endogeneity and valid instrument variables, i.e., the validity of the instruments was established by performing a simple falsification test: if a variable is a valid selection instrument, the instrumental variable affects the adoption decision, but it does not affect the outcome variables (Appendix E). Additionally, measurement error was addressed through rigorous enumerator training and pretesting of survey tools to minimize misinterpretation and recording errors. Cronbach's alpha was applied to evaluate the internal consistency of items measuring the same construct. These steps helped ensure data reliability and validity.

3.5.6 Analysis of Synergies and Trade-offs

The top five CSA practices were identified from a list of 18 practices on the basis of their score values. The five selected practices represented the highest-scoring CSA practices currently adopted by farmers. To assess the synergies and trade-offs of these five CSA practices in relation to food security and household resilience, smallholder farmers were asked to rate their preferred practices using a 3-point Likert scale**,** where high = 3**,** medium = 2**,** and low = 1**.**

The total score for each practice was computed by multiplying the number of responses at each performance level by its corresponding point value and then summing the results. Alternatively, the total score can be obtained by directly summing all individual ratings.

$$\text{Total score j} = \sum_{i=1}^{n} \text{Sij} \qquad (17)$$

These totals were then converted into average scores by dividing the overall score by the number of valid responses. For each CSA practice, the average score across respondents was calculated as follows:

$$\text{Mean Score j (Index score)} = \frac{\sum_{i=1}^{n} Sij}{n} \qquad (18)$$

Where S_{ij} = score given by respondent *i* to CSA practice *j*

n = total number of valid respondents

To facilitate comparison, the average scores were normalized to a scale from 0 to 1, where 0 indicates a low contribution and 1 indicates a high contribution.

$$\text{Normalized score} = \frac{\text{Average score} - \text{Minimum}}{\text{Maximum} - \text{Minimum}} \qquad (19)$$

Based on the normalized values, performance was classified into three categories: low (0.00–0.33), medium (0.34–0.66), and high (0.67–1.00), following the categorization defined by Tilahun et al. (2023b).

Normalized food security scores and resilience scores associated with each CSA practice were visualized via radar (spider) plots, which allow simultaneous comparisons of multiple practices across food security and resilience capacity. Larger and more balanced areas in the radar plot indicate synergistic effects, whereas lower or uneven scores reflect potential trade-offs among practices.

Additionally, qualitative data were analyzed via thematic analysis. Thematic analysis enabled the identification, organization, and interpretation of meaningful patterns within the textual data, providing an in-depth understanding of how CSA practices influence food security and resilience. The interview transcripts were systematically coded, and similar codes were grouped into themes representing synergies and trade-offs. These themes captured participants' experiences and perceptions of CSA practices in relation to food security and household resilience.

3.6 Definition of variables

Out-come variables: The outcome variables for this study were resilience and food security. In this study, resilience refers to households' ability to absorb, adapt to, and transform in response to climate change–related shocks. As proposed 3-D resilience framework proposed by Bene et al. (2012), which suggests that resilience arises from three key capacities: absorptive, adaptive, and transformative capacities. Each of these capacities results in different outcomes: persistence (the ability to maintain function), incremental adjustment (small, gradual changes), or transformational responses (significant changes in response to challenges). Following this framework, quantify household resilience capacity score by categorizing it on the basis of resilience dimensions.

The other outcome variable is food security, which measured by multidimensional household food security (MDFS) index and food consumption score (FCS). Maxwell et al. (2013), developed a MDFS index to capture four dimensions of food security. It measure daily food consumption patterns, food consumption increasing behaviors, dietary change preferences and high value foods consumption behaviors, rare behaviors in severe conditions, and stability; unlike the stand-alone indicators, the MDFS index measures food security status of households in totality.

Food consumption score is measured by food consumption score is defined as frequency weighted diet diversity score or a score calculated using the frequency of consumption of different food types consumed by an individual household. It is a combined score based on dietary diversity, food frequency, and relative nutritional importance of different food groups during a 7-day recall of consumed food items.

Dependent variables: The dependent variable in this study was the adoption intensity of the top five CSA practices, measured by the number of CSA practices adopted by each household. For the causal analysis, households that adopted the top five CSA practices during the 2023 crop growing year were considered the treatment group and were further categorized into discrete groups based on their level of adoption intensity: single adoption (one practice), partial adoption (two practices), multiple adoption (three to four practices), and full adoption (all five practices). In contrast, the control group consisted of households that did not adopt any of the selected CSA practices. The top CSA practices considered in this study included the efficient use of chemical fertilizers (DAP and UREA), improved crop varieties (high-yielding and pest-resistant varieties), small-scale irrigation, agrochemicals (pesticides and herbicides), and compost application.

Furthermore, observed covariates influencing both treatment assignment and outcome variables were employed in the analysis (Table 3.6).

Table 3.6:Variables used in econometric analysis

Variables	Description/definition	Measurement	Hypothesized
Outcome Variables			
Food security	Food security status of the household	Continuous MDFS and FCS score	
Resilience	Households' resilience to climate related shocks	Indices of resilience (low: 0 to 0.33, medium: 0.34 to 0.66, and high: 0.67 to 1).	
Dependent Variable			
Intensity of CSA practices	Number of adoption of top CSA practices	Adopt nothing, single (adopting one CSA), partial	

		(adopting two CSA), multi (adopting 3 t0 4 CSA) & full (adopting 5 CSA)	
Explanatory variables			
Socioeconomic factors			
Age	Age in years of the household head	Total age of households since birth up to now	+-
Sex	Sex of the household head	Dummy=1 if male 0=female	-
Education	Educational levels of household head	0=if the uneducated household head, 1 informal educated, 2 primary educated, 3 secondary educated	+
Family size	Total family size who live under one household	Number of family members (count)	+-
Dependency ratio	Household members aged below15 and above 64	Aged below15 and above 64 divided total family size	-
Livestock holding	Total livestock holding	By changing livestock number in to TLU and sum it	+
Asset	Value of productive farm assets	Value of farm productivity in Birr	+
Land	Own cultivated land	Total size of farm land in hectare	+
Off farm	Participate off farm activity	1 if yes, 0 otherwise	+
Institutional & biophysical factors			
Training	Households' participate in training on land management	1 if trained 0 otherwise	+
Extension	Access to extension	1 if perceived 0 otherwise	+
Soil fertility status	Households' perception about Soil fertility	1 if perceived 0 otherwise	-
Climate change	Households' perception about climate change	1 if perceived 0 otherwise	+
Market	Access to near market	1 if perceived 0 otherwise	+
Membership	Household head is a member of a farmer-related group or RuSACCOs	1 if member 0 otherwise	+
Credit	Access to credit	1 if yes 0 otherwise	+

Source: Adopted from (Mossie, 2022; Ogola & Ouko, 2021; Shiferaw, 2021; Tilahun et al., 2023a; Zeleke et al., 2024; Zeleke Tessera & Demeke Molla, 2025)

CHAPTER FOUR: RESULTS AND DISCUSIONS

This chapter presents the key findings derived from household surveys, key informant interviews, and focus group discussions. It highlights the adoption rates of CSA practices and evaluates their impacts on household resilience and food security using a multinomial endogenous switching regression model. Additionally, the chapter explores the synergies and trade-offs inherent in these practices, providing a detailed discussion of the results to illustrate how CSA contributes to overall adaptive capacity.

4.1 Characteristics of Sample Households

Table 4.1 indicates the characteristics of sample households related to categorical variables. As indicated, 82.25% of respondents were male-headed while the rest, 17.75%, are female-headed households. 41.69% of respondents were none-educated 21.13% were informal educated, 31.83% and 5.35 were primary and secondary educated. Regarding credit access, only 7.32% of respondents reported having access to credit, while 92.75% had no access. This finding indicates a very low level of financial inclusion among rural households in the study area. Given that more than 90% of households are excluded from credit services, access to finance can be considered severely constrained. Access to credit is widely recognized as a key factor in enabling agricultural investment, technology adoption, and livelihood diversification. Therefore, the extremely low proportion of households with access to credit suggests that limited financial services remain a significant barrier to agricultural development and household resilience (Diagne & Zeller, 2001; Feder et al., 1990; World Bank, 2022).

Besides this, 62.25% of respondents had access to extension services while 37.75% of respondents had no access to extension services. In addition to this, 67.68% of respondent were member RuSACCOs, while only 32.39% of them were none members. Most households in the study area have access to extension services and membership in RuSACCOs. Table 4.1 also presents the Chi-square test of dependence, which indicates these categorical variables are associated with adoption categories of CSA practices. The Chi-square test showed that, there is a significant associated between CSA adoption groups in all variables suggesting that these variables may be significantly related to house holds' decision to adopt CSA.

Table 4.1: Descriptive statistics result for discrete explanatory variables

Variables	Name of Variable	None adopter	Single adopter	Partial adopter	Multiple adopter	Full adopter	Total	chi2
Sex	Female	7.32	34.79	3,94	1.13	0.5	17.75	12.05**
	Male	22.82	16.34	19.44	14.08	9.58	82.25	
Education	None	18.59	11.27	7.04	3.94	0.85	41.69	54.77***
	Informal	5.07	2.82	6.48	3.94	2.82	21.13	
	Primary	5.92	5.92	9.01	5.92	5.07	31.83	
	Secondary & above	0.56	1.13	0.85	1.41	1.41	5.35	
Access of Extension	No access	27.04	16.62	11.55	4.79	2.25	62.25	95.09***
	Access	3.1	4.51	11.83	10.42	7.89	37.75	
Access to Training	No access	29.86	18.87	18.31	6.2	4.51	77.75	99.76***
	Access	0.28	2.25	5.07	9.01	5.63	22.25	
Access to Credit	No access	29.86	19.72	22.54	12.68	7.89	92.68	26.88***
	Access	0.28	1.41	0.85	2.54	2.25	7.32	
Membership in RuSACCO	No member	26.2	14.93	16.34	6.48	3.66	67.61	26.87***
	Member	3.94	6.2	7.04	8.73	6.48	32.39	
Access to remittance	No access	29.58	19.72	20.85	12.11	7.32	89.58	50.46***
	Access	0.56	1,41	2.54	3.1	2.82	10.42	

, * indicates significance at 1% & 5% probability level of significance, respectively.

Source: Author survey result (2024)

Table 4.2 summarizes the continuous socio-economic characteristics of sample households in the study area, with categorized into various groups: non-adopters, single adopters, partial adopters, multiple adopters, and full adopters of CSA. Notably, the average age of the household head is 47.91 years. Furthermore, the average family size across the sample households is 3.66, which can be rounded to approximately four members per household. The analysis also includes a mean comparison test (ANOVA) that reveals a significant difference in family size among the different adopter groups, with a p-value of less than 1%. This finding underscores the varying dynamics of household size depending on the level of CSA adoption.

Furthermore, Table 4.2 presents data on the average tropical livestock unit[3] and land size of the sample households, which are reported as 2.3 and 0.86 hectares, respectively. The mean comparison test for these variables further indicates significant differences between the various

[3] A tropical livestock unit is a live weight of an animal equivalent to 250 kg.

adopter categories, with a p-value of less than 1%. Overall, these findings suggest that the socio-economic characteristics of households play a crucial role in influencing the adoption of CSA practices within the study area.

Table 4.2: Relationship between continuous variables with level of CSA adoption

Variables	None adopter		Single adopter		Partial adopter		Multiple adopter		Full adopter		Total		F-value
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
Age	50.5	9	48	7.85	47.2	7.9	47.83	8.82	48	7.58	47.91	7.58	2.14
Family Size	3.35	0.9	3.77	0.93	3.77	0.9	3.66	1	4.1	0.93	3.66	0.96	5.21***
livestock holding	1.15	1.2	1.88	1.56	2.38	1.6	3.73	1.49	4.3	1.55	2.31	1.81	48.07***
Farming Size	0.75	0.2	0.82	0.18	0.89	0.2	0.99	0.27	1	0.24	0.86	0.23	14.11***
Market Distance	0.74	0.3	0.6	0.31	0.58	0.3	0.55	0.4	0.5	0.23	0.61	0.33	6.65***

*** indicates significance at <1% probability level of significance

Source: Author survey result (2024)

4.2 CSA Practices in Study Area

As shown in Figure 4.1, the five most prominent CSA practices among the respondents were chemical fertilizers (50%), improved crop varieties (33%), small-scale irrigation systems (27%), agrochemicals (23%), and compost (22%). The relatively high adoption of chemical fertilizers, with half of the farmers applying them correctly in terms of timing, quantity, and method, indicates that farmers recognize their immediate benefits for crop productivity. The adoption of improved crop varieties by approximately one-third of respondents, particularly pest-resistant and high-yielding varieties, further reflects a partial uptake of climate-smart strategies. However, the overall adoption levels suggest that these practices are not yet widespread, highlighting persistent barriers such as access to inputs, security, and financial constraints. The relatively high use of chemical fertilizers aligns with studies indicating that farmers tend to prioritize practices with immediate and visible yield benefits, especially under resource constraints (Ali et al., 2018; H. Teklewold et al., 2019a). Similarly, the moderate adoption of improved crop varieties is consistent with findings by Negera et al. (2022b), who reported that improved seeds are commonly adopted but are still limited by access, cost, and information barriers. However, the low adoption of practices such as composting and small-scale irrigation contrasts with (Canton, 2021). Overall, the results confirm a common pattern in the literature:

farmers tend to adopt low-risk, productivity-enhancing practices first, whereas practices that require more resources, labor, or technical knowledge are adopted more slowly.

> *The case of low adoption of CSA practices was highlighted through evidence gathered from FGDs and KII. Focus group participants stated that "the ongoing conflict between Fano and government forces has severely disrupted access to essential agricultural inputs, such as fertilizers, improved seeds, and pesticides, and has also aggravated their costs. Another participant added. "Many households simply lack the finances to buy new seeds, and chemical fertilizers." One key informant said that " due to transport costs are high, there are no improved seeds or fertilizers available nearby, and. Even when inputs are supplied, they are often insufficient or arrive late." Another key informant said "Many farmers perceive composting as time-consuming and believe it increases the risk of disease." This observation is consistent with the findings of* Emmanuel and Oba (2019)*, who identified limited government support and the absence of improved seed varieties as key barriers to the adoption of sustainable farming practices. This is consistent with (*Gashu et al., 2025*;* Kidane et al., 2025*).*

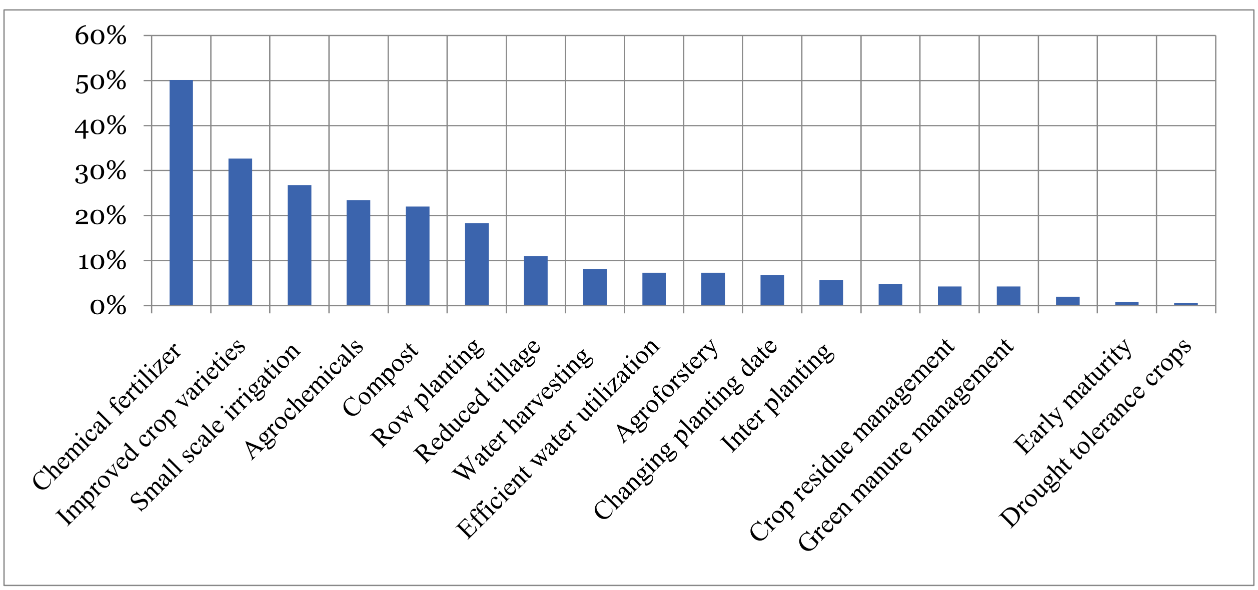

Figure 4.1: Adoption status of CSA practices
Source: Author survey result (2024)

4.3 Rural Households Resilience

4.3.1 Dimensional Resilience Capacity

The current study advanced by proposing 14 variables as hypothesized sources of resilience. Each indicator (component) was generated from variables. Resilience dimensions were proposed from indicators. The researcher presents summary of how the observed variables contribute to each of these indicators based on how their loadings turn to be significant (stage one) and ultimately how each of the estimated resilience dimensions contribute to households' resilience (stage two).

