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ANALYSIS OF FARMERS' CLIMATE SMART CONTRIBUTIONS TO HOUSEHOLD FOOD SECURITY IN DEJEN WOREDA, NORTHWEST ETHIOPIA

MASTER'S DEGREE IN CLIMATE CHANGE POLICY

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ANALYSIS OF FARMER'S CLIMATE-SMART CONTRIBUTIONS TO HOUSEHOLD FOOD SECURITY IN THE EAST GOJJAM ZONE, NORTHWEST, ETHIOPIA

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Analysis of Farmers' Climate Smart Contributions to Household Food Security in Dejen Woreda , Northwest Ethiopia

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DEDICATION

My job is dedicated towards the loving memory of my beloved mother, Tarik Tamiru. May her soul rest in eternal peace. Her unwavering love and sacrifices remain an enduring source of inspiration in my life.To my father, Asefa Ferede, whose support and encouragement have always been my foundation. Your guidance has been invaluable in shaping my path.I also dedicate this thesis to my cherished sisters, Etenesh Asefa and Yirgedu Asefa, and my brother, Ayalew Asefa, for their constant love, encouragement, and belief in my abilities.Lastly, to my dear friend Zegey Mossie and all others who have supported me in various ways throughout this journey your kindness, advice, and encouragement have left an indelible mark on my life.

With heartfelt gratitude, I acknowledge you all.

AUTHOR'S STATEMENT

By my signature below, I, **Manaye Asefa Ferede** I authorise that this thesis or dissertation is my first work by signing below. During the process of planning, collecting, and analyzing the data for this thesis or dissertation, I have followed all academic ethical standards. I have correctly cited and acknowledged all academic materials. I confirm that every source used in this work has been properly credited and referenced. I have taken all necessary measures to avoid plagiarism. By submitting this document, I am fulfilling part of the graduation requirements from Pan African University with master’s degree in climate change policy . According to library policies, this document can be accessed by patrons at the PAU Library. I attest that I haven't sent in this paperwork to any other institution in hopes of earning a degree, diploma, or certificate.

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Master's of Art in Climate Change Policy

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BIOGRAPHICAL SKETCH

Manaye Asefa Ferede, the writer, was born in Debre Markos Town, Amhara Regional State, East Gojjam Zone, Ethiopia, on August 22, 1994. He completed his elementary education at Gemo First level School and his junior education at Gozamin Level School in Debre Markos. He then continued his preparatory study at the Ethio-Japan Secondary and Higher Preparatory School.

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The author was accepted to the Pan African University Institute of Water and Energy Sciences (PAUWES) in 2023 to pursue a master's degree with a focus on climate change policy.

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ABBREVIATION AND ACRONYMS

AE	Adult Equivalent
ATA	Agricultural Transformation Authority
ATE	Average Treatment Effect
ATT	Average Treatment Effect on the Treated
CSA	Climate Smart Agriculture
CSI	Copping Strategies Index
EMI	Ethiopia Metrological Institute
FCS	Food Consumption Score
GHG	Green House Gases
HDDS	Household Dietary Diversity Score
HFCS	Household Food Consumption Score
IPCC	Intergovernmental Panel on Climate Change
MoFED	Ministry of Finance and Economic Development
NAMA	Nationally Appropriate Mitigation Actions
NMA	National Meteorology Agency
NRM	Natural Resource Management
PSNP	Participatory Safety Net Program
SSA	Sub Saharan Africa
TLU	Tropical Livestock Unit
UNFCCC	United Nations Framework Convention For Climate Change
VIF	Variance Inflation Factor

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ABSTRACT

In Ethiopia, a country already struggling with poverty and rain-fed agriculture, food insecurity is made worse by climate change, which operates as a vicious cycle. This study's primary objective was to investigate how climate-smart crop production affects household food security in Dejen Woreda. Purposive and simple random sampling will be combined in a random multistage sampling method to choose the study areas and sample respondents of 271 households. Household data was gathered and analyzed using a cross-sectional study methodology. Together numerical and qualitative methods were applied in the investigation. Additionally, data was collected from both primary and secondary sources. The quantitative data was analyzed using multinominal logit and multinominal endogenous switching regression models, while the qualitative data was assessed using Explanation and generalized reasoning. The background characteristics of the sampled units were described using descriptive statistics. Multinominal logistic regression and MNESR models were applied for the impact evaluation to analyze the primary determinants of Shaping farmers' adoption of Climate-Smart Agricultural practices and assess the subsequent impact of these actions on household food security. Statistical techniques such as chi-squared and F-test were applied to look at the changes in features among households that practiced and those that didn't. The findings of an MNESR model showed that increasing the number of CSA combinations enhanced household FCS and HDDS when compared to not implementing new practices. According to the study's empirical findings, the government ought to provide the highest-yielding crops and climate-appropriate organic fertilizers, and seasoned family heads ought to impart their expertise to local CSA practices.

Keywords: Climate Change, Climate-Smart Agriculture, Dejen Woreda, Food Security, Ethiopia

Manaye Asefa Ferede

Analysis of Farmers' Climate Smart Contributions to Household Food Security in Dejen

Woreda, Northwest Ethiopi

1. INTRODUCTION

1.1 Background

Climate change poses a severe risk to global agriculture and the expansion of the economy, especially in developing nations(IPCC, 2022). It impacts ecosystems, water supplies, communities, and human health, causing floods and droughts and jeopardizing farmers' livelihoods. One of the most urgent challenges that society has ever encountered. Climate change carries a threat to global food security and household income development, especially for rural populations in low-income nations like Ethiopia (Nielsen et al., 2024; Endale et al., 2017; Thomas et al., 2019). This is because, in developing countries, rain-fed crops represent a significant source of income for rural residents. Accordingly, rural smallholder farmers in developing nations are at risk from prolonged drought, unpredictable rainfall patterns, and intense rain events (Bolan et al., 2024). The agricultural sector, which encompasses cattle, crops, aquaculture, forestry, and apiculture, is essential to boosting food availability and promoting food security in developing nations (WB, 2021; Bolan et al., 2024).

This industry is the main source of revenue and export goods both nationally and domestically. Therefore, agriculture, which employs about 63.66% of the workforce, generates 72% of exports, and accounts for 32.4% of GDP, is the main driver of Ethiopia's economy (World Bank, 2021). The agricultural industry, which comprises aquaculture, forests, apiculture, crops, and livestock, is crucial to increasing food availability and promoting food security in developing nations (WB, 2021; Bolan et al., 2024). Both domestically and nationally, this industry is the primary source of income and export commodities. Ethiopia's development is therefore mostly dependent on agriculture, which provides roughly 63.66% of the workforce, accounts for 72% of exports, and contributes 32.4% of GDP (World Bank, 2021). In Ethiopia, small-scale farmers dominate the agricultural sector, producing over 90% of the nation's agricultural yield (Aweke et al., 2017)Nonetheless, research by (D. M. Asfaw, 2021) indicates that current agricultural practices—such as crop cultivation and cattle production among smallholder farmers are inefficient, utilizing sub-optimal inputs, yielding inconsistent outputs, demonstrating low-risk tolerance, and lacking resilience to long-term climate change (Asfaw, 2021). Climate change events, including droughts and intense rainfall, further disrupt this sector. Accordingly, it is estimated that by 2050, climate change will decrease the nation's GDP by 8–10%, whereas agricultural adaptation measures might reduce climate-related shock by 50% (USAID, 2017).

In the study region, agriculture is the major sector that gives millions of people a place to live (ANRS). From this region, 83% of the rural population is employed in this sector. It supports 83% of the region's rural population and accounts for 56% of its GDP(Agegnehu et al., 2020). In terms of agricultural production supplied to the nation, the Amhara region ranks second. Out of all the grains produced in Ethiopia, it provides 33 percent of the country's overall production; only wheat and tef account for 29 and 39 percent, respectively. Like Ethiopia, where it is home to 29% and 27% of the country's total cattle and small ruminant populations, respectively, ANRS has the second-largest livestock resource (Agegnehu et al., 2020). The East Gojam zone, an area of Ethiopia that experiences moisture stress, is similarly threatened by the use of traditional agricultural methods combined with a growing population and the depletion of natural resources, especially soils, and vegetation, which results in a persistent food shortage under current agricultural standards.

Since smallholder farmers Face more significant consequences due to climate change, several solutions have been put up to lessen its negative effects and increase their ., 2016). Following the introduction of the Climate Resilient Green Economy (CRGE) initiative in 2011, Ethiopia has significantly advanced its climate-smart agricultural sector. Climate-Smart Agriculture (CSA) is one such program. CSA techniques are farming methods that increase climate change resilience, decrease or eliminate greenhouse gas emissions, and sustainably increase production Giving to (Ata et al., 2016; Hailemariam et al., 2019).

Consequently, several global initiatives are being undertaken to make agricultural output climate-proof, one approach could be to increase CSA (Victory et al., 2022). CSA was created to address the three aspects of food security, adaptation, and mitigation(Victory et al., 2022). CSA has garnered a lot of attention, especially in developing countries, due to its potential to lower GHG and improve the resilience and food security of farming systems (Lipper & Cavatassi, 2024). CSA seeks to enhance agricultural productivity and earnings in a sustainable manner by reducing and/or eliminating greenhouse gas production compared to conventional ways and enhancing and adapting to climate change (Lipper & Cavatassi, 2024). However, only a limited number of CSA practices, including conservation agriculture and agroforestry, are still being adopted by smallholder farmers. More public and private support is needed to make it easier for farmers to access improved inputs, financing, equipment, and insurance programs, which will increase their capability to manage risks and participate in long-term climate efforts (USAID, 2020).

Therefore, policymakers' and other development partners' methods for boosting the adoption and efficacy of CSA techniques in farm household production systems depend heavily on a deeper understanding of farmers' acceptance of CSA activities and the potential welfare implications. Therefore, the goal of this research is to determine the main CSA activities that farm households in the study area employ, as well as to look into the variables that affect how they combine and how that affects household food security.

1.2. Problem Statement

By 2030, the population of Ethiopia is projected to grow to more than 129 million (Solomon et al., 2023), placing pressure on the nation's finite natural resources and arable land while also increasing demand for crop production and agricultural performance. The capacity of this industry to supply the rising demand for food is further complicated by climate change. Land productivity has dropped dramatically in recent years, according to (Zerssa et al., 2021b), more than 40% of farming land and roughly 85% of Ethiopia's total area degrading as a result of climate change, become less viable for cultivation.

Climate change significantly impacts Ethiopia's agricultural sector, on which over 85% of the population relies. Ethiopian agriculture, is especially susceptible because it relies on rain-fed crops. Research has indicated a reduction in precipitation throughout the critical growing season, resulting in frequent droughts. (UNFCCC, 2022). Food production and lives are put at risk by this unpredictability, which also throws off crop cycles and lowers agricultural productivity. Furthermore, increased soil erosion and the loss of essential nutrients are two ways that climate change makes land less fertile (Meseret, 2016). This further reduces the productivity of the land, creating a negative feedback loop. Ethiopia and the Amhara area face a dire situation due to the environmental impact and combined consequences of land degradation and climate change (UNFCCC, 2022). Erratic rainfall patterns, declining agricultural productivity, and land degradation all contribute to food shortages and malnutrition. This disproportionately affects the most vulnerable populations, particularly smallholder farmers and their families. The situation is further compounded by population growth, putting additional strain on already limited food resources. According to the Organization for Food and Agriculture (FAO) emphasizes the link between climate change, land degradation, and food insecurity in Ethiopia, highlighting the urgent need for interventions (UNFCCC, 2022).

The case region of this research Ethiopia, which is renowned for its extensive farming potential then rich farming history, is seeing increasing difficulties due to CC. Floods and droughts are becoming increasingly common and severe as a result of weather systems being disrupted by erratic rainfall and increasing temperatures (Araro et al., 2019). The region's rain-fed agriculture, which provides millions of Amhara residents with their main source of income and food security, is seriously threatened by this precipitation fluctuation.

Farmers' livelihoods are at risk due to decreased agricultural yields and land degradation, which is further impoverishing them. The effects go beyond agriculture; they also influence public health, and water availability, and cause food insecurity-related relocation.(Araro et al., 2019). This situation demands urgent attention. With a growing population and limited resources, the Amhara region needs innovative and sustainable solutions to adjust to the shifting climate.

In response towards this multifaceted crisis, CSA emerges as a strategic and holistic approach(USAID, 2020). Its philosophy centers on three interconnected pillars, each crucial for building a more resilient agricultural sector: mitigation, adaptation, and increased productivity. Mitigation strategies tackle agriculture's role in climate change by dipping greenhouse gas emissions. Practices like composting, improved manure management, and using cover crops can significantly curb methane emissions, a potent greenhouse gas. Adaptation empowers farmers to navigate the changing climate. This includes adopting drought-resistant crop varieties, employing water-saving irrigation like drip systems, and encouraging the preservation of soil and water by using terraces and bunds(Amare & Adelekan, 2018). These methods protect agricultural output and lives by acting as a buffer against the whims of CC.

CSA places a high priority on enhanced agricultural output, which is important to ending the cycle of economic deprivation and lack of food access, in addition to adaptation and mitigation. Crop rotation, intercropping, and integrated pest control are among the techniques that help create healthier soils that are brimming with organic matter and helpful microorganisms.(USAID, 2020). This translates to improved nutrient retention, increased water holding capacity, and ultimately, enhanced crop yields. This not only bolsters food security within Ethiopia and the Amhara region but also empowers farmers economically. Higher yields translate to higher incomes, enabling them to invest in further climate-resilient technologies like efficient irrigation systems or drought-tolerant seeds(Araro et al., 2019). In the agriculture industry, this positive cycle promotes resilience and prolonged continuity. Despite the challenges faced by climatic change, CSA methods can dramatically boost Ethiopian agricultural productivity, according to studies by IFPRI (USAID, 2020).

To learn more about the factors impacting Ethiopian farmers' adoption of CSA methods, several research has been carried out. However, the vast majority of this research has only examined particular strategies, such as water and soil conservation (SWC). For example, (Atinkut & Mebrat, 2016; Assen & Ashebo, Berhanu, 2016,2018; Fantay Gebru et al., 2019) have conducted a study on SWC. To mitigate and control the consequences of climate change, farmers are frequently provided with a list of potential substitutes or supplements (Hailemariam et al., 2013). A more environmentally friendly farming system can be produced by combining several CSA approaches.

The Choke Mountain Watershed in the Amhara region was the subject of another study (Belay et al., 2016) , which indicates that local farmers with small-scale operations are extremely sensitive to climate change because of things like unpredictable rainfall and little supplies. The study emphasizes watershed activities as a CSA adaptation method and climate change susceptibility, however, it does not demonstrate the effects on household food security. The other research (WUDU, 2017) conducted in the Gozzamen District, Amhara region, found that several factors influence farmers' adoption of improved wheat technology. Education, farm size, available labor, crop income, access to inputs, extension agent contact, and engaging in off-farm activities all positively impacted adoption. On the other way, the acceptance of these new CSA technologies was found to be discouraged by age and market distance. However, the study's scope is restricted to "Adoption of Improved Wheat Technology practices," and did not examine the impact on nutritional security. which ignores other practices such as agronomic and agro-chemical practices which have a tremendous contribution to increasing farm production and productivity.

Despite the promotion of CSA techniques, little is known about how they impact household food security in the agricultural sector. Unlike conventional approaches, climate-smart agriculture seeks to do this by improving production and profits while simultaneously adapting to and strengthening resilience to climate change (Lipper & Cavatassi, 2024). Localized and comprehensive evaluations are necessary to identify feasible activities that could be included in an efficient CSA strategy under various climatic conditions. By investigating the particular contributions and contributing components of farmer-adopted CSA systems to attaining food security.

1.3. Objective of the study

1.3.1. General objective

To analyze the contributions of Climate-Smart crop production to household food security in the East Gojjam Zone, Northwest, Ethiopia

1.3.2. Specific objectives

- To identify climate-smart crop production practices that farmers employed in the crop sector in the study area
- To identify determinants influencing farmers ‘climate-smart crop production practices in the area of study.
- To examine the farming households' food security status and food coping practices in the study area
- To examine the contribution of climate-smart crop production to household food security in the study area

1.4. Research Question

- What are some of the climate-smart agriculture (CSA) practices used by crop farmers in the Dejen Woreda, Ethiopia?
- What are the main factors affecting farmers' use of climate-smart agriculture (CSA) practices in crop production within the Dejen Woreda of northwest Ethiopia?
- How significantly does the implementation of climate-smart agriculture (CSA) in the crop sector enhance the food security status of farming households in the study area?
- What are the contributions of CSA practices on household food security in the crop sector of Dejen Woreda, Northwest Ethiopia?