Absorptive capacity: The size of the component loading for each variable is important for policy implications; specifically, higher loadings indicate greater importance and should receive more policy attention. Before the absorptive capacity was estimated, each household's component scores were indexed (predicted) through PCA. Accordingly, the latent variable (ABPC) score was calculated via Equ (6), which represents the sum of the principal component scores multiplied by the proportion of variation (weight) explained by each component.

$$ABPC_i = pc1 * 0.234 + pc2 * 0.119 + pc3 * 0.102 + pc4 * 0.095 \quad (6)$$

Where $ABPC_i$ = absorptive capacity score for the ith household; pc1, pc2 pc3 pc4= component score of the *i*th household.

Table 4.3 presents the component loadings of the variables used to estimate absorptive capacity (ABPC). As indicated, four components were retained because their eigenvalues exceeded one. The Bartlett test of sphericity was significant ($\chi2$=1061.84, p<.0.01), confirming that all 14 variables were statistically significant, indicating adequate correlation with the components. The KMO value was 0.705 and was well above 0.5 for the individual variables used in the model. Each variable exhibited loadings greater than 0.3 or less than -0.3, reflecting their substantial contributions to ABPC. Thus, the necessary statistical criteria for a robust PCA model were fulfilled, as outlined by Kaiser's rule (KMO values above 0.5).

As indicated in Table 4.3, the first, second, third, and fourth components accounted for 23.4%, 11.9%, 10.2%, and 9.5% of the variation, respectively. Together, these variables explain 55.03% of the total variation. The findings revealed that, excluding remittances and formal aid, all other variables were positively and significantly associated with ABPC (p<0.01). This suggests that locally accessible and socially embedded resources, rather than external transfers, are more predictive of households' ability to absorb shocks. Notably, access to weather information, ownership of communication devices (such as radios, TVs, and mobiles), livestock sales, and informal social insurance had strong loadings on the first component, indicating their significant contributions to estimating ABPC. This finding aligns with Demisse et al. (2024) that of , who reported that safety nets and mobile phones significantly contribute to ABPCs. Similarly, the importance of productive safety nets, meal reduction strategies, and grain borrowing from neighbors were major contributors to ABPCs. This finding is consistent with that of Sunday et al. (2023), who reported that access to informal safety nets is vital for enhancing the absorptive capacity of rural households in Uganda. This finding suggests that access to weather information, communication devices, and informal safety nets is more critical for enhancing households' ability to absorb shocks.

Table 4.3: Component loadings of the variables used to estimate the ABP

	Rotate, varimax			
Variables	Comp1 (Disaster mitigation and early warning system)	Comp2 (Risk-management)	Comp3 (Informal social safety net)	Comp4 (Formal social safety net)
Productive safety net				0.610
Friend support			0.579	
Formal aid (NGO & GO)				-0.698
Remittances		-0.386		
Informal social insurance	0.304			
Access to weather information	0.541			
Mobile phone communication	0.415			
Ownership of radio & TV	0.511			
Decrease quantity of meal			0.331	
Decrease number of meal		0.623		
Decrease diversity of meal		0.625		
Borrow grain from neighbors			0.533	
Sales of livestock	0.335			
provision of farm labor			0.361	
proportion of variance	0.234	0.119	0.102	0.095

Total variance explained/Rho: 55.03%

Scale reliability coefficient/cronbach's alpha: 0.544
Bartlett Test of Sphericity: Chi-Square=1061.84, p=.000
KMO Measure of Sampling Adequacy=0.706

Source: Author household survey, 2024

Adaptive capacity: As shown in Table 4.4, the KMO value was 0.719, indicating that the sample size was sufficient to conduct PCA. Additionally, Bartlett's test of sphericity was significant ($p = 0.01$, $\chi 2 = 2138.058$), demonstrating significant correlations between each component and the variables. Therefore, the PCA model was deemed satisfactory and was used for estimation.

As indicated in Equ. 7, each household's component scores were indexed (predicted) through PCA. The ABPC score was subsequently computed using the component scores and the relative variance explained by each component as weights. Therefore, the ADPC score for each household was calculated as the weighted sum of its scores times the variance of each of the six components.

$$ADPC_i = pc1 * 0.23 + pc2 * 0.14 + pc3 * 0.09 + pc4 * 0.08 + pc5 * 0.06 + pc6 * 0.06 \quad (7)$$

Where $ADPC_i$ = adaptive capacity score for the ith household; pc1, pc2 pc3 pc4 pc5 pc5= component score of the *i*th household.

As indicated in Table 4.4, six components were extracted to calculate the ADPC scores on the basis of the criterion of eigenvalues greater than 1, accounting for 67% of the total variance in the model. Subsequently components generated were significant in terms of the proportion of total variance explained, and both were considered the underlying ADPC. Notably, the first, second, third, fourth, fifth and sixth components obtained 23.1, 14.3, 9.5, 7.9, 6.2, and 6% variation, respectively.

Except for the sex of the household head, all other variables were strongly and positively correlated with ADPC at $p<0.01$, indicating their significant contribution to the ADPC. The negative loadings of sex indicate that ADPC decreases as the head of household becomes female. Physical assets, average annual income, and cash savings were grouped together, and their highest component loadings were exhibited on the first component. Moreover, educational level, farming experience, and the age of the household head had higher loadings on the second component. Annual income, improved seed varieties, and water harvesting technologies were grouped together and presented the highest component loadings on the fourth component, indicating that these variables play a significant role in shaping household adaptive capacity. These findings align with evidence from Bekuma (2024), who noted that improved seed varieties and water conservation practices enhance both productivity and resilience among smallholder farmers. Similarly, Negera et al. (2025) reported that income diversification through off-farm employment strengthens adaptive capacity by reducing dependence on rain-fed agriculture and mitigating climate risk.

Table 4.4: Component loadings of the variables used to estimate the ADPC

Variables	Rotate, varimax					
Variables	Comp1 (Wealth and income)	Comp2 (Socioeconomic)	Comp3 (Demographic characteristics)	Comp4 (Adaptive strategy)	Comp5 (Food security)	Comp6 (Off farm income)
Sex household head			-0.665			
Marital status			0.666			
Education level of HH		0.463				
Farming experience		0.601				
Labor availability						0.399
Age of household head		0.601				
Different crops planted	0.386					
Improved verities				0.363		
Water harvesting technologies				0.329		
Working none-farm	0.306					
Working off-farm						0.839
Physical asset	0.455					
Average annual income	0.401			0.601		
Cash saving	0.449					
MDFS					0.777	
FCS				0.514		
proportion of variance	0.231	0.143	0.095	0.079	0.062	0.061
Total variance explained/Rho: 67%						
Scale reliability coefficient/alpha: 0.704						
Bartlett Test of Sphericity: Chi-Square= 2138.058, p=.000						
Kaiser–Meyer–Olkin Measure of Sampling Adequacy: 0.719						

Source: Author household survey (2024)

Transformative capacity: Transformative capacity is the third latent variable of resilience capacity, which enables conditions that foster resilience. Before the transformative capacity (TRNC) was estimated, each household's component scores were indexed (predicted) through PCA. The TRNC was calculated on the basis of the component scores and the relative variance explained by each component as weights. The TRNC score for each household was derived as the weighted sum of its scores multiplied by the variance of each of the six components (Equ 8).

$$TRNC_i = pc1 * 0.308 + pc2 * 0.154 + pc3 * 0.126 + pc4 * 0.077 \quad (8)$$

All the statistical requirements for a valid PCA model were tested and met, which is consistent with the Kaiser criterion. Specifically, the sample size was sufficient to run PCA, as indicated by the KMO measure (0.783) and Bartlett's sphericity test, which was significant ($p< 0.01$, $\chi 2=$ 1617.5). To estimate transformative capacity, 13 observed variables were included in the PCA model. Four independent components were retained for calculating the TRNC scores on the basis of an eigenvalue greater than 1. Together, these variables explain 66.5% of the total variation.

As presented in Table 4.5, all thirteen variables were found to be positive and statistically significant, with component loadings greater than 0.358. The positive and high loadings of these variables indicate their significant contribution to estimating transformative capacity. Specifically, access to extension services, agricultural training, all-weather roads, and electricity, as well as the distance to the nearest school, health institution, and market, had strong loadings, indicating that each significantly contributes to the estimation of transformative capacity. This finding aligns with (Asmamaw et al., 2019; Dessie & Demsie, 2024).

Table 4.5: Component loadings for the variables used to estimate the TRNC

	Rotate, varimax			
Variables	Comp1 (Training, information and basic services	Comp2 (Infrastructure)	Comp3 (Social network)	Comp4 (Social services)
Access to extension				0.676
Access to training				0.537
Membership in iqub		0.495		
Membership RUSACO		0.609		
Access to credit		0.586		
Access to irrigation				0.409
Distance to nearest	0.581			

school				
Distance to nearest market	0.555			
Distance to nearest health institution	0.594			
Distance to drink water			0.489	
All-weather road			0.509	
Clear drink water and sanitation			0.358	
Electricity			0.588	
proportion of variance	0.308	0.154	0.126	0.077
Total variance explained/Rho: 66.5%				
Scale reliability coefficient/alpha: 0.746				
Bartlett Test of Sphericity (chi-Square= 1617.5,P =.000				
Kaiser–Meyer–Olkin Measure of Sampling Adequacy: 0.783				

Source: Author household survey (2024)

Composite resilience capacity: As presented in the methodology section, PCA was conducted in the second stage to calculate the overall resilience capacity index (RCI) via the results from the three dimensions of resilience capacity. As a result, the Bartlett test of sphericity was significant ($p<0.01$, $\chi2=60.076$), indicating sufficient correlations among the variables and their corresponding components. The KMO measure of sampling adequacy was 0.59. Therefore, all the statistical criteria for the goodness of fit of the principal component analysis model were met.

Following the Kaiser criterion, one component was retained because its eigenvalue was equal to or greater than one, accounting for approximately 50% of the total variance. As indicated in Figure 4.2, only the first principal component exceeds the Kaiser Criterion threshold of 1, which is a value of 1.45, indicating that it captures a significant portion of the variance and can be used to construct a composite resilience capacity index.

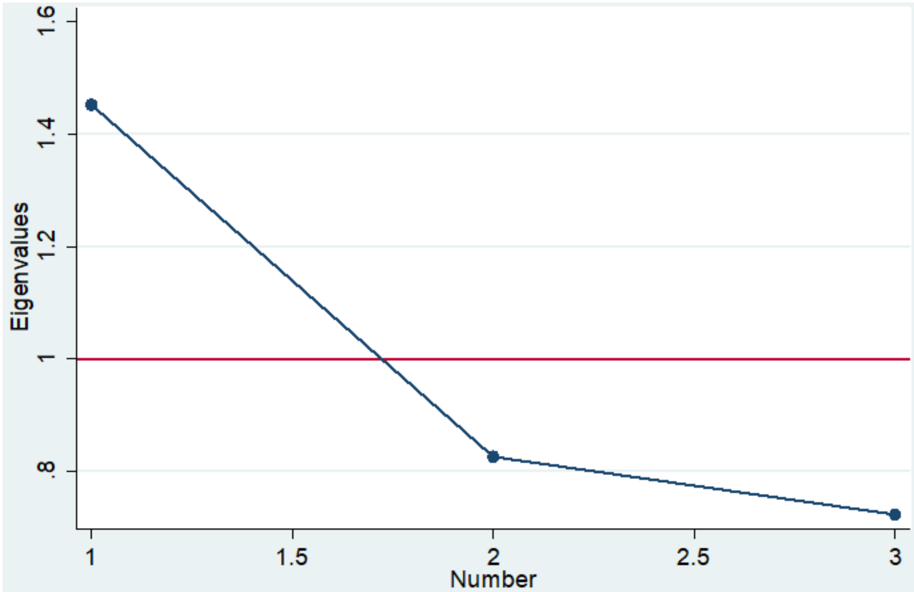

Figure 4.2: Screen plot of eigenvalues after PCA

As indicated in Table 4.6, the component loadings for absorptive, adaptive and transformative capacity were 0.612, 0.534, and 0.583, respectively, indicating that absorptive capacity is a key contributor to enhancing resilience in rural households. This finding aligns with work in Somalia by Martin (2019) and in Ethiopia by Dessie and Demsie (2024), who reported that absorptive capacity had the highest component loadings and largest contribution to household resilience. However, Asmamaw et al. (2019) reported that transformative capacity is pivotal in influencing household resilience. Additionally, studies conducted in Tanzania and Uganda by d'Errico et al. (2018) revealed that adaptive capacity is the primary contributor to enhancing resilience capacity. In contrast, Dessie and Demsie (2024) reported a negative correlation between transformative capacity and household resilience, suggesting that structural factors may not uniformly translate into improved outcomes without complementary enabling conditions. Overall, this finding suggests that absorptive capacity is the most critical factor for overall household resilience in rural households, significantly enhancing their ability to respond to shocks and stresses.

Table 4.6: Component loadings of resilience capacity to climate change

	Rotate, varimax
Dimensions	Comp1 (composite resilience capacity)
Absorptive capacity	0.612
Adaptive capacity	0.534
Transformative capacity	0.583

Variance: 0.4841
Total variance explained/Rho: 0.484
Scale reliability coefficient/alpha: 0.409
Bartlett Test of Sphericity: Chi-Square= 50.44, p=.000
Kaiser–Meyer–Olkin Measure of Sampling Adequacy:0.591

Source: Author household survey (2024)

4.3.2 Household Resilience Capacity Status

As indicated in Figure 4.3, approximately 19% of the rural households in the study area were found to have high resilience capacity. This proportion is moderately consistent with findings of Ali et al. (2023b), who reported that 12.23% of households exhibited high resilience. Moreover, 44% of the households in the current study fell into the low-resilience category, suggesting that nearly half may be vulnerable to climate-related shocks. This is consistent with (Wereta et al., 2025). Additionally, this vulnerability pattern aligns with that of Atara et al. (2020), who reported that 61% of households in the Sidama zone were classified as non-resilient. The remaining 38% of households in Gubalafto demonstrated medium resilience capacity. This distribution contrasts slightly with that of Siminyu et al. (2020), whose study in a similar East African setting revealed that most households had resilience indices ranging between 0.34 and 0.66, indicating a predominance of medium resilience.

The study revealed that approximately half of the surveyed households exhibit low resilience capacity, as reflected in their resilience index. This indicates that a significant portion of the population remains vulnerable to climatic shocks, limiting their ability to adopt and sustain CSA practices. These findings are consistent with those reported by Demisse et al. (2024) because rural farmers depend on rain-fed agriculture, have limited access to resources, experience low income levels, and face inadequate infrastructure. Furthermore, this finding aligns with focus group insights, which emphasize that poor infrastructure and economic constraints hinder rural households' ability to adapt to climate change. In contrast, the finding that only a small proportion of households attain high resilience capacity highlights a critical development gap in rural adaptation systems. This limited resilience suggests that most farming households remain highly susceptible to climate-related shocks. This result was in agreement with work in the central rift valley of Ethiopia by Ali et al. (2023b), in the central highlands of Ethiopia by Demisse et al. (2024), in southern Ethiopia by Atara et al. (2020), and in Bungoma by Siminyu et al. (2020).