1.5. Scope and Limitation of the Study

Four kebeles in Ethiopia's Dejen Woreda, East Gojjam Zone, were the subject of the study, which aimed to assess the contributions of CSA to household food security in the crop sector. It solely examined climate-smart crop production techniques to raise local people's levels of food security, with particular attention to Ethiopia's Dejen Woreda, Amhara Region. Additionally, when evaluating the factors influencing CSA practices, the study only examined sociodemographic, institutional, and economic factors. Political and environmental concerns were not included, which could have broadened the study's scope and made it more difficult to focus on important issues related to CSA practices.

This study sought to examine how CSA practices and food security were related to one another. Since there was little overlap in the discussion of the main factors influencing CSA practices, several concerns were found to be covered under multiple sections, even though the level of information varied. Readers were made aware of these overlaps.

There were certain shortcomings in the structured questionnaire data collection process used for households. The actual and observable realities in the area were not always reflected in the answers provided by household heads to some of the questions. Despite orientation being conducted on the study's goal, this occurred partially because of miscommunication and partially because of mistrust of the entire investigation. The enumerators and the researcher spent a significant amount of time in the field addressing these issues.

Finally, the recommendations drawn from this study were strictly applicable to Dejen Woreda Administration rural kebeles because of the context-specific nature of CSA practices. However, the findings could be used as a springboard for more detailed studies and similar contexts in other areas.

1.6. Significance of the Study

This study's significance was divided into two categories. First and foremost, its primary objective was to advance understanding of the relationship between climate CC and CSA in particular areas experiencing food insecurity. This type of understanding allowed for a more thorough discussion of the problems. Second, the research had practical implications for development actors (i.e., NGOs, local and federal governments) participating in the socioeconomic development of local populations experiencing food insecurity. These development players were able to become more aware of the connections among food security, climate change, and CSA practices thanks to the findings. Additionally, conclusions from these community-level research were thought to have policy ramifications that went beyond the micro level.

2. LITERATURE REVIEW

2.1. Concepts of Climate Change, Climate Smart Agriculture, and Food Security

2.1.1. Climate change

Climate change is defined as the gradual change in local and global temperatures and typical weather patterns. The term "climate change" may be used to describe a particular location or the entire world (UNFCCC, 2025). Weather patterns may become difficult to predict and forecast due to CC. The temperature in a location may be higher or lower than normal. Floods, Droughts, and storms may become more regular and intense due to climate change. Climate change is defined as a shift in the climate that may be directly ascribed to both natural climatic fluctuations that take place over a comparable period and human activities that alter the composition of the global atmosphere (Bolan et al., 2024; UNFCCC, 2025). Climate change brought on by human activity results in rising temperatures and fluctuating precipitation(IPCC, 2007; Zegeye, 2018)

2.1.2. Climate-smart agriculture

A process for developing agricultural policies that ensure food security and nutritional demands are met, respect the planet's natural boundaries, help to mitigate CC, and upsurge the resilience of all those involved in food and agriculture (Li et al., 2024; FAO, 2013). By tackling the issues of food availability, resilience, ecosystem preservation, and ecological conservation together, it unifies the three pillars of sustainable growth social, economic, and environmental.

CSA is considered to be more functionally descriptive than definitive due to its utilization of context-specific procedures or practices (Li et al., 2024; Chandra et al., 2018). Additionally, in many circumstances, CSA works with various stakeholders farmers are one of them, development professionals, legislators, and scholars, to achieve the threefold aims of mitigation, adaptation, and enhance food security through increased productivity (Lipper & Cavatassi, 2024; Steenwerth et al., 2014). Because of this, different stakeholders may accomplish different goals under various circumstances without always acting in the same way to get the same results (Brandt et al., 2017; Lipper et al., 2014) These answers suggest that CSA incorporates several previous agronomic and environmental management practices. Crop rotation, Improved seed, Commercial fertilizers, Agroforestry, agriculture conservation, and holistic soil fertility management (Teklewold et al., 2017; Lipper et al., 2014; FAO, 2013).

Several catchment management strategies, including contour trenches, terraces on steep slopes, stone bunds, and other similar tactics, are incorporated into climate-smart agriculture (CSA)..

Table 1:Common climate-smart agriculture practices in Ethiopia

CSA practices	Components of CSA practices	Why is it climate-smart?
CA	▪ Using mulching techniques to manage crop wastes ▪ Putting minimal tillage techniques into practice ▪ Using intercropping or crop rotation, mixing grains and legumes	▪ Cut down on current emissions ▪ Sequestration of carbon and resistance to hot and dry environments
ISFM	▪ Management of manure and compost ▪ Effective fertilizer application methods (quantity, duration, and method)	▪ Decreased methane (CH4) and nitrous oxide emissions Enhanced soil productivity
Agroforestry	▪ Tree-based conservation agriculture is used both conventionally and as an enhanced method. ▪ Natural regrowth under farmer management	▪ Large amounts of carbon dioxide are stored by trees, which can promote agricultural resilience and increased productivity.
Crop diversification	▪ The spread of new crop types and crops ▪ High producing, drought-tolerant, pest-resistant, and short-season	▪ Maintaining food security, ▪ enhancing revenues, and ▪ being resilient to weather fluctuations
Improved livestock feed and feeding practices	▪ Decreased open or zero grazing ▪ Enhancement of feed and rangeland management and forage development ▪ Enhancement of livestock breeding and diversification	▪ Increased livestock output, ▪ decreased greenhouse gas emissions, and ▪ decreased CH4

(Source: Adapted from (FA0, 2017) and Jirata *et al.,* 2016

These techniques improve water percolation and retention throughout croplands, reduce soil erosion, and promote agricultural productivity in arid places (Branca et al., 2017). Watersheds are essential to Water conservation methods, soil productivity, farm systems, and natural resource management. because they are made up of watershed areas in a given landscape that drains water toward a common point. Therefore, watershed development has become essential for controlling agricultural groundwater supplies and providing ecosystem services, particularly in regions that are deeply exposed to the repercussions of CC (Beyene, 2018). Given the new realities of climate change, several countries are employing this tactic to reorganize and modify agricultural systems to increase food security.

2.1.3. Concepts of food security

The main objective of the Millennium Development Goals is to end hunger, as there will be roughly 9 billion people to feed by the mid of the century (Clapp et al., 2022). For decades, the ability of agriculture to meet rising demand has been a source of concern and remains high on the global policy agenda (Clapp et al., 2022), particularly because 805 million people remain under the poverty line (IFAD & WFP, 2019). The global food system is under tremendous strain, and one of the main causes making the job more difficult is climate change.

The status of having the physical ability to obtain sufficient financial and social resources and healthy sustenance to meet one's dietary needs and food choices is known as food security (UNICEF, 2024). The four pillars are thought to have a beneficial or negative impact on food security. The availability, stability, use, and accessibility of food supplies are the foundations of food security (Cheteni et al., 2020). Purchasing power, production location, food availability, and the distribution and accessibility of resources for food production are additional aspects that constitute food security (Cheteni et al., 2020). All four of these elements must be taken into account, though, to fully understand the connection between agriculture, climate change, and food security. Climate change, which also impacts agricultural productivity (availability) by shortening the growing season and increasing the incidence of sever wether occurance such as storms, droughts, and flooding, also reduces the stability of such food (IPCC, 2024). There are many different aspects of food security, including those at the international, regional, national, local, family, and individual levels (Nasir et al., 2017). As per the operational definition of food security employed in this research, it encompasses the consistent availability of food for every member of the family, in addition to additional conditions for a healthy lifestyle and daily caloric requirements.

The various facets of food security and how it dynamically interacts with agriculture and climate change highlight the necessity for such a notion, as well as the difficulty of the task facing CSA. From the farm to the global stage, food and agricultural systems need to be made more robust and efficient. They developed the concept of CSA as a solution for food security and agricultural productivity in a changing climate, particularly to address this challenge. By implementing suitable practices and creating institutions and laws that facilitate them, CSA seeks to raise food security, assist communities in responding to the effects of climate change, and contribute to climate change adaptation and mitigation.

2.2. Major Elements and Practices of Climate-Smart Agriculture

2.2.1. Major elements of climate-smart agriculture

Misallocating human and financial resources and developing agricultural systems that are unable to alleviate the repercussions of CC and increase food security if we don't alter the way we plan and invest in agricultural growth and development. By integrating climate change considerations into the creation and application of sustainable agricultural methods, CSA offers the potential to avoid this "lose-lose" scenario (Raihan et al., 2024). CSA assesses trade-offs between food security, adaptation, and mitigation to help direct and refocus policy in response to climate change. The IPCC predicts that if such measures are not taken, food security will become more unstable, and agricultural and food systems will become less robust (IPCC, 2019). Decision-makers at all governmental levels, from the farm to the global, are urged by Climate Smart Agriculture to strengthen agricultural systems' and livelihoods' resilience to reduce the risk of food insecurity now and in the future (IPCC, 2019).

To ensure the successful implementation of the CSA, governmental, corporate, and civil society actors need to move quickly in four areas, from the global to the local (IPCC, 2019). (1) offering evidence-based and assessment methodologies; (2) evolving integrated and policy framework grounded in evidence; (3) strengthening local and national institutions; and (4) increasing funding and its effectiveness.

Governmental, corporate, and civil society actors must act swiftly in four areas—from the global to the local—to guarantee the CSA's successful implementation (IPCC, 2019). (1) providing methods for assessment and evidence; (2) fortifying nationwide and local institutes; (3) creating evidence-based and integrated policies; and (4) expanding funding and its efficacy.

Both national and local decision-makers lack sufficient access to the existing body of evidence, rendering it unsuitable for facilitating effective decision-making (FAO, 2018a). Most studies on how climate change is affecting agriculture are carried out at spatial and temporal scales that are inappropriate for regional and national planning. The reason for this is that little is known about how future changes in climate variability will impact agriculture, which may be far more significant to localized communities as opposed to long-term trends in climatic variables. Downscaling models to decision support-appropriate scales presents additional technical challenges (FAO, 2018a). Finding effective measures in the face of uncertainty can be aided by the creation and use of problem-oriented approaches to adaptation planning. A comprehensive study is also necessary to understand what works in specific agroecology and agricultural systems and why. This will make it easier to define climate "smartness" in various biophysical and socioeconomic circumstances.

Expanding national and local institutions' access to resources, with an emphasis on information, to improve their ability to adapt more successfully, is CSA's second priority action area (FAO, 2018a). Agricultural development initiatives have traditionally relied heavily on institutional development, but their effectiveness has fluctuated due to a lack of funding or planning. Empirical evidence indicates that public support is needed in four crucial areas to support private efforts: (1) Coordinated actions where practices result in positive side effects, like lowering the risk of floods, pest infestations, or protecting biodiversity; (2) thorough risk-management strategies for dealing with extreme weather events that affect multiple farmers; and (4) facilitating the exchange of extension services and information, particularly about using evidence to tailor practices to local conditions (FAO, 2018a).

The third major area of attention for Climate-Smart Agriculture (CSA) is improving policy alignment across food systems, environmental management, and agriculture to create supporting regulatory and policy frameworks. A conversation across pertinent government organizations to reduce duplication, find gaps, and handle disagreements is necessary to promote alignment across policy domains and create an enabling policy environment (FAO, 2009). Agricultural policies, investment frameworks, and strategic plans at the national level, as well as climate change instruments like nationally applicable mitigation actions (NAMAs), national adaptation programs (NAPs), and climate change investment plans, all require coordination, which is especially crucial(IPCC, 2019). The last area is Building coordinated approaches to agriculture and food security policy areas, as well as to climate change, which is necessary to ensure that national CSA measures are made possible by financing, technology development/transfer, and capacity building.

2.2.2. Practices of climate-smart agriculture

Due to the great diversity of CSA techniques across contexts, adoption is frequently site-specific, particularly for smallholder farmers in developing nations (Arslan et al., 2015; S. Asfaw et al., 2015). It follows that the impacts of CSA acceptance and adoption are frequently not generalizable outside of the local environment (Chandra et al., 2018; Lipper et al., 2014). Adoption estimates across contexts are hindered by conceptual ambiguity, specifically in the absence of a well-defined structure for identifying and implementing CSA studies. It also makes it challenging to pinpoint the conditions under which such community support initiatives should be most effectively implemented, as well as to select and promote the CSA practices with the largest adoption potential (Chandra et al., 2018).

Climate change mitigation is made possible by CSA practices, which also promote economic expansion and the advancement of the agricultural industry(IPCC, 2019). Practices are deemed climate-smart for this profile if they maintain or surpass productivity gains in addition to at least one of the other goals of climate-smart agriculture (mitigation and adaptation). Globally, hundreds of behaviours and technologies are categorized as part of CSA(FAO, 2024). For example, it has been discovered that the combination of stone bunds built along contours and Zai pits filled with composts or manure can boost yields of millet and sorghum by up to 1t/hectare (100%) when compared to unimproved land (S. Asfaw et al., 2015). The main goal of using better crop varieties is adaptability, but they also support other CSA initiatives. All agroecological zones and nations utilize improved, highly productiveVarieties of cereals, grain legumes, and root crops that are resistant to drou, and tubers that are resistant to major diseases and pests. These varieties are produced through national programs in collaboration with research centers (S. Asfaw et al., 2015).

The most common fertilizer used by small-scale farmers in Eastern Africa is organic fertilizer made from household organic waste and farm yard manure. (Oloka-Onyango, 2018),asserts that intensive maize cultivation using large amounts of inorganic fertilizer may cause soil degradation. Organic manure includes things like compost, animal feces, green manure, tree leaves, and crop leftovers. Because it increases productivity while reducing the need for chemical fertilizers, which increase greenhouse gas emissions, it is a climate-smart decision.

You can use organic fertilizers exclusively or in certain ratios in combination with inorganic fertilizers. Increased productivity and improved soil health can be achieved by combining organic and inorganic fertilizers at half the recommended nutrient levels (Oloka-Onyango, 2018).

The agriculture of Ethiopia is varied in terms of socioeconomic circumstances, food production methods, and climate zones. When agriculture lowers GHG emissions, strengthens its resilience to CC, and sustainably boosts agricultural output and incomes, it is deemed climate-smart. (Harvey et al., 2018; Brandt et al., 2017).a scoping study to examine different farming methods in Ethiopia. The study produced a list of climate-smart farming techniques currently used by Ethiopian smallholder farmers (FAO, 2016a). Organic fertilizers, pest and disease-resistant crop varieties, improved rangeland management, livestock feeding practices, adoption of livestock species or breeds better suited to water scarcity and disease resistance, Decreasing livestock numbers while enhancing yield and efficiency, and agroforestry—which combines crops with trees and shrubs—are all examples of efforts to increase resilience and productivity, even though conventional production methods are still widely used (FAO, 2016a).

In certain regions of northern and southern Ethiopia, there are also viable landscape natural resource management techniques, such as exclosures that forbid livestock and human involvement on hillsides and hilly areas designated for restoration (FAO, 2016a). Additionally, Ethiopia has embraced and implemented several traditional climate-smart farming techniques. (Teshager, 2015) points out that these farming methods include crop rotation, which is used by farmers all over the country, the Konso cultural landscape, indigenous agroforestry in Gedeo, East Shewa, East Wollega, and West Gojam zones, soil and water conservation techniques in the Hararghe Highlands, cattle fattening methods in Hararghe, small-scale irrigation systems, and manure management strategies in Ankober.

2.3. Factors Affecting Climate-Smart Agriculture Practices

The following factors influencing farmers' acceptance of CSA techniques have been the subject of numerous studies. In the cities of Guto Gidda and Sasigga in Ethiopia's Oromia Regional National State, researchers (Aryal et al., 2018; Bekabil & Bedemo, 2015) looked at the variables influencing farmers' involvement in conservation agriculture. The logit estimate's findings demonstrated that the number of active family workers, the head of the household's primary occupation, and the head's educational attainment were significant determinants of

CSA behaviors. Similar research was done in Ethiopia's Oromiya Regional State and found that the adoption of CSA practices was significantly and positively correlated with the sex of household heads, their level of education, their off-farm income, the number of livestock they owned, their participation in field days, their knowledge of environmental regulations, their access to extension services, and their membership in organizations. (Tewodros, 2018) .

A study on the subject revealed that subsistence farmers in Ethiopia's Central Rift Valley have been adopting various CSA practices to deal with the impacts of climate change. Crop diversification, planting schedule adjustments, water and soil conservation, input optimization, crop and livestock system integration, and afforestation promotion are some of these tactics. Important factors influencing farmers' adoption of climate-smart agricultural (CSA) practices were identified by the econometric analysis. These factors included income levels, market accessibility, household demographics, gender, age, livestock assets, farming experience, and the degree of use of agricultural extension services (Belay et al., 2017).