Those authors stated that many households are encountering challenges related to climate resilience, indicating that they are not resilient.

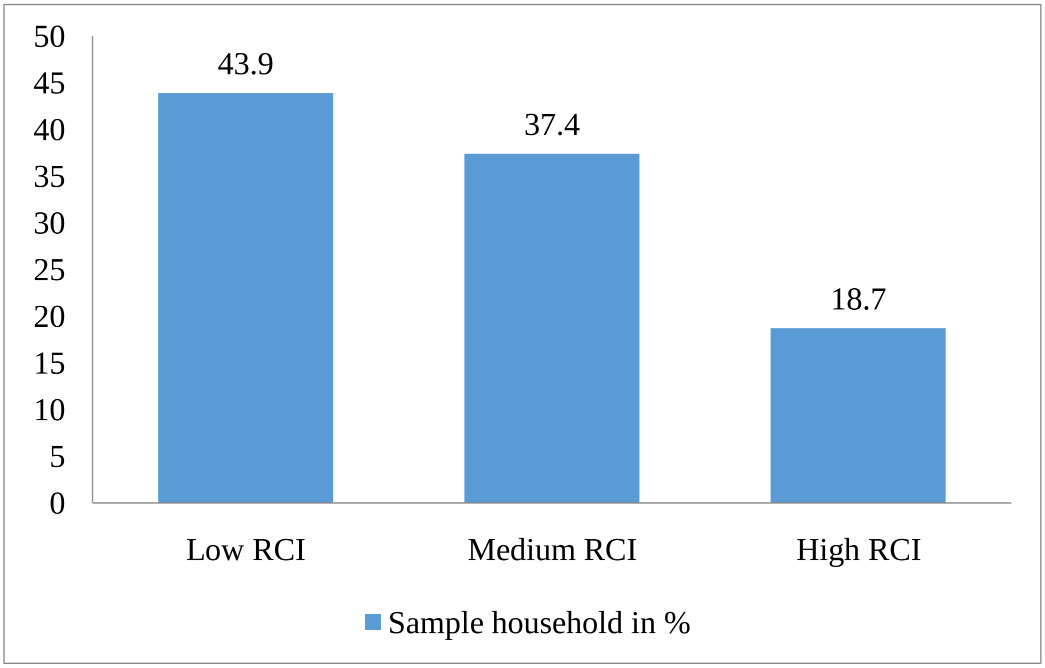

Figure 4.3: Resilience status of households

4.3.3 Agroecological-wise of Resilience Capacity

The resilience index for each agroecological type offers a nuanced understanding of how different areas cope with challenges. As described in Joerin et al. (2014), this approach allows better visualization of resilience across agroecological contexts. To do so, one-way ANOVA was employed to test the mean difference in household resilience capacity among the different agroecological zones.

Table 4.7 presents the mean values of the composite resilience index and its corresponding dimensional capacities. Accordingly, the mean resilience score in terms of transformative capacity (0.239) was lowest for the other resilience capacities, whereas the mean absorptive capacity (0.465) was highest. This result is consistent with that of Asmamaw et al. (2019), who reported that transformative capacity is greater than other dimensions of resilience capacity.

The mean ABPCI in the highlands was 0.485, exceeding the values of the other two agroecological zones. In contrast, the midland agroecology had a mean index of 0.422, which was lower than those of the highlands and lowlands. Another plausible interpretation is that the mean ABPC in the midland area was 0.061 units lower than that in the highland area, with a significance level of 0.032. These findings indicate that the mean ABPC in the midland area was approximately 6.1% lower than that in the highland area. Similarly, there was a mean difference of 0.059 in ABPC between lowland and midland, with a significance level of 0.041. This means that the mean ABPC of the lowland is 5.9% greater than that of the dega, suggesting that the mean ABPC in the lowlands is greater than that in the midland (see Table 4.8). Compared with those in the highlands, many farmers in the midland lack access to government aid and the Productive Safety Net Program (PSNP), which may contribute to the lower absorptive capacity in the midlands. Additionally, farmers in the midland area had limited access to remittances compared with those in the lowland.

There was a statistically significant difference in ADPC scores among the three agroecology, with a significance level of 0.0318. The average ADPC score was highest in the lowland (0.339), followed closely by that in the highland (0.332), while that in the midland was the lowest at 0.282 (see Table 4.7). Table 4.8 further confirms that the difference in the mean ADPC between lowland and midland was 0.057, with a significance level of 0.041. This means that the ADPC of the lowland was 0.057 times greater than the mean ADPC of the midland. These findings suggest that the conditions in lowland may lead to better ADPC outcomes than those in midland.

Table 4.7: One-way ANOVA: Resilience status of agroecological zones

Agro-ecology	ABPC	ADPC	TRNC	CRI
Highland	0.485	0.332	0.208	0.307
Midland	0.422	0.282	0.23	0.253
Lowland	0.481	0.339	0.277	0.416
Mean	0.466	0.320	0.239	0.331
Std. dev.	0.179	0.176	0.208	0.323
Prob > F	0.015	0.032	0.027	0.001

Source: Author household survey (2024)

A One-way ANOVA was conducted to assess the mean differences in resilience indices across agroecological zones, revealing an overall mean RCI of 0.33 (Table 4.8). Surprisingly, the lowland had the highest mean RCI (0.416), followed by the highland (0.307), whereas the midland had the lowest mean RCI (0.253). This result indicated a significant mean difference among the agroecology zones, with a p value of 0.01. Specifically, lowland had a significantly greater mean RCI than highland did, with a p value of 0.02, indicating a difference of 0.162 in the mean RCI. Similarly, lowland was higher than by 0.109 mean RCI as compare to midland. This finding is in line with that of Tofu et al. (2023), who reported that the resilience index of lowland agro-pastoral livelihoods are comparatively better adapted to climate variability. This finding suggest that lowland communities exhibit higher resilience than those in the midland and highland areas, likely due to more favorable conditions such as better access to irrigation, remittances, larger landholdings, and lower rates of soil erosion, all of which enhance their adaptive capacity. In contrast, highland areas are characterized by steep slopes, severe soil erosion, shallow soils, and nutrient depletion, which limit the long-term effectiveness of chemical fertilizers. Although chemical fertilizers may increase crop yields in the short term, they do not address underlying soil degradation or improve soil organic matter. As a result, their contribution to long-term soil resilience in the highlands remains limited.

The findings of this study are broadly consistent with the work of Jayadas and Ambujam (2021), Aboye et al. (2023), and DEEP (2025), who confirmed that resilience varies across agroecological zones. The results of this study underscore the importance of the agroecological context in shaping household resilience outcomes.

Table 4.8: Multiple comparisons of marginal linear prediction of resilience capacity

	Contrast	Std. dev.	P>|t|
Absorptive capacity			
Midland vs. highland	-0.061	0.024	0.032**
Lowland vs. highland	-0.003	0.022	1.00
Lowland vs. midland	0.059	0.024	0.041**
Adaptive capacity			
Midland vs. highland	-0.049	0.023	0.104
Lowland vs. highland	0.008	0.022	1.00
Lowland vs. midland	0.057	0.023	0.041**
Transformative capacity			
Midland vs. highland	0.022	0.028	1.00
Lowland vs. highland	0.046	0.028	0.276
Lowland vs. midland	0.069	0.026	0.026**
Resilience capacity index			
Midland vs. highland	-0.053	0.042	0.628
Lowland vs. highland	0.109	0.039	0.02**
Lowland vs. midland	0.162	0.042	0.00***

Source: Author household survey (2024)

4.4 Determinants and Impacts of CSA on Resilience

4.4.1 Determinants of top five CSA Adoption

As expounded in section 4.2, the adoption of individual CSA practices are reported. For further analysis, the five most widely adopted CSA practices chosen from a list of 18 include the efficient use of chemical fertilizers, improved crop varieties (pest-resistant and high-yielding), small-scale irrigation systems, agrochemicals, and composting. As expounded in the methodological section, adoption extent or adoption intensity was assessed via count of these CSA practices adopted. On the basis of the adoption intensity score, households were categorized into distinct groups according to the number of CSA practices implemented on their farmland. According to this analysis approach, approximately 30% of the total households did not adopt any of the top CSA practices. Moreover, 21.4% of the respondents used two different farming CSA practices together and were categorized as partial adopters. Approximately 15% of the respondents were "multiple adopters," indicating that they implemented three to four CSA practices. While, 10% of the total respondents adopted all the top practices at their farms. Small portions of households had adopted full packages at their farms (Table 4.9). This uneven uptake suggests that a substantial portion of farming households either lack access to CSA knowledge or face constraints that prevent implementation. Moreover, relatively large proportion of households may prefer not to adopt any practices, whereas a few households prefer to adopt all practices. These results are consistent with earlier research conducted in Ethiopia by Ahmed et al. (2023a) and in Pakistan by Haq et al. (2021).

Table 4.9: Adopter categorization on the basis of the intensity of CSA practice adoption

Adopter groups	Description	Number	Adoption status (%)
None-adopter	Farmer did not apply any of the top 5 CSA practices	107	30.14
Single adopter	» applying any one top practice	75	21.13
Partial adopter	» applying 2 top practices together	83	23.38
Multiple adopter	» applying 3 to 4 top practices together	54	15.21
Full adopter	» applying all to 5 practices	36	10.14

Source: Author household survey (2024)

As shown in Table 4.10, the Wald chi-square statistic is significant at the 1% level, indicating that the explanatory variables are jointly significant and that their regression coefficients are not equal to zero. Similarly, the likelihood ratio (LR) test is statistically significant, confirming that the multivariate probit (MVP) model provides an adequate fit to the data.

The MVP results indicate that age has a statistically significant negative effect on compost adoption. Specifically, the marginal effects show that each additional year of age reduces the probability of adopting compost by 4.3%, suggesting that older farmers are less likely to adopt this practice, possibly because of higher labor requirements or greater resistance to change. The observed negative association between age and compost adoption suggests that older farmers may face specific barriers such as labor constraints, risk aversion, or limited access to training that reduce their likelihood of adopting labor-intensive practices such as composting. This finding aligns with those of previous studies (Asrat & Simane, 2017; Haq et al., 2021; Kurgat et al., 2020; Tilahun et al., 2023a).

Informal education has a statistically significant effect on the adoption of agrochemicals and compost at the 1% level. The marginal effects indicate that, relative to uneducated households, those with informal education are 26% and 29% more likely to adopt agrochemicals and compost, respectively. Family size has a statistically significant and positive effect on the adoption of chemical fertilizer and improved crop varieties at the 5% and 10% significance levels, respectively. The marginal effects indicate that each additional household member increases the probability of adoption by approximately 8%. This positive relationship likely reflects greater availability of household labor, which reduces labor constraints and facilitates the timely application of chemical fertilizers as well as the management requirements associated with improved crop varieties.

The dependency ratio has a statistically significant negative effect on the adoption of chemical fertilizer, small-scale irrigation, and improved crop varieties at the 1%, 5%, and 10% significance levels, respectively. The marginal effects indicate that, holding other factors constant, a one-unit increase in the dependency ratio reduces the probability of adopting chemical fertilizer by 20%, small-scale irrigation by 15%, and improved crop varieties by 11%. This suggests that households with greater dependency burdens face labor and financial constraints that limit their capacity to adopt input- and capital-intensive agricultural technologies.

Holding other factors constant, a one-unit increase in Tropical Livestock Units (TLU) raises the probability of adopting irrigation by 14% and agrochemicals by 9%. This finding indicates that wealthier households, as reflected by larger livestock holdings, are more likely to invest in climate-smart agricultural technologies, as livestock ownership enhances both financial capacity and risk-bearing ability. Similarly, logAsset significantly affected the adoption of chemical fertilizer and irrigation at the 1% level. Specifically, when other factors are constant, increasing logAsset by 1 unit increases the probability of adoption of chemical fertilizer and irrigation by 21% and 27%, respectively. These findings indicate that economic capacity plays a critical role in enabling CSA uptake. This suggests that households with greater financial and productive assets are better positioned to invest in input-intensive technologies, manage risk, and sustain long-term agricultural improvements. These findings are consistent with those of (Zeleke et al., 2024).

Households aware of climate change were significantly more likely to adopt chemical fertilizers, with a 27% greater probability, indicating that climate risk perception promotes CSA uptake. RuSACCOs membership positively influenced the adoption of improved crop varieties at the 10% level, increasing the likelihood of adoption by 16% and 31%, respectively. Implies, climate change awareness significantly increased the likelihood of fertilizer adoption, suggesting that access to reliable information on current and projected temperature and rainfall patterns may enable farmers to select appropriate agricultural inputs. This finding is consistent with those of previous studies (Sisay et al., 2023; Teklu et al., 2023). Furthermore, membership in RuSACCOs positively influenced the adoption of both improved crop varieties and compost, likely due to increased access to financial and informational resources.

In contrast, market access negatively affected the adoption of chemical fertilizer, small-scale irrigation, agrochemicals, and compost, reducing adoption probabilities by 43%, 53%, 39%, and 24%, respectively. This negative relationship may be attributed to higher transaction costs and input price volatility, which reduce incentives to invest in these CSA technologies. Households that perceived poor soil fertility were 19% more likely to adopt improved varieties and 15% more likely to use agrochemicals.

Table 4.10: Determinants of individual CSA adoption practices

	chemical fertilizer		Improved crop variety		Small scale irrigation		Agrochemicals		Compost	
Variables	Coef	dy/dx	Coef	dy/dx	Coef	dy/dx	Coef	dy/dx	Coef	dy/dx
Sex (male)	-0.448	-0.179*	-0.421	-0.168*	-0.534	-0.214*	-0.4	-0.16	5.086	2.034
Age	0.021	0.008	-0.009	-0.004	0.004	0.002	-0.017	-0.007	-0.043	-0.017**
Educ: Informal	-0.176	-0.070	0.249	0.099	0.055	0.022	0.669	0.26 ***	-0.725	-0.29***
Primary	-0.177	-0.071	0.045	0.018	0.127	0.051	-0.077	-0.031	-0.403	-0.161
Secondary	-0.753	-0.301*	0.015	0.006	0.851	0.340*	0.115	0.046	-0.357	-0.143
Family size	0.214	0.086**	0.192	0.077*	-0.143	-0.057	-0.059	-0.024	0.05	0.02
Dependency ratio	-0.494	-0.19***	-0.284	-0.114*	0.386	0.154**	0.019	0.008	-0.174	-0.069
TLU	0.025	0.01	0.063	0.025	0.368	0.147***	0.231	0.092**	0.029	0.0116
logfarm size	0.432	0.173	0.284	0.114	-0.49	-0.196	-0.209	-0.084	1.601	0.640***
logAsset	0.538	0.215***	0.134	0.054	0.683	0.273***	0.027	0.011	0.189	0.076
Off farm	-0.503	-0.201*	-1.023	-0.409***	0.238	0.095	-0.435	-0.174	-0.011	-0.004
Feeling of climate change	0.672	0.269***	0.278	0.111	0.34	0.136	0.252	0.101	0.295	0.118
Training	0.142	0.057	0.409	0.164*	-0.318	-0.127	-0.207	-0.083	0.364	0.146
RuSACCOs membership	0.126	0.050	-0.536	-0.214	-0.284	-0.113	0.06	0.024	1.027	0.411**
Credit access	-0.324	-0.129	0.258	0.103	0.936	0.374***	-0.046	-0.018	-1.145	-0.458**
Extension access	0.141	0.056***	0.094	0.038	0.029	0.011	-0.183	-0.073	0.239	0.096
Distance to market	-1.085	-0.43***	-0.849	-0.339	-1.3***	-0.529***	-0.977	-0.391***	0.607	0.243**
Soil fertility status	-0.292	-0.117	0.787	0.313	0.379	0.151	0.657	0.263	-0.31	-0.124
_cons	-3.185		-1.945		-7.46		-0.395		-5.589	

Wald chi2(90) = 392.16
Prob > chi2 = 0.0000
Likelihood ratio test of rho21 = rho31 = rho41 = rho51 = rho32 = rho42 = rho52 = rho43 = rho53 = rho54 = 0: chi2(10) = 66.5778 Prob > chi2 = 0.0000
*, **, and *** indicates statistically significant variables at 10%, 5%, and 1%, respectively.