The possibility and implementation of various tactics (such as agroforestry, water management, improved seeds, inorganic fertilizer, manure, crop diversification, soil conservation, and conservation tillage) were examined in a different study conducted in Ethiopia's Nile Basin (Teklewold et al., 2019). The outcomes demonstrated how well the various CSA approaches complement one another. The choice of the type and quantity of CSA practices is significantly influenced by social capital, tenure security, and climate shocks, according to econometric studies. According to a study by Amare (Fentie & Beyene, 2019) in Ethiopia's North Wollo Zone, labor availability, radio ownership, contact with government extension agents, and non-farm income also had an impact on the logit estimations of employing Quncho Teff row planting technology as CSA.

The results of (Tsige et al., 2020; Kifle et al., 2022) also demonstrated how restricted credit availability, restricted membership in cooperatives and water user associations, lack of access to land or user rights, skill development, informational barriers, and limited mobility impacted the CSA practices of Ethiopian women smallholders. Similar to this, the goal of the (Nyengere, 2017)study in Malawi was to determine the socioeconomic factors that influence farmers' decisions to employ organic manure as (CSA) technology. The findings indicated that the adoption of the technology was highly influenced by household size, income, and education. Given that the amount of schooling, total annual income, and household size have been found to impact the use of organic manure, these factors should be given special consideration while creating plans and putting this CSA technique into practice.

2.4. Impacts of Climate Smart Agriculture on Food Security

A substantial body of research has acknowledged the adoption of the CSA as one of the policy alternatives in response to food insecurity(UNFCCC, 2018; B. M. Wekesa, 2017). Because better crop varieties have a higher seed diversity within the same crop, using them is anticipated to result in higher average yields. (Teklewold et al., 2019), for instance, demonstrated that the introduction of new cultivars (vegetables) and trees (fruits) increases yields by 60% in Ethiopia; Chirwa, P. and Quinion, A. (2005) demonstrated that the average yield increase in seven African countries during 2004–05 was 44% as a result of the introduction of new bean varieties, though the gains varied greatly among the countries, ranging from 2% in Malawi to 137% in western Kenya (Teklewold et al., 2019).

Crop rotation and intercropping that guarantee differential nutrient uptake and usage (for example, between nitrogen-fixing crops like groundnuts, beans, and cowpeas and between crops like millet and sorghum) can result in higher crop yields. By reducing the need for artificial fertilizers and increasing the availability of nutrients for subsequent crops, these methods also increase soil fertility (Mendola, 2017). For example, (Pretty et al., 2018) showed that in the North Rift and Western regions of Kenya, maize yields increased to 3,4 t/ha (71% increase in yields) and bean yields increased to 258 kg/ha (158% increase in yields). There have been numerous reports of increased crop yields following a fallow period (Mendola, 2007); however, the amount of yield increment following each subsequent fallow is varied, and leaving land naked may raise the danger of soil erosion(Mendola, 2017).

2.5 Analytical Framework

Measuring food security

Food security can be assessed using various methods; however, the concept remains somewhat ambiguous (Headey et al., 2024) ,(Ballard et al., 2008). The IPC recognizes several direct outcome indicators, including the Household Dietary Diversity Score (HDDS), Household Hunger Scale (HHS), Food Consumption Score (FCS), Coping Strategies Index (CSI), Household Expenditure Survey Method (HESM), and Livelihood Coping Strategies (LCS). These indicators are commonly used to measure acute food insecurity. Kilocalorie intake is considered the gold standard for assessing food consumption and is often regarded as a key measure of food security. In this study, food consumption scores and household dietary diversity scores (HDDS) were used as proxies for food security (Headey et al., 2024; Ballard et al., 2008).

Food consumption score (FCS) is a widely used method to measure dietary diversity, frequency of consumption, and the nutritional quality of foods. Developed by the World Food Programme, to (WFP ,1996)), cited b(Marivoet, 2019), FCS considers various food groups and assigns them weighted scores based on their nutritional value. This tool is more comprehensive than HDDS and HHS because it captures both dietary diversity and nutritional adequacy over 7 days (WFP, 2008). Following that, this data is used to determine the relative nutritional values of the food types consumed. Foods that are high in nutrients, for instance, are valued higher than those that are deficient in nutrients, like tubers. A household's food intake can be categorized using this score into one of three groups: acceptable, marginal, or poor. The food consumption score is a ballpark estimate of the number of calories available in the home, according to (Marivoet, 2019). For this reason, it serves as the study's stand-in variable for food security.

Dietary diversity is defined by the Household Dietary Diversity Scale (HDD) (Ruel, 2003) as the amount of a single food or food group ingested over a given period; the reference interval may vary, although it is usually days or weeks earlier (Yigezu Wendimu, 2021b ; WFP, 2009).. The family Dietary Diversity Score (HDDS) calculates how many distinct food groups each family member consumes at home during the previous 24 hours, including home-cooked meals. packed lunches at home, but dining out (Swindale & Bilinsky, 2006 ; Hoddinott & Yohannes, 2002). According to (Swindale & Bilinsky, 2006)HDD can more accurately represent a high-quality diet when the number of different food kinds consumed is used instead of the overall number of items consumed.

According (FAO , 2010)The home Dietary Diversity Score, which is computed by adding the number of food types that respondents in the home consumed during the 24-hour recall period, is a measure of a household's availability of food. The values of the dietary variety variable for all brand new food groups and possible hard drive ratings ranging from 0 to 12 are then added. A higher score means that households eat from a wider variety of food groups. Low, medium, and high dietary diversity are denoted by HDDS values of 3, 4-5, and 6, respectively (Artificial Intelligence Index Report , 2021)

Household daily caloric consumption: According to (Sisay Mengesha, 2017), household food or calories obtained per day EA was used to define two groups, i.e., the food security group and the food insecure group. One of the most direct and widely used methods for assessing food security is the measurement of household daily caloric consumption. This method estimates the total number of calories consumed by a household per day, often compared to standard thresholds that define adequate caloric intake based on the age, gender, and activity levels of household members. The FAO's daily caloric requirement guidelines suggest that a typical adult requires about 2,100 calories per day, but this can vary depending on specific needs (FAO, 2001). By comparing household consumption to these standards, the method provides a concrete measure of food availability and access at the household level.

Household Expenditure Survey Method (HESM): This is an instant technique for obtaining information from households. Different time references, such as week(s) or month(s), were used when asking respondents to submit information about their expenditure on food and other (Bickel et al., 2000)requirements, particularly information on how much they spent on basic products and nutritionally sufficient food. Information on the amount of food purchased and the cost of individual items consumed inside and outside the home is necessary to obtain satisfactory data. In addition, the tool must capture more evidence about food established as a gift or received help from any family member and home-grown food. However, the method does not account for food aid, gifts, or homegrown food, which are critical in rural areas like Dejen Woreda.

Methods for impact evaluation

Experimental Method: The most efficient evaluation technique is frequently thought to be experimental designs, commonly known as randomization (Baker, 2000). The assignment technique itself creates similar treatments and manages statistically equivalent groups, of given sample sizes, by randomly allocating the intervention among eligible receivers. In a randomized experiment, the control and treatment samples were selected at random from the same population. In other words, each participant in a randomized experiment is randomly allocated to one of two groups: the treatment group or the non-treatment group. The researcher can determine an independent evaluation of a project's impact by carefully comparing the outcome variables for the two groups (Essama-Nssah, 2006). Under some circumstances, experimental design can be costly and time-consuming, particularly when gathering fresh or unprocessed data.

Propensity Score Matching Method: A non-experimental method for determining the average efficacy of programs is propensity score matching (Heckman et al., 1998). Propensity score characteristics: the closer the score, the more pertinent it is. The same people interviewed the good control group as the treatment group, and they came from the same socioeconomic background. Applications of the PSM approach have advanced significantly in recent years (Rosenbaum & Rubin, 1083;Jalan & Ravallion, 1999). A propensity score is an opportunity with conditions. More precisely, it is the probability that an individual or unit will participate in the intervention when its observable characteristics are considered. The "participation equation" yields this likelihood.

One is given to intervention participants and a value of zero to non-participants in probit or logit regression, where the dependent variable is dichotomous. The explanatory variables contain any observed characteristics (individuals, families, businesses, communities, or marketplaces) that may have an impact on participation but are not impacted by the intervention. Since the intervention cannot alter the baseline values of any variable, including outcomes, having baseline data makes it easier to achieve a stronger fit. The covariate-balanced propensity score is a more recent innovation that ensures that the covariates are more uniformly distributed before applying the propensity score to match by adding weight to the propensity score estimations (Imai, 2012).

In contrast to econometric regression techniques, PSM only relates equivalent observations, no longer relies on parametric assumptions to determine project impacts, and does not impose any particular type of outcome or practical results, thereby avoiding assumptions about functional form and error period distribution, such as imposing linearity, problems with multicollinearity, and variable variance. Similar to this, the matching strategy draws attention to the issue of common support, preventing bias brought on by extrapolation to the non-data zone. In this study, PSM can observe the outcomes of cluster participant smallholder farmers but cannot observe the outcomes of non-cluster smallholder farmers (counterparts). PSM failed in the data. PSM's assumption that all coefficients are the same for non-cluster and cluster participant groups is empirically unhelpful. According to the literature, many impacts based on cross-sectional data have shifted toward an endogenously switching regression model (Heckman, 2001).

The study did not use PSM to account for unobservable factors, analyze the impact of the selection of variable counterparts, and account for selection bias. Unobservable factors may fall under personal, social, or institutional characteristics, such as farmer ability, skills, and motivation, and may influence both the level of CSA participation decision and household food security

Quasi-experimental design: Quasi-experimental design refers to assessments that lack the rigor of randomization in the experimental design. However, the goal is to methodically study treatment results by comparing treatment outcomes with outcomes from the untreated group. Because of the possible variations between the groups being compared and the forces not observed outside of the trial, semi-trial designs may be limited in their ability to draw causal inferences.

Nonetheless, in certain situations, it is feasible to create superior controls and quasi-experimental designs that might be quite beneficial in addressing research inquiries concerning resident outcomes. and neighborhood circumstances, such as environmental controls, treatment, assessment group identification, and combined accuracy data for both groups. Similar to experimental design, quasi-experimental design can be costly, intricate, and challenging to execute. Quasi-experimental designs can also do cost-effectiveness (but not cost-benefit) analysis if assessors successfully create appropriate comparison groups (Smith, 2011). Therefore, this impact assessment might be used in this study to evaluate the influence of CSA farming on household food security.

Instrumental Variables: Technique IV entails finding an instrument or variable that is directly tied to placement, treatment, or program participation, but does not use the phrase error or unobserved factors that influence outcomes. Care must be used when selecting the treatment variable. The low treatment variable should theoretically worsen the bias even more than when estimated by multiple linear regressions or ordinary least squares (OLS) if the error term's features or the variables that were left out but affected the result are related. The key drawback of the IV approach is that it is always difficult to find the best tool because to assess the impact of a treatment, you need at least one suppressor who decides to participate in the program, but is not always determined by the variables that influence the outcome(Blundell & Dias, 2000); Heckman, 1996).

Regression Discontinuity Design (RDD): is a pre-trial-post-trial quasi-experimental design that specifies a threshold, either above or below the threshold at which an intervention is indicated, with the goal of identifying the causal effects of treatments (Thistlewaite & Campbell, 2017). Although information on the results of candidates who are rejected may need to be gathered, it can also heavily utilize administrative statistics, which lessens the requirement for data collection. The method's drawback is the need for sufficient evaluation samples and clear assignment criteria. One challenge for RDD is the best-estimated impact on populations at the boundary. The estimate is called the local mean (late) treatment impact rather than the mean treatment effect for the entire treated group (White, Howard; Raitzer, David A, 2017). As a result, this model was not employed in this study.

Difference-In-Difference (DID): It is a study approach used to measure the impact of certain policy changes and activities that affect people differently. DID could be a desirable goal when adopting study designs that are solely focused on controlling confounding variables, or instrumental variables are considered undesirable, and pre-treatment data is available (Lechner, 2010). Generally speaking, the DID design is solely focused on comparing four different sets of items. Three of these groups were unaffected by the treatment. In many algorithms that aid in group differentiation, "time" is a crucial variable. The pre-treatment treated group is handled prior to treatment, the pre-treatment non-treated group is handled prior to treatment, the non-treated group is handled during the current period, and the post-treatment treated group has already received treatment(Lechner, 2010). However, a control group and baseline data are needed to implement this strategy.

Endogenous Switching Regression: Regression-based methods known as endogenous switching regression allow for endogenous selection in the treatment rule by modeling the resulting equations (two "modes"), one treatment mode, and one contrast mode (Maddala,1983). The transformation regression is the second-order equation (result) in this approach, which is a specific case of the Heckman model. One effect estimate is not provided by this method. The prediction outcomes for two equally valuable observations, treatment and control of the independent variables, are distinct due to the various coefficients in the two modes. For both treated and untreated populations, expected outcomes can be estimated for each possible outcome. Estimating ATT, ATE, and ATU is possible by comparing the predictive values of prospective outcomes for participants and nonparticipants with and without treatment. The model was expanded to encompass populations other than these populations and estimate the marginal effects of treatment for populations that were specifically defined (Moffitt, 2008). To estimate the effect of the simultaneity group and equations, this research will employ an endogenous switching regression model, which takes into account both observed and unobserved elements.

Therefore, this study uses an endogenous switching regression model. Cluster farm participation is likely not randomly assigned but rather influenced by factors that also affect food security outcomes. This endogeneity can bias traditional regression models. An endogenous switching regression model addresses this issue by accounting for the self-selection process into cluster farming and the potential correlation between unobserved factors that influence both participation and food security.

2.6. Methods for measuring climate-smart farming participation

CSA Participation is the dependent variable for the selection equation model's initial stage. A variety of alternative proxies were used to gauge CSA participation. As a dummy variable, participation is first measured; households that are part of the farmer group or CSA have a value of 1, while households that are not part of the farmer group have a value of 0. However, the dependent variable may not always be categorical; it can be multinomial.

Numerous studies demonstrate that both qualitative and quantitative evaluations are part of the model used to investigate the factors influencing involvement. Other qualitatively desirable models include Logit, Probit, and linear probabilistic models (Maddala,1983).

Linear Probability Model: One type of linear regression where the outcome variable is a binary (categorical) variable is called the Linear Probability Model (LPM), making it useful for analyzing decision-making processes. However, LPM has several limitations, including non-normality of error terms, heteroscedasticity in residuals, and an unreliable R^2 as a measure of model fit. Additionally, the model may generate estimated probabilities that assume constant marginal effects and fall outside of the acceptable range of 0 to 1. Despite these drawbacks, LPM remains popular due to its simplicity and ease of estimation, as it follows the structure of a standard multiple regression model (Aldrich, 1987).

Logit model: Logit regression analysis is a multivariate technique that predicts binary dependent outcomes from a set of independent variables in order to evaluate the likelihood that an event will occur or not. The logit model's main flaw is that it no longer makes the assumption that the logistic independent variables' variances are normal, linear, or homogenous. (Aldrich, 1984).

Probit Model: To address the shortcomings of LPM and the cumulative standard probability distribution utilized in probit analysis, the probit model—a non-linear probability model was developed. There are two kinds of dependent variables in the Probit model. There are two possible values for the binary dependent variable: 0 and 1 (Liao, 1994). Consequently, this model was not applied to this research.

Multinomial Logit (MNL) Selection Model: A popular econometric technique for simulating categorical choice behavior, where people choose one option from a range of discrete alternatives, is the Multinomial Logit (MNL) Selection Model. It assumes that the likelihood of selecting a specific option follows a logistic distribution and is dependent on the decision-makers and the alternatives' attributes. The random utility theory, on which the model is based, states that every option has a utility, and the decision-maker chooses the option with the highest utility. The Independence of Irrelevant Alternatives (IIA) assumption is imposed by the MNL model, which states that the existence or lack of additional options has no bearing on the relative probability of selecting any two options. As a result, this model was used in this study.

2.7. Empirical Studies on Climate-Smart Agriculture and Food Security

CSA refers to methods and tools that lower GHG emissions, help farmers adapt to climate change, and sustainably boost productivity. Governments can use it to further their objectives of reducing poverty and ensuring national food security. Climate-smart strategies can consist of a wide range of elements, from global policy and funding mechanisms to farm-level practices.

Since its inception, the Drought-Resilient Maize Program for Africa(DTMA) has developed and introduced over 100 new drought-resistant maize varieties and hybrids across 13 countries. This initiative, The United States Agency for International Development (USAID), the UK Foreign, Commonwealth & Development Office (FCDO), the Howard G. Buffett Foundation, and the Bill & Melinda Gates Foundation provided funding, aims to enhance agricultural resilience and ensure food security in drought-prone regions (Deressa et al., 2018). Each of these novel cultivars has been tailored to meet regional needs in terms of pest and disease resistance, cooking and milling qualities, and other attributes. (Deressa et al., 2018) These novel hybrids and varieties are currently being grown by more than 2 million smallholder farmers in sub-Saharan Africa, some of whom are in nations not officially part of the DTMA—a clear indication that the program is headed in the right direction. Even in mild drought conditions, farmers are reporting yields that are 20–30% more than what they would have obtained with their traditional varieties(Deressa et al., 2018).

In Vietnam, where more than 9 million farmers own less than half a hectare of paddy rice land, they are faced with the impacts of climate change. Here's when sustainable intensification enters the picture. (Pieters et al., 2019) found that while monetary outlays have decreased by up to 95%, yields from plots that combine synthetic and organic fertilizers are sometimes double those of plots that are handled traditionally. An experimental initiative in Vietnam's Dai Nghia commune in 2006 encouraged the use of less water, less nitrogen fertilizer, and less seed. Following the pilot's success, Oxfam and Vietnam's Plant Protection Department (PPD) established an extended collaboration(Pieters et al., 2019). The Ministry of Agriculture and Rural Development officially recognized the reduced input use as a technical advance in 2007. Following that, PPD started a national distribution campaign. Numerous extension strategies were employed, such as farmer-to-farmer training and intense farmer field schools. In 22 provinces and almost a million farmers, according to 2011 Ministry of Agriculture data, reduced their input use to 185,000 hectares(Pieters et al., 2019).

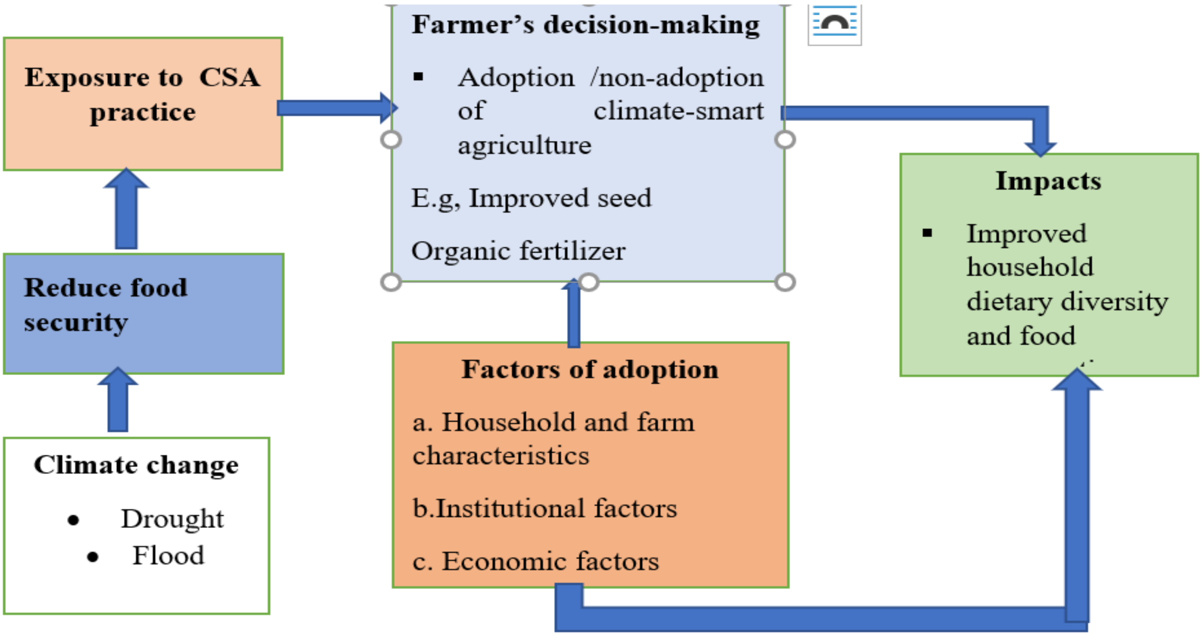
The outcomes have been outstanding. Compared to conventional methods, farmers have shown an average increase in yields of 9–15% while consuming 70–75% less seed, 20–25% less nitrogen fertilizer, and 33% less water. Their income has increased by US$95–260 per hectare throughout each farming season as a result. Using fewer inputs has also led to improvements in the environment and farmers' health, according to reports(Pieters et al., 2019).

2.8. Conceptual Framework

Various social, economic, and technological elements have a crucial role in determining the current fluctuation of the climate. Unchecked population development, land degradation, periodic droughts, unpredictable rainfall, and resource mismanagement are a few examples of causes that will probably raise the possible amount of material assets that are vulnerable to the hazards associated with climate change(FAO, 2013). The effects of these climate changes on agriculture and farming include decreased yields, crop damage and loss, and animal losses, among other things. In many marginal environments, less rainfall can prove to be a limiting factor for crops. Increased frequency of temperature spikes may harm plants, and extended drought may cause crops to perish. Yields can be drastically decreased by slight temperature fluctuations during critical growth phases (FAO, 2013).

In this sense, climate-smart agriculture explicitly takes into account the hazards posed by climate change, which is occurring more quickly and intensely than in previous years. To better the lives of people who are still trapped in food insecurity and poverty and to avoid undoing the progress that has already been made, new climate threats necessitate adjustments in agricultural technologies and techniques. The implementation of climate-smart agriculture is contingent upon the accessibility of essential resources, encompassing not only monetary and environmental resources but also expertise, technological aptitude, and institutional assets. Therefore, the sociodemographic (education level, sex, age, and dependency ratio) and economic (on-farm income, total livestock unit (TLU), land holding, and irrigation access) as well as institutional factors (credit availability, climate information, access to agricultural inputs, access to market information, and access to agricultural extension services) factors of CSA adoption are included in this study.

Additionally, a variety of CSA methods (such as biotechnology, climate-resilient crop varieties, early warning systems, conservation agriculture, and others) can be implemented. As a result, the household's food security may be impacted by these CSA practices. Food security can be measured using the following metrics: Food consumption score (average/year) (access/utilization), total calories consumed by adult equivalent per week (access), household annual net income from crop production (availability), and months of adequate HH food provisioning (stability).



Note: In this framework,

- **a.** Household and farm characteristics include age, gender, family size, education, and farm size of the household head.
- **b.** Economic factors include off-farm participation and livestock holding.
- **c.** Institutional factors include access to extension, credit, and training

Figure 1: Conceptual Framework of the Study (Source: Adopted from (FAO, 2007)

3. METHODOLOGY OF THE STUDY

3.1 The Study Area Description

The East Gojjam Administrative Zone, found in the southeast of Amhara Regional State, would be the study site. One of the ANRS's governmental regions, East Gojjam, is situated in Ethiopia's Blue Nile basin. The East Gojjam region is located 265 kilometers from Bahir Dar, the Amhara region's headquarters, and 300 kilometers from Addis Abeba, Ethiopia. This area is bordered to the south by the Oromia region, to the east by South Wollo, to the west by West Gojjam, and to the north by South Gondar. According to (BoFED , 2015)The East Gojjam zone has a total population of 2.45 million. According to (BoFED , 2015)The zone covers 14,010 square kilometers (1.40 million hectares). Elevations in East Gojjam range from 800 to 4200 meters above sea level (masl), including a wide range of geographical features. According to (Alemayehu & Bewket, 2016), the East Gojjam Zone is located in northwest Ethiopia at coordinates 9.900° to 11.193°. According to data from the Zonal Agricultural Office, the zone's topographic features are normally 7.8% mountainous,67.3% flat, and 24.9% canyon. Kolla accounts for 5.45% of the region's total area, followed by Weyina Dega (80.55%), Dega (11.9%), and Wurich (2.1%), which together comprise the four major agro-ecological zones of Eastern Gojjam (Amare & Adelekan, 2018). The average rainfall ranges from 900 to 1800 mm, and the precipitation pattern is predominantly unilateral. According to (BoFED, 2015)The region's average temperature ranges from 7.5 °C to 27 °C (Amare & Adelekan, 2018).

East Gojjam zone is one of the high-potential crop production locations in ANRS, according to the Zonal Office of Agriculture (2019), with a marketable surplus for the metropolitan markets(Agegnehu et al., 2020). The ability to grow a variety of crops is made possible by the availability of adequate and diverse agroecologies. Evidence suggests that 641 thousand hectares of land annually generate roughly 25 million quintals of various crops. Cereals are the dominant crop in this instance, accounting for 72% and 78%, respectively, of the zone's total crop production and cultivated land. Pulses (11%), oilseeds (4.3%), and potatoes (5.3%) are other important crops in terms of area coverage, while other crops are minor with area coverage below 1% (Agegnehu et al., 2020) Teff is the most important cereal crop, producing around 23% of all food grains and taking up roughly 30% of all food grain cultivation land. Wheat (22.5%), sorghum (5 %), barley (9.5%), faba bean (5.3%), maize (13.7%) , haricot bean (2.7%), sesame (3%), and triticale (2%), are additional significant crops in terms of area coverage (Agegnehu et al., 2020).

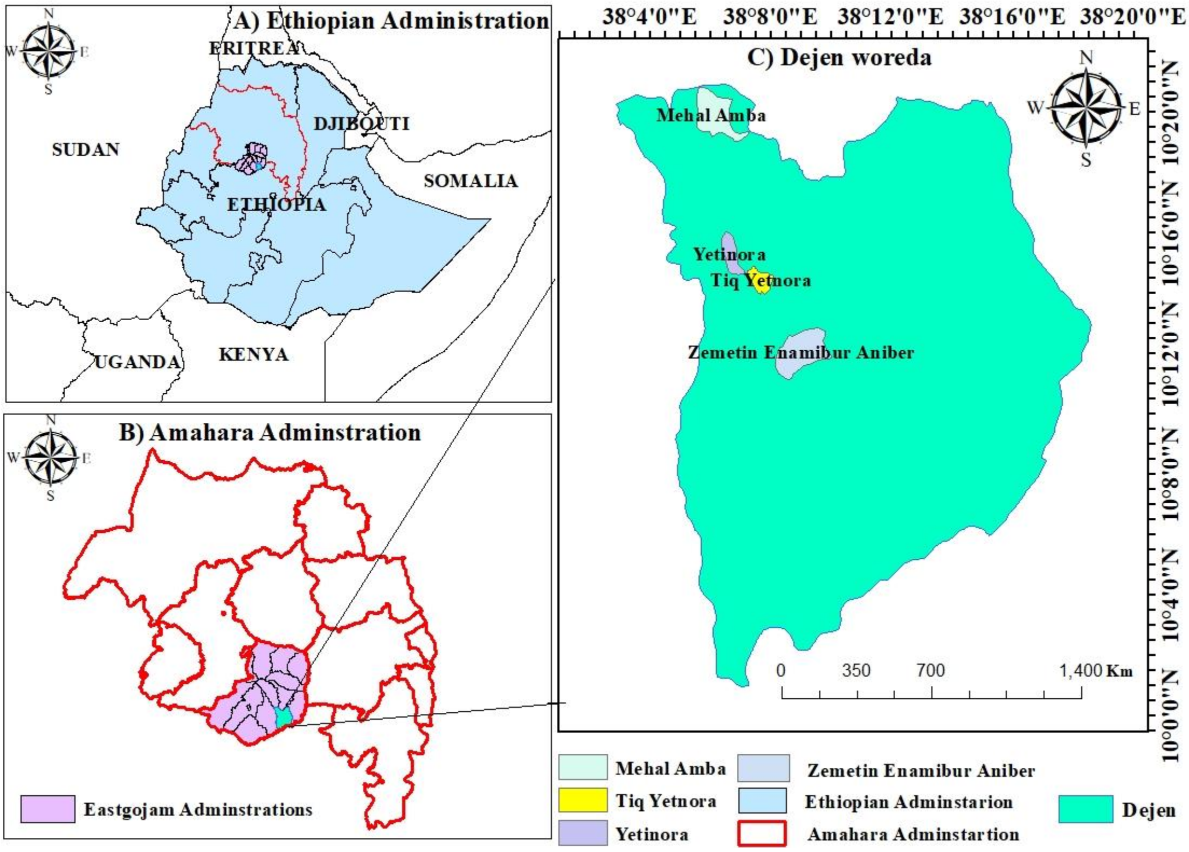


Figure 2: Map of the study area (source: own construction using Arc GIS version 10:8)

East Gojjam Administrative Zone in the Amhara Regional State consists of 17 Woredas, including Dejen Woreda, which is located in northwestern Ethiopia. Positioned in the southeastern part of the Amhara region, Dejen Woreda lies approximately 230 kilometers north of Addis Ababa. It is nearly enclosed by the Abbay River and its tributaries. Geographically, Dejen Woreda is situated between 10°01'00"N and 10°21'00"N (CSA, 2014) . It shares borders with Awabel Woreda to the west, the Oromia region to the south, Shebel-Berenta Woreda to the east, and Debay-Tilatgin and Enemay Woredas to the north.

Covering an area of approximately 570.9 km² ((CSA, 2014) Dejen Woreda is relatively small compared to other Woredas in East Gojjam. Its climate, like much of Ethiopia, is primarily influenced by altitude, though latitude and cloud cover also contribute to local variations. The Woreda features three distinct agroecological zones: kola, woina-dega, and dega, resulting from significant topographic differences. The woina-dega zone accounts for 48% of the land area, while kola and dega cover 39% and 13%, respectively. According to the Dejen Woreda

Agriculture Office (2018), the district experiences average temperatures ranging between 20 and 24°C, with an annual rainfall of 800 to 1200 mm (Amare & Adelekan, 2018)

3.2. Research Design

With both quantitative and qualitative elements, this study employed a cross-sectional research methodology for primary data and a longitudinal design for time series climate data. The cross-sectional design is both cost- and time-effective. The data can be used for a range of research projects because it captures a single moment in time and includes numerous variables at that time. This study, therefore, used a cross-sectional research strategy to gather data from a sample chosen to represent the entire population in the study locations at a particular moment. Therefore, the study used descriptive statistics, Methods include surveys, interviews, case studies, and observations on the study area.

3.3. Sampling Procedure and Sampling Techniques

Purposive and simple random sampling will be combined in a random multistage sampling method to choose the study areas and sample respondents. At the primary stage, one woreda of the East Gojjam zone was sampled purposively based on its covering large CSA practices and technologies. This method is chosen because, in light of the study's context-specific Climate-smart practices, it reduces the possibility of bias and helps produce a more representative sample of respondents. Then, three kebeles (lower administrative units) were selected at random from the assigned woreda. In the second phase, households were chosen proportionately from each of the three kebeles using a systematic random sampling technique. In this case, the list of the total households in each kebele was first secured from the respective kebeles‘ offices to be used as a sampling frame.

Several issues constrained the study's sample size. Constraints such as resources, logistics, human resources, budgets, and time constraints affect the sample size of the study. Therefore, an optimal, manageable, and representative sample size should be used when inferring the population. Various scholars have developed sample size determination techniques. Among these methods, prior researchers have frequently employed Yamane's (1967) sample size calculation technique. For instance, (Endalew et al. 2024) used the Yamane formula to calculate the sample size for their study on climate-smart agriculture practices and their effects on household food security in rural kebeles of the Dire Dawa Administration in Ethiopia.

However, due to many factors like heterogeneity and finite population, this research employed Cochran's formula to determine sample size from the population. It is intended especially for circumstances in which the population number is well-known and relatively small. This equation will be used to calculate the necessary sample size to guarantee a representative sample and trustworthy results. The margin of error, the required level of confidence, and the population percentage of those possessing a specific characteristic or attribute are all taken into account by Cochran's formula. Besides this, the reason I am using this formula is due to the following reasons

Representative sample: Cochran's formula is utilized to guarantee that the sample selected is representative of the complete population. A larger sample size reduces the likelihood of bias and increases the accuracy of the results.

Statistical power: Researchers can get enough statistical power by determining the sample size using Cochran's formula. The ability of a study to identify real effects or links is referred to as statistical power. A greater sample size improves the study's power, increasing the likelihood that significant outcomes Were discovered.

Precision and reliability: The intended margin of error and level of confidence are taken into account by Cochran's formula. Researchers can guarantee the accuracy and dependability of their study results by determining the sample size based on these considerations. The margin of error is decreased and the accuracy of the estimations is increased with a greater sample size.

Ethical considerations: The use of human beings in research requires adherence to ethical standards. Using Cochran's formula to calculate an acceptable sample size guarantees that the sample size is neither too small, which could produce inconclusive results, nor too large, which could expose too many people to unnecessary risks or obligations connected with participation.