4.4.2 Impacts of adoption intensity CSA practices on Household Resilience

This section of the impact evaluation presents the second stage of the multinomial endogenous switching results of average treatment effects on the treated using outcome variables with actual and counterfactual result comparisons. Hence, the impacts of chemical fertilizer, improved crop varieties, small-scale irrigation, agrochemicals, and compost on household resilience capacity were estimated via an endogenous switching regression model. Additionally, it assesses the effect of adoption intensity on resilience without providing an in-depth analysis of its underlying determinants. For clarity, the socioeconomic, institutional, and biophysical variables that influence adoption intensity are reported in Appendix F.

Table 4.11, on average, households that adopted chemical fertilizer experienced a 49% increase in their resilience capacity index, whereas nonadopters experienced a 32% decline (-0.32) in the index. The difference between the two groups was statistically significant at the 1% level. Similarly, households that adopted improved crop varieties recorded a 42% increase in their resilience capacity index, whereas nonadopters experienced a 67% decrease (-0.67), with the difference also statistically significant at the 1% level. On average, adopters of small-scale irrigation indicated a 21% (0.21) increase in their resilience capacity index compared with their counterparts, who recorded a 75% (-0.75 decline in the resilience capacity index. Households employing small-scale irrigation also demonstrate marked improvements in resilience relative to their counterparts. This suggests that small-scale irrigation substantially bolsters households' capacity to cope with climate variability, maintain consistent crop production, and reduce vulnerability to drought and erratic rainfall. These findings are consistent with those of prior studies by (Makate, 2017; Radeny et al., 2018). The findings suggest that CSA adoption supports Sustainable Development Goal 13 by strengthening household resilience to climate change.

In addition, adopters of households that adopt agrochemicals had a 4% (0.4) increase in the resilience capacity index, whereas nonusers registered a 64% decrease (-0.64). This difference is also highly significant at the 1% level. The findings suggest that, on average, households adopting CSA practices exhibit greater resilience capacity than their counterfactual scenario do had they not adopted these practices. Likewise, nonadopters could achieve greater resilience if they adopted CSA practices. Therefore, CSA adoption has a positive and statistically significant effect on enhancing the resilience of rural farming households in the study area.

> *The focus group and key informant participants highlighted role of adopting improved farming practices, one respondent said. "We found that farmers who adopt a wider range of practices tend to get higher crop yields and more diverse food on their tables, which strengthens their ability to cope with shocks." "Small-scale irrigation, composting, chemical fertilizers, and improved seed varieties were repeatedly mentioned as particularly important for boosting production," another participant added. "This mix of practices not only improves household diets but also generates income through surplus sales, and that economic benefit is a key part of increasing resilience." Implies, participants in the group discussions and key informants agreed that agricultural*

practices play a critical role in building resilience to climate change. The group's insights were consistent with literature, including findings by Kassie and Alemu (2021).

Table 4.11: Average treatment effect of CSA practice adoption on the resilience of households

CSA practices	Resilience capacity					
	Adopters (actual)	If they would not adopt	ATT	None-adopters (actual)	If they would adopt	ATU
Chemical fertilizer	0.51	0.02	0.49***	0.14	0.47	-0.32***
Improved crop variety	0.54	0.11	0.42***	0.24	0.91	-0.67***
Small scale irrigation	0.57	0.35	0.21***	0.22	0.97	-0.75***
Agrochemical	0.44	0.04	0.4***	0.29	0.93	-0.64***
Compost	0.49	0.5	-0.01	0.29	-0.28	-0.57***

Note: ***indicates significant variables at1%. Abbreviations: ATT, average treatment effect on the treated; ATU, average treatment effect on the untreated.

Table 4.12 presents the impact of CSA adoption intensity on the resilience capacity of rural households. As a result, the ATT revealed that adopting two CSA practices had a notable effect on the climate resilience capacity of actual adopters, with statistical significance at $p < 0.1$. On average, households that partially adopted CSA practices experienced a 7.4% increase in their resilience index. This finding implies that households that implemented two CSA practices together experienced a positive increase in their resilience. Furthermore, the positive sign of THE indicates that the impact of partial adoption is more pronounced among adopters than among nonadopters. Thus, this suggests that partial adopters are more beneficial than remaining nonadopters.

Similarly, the adoption of three to four CSA practices had a statistically significant effect on the resilience capacity of actual adopters ($p < 0.01$). On average, households that adopted multiple CSA practices experienced a 12% increase in their resilience index. These findings demonstrate that engaging with several CSA practices can lead to meaningful improvements in household resilience. In contrast, their counterparts (nonadopters) might have decreased their resilience index by 17 compared to if they had adopted multiple CSA practices. On the other hand, households that did not adopt multiple CSA practices would have experienced a significant positive increase in resilience if they had adopted multiple CSA practices. This implies that if households do adopt (but do not) possess greater potential for climate resilience than do those who actually do not, this finding highlights the potential benefits that nonadopters missed by not adopting these practices. Households that adopted five or more climate-smart agriculture (CSA) practices had a statistically significant improvement in their resilience capacity ($p < 0.01$). On average, full adopters indicated a 17% increase in their resilience index, indicating that those who fully adopted CSA practices benefited from a substantial and positive boost in resilience.

These findings underscore that combining multiple CSA practices enhances household resilience more effectively than does applying individual practices in isolation. This could be because using combined practices has a positive effect on improving soil nutrient use, soil moisture retention, fertility, and the adaptation of crops to moisture, pest and disease stress. These findings align with those of previous studies conducted in Ethiopia by (Ali et al., 2023b; Teklu et al., 2023), in India by (Samuel et al., 2024), in Zambia by (Khonje et al., 2018), and in sub-Saharan Africa by (Okoronkwo et al., 2024), which reported that the adoption of agricultural technologies in combination has improved resilience.

Furthermore, this finding is supported by key informants, who stated that merely adopting agricultural practices does not guarantee household resilience. They reported that nonadopting households have experienced poor economic conditions, relatively small farm sizes, and limited livestock, all of which influence their capacity for resilience. Moreover, the positive sign of THE indicated that the adoption of full CSA practices has a more pronounced effect for full adopters than for nonadopters. This substantial positive effect suggests that promoting full adoption among households significantly enhances resilience for those who are full adopters.

Table 4.12: Average treatment effect of adoption intensity of CSA on household resilience

CSA adoption intensity	**Households**	**Adoption decision: to adopt**	**Adoption decision: not to adopt**	**Treatment effect**
Single adoption	Adopter	0.27	0.25	ATT= 0.026
	None-adopters	0.05	0.11	ATU= -0.05
	BHE	0.22***	0.15 ***	THE=0.029
Partial adoption	Adopter	0.38	0.31	ATT=.074*
	None-adopters	0.1	0.04	ATU= 0.05
	BHE	0.28	0.27	THE=0.024
Multiple adoption	Adopter	0.64	0.51	ATT= 0.12***
	None-adopters	0.27	0.11	ATU=.- 0.17 ***
	BHE	0.36***	0.41 ***	THE=0.29
Full adoption	Adopter	0.73	0.55	ATT= 0.17*
	None-adopters	-0.39	0.11	ATU= -0.5 ***

BHE	1.1***	0.44***	THE=0.67

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Source: Author household survey (2024)

4.5 Impact of CSA Adoption and Food Security

4.5.1 Household Food Security Status

Table 4.13 illustrates a statistically significant variation in the percentage distribution of adopter categories across different levels of food security status, with a p value less than 0.01. Notably, 21% of the surveyed households were classified as food secure, as they achieved an acceptable level of food consumption. This implies that one-fifth of households consumed a variety of foods and achieved nutritional diversity. This classification indicates that a minority of households in the sample have adequate access to food, suggesting potential issues with food diversity. It is suggested that there are challenges in food security: fluctuating prices hinder access to nutritious food, whereas droughts and floods affect production. Poor soil and inadequate agricultural practices lead to low yields, and limited income opportunities restrict food purchases. Furthermore, among the food-secure households, 9% were classified as full adopters, 7.6% as multiple adopters, and 3% as partial adopters. This implies that fully adopting practices may have a greater impact on enhancing food security than partial or multiple adoptions do.

In contrast, more than two-thirds of the households had borderline FCS, which reflects that they were food insecure. Among these households, 27.3%, 16.6%, and 15.7% were classified as nonadopters, single adopters, and partial adopters, respectively. Furthermore, nearly 13% of the respondents had acceptable FCS, which signals a serious problem with food insecurity. This implies that a small proportion of households were food secure, while the majority were on the borderline of food insecurity. These findings align with previous research carried out by (Teklu et al., 2024). Similarly, the findings are in agreement with studies conducted in South Africa by Abegunde et al. (2022) and in Bangladesh by Hasan et al. (2018), both of which reported that close to 50% of households faced moderate levels of food insecurity.

As outlined in the methodology, food security was evaluated through four household status levels and four key dimensions. Approximately 10% of the respondents had multidimensional food security, among which 5.3% were full adopters and 3% were multiple adopters. In contrast, 60.3% were classified as mildly food insecure, and 6% faced severe food insecurity. This implies a precarious food security condition in the area. These findings correspond with earlier research by Gidelew et al. (2025), who reported that 67% of agricultural communities were mildly food insecure, and by Kassie et al. (2024), who reported a similar trend, affecting 43% of agricultural communities.

Table 4.13: Distribution of adopters by percentage of food security status

Adopter groups	Food consumption score				MDFS				
	Acceptable	Borderline	Poor	chi2	Food security	Mildly FI	Moderately FI	Severely FI	chi2
None adopter	0.56	27.32	2.25	175***	0.28	22.82	2.82	4.23	183 ***
Single adopter	1.13	16.62	3.38		0.56	18.03	1.13	1.41	
partial adopter	3.1	15.77	4.51		1.13	14.37	7.61	0.28	
Multiple adopter	7.61	5.07	2.54		3.1	3.66	8.17	0.28	
Full adopter	9.01	1.13	0		5.35	1.41	3.38	0	
Total	21.41	65.92	12.68		10.42	60.28	23.1011	6.2	

Significance level of the test of association: *** P< 0.01; Note: FI=food insecure

As described in the methods of analysis, the quantity dimension was assessed via 11 MDFS items, with possible scores for each respondent ranging from 11-44. In terms of food quantity, a score closer to 44 indicates greater food insecurity, whereas a score near 11 reflects better food security. As indicated in Figure 4.4, the average scores for this dimension were 19 for nonadopters, 17 for single adopters, 16 for partial adopters, 14 for multiple adopters, and 13 for full adopters. This trend suggests that households fully adopting the recommended practices had the lowest average score, indicating the highest level of food security. Conversely, households that did not adopt any practices had the highest average score, reflecting poor food security conditions.

Similarly, full adopters had the lowest mean scores for stability (3.2) and acceptability (2.2). The results suggest that households of full adopters have the lowest mean stability and acceptability scores, which implies that households adopting a combination of two or more practices exhibit better food acceptability and stability. The range of the stability score is 3-12, where a score closer to 3 reflects stronger food stability, whereas higher scores suggest greater insecurity. Similarly, accessibility scores range from 2 to 8, with values closer to 2 indicating better food acceptability, whereas higher scores reflect lower levels of acceptability. Overall, households that fully adopted climate-smart agricultural (CSA) practices recorded the lowest average scores in terms of quantity, stability, and acceptability, indicating greater food security across these dimensions.

Households that fully adopted climate-smart agricultural practices attained an FCS of 51, whereas nonadopters recorded a significantly lower score of 28. Similarly, full adopters had the highest mean score quality (21) (Figure 4.4). As noted earlier, a higher FCS score and quality dimension indicate a better food security status. Hence, the study revealed that full adopters had greater dietary diversity than did the other adopter groups.

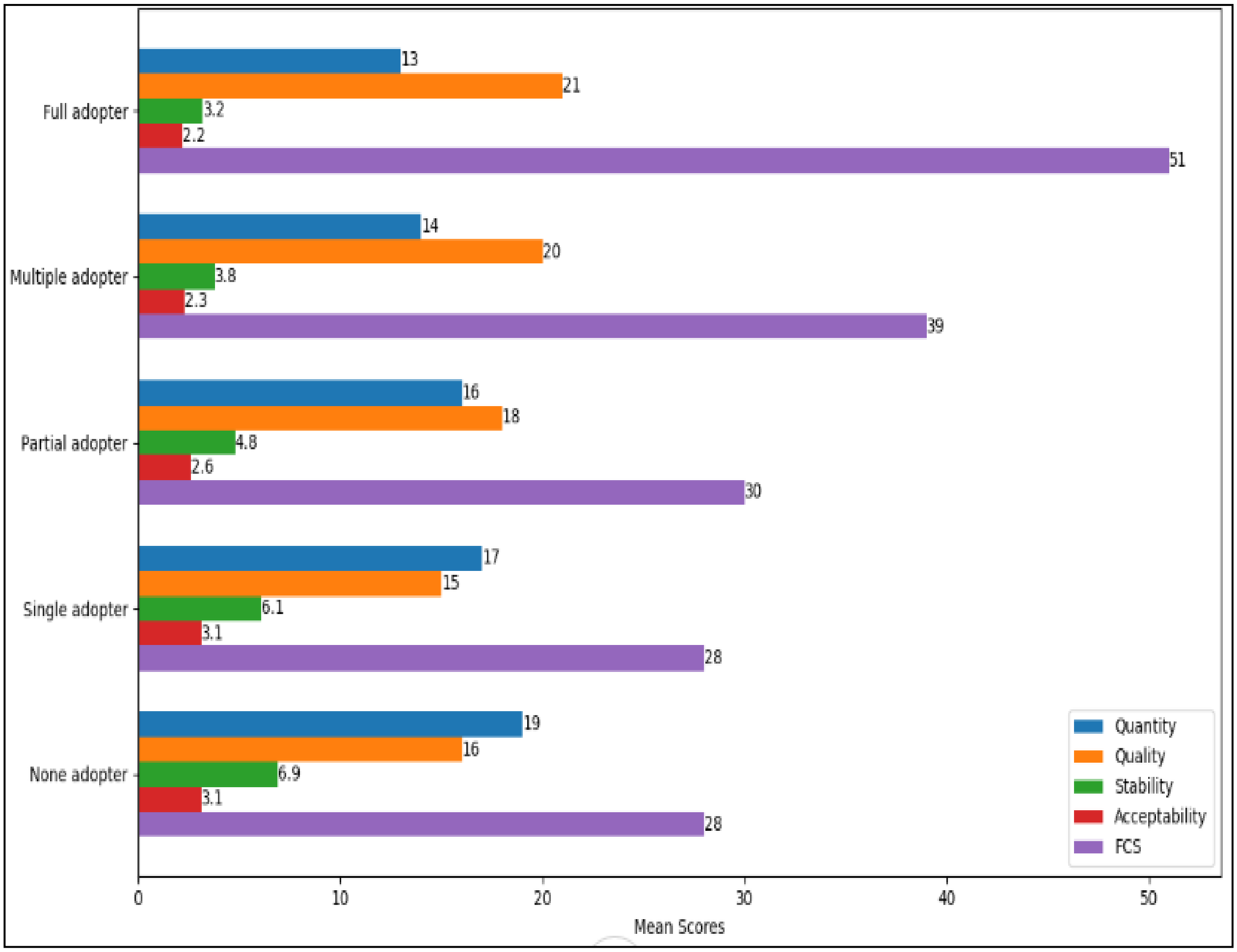

Figure 4.4: Mean food security score over adoption intensity

Note**:** Except for the quality and food consumption core, lower scores in the other dimensions indicate better food security**.**

Furthermore, this study highlights the mean difference in the dimensional food security score and FCS across adopter groups, i.e., measuring how much each group deviates from its respective group mean. To do this, multiple comparisons were conducted to test the mean differences in the dimensional food security score and FCS within each adopter group.

Table 4.14 displays the specific group means that differ significantly from one another, indicating a statistically significant mean difference at less than the 1% probability level. Specifically, compared with the nonadopters, the mean quantity score of the full adopter is less than 5.7. This finding indicates that the quantity score for full adopters was 5.7 points lower than that of nonadopters, with the difference being statistically significant ($P < 0.01$). Similarly, multiple adopters have a mean quantity score that is 4.9 points lower, and partial adopters have a score that is 3.2 points lower than that of nonadopters. This implies that full, multiple, and partial adopters result in better quantity scores than nonadopters do, indicating that these groups are likely to experience greater food security. This suggests that households that implement two or more CSA practices tend to experience higher levels of food security than those that have not adopted these practices.