Cochran's formula $\quad \mathrm{n} = \frac{Z^2\mathrm{PQ}}{(\mathrm{e}2)}$

Where p = population proportion n = sample size Q=1-P ,e = the error term (margin of error)

The study employs a 95% confidence level, corresponding to a Z-score of 1.96, with a margin of error of 0.06

$$n = \frac{Z^2 PQ}{(e2)} = \quad n = \frac{1.96^2 * 0.5(1 - 0.5)}{(0.65^2)} = 267$$

to increase the precision level, I take four more samples, and the total sample will be 271

The study area encompasses 1500 households, distributed across three Kebeles: Yetenora (600 households), Tik (500 households), and Zemeten (400 households).

The sample proportions are calculated as follows :

- Kebele 1 (yetnora)(600 HH): 600 / 1500 = 0.4
- Kebele 2(Tik) (500 HH): 500 / 1500 = 0.3333
- Kebele 3(Zemetin) (400HH): 400 / 1500 = 0.266

Allocate Sample Size Proportionally:

- Yetnora: 271 * 0.4 = 108.4 (round to 108 HH)
- Tik: 271 * 0.3333 = 90.5 (round to 91 HH)
- Zemetin : 271 * 0.2667 = 72.2 (round to 72HH)

3.4. Sources and Types of Data

Data sources from both primary and secondary sources were included. To collect primary quantitative data, a small sample of families was interviewed using a semi-structured questionnaire. Data was gathered on household production, dietary diversity (HDDS), land ownership, climate-smart agricultural methods, household dietary caloric intake, and the socioeconomic traits of farmers.

The primary data was collected not only from sample respondents but also from key informants such as agriculture office experts and extension agents. Key informants, as well as agricultural and rural experts, will be interviewed informally to gather qualitative data. The general purpose of qualitative data is to be collected to check the consistency of household survey responses and to identify important questions that the questionnaire does not capture.

Secondary data was gathered through document review at district-level agriculture and natural resource offices, micro-enterprises, central statistics agencies, and other governmental and non-governmental organizations. The sources of secondary information include yearly reports, statistical organizations, published and unpublished papers (in the library and office), published films on the internet, bulletins, and graphics in the districts.

3.5. Method of Data Collection

A structured questionnaire was created to gather primary data, and its completeness, clarity, and applicability would be pretested on ten respondents. In response to input from pretested respondents, the questionnaire was modified. To gather primary data, the sample respondents were interrogated using the modified questionnaire. In addition, primary data was formally collected by interviewing non-sampled, informed individuals (key informants) utilizing a checklist. Furthermore, primary/qualitative data were gathered by field observation in the study districts. Reviewing published and unpublished materials (CSA, journals, Agricultural Office, and Agricultural Research Institute) was used to collect secondary data. The following is a description of several common data collection techniques.

Interview scheduling: Semi-structured survey questions were created to gather information from sampled household heads based on the investigator's expertise and related types of literature. By focusing on the dietary information of the respondents, a 24-hour dietary recall survey was conducted to gather food category information for the household's food intake. The interview schedule for the household includes demographic, socioeconomic, and institutional elements as well as other topics pertaining to the factors that influence climate-smart farming and its impact on household food security.

Focus group discussion: Three focus group discussions (FGDs) with (8-12) participants each were held with farmers (including women, youth, and elders' groups) held three times to gather information about their attitudes toward CSA practices in rural study areas, the types of CSA practices they use, and their perceptions of the occurrence of climate variability and change. Closed-ended, structured questionnaires may have overlooked important details, but the focus of the focus group discussions (FGD) would allow for the collection of such data.

Key informant interview: Key informant interviews include development agents, kebele leaders, and non-sampled experienced farmers. Key informants were selected based on their long experience and knowledge that they have regarding climate-smart farming five key informants were interviewed

3.6. Method of Data Analysis

Descriptive statistics and econometric models were among the data analysis techniques used to analyze the data. Two statistical software programs, STATA 17 and SPSS version 26, were used in the study. Principal component analysis (PCA), descriptive statistics, and data entry were all done using SPSS version 26, whereas complicated econometric models like the multinomial endogenous switching regression model (MESRM) were done using STATA 17. F-tests, chi-squares, averages, and percentages were some of the descriptive statistics. To find the main CSA practices that are made up of sets or combinations of practices, a PCA was utilized. Factors influencing the adoption of potential combinations of CSA behaviors were examined using the two-stage MESRM model, and the impact of these activities on household HDDS and FCS was assessed.

3.6.1 Principal component analysis

First, the main CSA processes used in the study area were identified and grouped using PCA. Because the technique eliminates circumstances when only a few practices adequately represent the entire group and make drawing conclusions about it challenging, it is more effective than a normal grouping of activities. The orthogonal rotation method, often known as the Varimax approach, was used to rotate the components. By grouping less highly connected activities under each component, the Varimax approach facilitates comprehension and permits group generalizations (B. M. Wekesa et al., 2018).

The model below illustrates how farm households' CSA activities were grouped using PCA with iteration and varimax rotation by (B. M. Wekesa et al., 2018), as shown in the model below.

$$Y_1 = a_{11}x_{11} + a_{12}x_2 + \cdots + a_{1n}x_n \text{ ....(1)}$$

$$Y_j = a_{j1}x_{j1} + a_{j2}x_2 + \cdots + a_{jn}x_n \text{............(2)}$$

Where $Y_1, .. Y_j$= uncorrelated principal components, $a_1, .. a_n$= the correlation coefficient, and $x_1 to\ x_j$= factors affecting the selection of a particular practice.

Principal component analysis was used to identify and categorize the Climate-Smart Agriculture (CSA) activities. A recent study by Eshete et al. (2020) that was carried out before the field research helped to guide the choice of these techniques. The Food and Agriculture Organization of the United Nations' documentation of CSA technology and techniques used in Ethiopia, as well as the successful CSA methods created by Jirata et al. (2016), also aided in the selection processMultinomial Logit (MNL) Model: selection equation

After categorizing the CSA practices, the MNL model was applied to analyze the determinants influencing the adoption of various CSA practice combinations. In this analysis, the dependent variables represented different possible CSA practice combinations, while the independent variables identified the factors affecting their adoption.

It was believed that farm households would optimize their welfare, Yi, by comparing the income generated by M potential CSA practice combinations.. The condition for a farm household i to choose any practice, j over other alternatives M is that $Y_{ij} > Y_{iM}$ where $M \neq j$ that is j provides higher expected welfare outcome variables than any other practice.

Household dietary diversity and food consumption score are two predicted welfare outcome variables that are captured by the latent variable ${Y_{ij}}^*$. Both the observed and unobserved features of the farm and farmer households have an impact on this latent variable. Thus, the following is a possible way to write the expression for ${Y_{ij}}^*$

${Y_{ij}}^* = X_i\beta_j + \varepsilon_{ij}$ ……..(3)

where the error term ε_ij represents unobserved qualities and X_i represents observed attributes of the farm families. Since the anticipated value of $\varepsilon_{ij}$is given by $E(\varepsilon_{ij}|X_i = 0$ It is expected that the covariate vector X_i is uncorrelated with the characteristic unobserved stochastic component ε_{ij}. Furthermore, by the Gumbel distribution, we assume that the errors $\varepsilon_{ij}$are independently and identically distributed. This matches the inappropriate alternatives (IIA) hypothesis (Bourguignon et al., 2007). Consequently, the multinomial logit model (McFadden, 2001) that results from the selection model derived from equation (3) has the following probability of selecting the strategy$j(P_{ij})$.

$P_{ij} = P\left(\varepsilon_{ij} < 0|X_i\right) = \frac{\exp\,(X_i\beta_j)}{\sum_{M=1}^{j}\exp\,(X_i\beta_M)}$ ……….(4)

The "mlogit" tool in Stata Statistical Software (STATA 17) was used to estimate the MNL model in equation (4).

3.6.2.Multinomial endogenous switching regression model: Outcome equation

Using the selection bias correction model, the study used an MNESRM to investigate how different response CSA methods affected household food security (Bourguignon et al., 2007)The study's base group was the farm household with no CSA practices (j=0). Therefore, the welfare result equation is as follows for each potential regime (j):

$$\begin{cases} Regime\ 1: W_{i1} = X_i\gamma_1 + v_{i1}\ ,\ if\ \ i = 1 \\ \quad\quad\quad\quad\quad\quad\quad . \\ \quad\quad\quad\quad\quad\quad\quad . \\ \quad\quad\quad\quad\quad\quad\quad . \\ Regime\ j: W_{ij} = X_i\gamma_j + v_{ij},\ if\ \ i = j \end{cases} \quad \text{…………(5)}$$

where Xi is the vector of other covariates, v_{ij} is the unobserved stochastic component with zero as the conditional expected value, $E(v_{ij}/X_i) = 0$, and $var(v_{ij}) = \delta_j^2$. W_{ij}Is the welfare indicator of the ITH household in the regime $j, i = 1,2,3 \ldots N, j = 1,2,3, X_i$. If CSA procedures j are utilized, what happens when $Y_{ij}{}^* > {}^{max}_{M\neq 1}(Y_{im})$, and the error terms in equations (4) and (5) are not independent, then W_{ij} is observed. Consequently, it was discovered that the conventional least squares estimates for equation 5) were biased. The selection adjustment terms must be included in equation (5) in order to obtain a consistent estimation of the parameter γ_n for the different selections. The linearity assumption that underpins the MESRM is expressed as follows: $E(v_{ij}|\varepsilon_{i1} \ldots\ \varepsilon_{ij} = \delta_j \sum_{m\neq j}^{j} r_j(\varepsilon_{im} - E(\varepsilon_{im}))$ The correlation between the error terms in equations (4) and (5), by construction. With this presumption, eq. (5) can be written like this:

$$\begin{cases} Regime\ 1: W_{i1} = X_i\gamma_1 + \delta_1\lambda_1 + \omega_{i1}\ ,\ if\ \ i = 1 \\ \quad\quad\quad\quad\quad\quad\quad\quad . \\ \\ \quad\quad\quad\quad\quad\quad\quad\quad . \\ Regime\ j: W_{ij} = X_i\gamma_j + \delta_j\lambda_j + \omega_{ij}\ ,\ if\ \ i = j \end{cases} \quad \text{...……(6)}$$

The error terms in equation (6) with an expected value of zero are represented byω_{ij}, while the covariance between ε's and v is represented by δ_j. The estimated probabilities in equation (11) are used to compute the inverse Mills ratio, λ_j, as follows:

$$\lambda_j = \sum_{m\neq 1}^{j} \rho_j \left[\frac{\rho_{im}\ln(\rho_{im})}{1-\rho_{im}} + \ln(\rho_{ij})\right] \text{…………(7)}$$

ρ_j is the correlation coefficient between ε and υ in Equation (7). Due to the two-stage estimating procedure, the heteroskedasticity created by the generated regressors, represented byλ_j, was addressed by using a bootstrapping strategy to the standard errors in Equation (6) (Wekesa *et al*., 2018).

Utilizing selection instrumental factors that are automatically produced by the selection model's non-linearity is crucial to guarantee the identification of the outcome equation (Falco & Veronesi, 2014) Only through the adoption of CSA practices can these instrumental variables affect the welfare outcome indicators, and it is hypothesized that they have a direct impact on CSA practice adoption.

3.6.3. Estimation of average treatment effects

The average treatment effects on the treated and untreated were computed based on the previously indicated context by comparing the expected outcomes of the treated (adopters) and untreated (non-adopters) under real (actual) and unreal (counterfactual) circumstances (Falco & Veronesi, 2014).

For adopters of a specific CSA practice alternative, the real predicted value of welfare outcome variables is provided by:

CSA practice is given by:

$$E(W_{i2}|i = 2) = X_i\gamma_2 + \delta_2\lambda_2 \tag{8}$$

Adopters had decided not to adopt (counterfactual):

$$E(W_{i1}|i = 2) = X_i\gamma_1 + \delta_1\lambda_2 \tag{9}$$

For non-adopters (actual):

$$E(W_{ij}|i = j) = X_i\gamma_j + \delta_j\lambda_j \tag{10}$$

Non-adopter decided to adopt (counterfactual):

$$E(W_{1j}|i = j) = X_i\gamma_1 + \delta_1\lambda_j \tag{11}$$

Last but not least, in accordance with (Kassie et al., 2015), the average treatment impact on treated (ATT) and average treatment effect on untreated (ATU) might be calculated by deducting, respectively, equations (9), (8), and (10) from equation (11).

$$ATT = E(W_{i2}|i = 2) - E(W_{i1}|i = 2) \quad (12)$$

$$ATU = E\left(W_{1j}\middle|i = j\right) - E\left(W_{ij}\middle|i = j\right) \quad (13)$$

3.7. Variables Definitions and Working Hypotheses

3.7.1. Dependent variable

The dependent variable in this study is the adoption of a possible combination of CSA techniques. A pre-test of the interview schedule was first carried out to select CSA activities that are often utilized by households, carried out in the study region, and included in the questionnaire. Principal component analysis was then used to group the CSA practices that had been found. The farmer was then presented with a choice of n (13 in this study) combinations of j (3 packages) component practices that support the availability of food in the home as well as the diversity of the household diet. These choices included not adopting any CSA practices, adopting one or a few CSA practices, and adopting all CSA practices at once.

3.7.2. Outcome variables

A gauge of food security in the home: Living a long, healthy life free from hunger and starvation is known as food security. A person can afford a weighted average of 2200, according to the Ethiopian government (FAO, 2016b). Calories a day are regarded as food insecurity if it is less than 2200. Numerous instruments, such as the Household Dietary Diversity Scale (HDDS), Household Daily Calorie Consumption, and Household Food Insecurity Access Scale (HFIAS), can be used to evaluate food security (FAO, 2016b). However, the food security of participants and non-participants in the study area who practiced climate-smart farming was assessed using two instruments: the Household Dietary Diversity Scale and the Household Food Consumption score.

The Household Dietary Diversity Scale (HDDS): The number of food types consumed by the household respondent throughout the 24-hour recall period was added to determine the household dietary diversity score, a measure of the household's financial availability to food

(FAO, 2016b). Respondents were asked if they ate any of the 12 food groups. According to (Artificial Intelligence Index Report 2021), their "yes" answers were coded as 1 and their "no" answers as 0. Next, each of the extra food categories' dietary diversity variable values are added. For HDDs, the ultimate score could range from 0 to 12. A higher score meant that a wider variety of food groups were present in the diets of the households. Low, medium, and high levels of dietary variety are indicated by HDDS values of 3, 4, and 6, respectively.

Food Consumption Score: A popular tool for assessing dietary diversity, frequency of consumption, and food quality is the food consumption score (FCS). FCS, which was created by the (WFP ,1996)and quoted by (Marivoet, 2019), takes into account different food types and gives them weighted scores according to their nutritional worth. Because it records both dietary diversity and nutritional adequacy over 7 days, this technique is more thorough than HDDS and HHS (WFP, 2008). The relative nutritional values of the food types consumed are then used to weight this data. Foods having high nutritious content, for instance, are valued higher than those with low nutritional value, like tubers. A household's food intake can be divided into three groups based on this score: acceptable, marginal, and poor. The food consumption score, according to (Marivoet, 2019), is a ballpark estimate of how many calories are accessible in the home. As a result, this serves as the study's stand-in for food security.

3.7.3. Independent variables

It was anticipated that the explanatory elements of the multinomial logit model will influence farm households' adoption of CSA methods. A wide range of factors were included in these variables, including economic factors (like livestock ownership and household participation off-farm), institutional factors (like access to extension, credit, and training), and household and farm characteristics (like age, gender, education, experience of the household head, household size, and farm size). The empirical literature that has already been reviewed and the real-world circumstances in the study region that can be used to explain the dependent variable were taken into consideration while choosing the independent factors for this investigation. Consequently, in line with empirical research (Atinkut & Mebrat, 2016; Berhanu, 2016; Assen & Ashebo, 2018; Gebru *et al*., 2019; Kassa and Abdi, 2022; Belachew *et al*., 2020; Asfew *et al*., 2023; Kifle *et al*., 2022; Teklu *et al*., 2023), the explanatory variables are described, along with the descriptive statistics that go with them and their expected sign.

Age of household head (Age): Age, measured in years as a continuous variable, represents the age of the household head (Berhanu Sr et al., 2016; Gabia et al., 2022). This study posits that the household head's age may influence the adoption of climate-smart agriculture (CSA) practices either favorably or unfavorably, based on previous empirical findings. Elder farmers are frequently more inclined to adopt new technologies due to their extensive agricultural experience, access to resources, and greater decision-making power (Berhanu Sr et al., 2016; Gabia et al., 2022). However, a reported inverse relationship between household head age and CSA adoption suggests that younger farmers tend to be more open to adopting innovative agricultural techniques.

Gender of household head (Gender): If the head of the family is a man, this is a categorical variable that returns 1, and if not, it returns 0. In farm households, it is thought that men are more likely than women to use CSA techniques. The cause for this is that men generally have more access to and authority over land and other productive resources. Male farmers are more likely to employ CSA practices, according to Ethiopian researchers (Negera et al., 2022).

Education of household head (Education): The educational background (number of years of schooling) of the family head determines this continuous variable. The use of CSA approaches was believed to benefit from higher education. Higher educated farmers are more inclined to embrace CSA strategies because they are seen as having the ability to evaluate and comment on new methods. This is due to the fact that education is a crucial socioeconomic factor that encourages farmers to embrace CSA and fosters a positive attitude regarding the implementation of innovative farming techniques.. For example, (Belachew et al., 2020) have demonstrated that education has a major impact on the adoption of new technology and processes.

Household size (AE): Adult equivalent (AE) was used to measure it, and a good result was anticipated. The household's income can be greatly increased and the workload can be divided among many family members. Farmers have the chance to adopt cutting-edge CSA methods since they can readily apply them and increase their income due to the size of their domestic workforce. The household will have enough labor and be more inclined to employ agricultural practices if the majority of family members are of working age (Berhanu Sr et al., 2016; Gabia et al., 2022).

Table 2. : Explanatory Variables hypothesized to affect CSA practice in the study area

Independent variable	Description and measurement	Category of variable	Exp. sign
Age of the household head (AGEHH)	The number of years since the birthdate	Continuous	+
Sex of household head (SEXHH)	If the head of the household is male, 1; otherwise, 0	Dummy	+/-
Education level of household head (EDLHH)	1, if the household is literate 0, otherwise	Continuous	+
Family Size (FAMSZ)	The number of individuals living in a single home	Continuous +/_	
Farm size (FAS)	Size of cultivated land in hectares	Continuous	+
Non-farm income (NFI)	Annual income in ETB from off-farm income	Continuous	+
Livestock holding in TLU (LIVEHOLD)	Livestock holding in TLU	Continuous	+
Frequency to extension services (EXT-SERV)	The number of visits by extension agents annually	Continuous	+
Access to climate information (CLIMINFO)	1 = if HHH has access to climate information, 0 = otherwise	Dummy	+
Access to credit (CREDIT)	1 = access to credit, 0 = no credit	Dummy	+
Access to training to CSA	1 = if access to irrigation, 0 = no irrigation	Dummy	+
Economically active labor size (LABOR)	Number of economically active members of the family	Continuous	+/-
Membership of Cooperatives (MCOOP)	1 if Household membership to Cooperatives 0, if otherwise	Dummy	+

Farm Size:Farm size, a continuous variable measured in hectares, was expected to have a beneficial effect on farmers' adoption of CSA tactics. Some CSA strategies are more likely to be invested in by larger farmers. According to other scholars who have reached the same conclusion, farmers can lower risks to their productivity by diversifying their crops and livestock and using novel agricultural practices on larger land holdings. The studies of (Belachew et al., 2020; Kassa & Abdi, 2022), for instance, support this viewpoint. Furthermore, as evidenced by their research on the adoption patterns of climate-smart agricultural innovations for sustainable farming (Negera et al., 2022) claim that farmers with small land holdings are less likely to adopt numerous technologies.

Access to extension service (Extension): This continuous variable must be visited by the extension agent. In light of climate change, agricultural extension services assist farmers in comprehending the advantages of CSA practices and boosting agriculture (Fantay Gebru et al., 2019). Therefore, farmers are more probably to understand the advantages that CSA methods can offer to their agricultural output in the face of climate change if they have greater access to knowledge and technical help about agricultural operations (Asfew et al., 2023). Therefore, it was anticipated that the adoption of CSA practices would benefit from having access to extension services. Research by Asfew et al. (2023) has consistently demonstrated that farmers are more likely to adopt CSA methods when they have more access to extension services.

Access to credit (Credit): Credit availability is considered a categorical variable in this study. A value of 1 is given if the respondent has access to credit, and a value of 0 otherwise.. Credit makes it possible for farmers to buy essential supplies like fertilizer and better crop varieties. The availability of financial facilities is a major motivator for farmers to adopt policies like crop diversification, animal feeding, and soil water conservation, according to a study by Belachew et al. (2020) and Berhanu Sr et al. (2016).

They found that the adoption of CSA methods was negatively correlated with loan availability. According to these researchers, households that have access to financing are more likely to prioritize non-farm activities to improve their standard of living than to implement water and soil conservation measures.

Training on CSA practices: Training in this study refers to instruction provided to farmers in the study region on various CSA practices pertaining to issues like livestock management and soil-water management. It was anticipated that this variable, which was evaluated as a binary indicator, would increase the probability of CSA practice adoption. The following are some definitions of the explanatory variables and anticipated signs for the study's Logit Model.

Participating in CSA training provided by development agencies may increase farmers' awareness of CSA techniques (Babu et al., 2017 ; Belay et al., 2024). Thus, it was expected that training would significantly and favorably influence the adoption of CSA practices.

Access to weather/climate information: It was represented by a dummy variable that showed whether households could obtain weather information (1) or (0). Farmers are more likely to adopt CSA practices if weather and climate change information is available via a range of platforms, such as social media, weather services, extension agents, and the media. This access improves understanding and establishes ideal conditions for farmers to conduct their operations by giving them access to current weather data. Farmers' understanding of climate change, for instance, has a favorable impact on the adoption of high-yielding crop varieties that can withstand drought, improved agronomic practices, and soil and water conservation measures (Negera et al., 2023).

Off-farm participation (Off_farm): Since it was a dummy variable, its value would be 1 if a farm household participated in off-farm activities and 0 otherwise. CSA is more common among households with an off-farm source of income than among those without, according to Assen and Ashebo (2018) and Kifle et al. (2022). As a result, it was expected that farmers who used CSA practices would positively correlate with those who engaged in off-farm revenue-generating activities.

Total Livestock Holdings (Livestock): The total number of animals in tropical livestock units (TLU) is measured by this metric. Large livestock holdings can be used as assets by household farmers to make money, which can assist in defraying the expenses of introducing new CSA practices. (Berhanu, 2016) discovered that the adoption of CSA methods, like soil/stone bund terraces, was positively and significantly impacted.

4. RESULTS AND DISCUSSION

4.1. Climate Trends of Dejen Woreda

According to the National Meteorological Agency of Ethiopia, increasing temperatures and decreasing precipitation are indicators of climatic variability and change (EMI, 2017). Significant geographical variations exist in temperature and rainfall as well. A history of CC extremes, including drought and flood, as well as increasing and decreasing trends in temperature and precipitation, respectively, are other characteristics of Ethiopia's climate. Every decade, there has been a 0.37°C increase in the country's average annual minimum temperature and a 0.1 °C increase in the average annual maximum temperature(EMI, 2017). There was a general tendency for rising annual variability in the temperature distribution in the studied area. One of the factors influencing the local climate and weather patterns is temperature. The high and low temperatures are noted on a daily, monthly, and annual basis

4.1.1. Trend analysis of temperature

Over recent decades, Dejen Woreda in the East Gojam Zone of Ethiopia has experienced notable changes in temperature patterns, reflecting broader regional trends. Studies indicate a consistent increase in both maximum and minimum temperatures across various parts of Ethiopia. For instance, research analyzing data from 2001 to 2016 in Dejen, Ethiopia, found that all stations experienced an increasing trend in mean maximum temperature, with rates ranging from 0.01°C to 0.09°C per year. Similarly, mean minimum temperatures showed positive trends, with increases between 0.01°C and 0.06°C per year. These findings align with the national trend of rising temperatures observed over the past decades.

While specific temperature records for Dejen Woreda are limited, regional data provide insight into local climate behavior. In the Upper Blue Nile basin, which encompasses areas near East Gojam, studies have reported increasing trends in both minimum and maximum temperatures. For example, between 1984 and 2014, Jimma station recorded a significant increase in both maximum and minimum temperatures, with annual average temperatures rising by approximately 0.046°C per year. These regional trends suggest that Dejen Woreda has likely experienced similar warming patterns. However, due to the lack of localized data, it's challenging to pinpoint the warmest and coldest years or provide precise temperature values for

Dejen Woreda. For detailed and specific temperature records, consulting the Ethiopian Meteorological Institute is recommended.

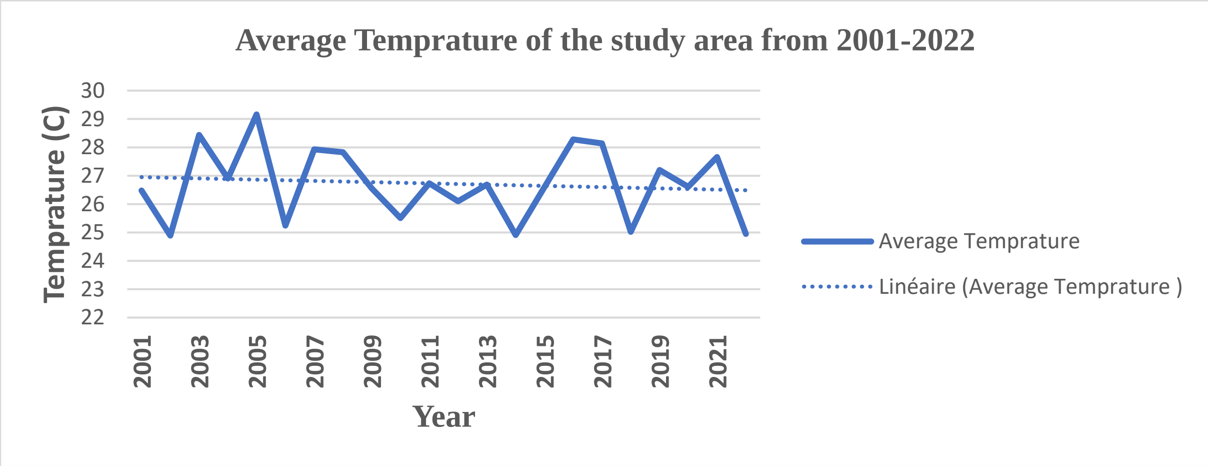


Figure 3. The trend in maximum, minimum & average precipitation of Dejen Woreda

Source: EMI, 2025

4.1.2. Trend analysis of annual rainfall

Ethiopia has three distinct seasons, according to (EMI, 2017)Bega (winter), Kiremt (summer), and Belg (spring). The Belg is Ethiopia's brief rainy season from February to May. Throughout this season, a considerable amount of rain falls on large areas of the northeast, center south, east, and south-east of the nation. Kiremt (June–September) is the main rainy season in the majority of Ethiopia, with the exception of the lowlands in southern and southeast Ethiopia. With the exception of the lowlands in south and southeast Ethiopia and the southwest, Bega (October–January) is primarily a dry season.. The research region has had an annual rainfall range of 189.4 mm at the lowest and 965.9 mm at the highest throughout the previous three decades(EMI, 2017). The historical precipitation trend indicates that while some years experience high rainfall, precipitation patterns have an increasing irregularity. This variability in rainfall affects water availability and crop productivity, making climate-resilient farming practices essential.

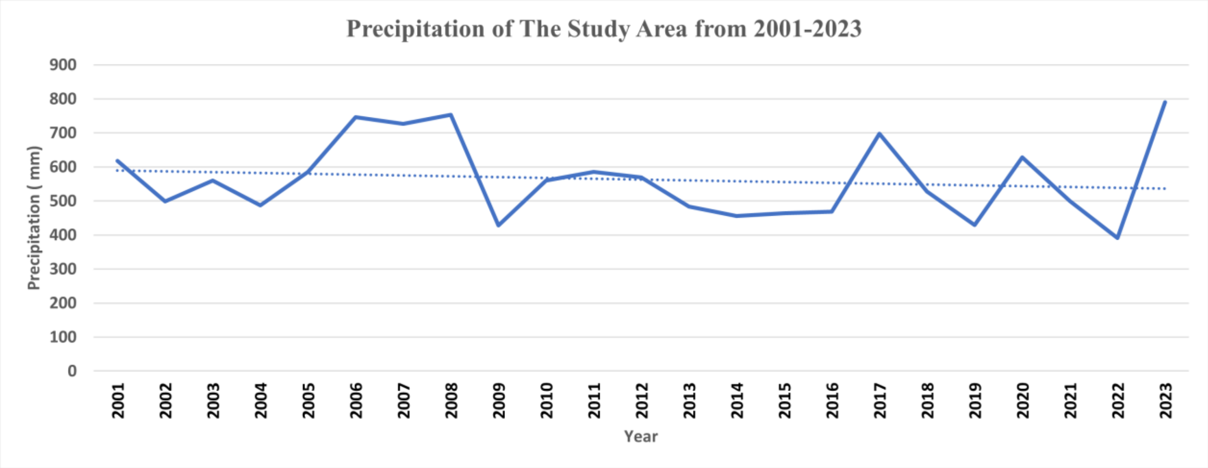


Figure 4. The trend in maximum, minimum & average precipitation of Dejen Woreda (Source: EMI, 2024)

4.1.3.Trend analysis of humidity

Relative humidity in Dejen Woreda has also exhibited a changing pattern over time. Historical data indicates that average humidity levels have fluctuated around 55%, with some years experiencing higher moisture levels. Future projections suggest a potential increase in relative humidity, reaching 58% under a low-emission scenario (SSP1-2.6) and exceeding 64% under a high-emission scenario (SSP5-8.5) by the end of the century. These increases in humidity could influence evapotranspiration rates, plant growth conditions, and disease prevalence, particularly affecting agricultural productivity and human health.

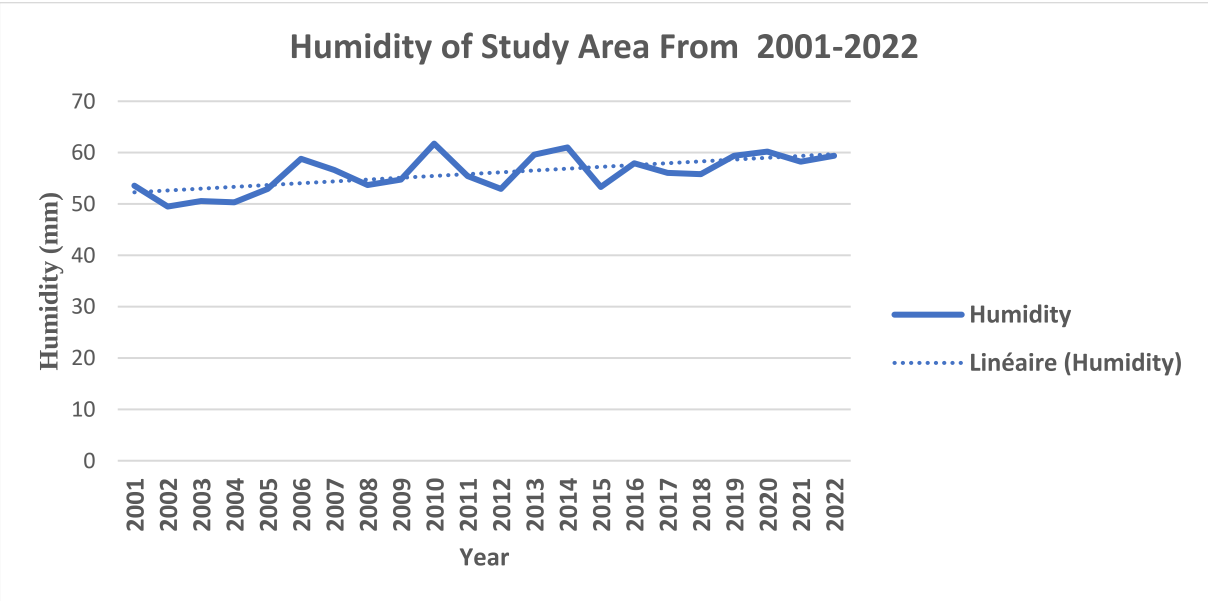


Figure 5.The trend in maximum, minimum & average humidity of Dejen Woreda Source: EMI, 2024

4.2. Climate forecasting of Dejen woreda

Dejen Woreda experiences a predominantly subtropical highland climate, heavily influenced by seasonal rainfall patterns driven by the Intertropical Convergence Zone (ITCZ)(EMI, 2023). Climate forecasting for this region shows considerable variability in precipitation and temperature, attributed to both natural climatic fluctuations and anthropogenic climate change. Historical trends indicate that the woreda is highly dependent on the kiremt rainy season (June to September) for agricultural productivity, which accounts for over 70% of the annual rainfall(EMI, 2023). However, recent forecasts predict increasing irregularity in the timing and intensity of these rains, leading to heightened vulnerability to droughts and floods. These changes, alongside rising temperatures, are expected to impact crop yields, water availability, and rural livelihoods(EMI, 2023).