Compared with nonadopters, single adopters, partial adopters, and multiple adopters, full adopters had a statistically lower mean stability score, with a p value of 0.01. The differences in the mean stability scores were -3.6, -2.8, -1.6, and -0.5, respectively. Similarly, multiple adopters had lower mean stability scores of -3.1, -2.3, and -1.1 than nonadopters, single adopters, and partial adopters did. These findings suggest that rural households with full, multiple, and partial adoption have greater stability than those who do not adopt any practices.

The quality of full adopters scored, on average, 4.9 points higher than that of households that did not adopt the practices, indicating that the mean quality of full adopters is 4.9 times higher than that of nonadopters, with the difference being statistically significant ($P<0.01$). In a similar pattern, households that fully adopted the practices presented a significantly greater average CS than nonadopters, single adopters, partial adopters, and multiple adopters did, with differences of 23.6, 23.2, 21.6, and 12.8, respectively. This suggests that households that implement two or more CSA practices tend to experience higher levels of food security than those that have not adopted these practices.

Table 4.14: Multiple comparisons of marginal linear prediction of food security dimension

	Food security dimension				FCS
	Quantity	Quality	Stability	Acceptability	
Adopter group	Contrast	Contrast	Contrast	Contrast	Contrast
Full adopter vs. Single adopter	-4.3***	5.1***	-2.8***	-0.8***	23.2***
Full adopter vs. partial adopter	-2.4***	2.9***	-1.6***	-0.4**	21.6***
Full adopter vs. Multiple	-0.8***	0.7	-0.5***	-0.1	12.8***

Multiple adopter vs. None	-4.9***	4.2***	-3.1***	-0.8***	10.8***
Multiple adopter vs. Single	-3.5***	4.3***	-2.3***	-0.7***	10.4***
Multiple adopter vs. partial	-1.6***	2.2***	-1.1***	-0.3	8.8***
partial adopter vs. None adopter	-3.2***	2***	-2***	-0.5***	2
partial adopter vs. Single	-1.8***	2.2***	-1.2***	-0.4***	1.6
Single adopter vs. None adopter	-1.4***	-0.1	-0.7	-0.05	0.3

** and *** represent p values less than 0.05 and 0.01, respectively.

4.5.2 Impact of Intensity of CSA Adoption on Food Security

To ensure the robustness of the instrumental variable, a falsification test was conducted under the assumption that it does not influence the outcome variable. In this case, market distance was selected as the instrument, and the test yielded a p value below 0.05, confirming its validity and indicating that it does not directly affect food security. This validation supports the good fit of the multinomial endogenous switching regression (MDSR) model, which was subsequently applied to examine various dimensions of food security via their respective scores and includes the food consumption score (FCS) as an additional outcome. Table 4.15 presents the estimated average treatment effects (ATEs) for both the treated (ATT) and untreated (ATU) groups, which are derived by contrasting actual outcomes with their counterfactual scenarios. A detailed analysis is provided below.

As indicated in 4.15, multiple adopters had 4.7 greater values of FCS than their counterfactual, which implies that multiple adopters increased their FCS by 12%. This would imply that adopting a combination of three to four practices (multiple adoptions) increased households' FCS. This suggests that households that actually adopt three to four practices have greater food security than their counterfactuals do. This suggests that households that adopted three to four practices experienced better food security. Similarly, on average, full adopters had 18 greater values in the FCS than their counterfactual, and this difference is statistically significant at P < 0.01. Implies full adoption practices increase the household FCS by 34%. Overall, the results of the estimated ATT indicate that the adoption of multiple or all recommended practices significantly enhanced household food security. This finding is consistent with that of (Wekesa et al., 2018). This finding aligns with earlier evidence from southern Ghana, where (Issahaku & Abdulai, 2020) reported that adopting climate adaptation practices led to a 15.2% increase in farmers' food security.

Quantity: This dimension focuses on evaluating the presence of food within households without considering its nutritional content. As indicated in Table 4.15, the ATT of multiple adoptions is statistically significant for the quantity score of the actual adopter ($p < 0.05$). On average, multiple adopters had 1.01 lower values of quantity scores than their counterfactual, which implies that multiple adopters decreased their quantity score by 7.3%. This would imply that implementing a mix of three to four practices can lead to improved food security for rural households. According to ATU, nonadopters had 2.43 (12.9%) higher values for the quantity score, indicating that nonadopters had greater quantity scores than their counterfactual did (if no adopters were adopted multiple times). Moreover, on average, households that fully adopted the practices experienced a 1.3-point (10%) reduction in quantity scores, with $P < 0.01$.

The findings suggest that households engaging in multiple or full adoptions of practices demonstrate greater food availability. This is because lower scores in this dimension correspond to better access to sufficient food. This result is expected, given that CSA practices are known to increase productivity, thereby contributing to a sufficient food supply within households. Legesse et al. (2024), reported that, on average, households adopting CSA practices had a 69.7% greater likelihood of being food secure. These findings are consistent with those of the study by Magrini and Vigani (2016a), which revealed that adopting agricultural practices contributed to increased production and improved food availability among farmers. Similarly, Katungi et al. (2024) reported that the use of crop varieties and fertilizers led to higher household income, which in turn supported better access to food or food availability.

Quality: Quality measures the diversity of foods consumed within a household, which plays a crucial role in determining the household's nutritional intake. According to the ATT, partial adopters presented quality scores that were 1.7 times greater than their counterfactual scores, which is $p < 0.01$. This suggests that adopting a combination of two practices (partial adoption) increased households' quality score by 9.7%. Similarly, on average, households that adopted multiple and full CSA practices had 3.35 and 2.75 greater values of quality scores, respectively. These results imply that these households increased their quality scores by 16.9% and 13.2%, respectively (Table 4.15).

The study revealed that households engaging in partial, multiple, or full adoption of CSA practices achieved greater nutritional intake than those who did not adopt any. This finding indicates that households implementing two or more climate-smart agricultural practices tended to achieve better food security outcomes. The results of this study align with the findings of (Ali et al., 2022). Similar patterns were observed in studies conducted across various countries: Ahmed et al. (2023a) in Ethiopia, Issahaku and Issahaku and Abdulai (2020) in Ghana, Abegunde et al. (2019) in South Africa, and Haq et al. (2021) in Pakistan. These studies consistently showed that rural households adopting a greater number of CSA practices tended to consume more diverse foods than did those with fewer practices in place. Researchers argue that climate-smart agricultural practices enhance farm productivity and increase income, thereby enabling households to access and consume a more diverse range of foods.

> *The group discussion participants emphasized that agricultural practices play a critical role in shaping farmers' dietary diversity, noting that those who adopt a broader range of practices tend to achieve higher crop yields and more varied food consumption; in particular, they said that "small-scale irrigation, composting, chemical fertilizer, and improved seed varieties are key contributors to agricultural output, and that this diversification not only enhances household diets but also generates economic benefits through the sale of surplus produce." The group's insights were consistent with the literature, including findings by* Kassie and Alemu (2021)*, which demonstrated that irrigation practices significantly improve food security among farming households.*

Acceptability: Acceptability reflects the degree to which food options align with individual preferences. This highlights the importance of ensuring that people have access to and can consume foods that suit their personal tastes, cultural traditions, and diet. The ATT estimation revealed that single adopters had 0.19 (6%) lower values of acceptability scores than their counterfactual, which was statistically significant at $p<0.05$ (Table 4.15). Similarly, full adopters had 0.30 (13.8%) lower acceptability scores. This suggests that full adopters had lower acceptability scores, indicating that they experienced higher levels of food security than their counterfactual counterparts did. It is argued that agricultural output is enhanced by CSA practices, thereby strengthening an individual's capacity to access and enjoy foods that align with their personal choices. Simply put, individuals who adopt farming practices are likely to have greater flexibility in choosing the foods they consume. Hussein (2024) and Abonesh et al. (2021b) argued that adopting CSA practices enhances farmer productivity and income. This finding is in line with earlier research by Teklu et al. (2022), who reported that farmers who adopt improved agricultural practices tend to achieve better food security outcomes than those who do not.

Stability: Stability refers to consistent and reliable access to sufficient food without the threat of shortages or uncertainty at any point in time. The ATT estimation revealed that partial adopters had 0.63 (13%) lower values of stability scores than their counterfactual, with the difference being statistically significant at $p < 0.05$ (Table 4.15). This implies that partial adoption decreased the stability score by 13%. This implies that households with partial adoption experienced higher levels of food stability than their nonadopting counterparts did. Because implementing CSA practices can increase agricultural productivity, households maintain a more consistent food supply throughout the year than do those not using such practices.

The MESR model results indicate that all levels of CSA adoption with the exception of single adoption significantly influence the MDFS as well as the FCS. The positive effect of full-package CSA adoption on dietary quality and food quantity is likely driven by higher staple crop yields from improved inputs and increased income from high-value irrigated cash crops. These gains enhance both household food availability and purchasing power, enabling access to more diverse and nutritious diets.

> *According to key informants' interviews, CSA practices play a vital role in enhancing food security. One respondent said that "CSA practices can enhance food security by increasing agricultural productivity." Other key informants said that "Improved seed varieties, soil conservation, and water-efficient farming enable us to raise yields and boost household income," another informant added. "Households that adopt combination of practices experience better diets because higher, more stable production improves access to diverse and nutritious food." Most key informants concluded "the greater the extent of adoption, the better the improvements in food availability and nutritional quality." Implies it is clear that CSA adoption has significantly improved food security in the study area.*

Table 4.15: Impact of the extent of CSA practices adopted on food security estimated via the MESR

Extent of CSA adaptation	FCS		**Four food security dimensions**							
			Quantity		Quality		Stability		Acceptability	
	ATT	ATU	ATT	ATU	ATT	ATU	ATT	ATU	ATT	ATU
Single	-0.28	0.6	-0.6	0.9^{***}	0.3	-0.2	0.043	0	-0.19^{**}	0.18^{***}

adoption	(0.9)	(2.6)	(3.4)	(4.8)	(1.6)	(0.9)	(0.6)		(6)	(6)
Partial adoption	-0.31 (1.0)	-1.9*** (6.8)	-0.5 (3.1)	0.9*** (4.8)	1.74*** (9.7)	-0.6*** (3.9)	-0.6*** (13)	0.86*** (12.7)	0.055 (2.1)	0.066 (1.9)
Multiple adoption	4.7*** (12.3)	-5.4*** (19.4)	-1.01** (7.3)	2.43*** (12.9)	3.35*** (16.9)	0.55** (3.5)	0.06 (1.6)	2.04*** (29.8)	0.3** (11.9)	0.06 (3.55)
Full adoption	18.1*** (34.7)	-0.8 (2.8)	-1.3*** (10)	0.9*** (4.8)	2.75*** (13.2)	-0.1 (0.6)	0.7** (21.8)	0	- 0.3** (13.8)	0.18*** (6)

The numbers in brackets are %; ** and *** represent statistical significance at the 5% and 10% levels, respectively.

4.6 Synergies and Trade-offs of CSA Practices

In this study, the performance of practices with values ≤ 0.33, representing low weights, was considered to induce trade-offs. In contrast, synergies were associated with medium to high weights (≥ 0.34). Moreover, strong synergies were observed in practices with weights ≥ 0.67. This ranking allows prioritization of the most effective practices perceived by farmers, guiding evidence-based decisions for enhancing productivity and resilience. The performance values of the 18 CSA practices are presented in Appendix B. As outlined in the methodology section, the five practices were selected for further analysis to focus on those with the greatest overall adoption. It is important to understand how these practices influence food security and resilience, thereby guiding sustainable farming by maximizing benefits and minimizing negative impacts.

As indicated in Figure 4.5, the study revealed that agrochemicals (pesticides and herbicides) provide a medium-level synergy for food security (0.38) by protecting plants and ensuring short-term productivity. However, they create a trade-off by reducing long-term resilience (0.19). This implies that agrochemicals act as an artificial buffer that stabilizes yields today (food security). However, they degrade the ecosystem's natural buffering capacity soil health, biodiversity, and pest resistance leaving the system highly vulnerable to future shocks (reduced resilience). As natural resilience drops, farmers become more dependent on agrochemicals to maintain the same yield, digging a deeper ecological deficit. It is consistence with (Ogola & Ouko, 2021). Therefore, policies heavily subsidize the purchase of chemical inputs. Instead, governments should pivot these subsidies toward "ecosystem services." For example, they could subsidize farmers for adopting integrated pest management (IPM), practicing hand weeding, and planting cover crops to minimize chemical runoff.

As presented in Figures 4.5 and 4.6, small-scale irrigation had high synergistic effects (0.99) on both food security and resilience to climate change. This indicates that it has emerged as the most effective CSA practice, achieving the highest performance value. This suggests that it plays a crucial role in reducing farmers' vulnerability to rainfall variability, stabilizing crop yields, and strengthening adaptive capacity against climate shocks. Moreover, smallholder farmers benefit from irrigation, as it supplements rainfall and moistens the soil during dry periods, helping to stabilize crop production. This result is in agreement with the findings of Tilahun et al. (2023b) and Ogola & Ouko (2021), who reported that irrigation had synergistic effects on productivity and adaptation. Furthermore, this finding is supported by Mango et al. (2018) and Hussein (2024), who confirmed that irrigation is one of the most effective CSA practices, as it increases household income while maximizing productivity and thereby enhancing food security.

As presented in Figure 4.5, the performance value of chemical fertilizer and compost, approximately 0.71, indicates a strong synergistic effect on improving food security, suggesting that chemical fertilizer and compost enhance crop productivity more effectively. This result aligns with those of studies conducted by Mahmud et al. (2021), Geffersa (2024), and Hussein (2024), which reported that the efficient use of chemical fertilizers has a strong synergistic effect on productivity. This finding is also in agreement with the work conducted in Kenya by Ogola and Ouko (2021), who reported that the efficient use of chemical fertilizers was highly synergistic with the productivity and adaptation pillar. As indicated Figure 4.5, the resilience values for chemical fertilizer and compost were 0.37 and 0.72, respectively indicating that compost contributes more to resilience than chemical fertilizer does. These findings imply that compost contributes more strongly to building resilience by improving soil health and sustainability, whereas chemical fertilizers provide relatively lower synergy, reflecting their limited role in long-term climate adaptation. This is consistent with (Mahmud et al., 2021; Tilahun et al., 2023b). Furthermore, studies by Beeby et al. (2020) and Rojas-Downing et al. (2017) highlighted that compost, including manure and compost, significantly improve soil fertility, increase crop productivity, and increase food security.

The results indicate that the average performance values of improved crop varieties were 0.58 for food security and 0.65 for resilience (Figures 4.5 and 4.6). These findings suggest that improved crop varieties contribute moderately to enhancing food security while having a relatively stronger effect on building resilience to climate change. The higher value for resilience implies that these varieties, particularly those that are drought tolerant or pest resistant, play an important role in helping farmers cope with climate variability. These results are consistent with those of previous studies (Ahmed, 2022; Geffersa, 2024; Hussein, 2024). Similarly, Geffersa (2024). Furthermore, the results are in agreement with work in Bangladesh by Rahman and Connor (2022), in Tanzania by Jha et al. (2020), and in Kenya by Ogola and Ouko (2021), who reported that improved crop varieties play a key role in enhancing agricultural productivity and food security.