According to studies using regional climate models like CORDEX-Africa, Dejen Woreda is predicted to gradually warm, with mean temperatures rising by 1.5°C to 2.0°C by the middle of the twenty-first century under scenarios with moderate emissions (Tegegne et al., 2021). Though less definite, precipitation estimates indicate increasingly unpredictable rainfall patterns, including a possible rise in extreme weather events like dry spells and heavy downpours. In order to increase resilience, climate-smart agriculture and better water resource management are required. Dejen Woreda can lessen the negative effects of climate change while preserving food security and ecosystem services by implementing early warning systems and sustainable land-use practices (Tegegne et al., 2021).

The following graphs provide a detailed depiction of the projected temperature, precipitation, and relative humidity trends

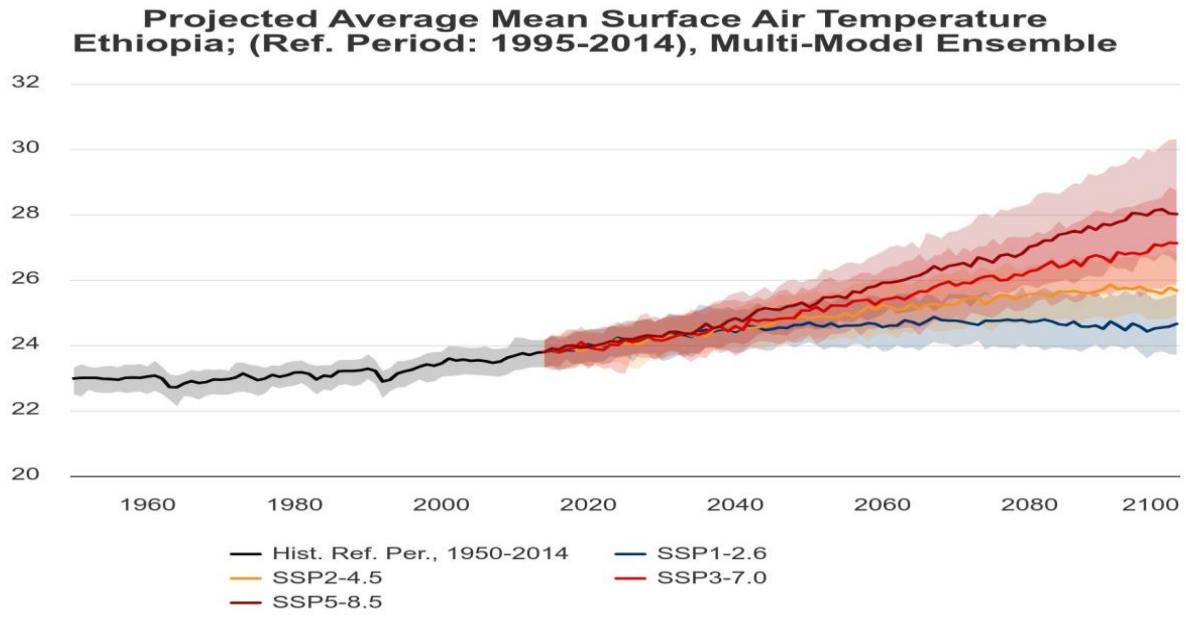


Figure 6 The projected average mean surface temperature of Ethiopia(source:https://climateknowledgeportal.worldbank.org/, 2024)

This graph illustrates the projected trends in Ethiopia's average mean surface air temperature from 1950 to 2100, using a multi-model ensemble. The black line represents historical data for the period 1950–2014, during which the temperature remained relatively stable, ranging from approximately 22°C to 24°C. This period serves as the baseline for comparison with future climate scenarios. The shaded region around the black line indicates the variability and uncertainty in historical temperature estimates.

Based on four unique Shared Socioeconomic Pathways (SSPs)—SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 the graph forecasts temperature changes starting in 2015. According to Shared Socioeconomic Pathways (SSP1-2.6), temperatures will rise slightly and stabilize at about 24.5°C by the end of the century, assuming low emissions and robust mitigation actions. This scenario depicts a hopeful future in which greenhouse gas emissions are successfully reduced by international cooperation.

In contrast, SSP5-8.5 assumes high emissions and minimal climate action, resulting in a steep and continuous temperature rise. By 2100, this pathway predicts average temperatures exceeding 30°C, with significant warming beginning as early as the mid-21st century. SSP3-7.0 and SSP2-4.5 represent intermediate scenarios with moderate to high emissions, showing temperature increases between those of SSP1-2.6 and SSP5-8.5. Notably, SSP3-7.0 indicates more rapid warming than SSP2-4.5 due to delayed or insufficient mitigation efforts.

Overall, the graph highlights the profound impact of global emissions trajectories on Ethiopia's future climate. Under high-emission scenarios, Ethiopia could experience severe warming, exacerbating the risks of climate-related encounters such as droughts, decreased agricultural efficiency, and heat stress. Conversely, achieving the low-emission pathway of SSP1-2.6 could help limit temperature increases, reducing the severity of potential impacts. This emphasizes the urgency of global climate mitigation efforts to protect vulnerable regions like Ethiopia

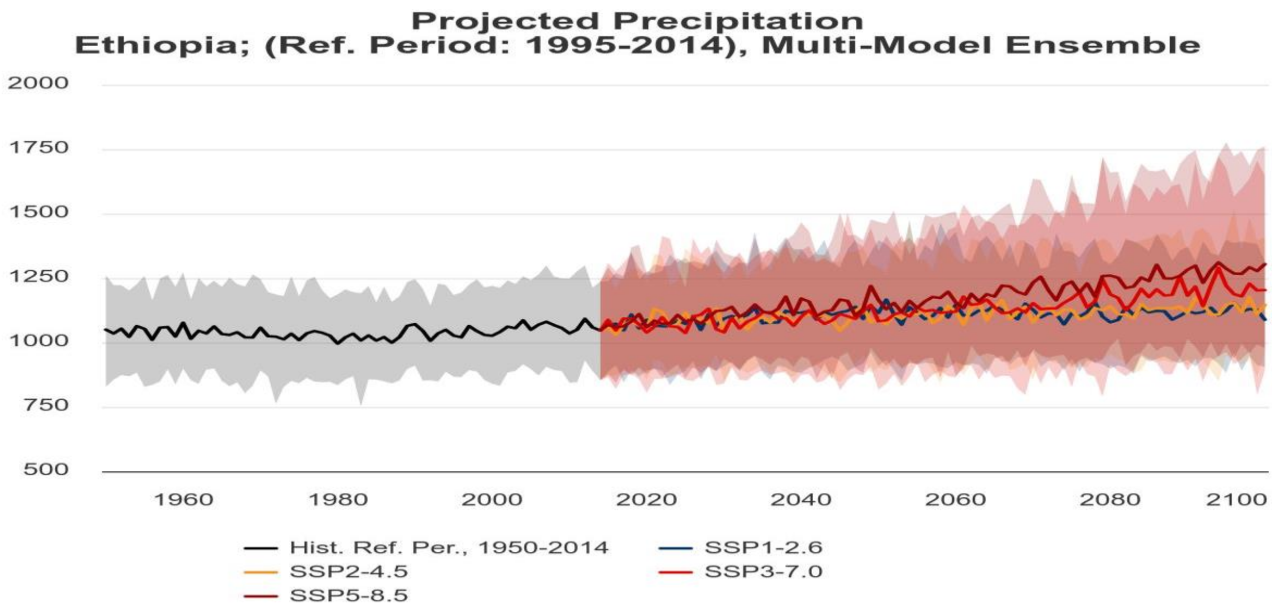


Figure: 7 The projected precipitation of Ethiopia(source:https://climateknowledgeportal.worldbank.org/, 2024)

The graph presents projected precipitation changes for Ethiopia over the period 1960 to 2100, based on a multi-model ensemble. The reference period for the historical data is 1995-2014. The graph includes four scenarios: SSP3-7.0, SSP1-2.6, SSP2-4.5, and SSP5-8.5 are indicators of varying degrees of socioeconomic development and greenhouse gas emissions.

Historical Precipitation: The black line in the graph represents the historical precipitation for the reference period (1995-2014). It shows a relatively stable pattern with some fluctuations around the average value of approximately 1000 mm. The shaded area around the line indicates the uncertainty in the historical data.

Projected Precipitation Trends: The colored lines represent the projected precipitation for the four scenarios. Overall, the projections suggest a general increase in precipitation over the 21st century. However, the magnitude and timing of the increase vary across the scenarios.

SSP1-2.6: This scenario is predicated on rapid socioeconomic development and low greenhouse gas emissions.. The projection shows a gradual increase in precipitation, with the average value reaching around 1250 mm by 2100. The uncertainty band is relatively narrow, indicating a higher level of confidence in this projection.

SSP2-4.5: This scenario assumes moderate greenhouse gas emissions and moderate socioeconomic development. The projection shows a more pronounced increase in precipitation compared to SSP1-2.6, with the average value reaching around 1400 mm by 2100. The uncertainty band is wider than in SSP1-2.6, reflecting greater uncertainty in this scenario.

SSP3-7.0: This scenario assumes high greenhouse gas emissions and slower socioeconomic development. The projection shows a significant increase in precipitation, with the average value reaching around 1600 mm by 2100. The uncertainty band is the widest among all scenarios, indicating the highest level of uncertainty in this projection.

SSP5-8.5: This scenario assumes very high greenhouse gas emissions and slow socio-economic development. The projection shows the most dramatic increase in precipitation, with the average value exceeding 1800 mm by 2100. The uncertainty band is also very wide, reflecting the high level of uncertainty in this scenario.

One important conclusion from the graph is that Ethiopia is probably going to see more precipitation in the future, with the amount of the rise varying according to the degree of socioeconomic growth and greenhouse gas emissions. While all scenarios show an increase, the higher emission scenarios (SSP5-8.5 and SSP3-7.0) project a more substantial rise in precipitation. It is crucial to remember that there is uncertainty surrounding these forecasts, especially as the century goes on.

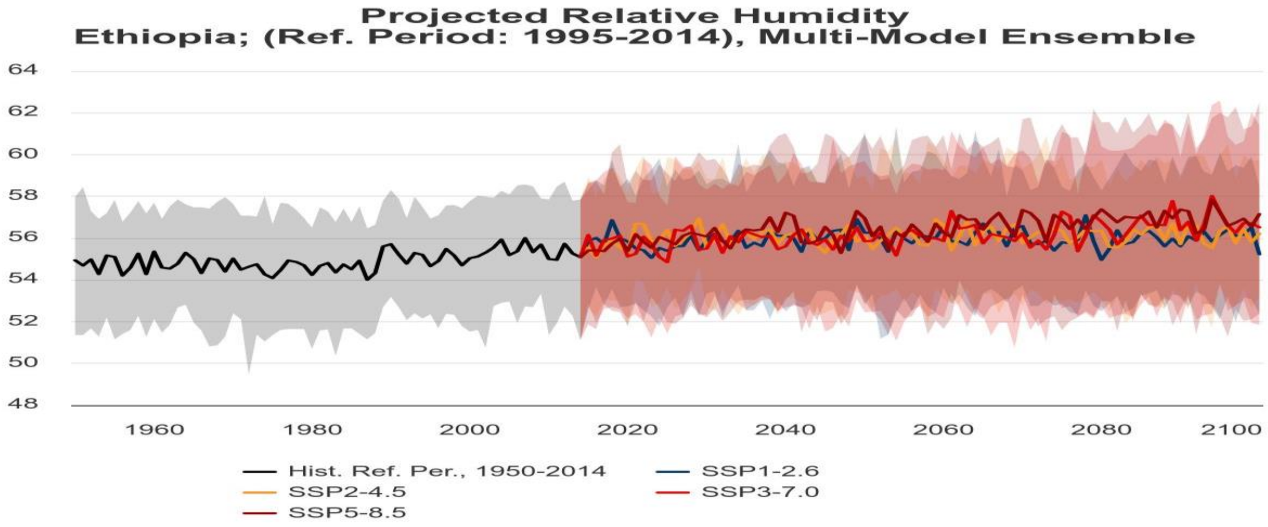


Figure:8 The projected relative humidity of Ethiopia(source:https://climateknowledgeportal.worldbank.org/, 2024)

Similarly, this graph also presents projected relative humidity changes for Ethiopia over the period 1960 to 2100, based on a multi-model ensemble. In the same way the reference period for the historical data is 1995-2014. The graph includes four scenarios: SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5, which represent different levels of greenhouse gas emissions and socioeconomic development.

Historical Relative Humidity:The black line in the graph represents the historical relative humidity for the reference period (1995-2014). It shows a relatively stable pattern with some fluctuations around the average value of approximately 55%. The shaded area around the line indicates the uncertainty in the historical data.

The colored lines represent the projected relative humidity for the four scenarios.

SSP1-2.6: This scenario assumes low greenhouse gas emissions and rapid socioeconomic development. The projection shows a gradual increase in relative humidity, with the average value reaching around 58% by 2100. The uncertainty band is relatively narrow, indicating a higher level of confidence in this projection.

SSP2-4.5: This scenario assumes moderate greenhouse gas emissions and moderate socioeconomic development. The projection shows a more pronounced increase in relative humidity compared to SSP1-2.6, with the average value reaching around 60% by 2100. The uncertainty band is wider than in SSP1-2.6, reflecting greater uncertainty in this scenario.

SSP3-7.0: This scenario assumes high greenhouse gas emissions and slower socioeconomic development. The projection shows a significant increase in relative humidity, with the average value reaching around 62% by 2100. The uncertainty band is the widest among all scenarios, indicating the highest level of uncertainty in this projection.

SSP5-8.5: This scenario assumes very high greenhouse gas emissions and slow socio-economic development. The projection shows the most dramatic increase in relative humidity, with the average value exceeding 64% by 2100. The uncertainty band is also very wide, reflecting the high level of uncertainty in this scenario.

In general, the graph indicates that Ethiopia is likely to encounter elevated levels of relative humidity in the future. The extent of this increase is contingent upon greenhouse gas emissions and socioeconomic development trajectories. While all scenarios project an upward trend, the higher emission scenarios (SSP3-7.0 and SSP5-8.5) foresee a more substantial rise in relative humidity.

The study's findings are presented and discussed in this chapter, with appropriate attention paid to the goals of the investigation. The descriptive results and analytical conclusions about CSA practices and their effects on food security are examined separately for the purpose of clarity and easy of comprehension.

4.3. Identification and Grouping of Climat Smart Agriculture Packages Used By Farmers

Farm households in the research area actively apply fourteen (13) climate-smart agriculture (CSA) methods, as shown in Table 4. Principal component analysis (PCA), which divided linked practices into discrete components according to their usage patterns, was used to methodically group these behaviors. This method worked well since it made it possible to incorporate grouped practices into the model for additional research and stronger findings. Less highly connected activities are combined under each component in the Varimax approach, facilitating group generalizations and easy comprehension. (A. M. Wekesa & Otieno, 2022) cited by(Fana et al., 2024). Unlike traditional grouping methods, PCA enhances accuracy by allowing the representation of an entire group through a subset of practices, thus facilitating more precise and reliable findings.

As the perception paradigm suggests, farmers' decision is shaped by the perception that CSA positively impacts improving food security (Uaiene & Arndt, 2019)Table 4 presents thirteen

(13) climate-smart agriculture (CSA) practices utilized by farm households in the study area. The most widely adopted practice is applying organic fertilizer, with a user percentage of 69.90%. Users of crop rotation follow this at 64.21% and users of improved seed at 43.17%. Other practices include early maturing crop varieties used by 36.16% of respondents, users of small-scale irrigation at 35.06%, mixed/intercropping at 33.12%, users of pesticides at 31.73%, hillside terraces at 29.15%, mulching at 28.04%, minimal tillage at 27.31%, check dams at 19.19%, rainwater harvesting at 14.39%, and using improved post-harvest technology at 11.44%. This study focuses on the top three practices used by farmers in the study area to identify factors affecting their participation and to evaluate their impact on food security.

Table 4: Climate-smart agriculture practices used by farmers in the study area

Name of CSA Practices	Users		Non-users	
	Frequency	Percentage	Frequency	Percentage
Applying organic fertilizer	184	67.90	87	32.10
Using Crop Rotation	174	64.21	97	35.79
Using Improved Seed	117	43.17	154	56.83
Using Early maturing crop varieties	98	36.16	173	63.84
Use Small scale irrigation	95	35.06	176	64.94
Mixed/Inter cropping	90	33.12	181	66.79
Using pesticides	86	31.73	185	68.27
Hillside Terraces	79	29.15	192	70.85
Mulching	76	28.04	195	71.96
Minimal Tillage	74	27.31	197	72.69
Check dams	52	19.19	219	80.81
Rain Water Harvesting	39	14.39	232	85.61
Using improved post-harvest technology	31	11.44	240	88.56

Sources: Own Constracted From Survey 2025

The adoption of various combinations of climate-smart agriculture (CSA) practices significantly influences household expenditure on food consumption and dietary diversity (Table 5). Based on the results of the Principal Component Analysis (PCA), household farmers can select from eight possible combinations of CSA practices. Table 5 presents these combinations, revealing that farmers adopted five out of the eight possible packages.