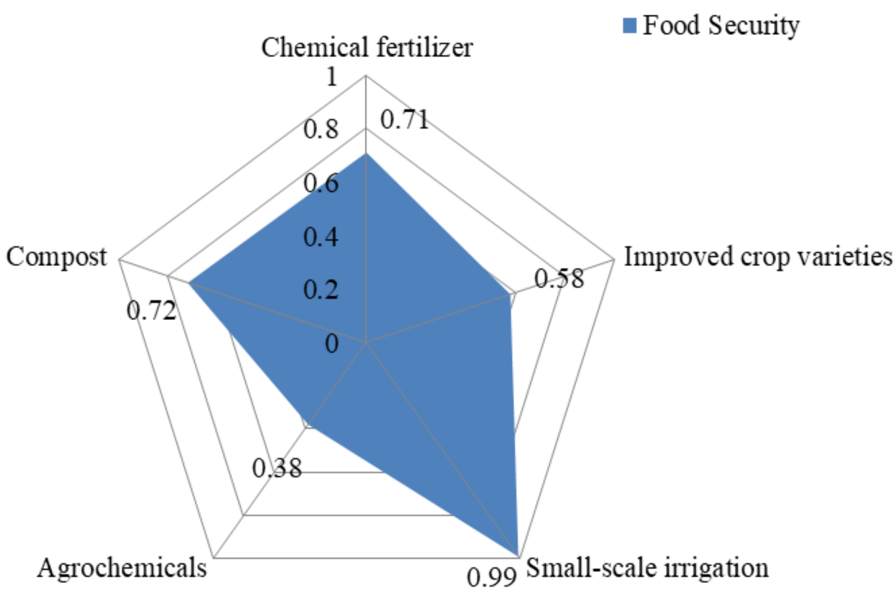

Figure 4.5: Performance of the CSA practices on food security

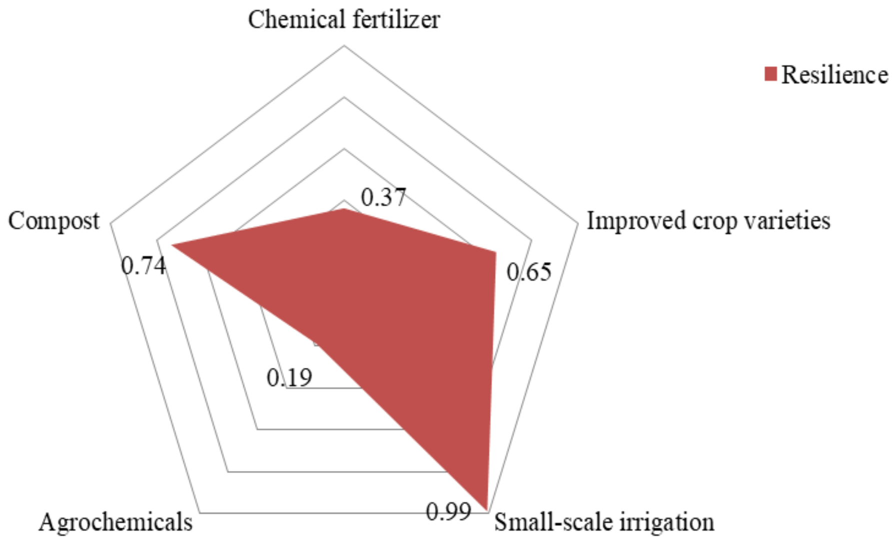

Figure 4.6: Performance of the CSA practices on resilience

During the focus group discussions, the discussants were invited to describe the synergies and trade-offs of the top 5 CSA practices, which were subsequently compared with those reported in the literature (Table 4.16). The discussion revealed that these practices involve both synergies and trade-offs across productivity and food security, resilience, and mitigation.

As presented in Table 4.16, discussants noted that "the application of chemical fertilizer may improve productivity; however, the continuous and excessive use of chemical fertilizers has been found to cause soil toxicity." These findings suggest that the application of chemical fertilizer may cause deficiencies in both major and minor nutrients, leading to the deterioration of soil quality and increased environmental emissions. These findings are consistent with those of previous studies (Abera et al., 2018; Verhagen et al., 2014). Similarly, research conducted in Kenya by Ogola and Ouko (2021) reported that the efficient use of chemical fertilizers can generate strong synergies for both productivity and climate adaptation.

Key informant participants highlighted the role of adopting improved crop varieties. One respondent stated that "improved crop varieties contributed to increased productivity, food security, and resilience and that they were resistant to pests and diseases while producing higher yields. In contrast, improved crop varieties often lead to increased use of agrochemicals, which in turn increases greenhouse gas (GHG) emissions from chemical inputs." This observation is consistent with (Geffersa, 2024) and is further supported by Okello et al. (2016) and Wainaina et al. (2014), who argue that adopting improved crop varieties tends to increase the use of pesticides, herbicides, and chemical fertilizers, creating trade-offs rather than synergies in the mitigation pillar.

The focus group participants and key informant participants emphasized that agricultural practices play a critical role in shaping farmers' dietary diversity, noting that those who adopt a broader range of practices tend to achieve higher crop yields and more varied food consumption; in particular, they stated that “small-scale irrigation, composting, chemical fertilizer, and improved seed varieties are key contributors to agricultural output and that this diversification not only enhances household diets but also generates economic benefits through the sale of surplus produce." The group’s insights were consistent with the literature, including findings by Kassie and Alemu (2021), which demonstrated that irrigation practices significantly improve food security among farming households.

Moreover, discussants noted that “small-scale irrigation enables the production of up to three crop cycles per year, provides higher yields, and increases household income, while simultaneously improving food security and strengthening resilience. This finding is in line with Antwi et al. (2023), who reported that the adoption of appropriate irrigation systems was economically profitable (Lankoski et al., 2018). Similarly, Verhagen et al. (2014) reported that irrigation as a response to drought creates synergies for crop production by increasing yields. In contrast, discussants stated that “small-scale irrigation can have negative effects, primarily owing to the increased energy (fuel) consumption required for operation, which adversely affects the mitigation pillar.” These observations align with those of Antwi et al. (2023), who reported that fuel-powered irrigation contributes to higher greenhouse gas emissions and stimulates the release of nitrous oxide from soils.

Table 4.16: Synergies and trade-offs of CSA practices from FGD and KII

CSA practice	Synergies	Trade-offs	Literature support
Chemical fertilizer	− Enhanced nutrient availability − Increase crop productivity − Increase farmer income − Strengthen food security	− Decrease soil quality − Water pollution − Greenhouse gas emissions: nitrogen fertilizers release nitrous oxide − High input costs: purchase	(Abera et al., 2018; Geffersa, 2024; Ogola & Ouko, 2021; Verhagen et al., 2014)

		and transport increase farmers' expenses	
Improved crop varieties	− Increase productivity − Enhanced resilience: tolerate drought, pests, and diseases. − Improves income − Enhances households food − Increases the availability of biomass for livestock feed and mulching	− Higher input demand − Increases farmers' financial burden and production costs − Increases the use of agrochemicals − Increases greenhouse gas emission from chemical inputs	(FAO, 2016; Geffersa, 2024; Ogola & Ouko, 2021; Warra & Prasad, 2020)
Small-scale irrigation	− Achieve three rounds of crop output per year − high yields and reduced production variability − Increasing income, while also building resilience − Enhance food security	− Raises GHG emissions when fuel-powered − Adds extra financial costs to farmers − Cause soil salinization	(Antwi et al., 2023; Lankoski et al., 2018; Tilahun et al., 2023b; Verhagen et al., 2014)
Agrochemicals/pesticides and herbicides	− Increase crop yields: protect plants from pests and weeds. − Reduce labor demand − Boost farmer income − Enhance food security: ensure stable production and supply	− Environmental pollution and health risks − Loss of biodiversity: non-target species, including pollinators, may be affected − High costs: purchase and repeated application increase farmers' expenses − Soil degradation: long-term use can reduce soil health and fertility	(Abera et al., 2018; Ethiopia Report, 2022; Ogola & Ouko, 2021)
Compost	− Increase soil fertility: supply diverse nutrients gradually − Enhance crop resilience: strengthen tolerance to disease − Increase income and food security	− Higher labor demand − Potential weed seeds/pathogens: if not well-processed − Limited scalability: difficult to meet nutrient needs for large-scale farming − Health risks to farmers if mismanaged	(Hussein, 2024; Mango et al., 2018; Tilahun et al., 2023b)

Source: FGD and KII (2024)

CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The study found that CSA adoption in Gubalafto Woreda is mainly focused on chemical inputs and crop diversification rather than conservation-based practices. Farmers tend to prioritize short-term productivity gains over long-term ecological sustainability. Adoption of low-cost and nature-based practices, such as crop residue management, natural regeneration, and early-maturing crops, remains very low, indicating significant barriers to sustainable adaptation strategies. Overall, CSA adoption in the study area is limited, leaving many households unable to fully benefit from effective CSA practices.

Households in the study area demonstrate a relatively somewhat moderate capacity to anticipate and prepare for climate-related shocks before they occur. However, their ability to withstand and recover from shocks during and after climate-related events remains limited, making many rural households in Gubalafto Woreda highly vulnerable. The findings further indicate that low adoption of CSA practices is associated with weaker household resilience, highlighting the importance of promoting wider CSA adoption to strengthen adaptive capacity and long-term resilience.

The study reveals significant agroecological differences in household resilience across Gubalafto Woreda. The findings demonstrate that resilience is context-specific and strongly influenced by geographic conditions and access to livelihood resources. As a result, households in different agroecological zones experience varying levels of vulnerability, adaptive capacity, and resilience, highlighting the need for location-specific interventions and policies.

Furthermore, the findings point to a serious food security challenge in the study area, suggesting that food insecurity is a widespread and systemic issue rather than an isolated household problem. Therefore, improving resilience and food security requires integrated strategies that enhance access to resources, strengthen adaptive capacity, and address the specific needs of households across different agroecological settings.

The study demonstrates that the benefits of CSA depend not only on the adoption of practices but also on the intensity and diversity of adoption. Households that adopt a broader and more integrated combination of CSA practices exhibit greater resilience and improved food security outcomes. However, the findings also reveal that CSA practices do not contribute equally to all CSA objectives. While some practices generate synergies by simultaneously enhancing productivity, resilience, and food security, others may involve trade-offs, improving one dimension at the expense of another. These results highlight the importance of promoting context-specific and integrated CSA packages that maximize synergies, minimize trade-offs, and support sustainable agricultural development and climate resilience.

5.2 Recommendations

In line with the result of this study and the conclusions drawn, recommendations were made towards increasing the use of CSA in the Gubalafto Woreda in order to boost agricultural productivity, strengthen household resilience against climate shocks, and secure long-term food stability for both the study area and other similar contexts.

- A large proportion of households in Gubalafto Woreda remain highly vulnerable to climate shocks due to limited access to effective CSA practices and weak resilience capacities. Expanding low-cost, nature-based CSA solutions, alongside investments in rural infrastructure, irrigation, market access, extension services, early warning systems, and social protection, is essential to strengthen household resilience. Priority should be given to highland and midland areas, where vulnerability is greatest and resilience levels are lowest.
- Scale up the success of small-scale irrigation to generate substantial benefits for rural livelihoods. At the same time, strengthening soil conservation measures and promoting nature-based solutions are essential for addressing the challenges faced by low-resilience households. Together, these interventions can improve adaptive capacity, reduce vulnerability to climate shocks, and support sustainable agricultural development.
- Rather than focusing solely on fertilizer use, agricultural policies should encourage balanced and integrated soil fertility management approaches, including composting, crop rotation, cover cropping, agroforestry, and integrated nutrient management. Strengthening extension services and promoting diversified CSA practices can help

farmers maintain productivity while enhancing resilience, thereby reducing the risk of resilience traps associated with excessive dependence on chemical inputs.

- Policymakers should strengthen weather-indexed insurance schemes and improve access to credit through Rural Saving and Credit Cooperatives to support the adoption of nature-based CSA practices. Extension programs should promote location-specific CSA bundles rather than individual practices. For example, in low-resilience midland areas, a package combining small-scale irrigation, compost, and improved seeds should be prioritized to maximize resilience and food security benefits.
- Food insecurity remains a major challenge in Gubalafto Woreda, requiring urgent efforts to stabilize food production and strengthen household food security. The findings demonstrate that adopting a diverse and integrated set of CSA practices significantly improves both resilience and food security. Therefore, development interventions should prioritize the promotion of comprehensive CSA packages rather than isolated practices to achieve sustainable improvements in agricultural productivity, resilience, and food security.
- The findings indicate that CSA practices can generate both synergies and trade-offs across different CSA pillar. While some practices, such as agrochemical use, may enhance short-term crop productivity and food security, they can simultaneously undermine long-term household resilience. This highlights the importance of carefully designing and promoting CSA interventions that balance productivity gains with resilience outcomes. To minimize potential trade-offs, policymakers and practitioners should support sustainable alternatives such as integrated pest management (IPM), hand weeding, and cover cropping. In addition, greater policy coordination and harmonization are needed to maximize the overall benefits of CSA while ensuring long-term agricultural sustainability and resilience.

6. Limitations of the Study

Acknowledging research limitations is essential for refining future scholarly work and ensuring the proper interpretation of results. This study may face certain methodological, data-related, and contextual constraints that may influence the external validity of its conclusions.

- Methodological constraints: the use of a three-point Likert scale and normalized scores may oversimplify the complex interactions between CSA practices, food security, and resilience. To address this, future research should employ Multi-Criteria Decision Analysis and multi-stakeholder analysis to better quantify synergies and trade-offs. This approach better captures how CSA practices interact with food security and resilience.
- Data limitations: the study is subject to inherent limitations, primarily stemming from the use of cross-sectional data, which precludes the observation of adoption dynamics over time and may introduce endogeneity bias. Additionally, the reliance on self-reported data for food security, income, and the perceived impacts of CSA introduces a degree of subjectivity and potential recall bias, which may affect the overall accuracy of the assessments. To enhance the validity and robustness of future findings, subsequent research should incorporate longitudinal datasets to capture temporal trends and triangulate farmer-reported data with agricultural extension records and multi-stakeholder analyses.
- Contextual constraints: this study was conducted within the specific context of one Woreda, which may impose contextual constraints on the broader applicability of the findings. Since agro-ecological and socio-economic conditions vary significantly across regions, the results may not be fully representative of other areas in Ethiopia. To enhance generalizability, future research should expand the geographic scope to include diverse districts, allowing for a more comprehensive understanding of CSA adoption across a wider landscape.

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Appendixes

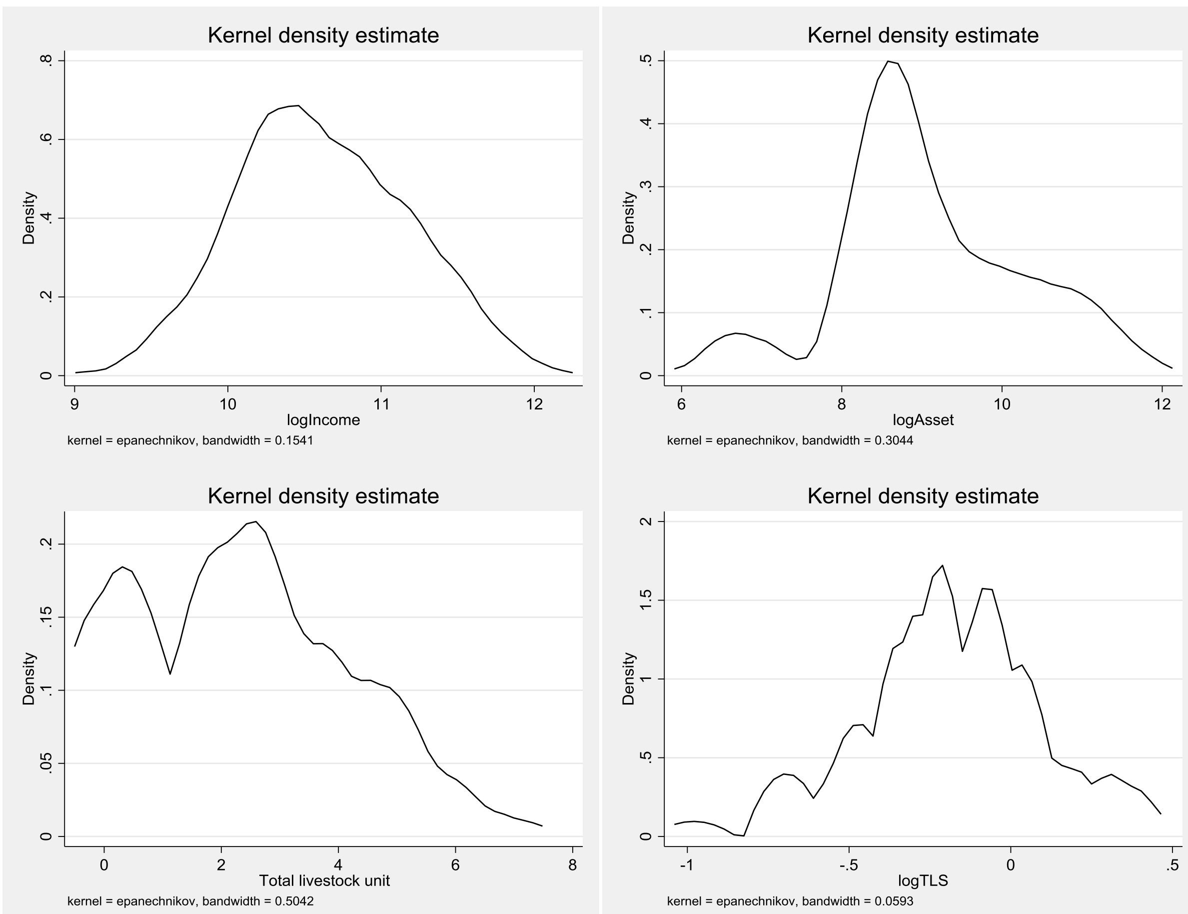
Appendix A: Prevalence and rank of CSA practices

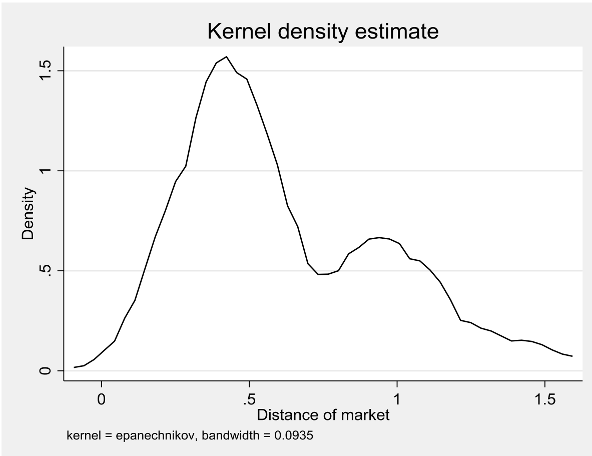
CSA practice	Frequency	Percentage (%)	Average score	Rated point	Total score	Rank
Efficient inorganic fertilizer application	178	50.14	0.501	5	890	1
Improved crop varieties	116	32.68	0.327	4	464	2
Small scale irrigation	95	26.76	0.268	3	285	3
Efficient use of agrochemicals	83	23.38	0.234	2	166	4
Compost	78	21.97	0.22	1	78	5
Row planting	65	18.31	0.183			
Reduced tillage	39	10.99	0.11			
Water harvesting In situ and pond construction	29	8.17	0.082			
Efficient water utilization	26	7.32	0.073			
Tree-based conservation agriculture	26	7.32	0.073			
Changing planting date	24	6.76	0.068			
Intercropping with legumes	20	5.63	0.056			
Seasonal/Year-round cropping	17	4.79	0.048			
Crop residue management–mulching	15	4.23	0.042			
Green manure management	15	4.23	0.042			
Farmer-managed natural regeneration	7	1.97	0.02			
Early maturity/short season crops	3	0.85	0.009			
Drought tolerance crop varieties	2	0.56	0.006			

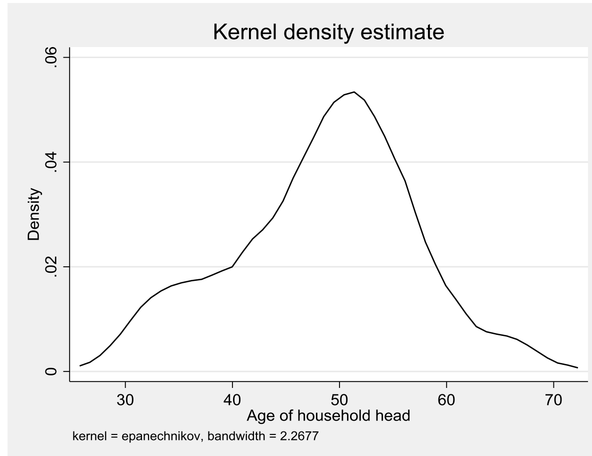
Appendix B: Calculating the MDFS score

=IF(AND(A2=1,B2=1,C2=1,D2=1,E2=1,F2=1,G2=4,H2=4,I2=1,J2=1,K2=1,L2=1,M2=1,N2<3,O2<3,P2<3,Q2<3,R2<3,S2<3,T2>1,U2>1,V2>1,W2>1,X2>1),"1",IF(OR(G2=3,H2=3,I2=2,J2=2,K2=2,L2=2,M2=2,N2=3,O2=3,P2=3,Q2=3,R2=3,S2=3,T2=1,U2=1,V2=1,W2=1,X2=1),"2",IF(OR(A2=2,B2=2,C2=2,D2=2,E2=2,F2=2,G2=2,H2=2,I2=3,J2=3,K2=3,L2=3,M2=3,N2=4,O2=4,P2=4,Q2=4,R2=4,S2=4),"3",IF(OR(A2>2,B2>2,C2>2,D2>2,E2>2,F2>2,G2=1,H2=1,I2=4,J2=4,K2=4,L2=4,M2=4),"4","5"))))

Appendix C: Normally distributed data via kernel density







Appendix D: Multicollinearity via vif

```
. vif
```

Variable	VIF	1/VIF
logIncome	2.68	0.372899
logAsset	2.25	0.444458
TLU	1.93	0.518661
logTLS	1.71	0.585179
Market_dis~e	1.20	0.832000
Age	1.08	0.926045
Mean VIF	1.81	

Appendix E: Multinomial endogenous switching regression model assumption test

```
Tests of endogeneity
H0: Variables are exogenous

Durbin (score) chi2(1)          =  24.9673  (p = 0.0000)
Wu-Hausman F(1,336)             =  25.4187  (p = 0.0000)

First-stage regression summary statistics
```

Variable	R-sq.	Adjusted R-sq.	Partial R-sq.	F(1,337)	Prob > F
CSA_from_5~e	0.6233	0.6043	0.0579	20.7124	0.0000

```
Minimum eigenvalue statistic = 20.7124

Critical Values                      # of endogenous regressors:    1
H0: Instruments are weak             # of excluded instruments:     1
. estat overid
no overidentifying restrictions
```

Appendix F: Determinants of adoption intensity of CSA practices

CSA_from_5_lable	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Non_adopter	(base outcome)					
Single_adopter						
Age	-.0920874	.0317019	-2.90	0.004	-.154222	-.0299529
Sex1_01	.031577	.5208943	0.06	0.952	-.9893572	1.052511
Eds1	-.3964736	.2720635	-1.46	0.145	-.9297082	.136761
Labor	.9972684	.3378797	2.95	0.003	.3350363	1.6595
TLU	-.3582746	.1749528	-2.05	0.041	-.7011758	-.0153733
Offarm1	-1.838916	.7037888	-2.61	0.009	-3.218317	-.4595156
Awether1	.1316655	.7703624	0.17	0.864	-1.378217	1.641548
logAsset	.3213098	.3167402	1.01	0.310	-.2994896	.9421091
logTLS	.0085271	.8899567	0.01	0.992	-1.735756	1.75281
Trianing1	1.659386	.9334942	1.78	0.075	-.1702286	3.489001
Extension	-.2882452	.5302185	-0.54	0.587	-1.327454	.750964
Soil_fertility2	.8869598	.505226	1.76	0.079	-.103265	1.877185
Fclimate1	.9408192	.6332004	1.49	0.137	-.3002307	2.181869
Credit	-1.572707	1.474605	-1.07	0.286	-4.46288	1.317466
logIncome	3.607474	.7977875	4.52	0.000	2.043839	5.171108
RUSACOm	1.837705	1.070832	1.72	0.086	-.2610877	3.936498
Market_distance	-2.181932	.6479183	-3.37	0.001	-3.451829	-.9120358
_cons	-36.1905	8.130725	-4.45	0.000	-52.12643	-20.25457
partial_adopter						
Age	-.0759422	.0342086	-2.22	0.026	-.1429898	-.0088945
Sex1_01	-.8409672	.556032	-1.51	0.130	-1.93077	.2488355
Eds1	-.2922864	.3035559	-0.96	0.336	-.887245	.3026723
Labor	.7555512	.3776349	2.00	0.045	.0154004	1.495702
TLU	-.443326	.1910174	-2.32	0.020	-.8177132	-.0689389
Offarm1	-2.676787	.8351426	-3.21	0.001	-4.313636	-1.039938
Awether1	.2957898	.8174842	0.36	0.717	-1.30645	1.898029
logAsset	.52819	.342777	1.54	0.123	-.1436406	1.200021
logTLS	.1898407	1.000591	0.19	0.850	-1.771282	2.150964
Trianing1	1.72358	.9678537	1.78	0.075	-.1733786	3.620538
Extension	-.2595884	.5695454	-0.46	0.649	-1.375877	.8567001
Soil_fertility2	1.710033	.6371018	2.68	0.007	.4613367	2.95873
Fclimate1	1.102563	.6961872	1.58	0.113	-.2619384	2.467065
Credit	-1.518036	1.516252	-1.00	0.317	-4.489835	1.453763
logIncome	4.806022	.8790698	5.47	0.000	3.083077	6.528967
RUSACOm	1.714771	1.211273	1.42	0.157	-.6592811	4.088823
Market_distance	-3.448486	.7537395	-4.58	0.000	-4.925789	-1.971184
_cons	-50.36356	8.94028	-5.63	0.000	-67.88618	-32.84093

Multiple_adopter						
Age	-.0803954	.0411027	-1.96	0.050	-.1609553	.0001644
Sex1_01	-.9286047	.8061755	-1.15	0.249	-2.50868	.6514703
Eds1	-.6531088	.3721979	-1.75	0.079	-1.382603	.0763856
Labor	.7159718	.41731	1.72	0.086	-.1019407	1.533884
TLU	-.1149667	.2133618	-0.54	0.590	-.5331481	.3032146
Offfarm1	-4.30865	1.334438	-3.23	0.001	-6.924101	-1.6932
Awether1	.9736838	.9297217	1.05	0.295	-.8485373	2.795905
logAsset	.7406961	.3915063	1.89	0.059	-.0266422	1.508034
logTLS	-1.17212	1.179344	-0.99	0.320	-3.483592	1.139352
Trianing1	2.49566	1.0285	2.43	0.015	.4798373	4.511483
Extension	-.8821171	.6870279	-1.28	0.199	-2.228667	.4644328
Soil_fertility2	1.379832	.7072368	1.95	0.051	-.006327	2.76599
Fclimate1	1.012903	.8632764	1.17	0.241	-.6790881	2.704893
Credit	-2.039211	1.592085	-1.28	0.200	-5.15964	1.081219
logIncome	7.147688	1.031575	6.93	0.000	5.125837	9.169538
RUSACOm	.8391496	1.327842	0.63	0.527	-1.763373	3.441672
Market_distance	-3.970925	.9322239	-4.26	0.000	-5.79805	-2.1438
_cons	-77.29878	10.57117	-7.31	0.000	-98.0179	-56.57966
Full_adopter						
Age	-.1759194	.1036664	-1.70	0.090	-.3791018	.0272631
Sex1_01	-4.173076	3.061394	-1.36	0.173	-10.1733	1.827147
Eds1	-1.587445	.9348585	-1.70	0.089	-3.419734	.2448441
Labor	.5700362	1.00516	0.57	0.571	-1.400042	2.540115
TLU	-.294058	.3643737	-0.81	0.420	-1.008217	.4201013
Offfarm1	-16.83524	1887.381	-0.01	0.993	-3716.033	3682.363
Awether1	1.070255	1.725728	0.62	0.535	-2.31211	4.45262
logAsset	1.619951	1.04577	1.55	0.121	-.4297195	3.669622
logTLS	-9.757883	3.931249	-2.48	0.013	-17.46299	-2.052776
Trianing1	.6497129	1.721385	0.38	0.706	-2.724139	4.023565
Extension	-1.534633	1.698636	-0.90	0.366	-4.863899	1.794633
Soil_fertility2	17.44586	1452.949	0.01	0.990	-2830.282	2865.174
Fclimate1	17.36422	755.0602	0.02	0.982	-1462.527	1497.255
Credit	2.067394	2.745394	0.75	0.451	-3.313479	7.448266
logIncome	16.24832	3.411408	4.76	0.000	9.562079	22.93455
RUSACOm	.0484458	2.402887	0.02	0.984	-4.661125	4.758017
Market_distance	-.2555811	2.491727	-0.10	0.918	-5.139277	4.628115
_cons	-215.8152	1637.95	-0.13	0.895	-3426.139	2994.508

Appendix G: Questions used in multidimensional food security indicators

No	Indicator	Name	Questions	Dimension
1	HFIAS/HHS	NOEAT	How often did you or any HH member have to go a whole day without eating?	Quantity
2	HFIAS/HHS	SLPHUN	How often did you or any HH member go to sleep at night hungry?	Stability*
3	HFIAS/HHS	NOFOOD	How often was there ever no food in your HH?	Quantity
4	CSI	SKIPEAT	How often has the HH had to skip entire days without eating?	Quantity
5	CSI	SENDBEG	How often has the HH had to send HH members to beg?	Quantity
6	CSI	SENDEAT	How often has the HH had to send HH members to eat elsewhere?	Quantity
7	FCS/HDDS	PULSES	How often has the HH eaten any pulses?	Quality/diversity
8	FCS/HDDS	GRAIN	How often has the HH eaten any food made from grain?	Quality/diversity
9	CSI	EATSEED	How often has the HH had to consume seed stock held for next season?	Quantity
10	CSI	WILD	How often has the HH had to gather wild food, hunt, or harvest immature crops?	Quantity
11	CSI	FDCRED	How often has the HH had to purchase food on credit?	Quantity
12	CSI/rCSI	BORROW	How often has the HH had to borrow food, or rely on help from a relative?	Quantity
13	HFIAS	NOTWNT	How often did you or any HH member have to eat foods you did not want to eat?	Acceptability
14	HFIAS	LIMVAR	How often did you or any HH member have to eat a limited variety of foods?	Quality/diversity
15	HFIAS	PREFER	How often were you/any HH member not able to eat the kinds of foods you preferred?	Acceptability
16	CSI/rCSI	RMEAL	How often has the HH had to reduce the number of meals eaten in a day?	Quantity
17	CSI/rCSI	LMTPORT	How often has the HH had to limit portion size at meal times?	Quantity
18	HFIAS	WORRY	How often did you worry that your HH would not have enough food?	Stability

19	SAFS	SAFS	Self-assessed food security during past 30 days	Stability
20	FCS/HDDS	DAIRY	How often has the HH eaten any dairy products?	Quality/diversity
21	FCS/HDDS	EGGS	How often has the HH eaten any eggs?	Quality/diversity
22	FCS/HDDS	MEAT	How often has the HH eaten any meat, fish?	Quality/diversity
23	FCS/HDDS	FRUIT	How often has the HH eaten any fruits?	Quality/diversity
24	FCS/HDDS	VEGET	How often has the HH eaten any vegetables?	Quality/diversity

Appendix H. CSA synergies and trade-offs (normalized data)

		Performance CSA on Food Security				Performance CSA on resilience		
No	CSA Practices	Total score	frequency/valid responses	Average score	Normalized Value	Total score	Average score	Normalized value
1	Efficient use of inorganic fertilizers	440	178	2.47191	0.71	316	1.775281	0.37
2	Use of improved crop varieties	260	116	2.241379	0.58	262	2.258621	0.65
3	Small scale irrigation	275	95	2.894737	0.99	272	2.863158	0.99
4	Efficient use of chemical/pesticides & herbicides	157	83	1.891566	0.38	122	1.46988	0.19
5	Use of organic fertilizers/compost	194	78	2.487179	0.72	189	2.423077	0.74
6	Mulching	19	15	1.266667	0.026	17	1.133333	0.0001
7	Minimum tillage	59	39	1.512821	0.16	55	1.410256	0.16
8	Inter cropping	26	20	1.3	0.04	29	1.45	0.18
9	Green manure	33	15	2.2	0.56	29	1.933333	0.46
10	Seasonal cropping |Year-round cropping	33	17	1.941176	0.41	39	2.294118	0.67
11	Water harvesting/pond construction	72	29	2.482759	0.72	66	2.275862	0.66
12	Efficient water utilization	54	26	2.076923	0.48	51	1.961538	0.47

13	Planting trees on crop land	54	26	2.076923	0.48	63	2.423077	0.74
14	Farmer managed natural regeneration	18	7	2.571429	0.77	16	2.285714	0.66
15	Drought tolerant crop varieties	5	4	1.25	0.01	7	1.75	0.35
16	Planting early maturity varieties	9	4	2.25	0.58	7	1.75	0.35
17	Changing planting date	32	24	1.333333	0.06	38	1.583333	0.26
18	Row planting	129	65	1.984615	0.43	133	2.046154	0.52

Appendix I

Survey Questionnaire

Bahir Dar University

Institute of Disaster Risk Management and Food Security Studies

Dear Sir/Madam;

Request for a Response to the Questionnaire

I am a PhD student in disaster risk science at Bahir Dar University; currently, I am studying under the title "**Impact of Climate Smart Agriculture Practices on smallholder Farmers' Resilience and Food Security: The Case of Gubalafto Woreda, Ethiopia**" to complement my PhD at Bahir Dar University. I would be very happy if you were going to participate in this study. You have been selected as one of the respondents to provide the required information for this study. I would like to ask you about your household experience with climate-smart agricultural practices, resilience, and food security status. The information gained from you could have added value for the success of the study and for the planning of future works. The entire interview took 30 minutes. I would like to assure you that all the information gained from you will be kept secret. The information provided is visible only to the researcher. Participation in the study relies only on your permission. You have the right to refuse all or part of the questions. However, owing to the importance of the study, I expect your active participation. You can ask any question, if you have any?

Thank you in advance for your kind cooperation.

Melkamu Sete Wereta

Would you be willing to participate?

Yes-------1------Proceed to ask questions

No--------0----- leave it

Date of Interview	_ _/_ _/_ _ E.C
Household Number	……………..
Woreda Name	……………..
Kebele Name	……………..

Part I: Household Characteristics

1	Sex of HH head	0. Female, 1. Male		
2	Age of the HH head	___________ Years		
3	Sex of HH members	Age of household members per sex		
	Male:----------	_____ ,_____ ,_____ ,_____ ,______ ,_____, _____, _____, _____		
	Female:-----------	_____ ,_____ ,_____ ,_____ ,______ ,_____, _____, _____, _____		
4	Education status of HH head	1.Not educated 2.Informal education(read and write) 3.Primary education 4.Secondary education 5.Diploma and above		
5	Marital status of HH head	1. Single 2. Married 3. Widowed 4. Divorced		
6	Religion of HH head	1. Orthodox 2. Muslim 3. Protestant 4. Others		
7	Farming Experience of HH	___________ Years		
8	Number of health shocks occurred to the household heads per year in number----------			
9	General health of family (√)	Excellent	Good	Bad

Part II: Climate-Related Information, CSA practices and their Synergies and Trade-offs

1	Did you have access of the issues of weather information?	0) No 1)Yes

2	If yes from whom: 1.DA, 2. Radio, 3. friends/other farmers' 4. Others	
3	Do you feel there is a change in the climate from time to time in your Kebele's? (perception of climate change)	0) No 1)Yes
4	If yes, what changes you observed in temperature conditions in your kebele?	1. Increase, 2.Decrease, 3.No change, 4. I don't know
5	If yes, what changes has there been conditions of rainfall?	>>
6	Are you adopting climate-smart agricultural practices in your farm plots? Please ask for each adapting practice **for the last 12 months.** Put "**00**"if not available. Next, If yes, indicate synergies and trade-offs; Please (√)	

##	Types CSA Practices	**0)No 1)Yes**	Contribution of selected CSA practices:					
			On food security			On climate resilience		
			Low/1	Medium/2	High/3	Low/1	Medium /2	High/3
4.1	Mulching							
4.2	Zero/Minimum Tillage							
4.3	Crop rotation							
4.4	Inter cropping with legumes							
4.5	Compost							
4.6	Green maturing							
4.7	Effective chemical fertilizer application							
4.8	Small scale irrigation							
4.9	Year round cropping							
4.10	Water harvesting - In situ and pond construction							
4.11	Efficient water utilization							
4.12	Tree based							

	conservation agriculture							
4.13	Farmer managed natural regeneration							
4.14	Improved crop varieties/Pest resistance, high yielding							
4.15	Drought tolerant crop varieties							
4.16	Planting early maturity varieties/Short season crops							
4.17 4.18	Changing planting date Efficient use of agrochemicals (pesticides &herbicides)							
4.19	Row planting							

Part III: Climate Resilience Related Variables

201	**Natural assets and crop production**			
No	Question Types (a)	**0)No 1)Yes**	Question Types (b)	Amo unt
1	Did you have your own cultivated land?		If yes how many hectare of **agricultural land** do your household **owns**?	
2	Do you have rented in cultivated land?		If yes, what is its size in hectare?	
3	Do you have rented out cultivated land?		If yes, what is its size in hectare?	
4	Does your household have **access to irrigation water**?		If yes, how many hectare of agricultural land do you **irrigate**?	
5	How do you explain the **quality** of your		1) Infertile 2)Medium 3)Fertile	

	agricultural land?			
6	Did you have cultivated different crop planted?			
7	Did you practice teff, sorghum, maize, finger millet & others production			
8	Did you practice barley, Oats, wheat & others production		If yes, total production in quintile	
9	Did you practice pulse crop production like Beans. Peas, groundnuts, lentil & others		If yes, total production in quintile	
10	Did you practice Oil crops production like Sunflower, nut &others		If yes, total production in quintile	
11	Did you practice vegetable , fruit & root production like mango, banana, carrot, potatoes, onion, other tubers		If yes, total production in quintile	
12	Did you practice leaves vegetable production like Swiss chard, cabbage, chat, & others in basket		If yes, total gained in Birr	
13	Did you crop stored for future consumption (surplus)?		If yes, amount of crop stored for future consumption in quintal	

202	**Income of the household in last 12 months**		
1	Main sources of income for HHs	1. Agriculture, 2. Off farm, 3. Nonfarm	
2	Did you have gained income in last 12 months by selling milk, butter, cheese, honey, egg, skin	0)No 1)Yes	If yes, income in Birr
3	Did you have gained income in last 12 months by selling cow, sheep, goat and hen		»
4	Did you have gained income in last 12 months by forest products like wood, charcoal		»
5	Did you have gained income in last 12 months by selling of handcraft products		»

6	Did you have gained income in last 12 months by trading of animals, crop, food and drink		»
7	Did you have gained income in last 12 months from carpentry		»
8	Did you or any of family members engaged in hired on other farmers farming activities (Do you provide farm labor)		»
9	Did you or any of family members engaged in self-employment business like salaried job, Daly work,& other employment		»
10	Do you have access to remittance from abroad or country side		»
11	Do you have participated in PSNP?		»
12	Do you have support from friends and related family?		»
13	Do you have gotten aids from NGO & Gov.?		»
14	Did you have food gifted or borrowed grain of crop from anybody in last 12 months		If yes, income in kg

203	Ask how many (livestock type) does the household have? Put "**00**"if not available				
	Livestock	**Number**		**Livestock**	**Number**
1	Cow		7	Donkey (Adult)	
2	Ox		8	Donkey (Young)	
3	Heifer and Bull		9	Sheep and Goat (adult)	
4	Weaned calf		10	Sheep and Goat (young)	
5	Calf		11	Camel	
6	Horse/Mule		12	Chicken	

204	**Physical Asset**				
	Please state the number & price of owned by the household? Put "**00**"if not available				
No	**Type of Asset**	**Price in Birr**	**No**	**Type of Asset**	**Price in Birr**
1	Radio		9	Plow	
2	Mobile		10	Sickle	
3	Table		11	Axe	
4	Chair		12	Hoe	
5	Bed		13	Beehive	
6	Wrist watch		14	Energy saving stove	

7	Jewelry/Gold, Silver, Bronze		15	Water pump	
8	Grain mill		16	Other, specify	
9	Does your household have access to **electricity**?				0) No 1)Yes
10	Does your household have access to **clean drinking water**?				0) No 1)Yes
11	What type of **home** did you own?	1) grass 2) Wood and mud 3) Stone, Bricks, Cement			

205	**Institutional and financial asset**	0)No 1)Yes
1	Do you have access to extension services whenever you require it?	
2	Do you have access of the issue of agricultural training in last 12 months	
3	Did you take training on weather information by an organization	
4	Did you participate in tree planting in group?	
5	Do you have access to all-weather road from market center up to your home?	
6	Do you have Informal social insurance? Like Zakat, Meredaja when animal died, burning house,	
6	Do you have bank account?	
7	If yes, how much money do you have saved in financial institutions in Birr	If yes how much money saved
8	How money saved at home?___________________________ if none put 00	
9	Can you have anyone/institution who could give you **credit** (borrowed) in last 12 months if you need so?	If yes how much received
10	What is the average walking time from the homestead to nearest school in hours? ----	
11	What is the average walking time from the homestead to nearest market in hours? ---- ______	
12	What is the average walking time from the homestead to nearest health institution?--- ______	
13	What is the average walking time from the homestead to dirk water?--------	

Part V: Measures of Household Food Security

Multidimensional food security						
	Indicator Questions (30 days recall period)		Possible Response Options			
No	Indicator	Questions	Never(1)	Rarely (2)	Sometimes(3)	Often(4)
1	HFIAS/HHS	How often did you or any HH member have to go a whole day without eating?				
2	HFIAS/HHS	How often did you or any HH member go to sleep at night hungry?				
3	HFIAS/HHS	How often was there ever no food in your HH?				
4	CSI	How often has the HH had to skip entire days without eating?				
5	CSI	How often has the HH had to send HH members to beg?				
6	CSI	How often has the HH had to send HH members to eat elsewhere?				
7	FCS/HDDS	How often has the HH eaten any pulses?				
8	FCS/HDDS	How often has the HH eaten any food made from grain?				
9	CSI	How often has the HH had to consume seed stock held for next season?				
10	CSI	How often has the HH had to gather wild food, hunt, or harvest immature crops?				
11	CSI	How often has the HH had to purchase food on credit?				
12	CSI/rCSI	How often has the HH had to borrow food, or rely on help from a relative?				

13	HFIAS	How often did you or any HH member have to eat foods you did not want to eat?				
14	HFIAS	How often did you or any HH member have to eat a limited variety of foods?				
15	HFIAS	How often were you/any HH member not able to eat the kinds of foods you preferred?				
16	CSI/rCSI	How often has the HH had to reduce the number of meals eaten in a day?				
17	CSI/rCSI	How often has the HH had to limit portion size at meal times?				
18	HFIAS	How often did you worry that your HH would not have enough food?				
19	SAFS	Self-assessed food security during past 30 days	Food secure, Mildly Moderately, and severely food insecure			
20	FCS/HDDS	How often has the HH eaten any dairy products?				
21	FCS/HDDS	How often has the HH eaten any eggs?				
22	FCS/HDDS	How often has the HH eaten any meat, fish?				
23	FCS/HDDS	How often has the HH eaten any fruits?				
24	FCS/HDDS	How often has the HH eaten any vegetables?				

Household Food Consumption Score (FCS)
During the last seven days, how many days did you and your family members consume foods from each group?

No	Food Group	frequency: number of days out of the past seven: (Use numbers 0 – 7 to answer number of days; Use 0 for not applicable)
1	Cereals: Rice, millet, sorghum, maize, wheat, barley and other cereals, e.g.-bread (kitta), Genefo, injera, spaghetti, macaroni, pasta, biscuits	
	Root and tubers: Cassava, potatoes and sweet potatoes, other tubers, plantains	
2	Pulses/legumes: Beans. Peas, groundnuts, any foods made from beans, peas, lentils, or nuts	
3	Vegetables, leaves, leaves, leaves: carrot, cabbage, onion	
4	Fruits: Banana, orange, mango, papaya	
5	Meat, poultry: Beef, goat, poultry, pork, eggs and fish	
6	Milk and milk products: Any cheese, yogurt, milk and other diary	
7	Oil/fats: any foods made with oil, fat, or butter	
8	Sugar and sugar products, honey	
9	Any other foods, such as condiments, coffee, tea	

	Food risk and Coverage
1	Have you decrease quantity of meal when encounter risk 0)No 1)Yes
2	Number of months in which the households do not have enough foods
3	Can you cover your household food need by yourself (in production or purchase)? 0)No 1)Yes
4	If **NO**, for how many months you face food shortage/enough foods?----------- months
5	If you are purchase, amount of money spent to buy food items in Birr like cereals, pulse, fruit and vegetable, egg , meat sugar and others----------- otherwise 0

Appendix J: Focus Group Discussion Guidelines

1. Climate Conditions and Perceptions

- In your experience, how do you think today's climate conditions compare to what you remember from earlier times? ---Have you noticed any significant differences? " ---
- What changes have you observed in rainfall patterns over the past several years? ---
- What changes you observed in temperature conditions in your kebele?---
- Is climate change a concern for crop production activities? If yes why it is the concern)?---.

2. Climate change impact and adoption of CSA practices

- What are the impacts of climate change on farming activity?--
- What is done to remedy climate change impact?--
- What are the crop-related technologies introduced or best practices in crop farming in your Woreda (to improve soil fertility, productivity, and resilience)? ---
- What are the purposes of using CSA practices on your farms? ---
- How has the adoption of CSA practices changed your farming methods compared to previous years?--.
- What challenges (main constraints) have you faced in adopting CSA practices?--

3. Synergies and Trade-offs of CSA Practices

- What benefits have you experienced from adopting CSA practices?---
- Have you noticed any trade-offs or drawbacks associated with these practices?---

- How do you perceive the relationship between CSA practices and food security in your household?---
- How do you perceive the relationship between CSA practices and resilience in your household?---

4. Impact of CSA Practices on Resilience and Food Security

- What specific CSA practices do you believe contribute most to your resilience against climate change?---
- How do CSA practices affect income stability or economic resilience? --
- In what ways have CSA practices improved your ability to cope with climate-related shocks?---
- Have you observed any long-term changes/resilience in your farming output since adopting CSA practices? --
- Please share any experiences where you feel more resilient due to the use of CSA practices?---
- How would you rate your household's food security (access to food throughout the year) before and after adopting CSA practices?--
- What specific changes in crop production or food availability have you experienced since the implementation of CSA?---

Appendix K: Key Informant Interview Checklist

1. Climate Conditions and Perceptions

- How do today's climate conditions compare to earlier times in your experience?-----------------------------------Have you noticed any significant differences?--------------
- What changes have you observed in rainfall patterns over the past several years?--
- What changes have you observed in temperature conditions in your kebele?-------------------------------

2. Climate change impact and adoption of CSA practices

- What are the impacts of climate change on farming activity?---
- What actions are taken to remedy climate change impacts?---
- Is climate change a concern for crop production activities?----------- If yes, why?--
- What crop-related technologies or CSA practices have been introduced at your farm to improve soil fertility, productivity, and resilience?--
- What are the purposes of using CSA practices on your farms?---
- What challenges or main constraints have you faced in adopting CSA practices?---

3. Synergies and Trade-offs of CSA Practices

- What benefits have you experienced from adopting CSA practices?--
- Have you noticed any trade-offs or drawbacks associated with these practices?---
- How do you perceive the relationship between CSA practices and food security in your household?---

- How do you perceive the relationship between CSA practices and resilience in your household?---

4. Impact of CSA Practices on Resilience and Food Security

- What specific CSA practices do you believe contribute most to your resilience against climate change (orderly)?--
- In what ways have CSA practices improved your ability to cope with climate-related shocks?--
- Have you observed any long-term changes in resilience or farming output since the adoption of CSA practices?--
- How would you rate your household's food security (access to food throughout the year) before and after adopting CSA practices?---
- What specific CSA practices do you believe contribute most to your food security against climate change (orderly)?--
- What success stories have you observed regarding CSA practices and their impact on productivity and food security?---
- Please share any experiences where you feel more resilient and food security due to the use of CSA practices.--

5. Open Sharing

Is there anything else you would like to share? Please feel free to discuss any issues.--