Notably, 12.9% of farmers did not adopt any CSA practices ($F_0Cr_0I_0$). About 19.2% adopted the $F_0Cr_1I_0$ package, which involved only crop rotation, while 20.3% utilized the $F_1Cr_1I_1$ package, incorporating crop rotation, improved seeds, and organic fertilizer. Additionally, 22.9% of farmers adopted the $F_1Cr_0I_1$ package, which combined organic fertilizer and improved seeds. The largest proportion, 24.7%, adopted the $F_1Cr_1I_1$ package, integrating organic fertilizer and crop rotation.

According to these results, most farmers would rather use CSA methods in combination than alone. A plan to increase income and attain food security in the face of climate change is reflected in this method. The findings are in line with those of (M. Hailemariam et al., 2019), who found that most Ethiopian farmers used integrated CSA techniques to enhance their agricultural output.

Table 5: Identification of the combination of climate-smart agriculture practices used by farmers

Choose (j)	Packages	F=Applying organic fertilizer		Cr= Using Crop Rotation		I= Using Improved Seed		Frequency	Percentage
		F_0	F_1	Cr_0	Cr_1	I_0	I_1		
1	$F_0Cr_0I_0$	✓		✓		✓		35	12.9%
2	$F_0Cr_1I_0$	✓		✓			✓	52	19.2%
3	$F_0Cr_1I_1$	✓			✓		✓	0	0.0%
4	$F_1Cr_1I_1$		✓		✓		✓	55	20.3%
5	$F_1Cr_1I_0$		✓		✓	✓		67	24.7%
6	$F_1Cr_0I_0$		✓	✓		✓		0	0.0%
7	$F_1Cr_0I_1$		✓	✓			✓	62	22.9%
8	$F_0Cr_0I_1$	✓			✓	✓		0	0 %
Total								271	100

Own constructed from Survey 2025

The potential CSA packets are represented by the binary triplicate. For a CSA combination, each of the three elements in triplicate—organic fertilizer (F), crop rotation (Cr), and improved seed (I)—is a binary variable. Adoption is indicated by subscript 1 and otherwise by 0.

4.4. Descriptive Statistics of the Variables

4.4.1. Descriptive statistics of the explanatory variables

The study looks at several variables that affect the uptake of climate-smart agriculture (CSA) techniques. Tables 6 and 7 categorize and summarize these variables, with Table 6 showing dummy variables and Table 7 showing continuous variables. The F-test for continuous variables and the chi-square test for dummy variables were used to examine the connections and variations between the various groups of CSA practice adopters. These variables' descriptive statistical findings are described.

Categorical /Dummy Variables

The sex of respondents is an important parameter in determining CSA practices in the households (Abay et al., 2019). This is mainly significant because all decisions within the rural household are centered on the head of that household. The data indicate that 91.51% of households were male-headed, while only 8.49% were female-headed. Examining the sex distribution across CSA adoption groups reveals distinct patterns. Among farmers who did not adopt any CSA practice ($F_0Cr_0I_0$), 91.43% of the 35 respondents were male-headed, with 8.57% female-headed. For those adopting only crop rotation ($F_0Cr_1I_0$), 96.15% of the 52 respondents were male-headed, and 3.85% were female-headed. In contrast, respondents adopting all CSA practices—organic fertilizer, crop rotation, and improved seeds ($F_1Cr_1I_1$)—were 94.55% male-headed out of 67 respondents.

Furthermore, 91.04% of the 62 respondents who adopted organic fertilizer and crop rotation ($F_1Cr_1I_0$) were male-headed, while 8.96% were female-headed. Lastly, among respondents adopting organic fertilizer and improved seeds ($F_1Cr_0I_1$), 85.48% were male-headed, and 14.52% were female-headed. Despite the evident dominance of male-headed households, the Chi-square value (χ^2=5.01) suggests that the association between household head sex and CSA adoption is not statistically significant.

The results indicate that access to training on climate-smart agriculture (CSA) practices is unevenly distributed among different groups of adopters. The proportion of farmers who received training varies significantly, with the lowest training participation observed among non-adopters (45.71%) ($F_0Cr_0I_0$), and those adopting only crop rotation (44.23%)($F_0Cr_1I_0$). In contrast, higher percentages of training participation were reported among households adopting more comprehensive practices, such as organic fertilizer with improved seeds (70.97%) ($F_1Cr_1I_0$), and the full combination of CSA practices (76.36%)$F_1Cr_1I_1$). This highlights a trend where greater adoption of CSA practices correlates with higher access to training opportunities.

The chi-square test revealed a statistically significant relationship between training access and the five groups of CSA adopters at the 1% significance level. This suggests that training is one of the primary elements impacting the adoption of CSA practices. The higher adoption rates among populations with better access to training demonstrate the need of targeted capacity-building initiatives to promote sustainable agricultural practices and boost household resilience to climate hazards.

According to the study, 87.08% of respondents reported having access to weather information, while 12.92% did not. Access to climate information is a critical factor in the adoption of climate-smart agriculture (CSA) practices, as demonstrated by the consistently high access rates across all groups. Access ranged from 77.14% among non-adopters ($F_0Cr_0I_0$) to 94.03% among households adopting organic fertilizer with improved seeds ($F_1Cr_1I_0$), which had the highest rate of access. This finding underscores the pivotal role of weather information in enabling the adoption of advanced CSA practices. Farmers who adopted crop rotation only ($F_0Cr_1I_0$) reported an 88.46% access rate, Farmers who adopted organic fertilizer and improved seed together had 82.26 %($F_1Cr_0I_1$), while those adopting all CSA practices together ($F_1Cr_1I_1$) reported 89.09% access. The results of the chi-squared statistical test for the sampled households' Access to Climate Information revealed that, at a 1% significance level, there was a significant difference ($\chi^2 = 7.52$) between the two groups. The results are in line with those of (MULUNEH et al., 2022), who stated that a crucial policy intervention to promote the adoption of sustainable agriculture practices is the fast, accurate, and targeted transmission of weather information.

Regarding credit access, 66.42% of the total respondents had access to credit, while the remaining 33.58% did not. The statistical analysis reveals varying levels of credit access across the adoption groups: 37.14% for non-adopters ($F_0Cr_0I_0$), 75% for those adopting crop rotation only ($F_0Cr_1I_0$), 89.09% for households adopting all CSA practices ($F_1Cr_1I_1$), 64.18% for those adopting organic fertilizer with improved seeds ($F_1Cr_1I_0$), and 58.06% for farmers adopting organic fertilizer with crop rotation ($F_1Cr_0I_1$).

Table 6: Summary statistics of dummy explanatory variables.

	Adoption of a possible combination of CSA practices						Chi^2 value
Variables	$F_0Cr_0I_0$ N=35 %	$F_0Cr_1I_0$ N=52 %	$F_1Cr_1I_1$ N=55 %	$F_1Cr_1I_0$ N=67 %	$F_1Cr_0I_1$ N=62 %	All sample N=271 %	
Sex (Male=1)	91.43	96.15	94.55	91.04	85.48	91.51	5.01
Access to Climate_inf (Yes=1)	77.14	88.46	89.09	94.03	82.26	87.08	7.52 ***
Access to Labor during pick season (1=yes)	74.29	73.08	76.36	88.06	75.81	78.23	5.26
Cooperative membership(1= yes)	37.14	59.62	89.09	35.82	37.10	51.66	47.1***
Access to Credit (Yes=1)	37.14	75.00	89.09	64.18	58.06	66.42	29.9***
Access to training to CSA (Yes=1)	45.71	44.23	76.36	56.72	70.97	41.34	17.92***

Sources: Own constructed from Survey 2025. Note: * and *** mean significance at 10%, and 1% respectively. N and % are numbers and percentages, respectively.

Credit access and CSA adoption are statistically significantly correlated across all five groups, according to the chi-square test (χ^2 = 29.9), with differences being significant at the 1% probability level. This outcome is consistent with the findings of (Fana et al., 2024) ,which highlight how important finance availability is in encouraging the use of climate-smart agriculture (CSA) techniques. The availability of credit enables farmers to make investments in necessary technologies and inputs, allowing them to successfully adopt productive and sustainable farming methods.

Access to labor during peak seasons is a critical factor influencing the adoption of climate-smart agriculture (CSA) practices. The study indicates that 78.23% of farmers had access to labor during peak seasons, while 21.77% did not. Labor access varied across adoption groups, with 74.29%, 73.08%, 76.36%, 88.06%, and 75.81% of farmers accessing labor among those adopting $F_0Cr_0I_0$, $F_0Cr_1I_0$, $F_1Cr_1I_1$, $F_1Cr_1I_0$, and $F_1Cr_r0I_1$, respectively.Households adopting organic fertilizer with improved seeds ($F_1Cr_1I_0$) reported the highest labor access (88.06%), suggesting that labor availability is essential for implementing more labor-intensive practices. The results show that labor availability has a supportive role in encouraging the adoption of CSA, especially for practices that require higher labor input, even though the chi-square test does not show a statistically significant difference between the groups. This emphasizes how crucial it is to guarantee labor access in order to promote the use of sustainable farming methods.

Cooperative membership was an important variable to get agricultural inputs. The results indicate that 51.66% of the sampled households were cooperative members, highlighting the critical role of collaborative participation in fostering resource access and community engagement. Conversely, 48.34% of households were non-members, revealing a considerable gap in cooperative involvement that could impact resource access and adopting sustainable practices. Cooperative membership varied significantly across CSA adoption groups, with membership rates of 37.14%, 59.62%, 89.09%, 35.82%, and 37.10% among farmers adopting nothing ($F_0Cr_0I_0$), adopting crop rotation only ($F_0Cr_1I_0$), adopting organic fertilizer, crop rotation, and improved seeds together ($F_1Cr_1I_1$), adopting organic fertilizer and crop rotation($F_1Cr_1I_0$), and adopting organic fertilizer with improved seed ($F_1Cr_r0I_1$)practices, respectively. The Chi-square statistic (χ^2=47.1) further demonstrates a strong and statistically significant association between cooperative membership and CSA adoption levels, significant at the 1% level and complements the results of (MULUNEH et al., 2022).

The age of the respondents has a substantial impact on the rate at which agricultural families adopt climate-smart agriculture (CSA) methods. The average age of all sampled respondents in this study was found to be 48.07 years (shown in Table 7). When analyzed across the CSA adoption groups, the mean ages were 47.29, 48.52, 44.67, 47.79, and 51.44 years for $F_0Cr_0I_0$ (Nonadopters), Only crop rotation adopters ($F_0Cr_1I_0$), Respondents adopted all packages

($F_1Cr_1I_1$), organic fertilizer and crop rotation adopters ($F_1Cr_1I_0$), and respondents adopted organic fertilizer and improved seed ($F_1Cr_0I_1$), respectively. The F-test results (F-test=3.13) indicated a statistically significant difference in mean ages among the five groups, with the variation being significant at the 5% level. This finding highlights the role of age as a critical factor influencing the adoption of CSA practices.

Education is a crucial instrument for informing farmers generally and spreading new extension innovations. Additionally, it plays a critical function in raising people's awareness of opportunities for earning a living and is seen to be a major element in the adoption of practices and technology. This study also examined the sampled household head's level of education. The average number of years of education completed by all participants was 4.82, according to the research findings. The mean education for nonadopters ($F_0Cr_0I_0$), Only crop rotation adopters ($F_0Cr_1I_0$), Respondents adopted all packages ($F_1Cr_1I_1$), organic fertilizer and crop rotation adopters ($F_1Cr_1I_0$), was found to be 1.49,3.65,7.04,5.33,5.18 respectively. The result of the F-test for the difference in the educational status of the sampled households between the Different groups confirmed that there was a statistically significant difference (F-test = 59.07) at a 1% significance level.

When evaluating smallholder farmers' food security, especially in light of the effects of climate-smart agriculture (CSA) practices, land is a crucial consideration. In this regard, the study discovered that the studied households' average landholding size was 2.88 hectares, with a standard deviation of 0.88 hectares. While comparing the groups in the average land holding of the respondents 2.60,2.48,3.18,2.95 and 3.04 were to be the mean land holding size for nonadopters ($F_0Cr_0I_0$), Only crop rotation adopters ($F_0Cr_1I_0$), Respondents adopted all packages ($F_1Cr_1I_1$), organic fertilizer and crop rotation adopters ($F_1Cr_1I_0$), and respondents adopted organic fertilizer and improved seed ($F_1Cr_0I_1$), respectively. Participants and non-participants in CSA activities had a statistically significant mean difference at a 1% significance level, according to the results of the F-test (6.11) for the groups' average landholding differences.

Similarly, the average family size, measured in adult equivalents across all sampled respondents, was 4.79 persons, with a standard deviation of 1.46 (Table 7). When disaggregated by adoption categories, the mean family size was found to be 4.63 for non-adopters ($F_0Cr_0I_0$), 4.71 for respondents who adopted only crop rotation ($F_0Cr_1I_0$), 4.78 for those who adopted all three packages ($F_1Cr_1I_1$), 4.76 for adopters of organic fertilizer and crop rotation ($F_1Cr_1I_0$), and

4.97 for respondents who adopted organic fertilizer and improved seed ($F_1Cr_0I_1$). There was a statistically negligible difference in the average family size of participants and non-participants, according to the F-test result (F-test = 0.38), which was also in line with the findings of Muluneh et al. (2022).

Annual income from crop production, livestock and their products, and other income from non-farm activities are important sources of cash income for small-holder farmers. Earning higher annual income smoothens the financial problem and eases the farmer‘s decision to participate in new agricultural technologies. The study expected that respondents would be reluctant to mention their real annual income due to difficulty in remembering their income as a result of a lack of record keeping.Accordingly, the survey result found that the mean annual income from crop production was 7226.13ETB with a standard deviation of 2451.3 for the total sampled respondents. Additionally, the mean annual income of each categorization was found to be 5060.86ETB,5672.12ETB,9376.36ETB,7655.22ETB, and 7380.65ETB for nonadopters ($F_0Cr_0I_0$), Only crop rotation adopters ($F_0Cr_1I_0$), Respondents adopted all packages ($F_1Cr_1I_1$), organic fertilizer and crop rotation adopters ($F_1Cr_1I_0$), and respondents adopted organic fertilizer and improved seed ($F_1Cr_0I_1$), respectively. The F-test result (F = 34.84) confirmed a statistically significant difference in average nonfarm income between different groups.

With a standard deviation of 0.93, respondents in the research area had an average of 1.88 encounters with agricultural extension workers annually. For each of the adoption categories, the average number of extension contacts was as follows. 1.50 for non-adopters ($F_0Cr_0I_0$), 1.50 for crop rotation-only adopters ($F_0Cr_1I_0$), 2.42 for respondents who adopted all packages ($F_1Cr_1I_1$), 1.82 for adopters of organic fertilizer and crop rotation ($F_1Cr_1I_0$), and 2.13 for adopters of organic fertilizer and improved seed ($F_1Cr_0I_1$). The F-test result (F = 14.10) confirmed that Extension contact is a statistically significant variable.

Additionally, the average livestock holding of the sampled households, measured in Tropical Livestock Units (TLU), was found to be 4.55 TLU, with a standard deviation of 2.65. Disaggregating the livestock holdings by adoption categories, the mean livestock holdings were 2.96 TLU for non-adopters ($F_0Cr_0I_0$), 4.01 TLU for crop rotation-only adopters ($F_0Cr_1I_0$), 6.42 TLU for respondents who adopted all packages ($F_1Cr_1I_1$), 4.29 TLU for adopters of organic fertilizer and crop rotation ($F_1Cr_1I_0$), and 4.51 TLU for adopters of organic fertilizer and improved seed ($F_1Cr_0I_1$).The result of the F-test (F = 12.52) It was determined that, at a 1%

significance level, there was a statistically significant difference between the average livestock holdings of the groups and those who did not engage in CSA practices (Table 7).

Table 7: Summary statistics continuous explanatory variables

	Adoption of a possible combination of CSA practices						
Variables	$F_0Cr_0I_0$ N=35 Mean (SD)	$F_0Cr_1I_0$ N=52 Mean (SD)	$F_1Cr_1I_1$ N=55 Mean (SD)	$F_1Cr_1I_0$ N=67 Mean (SD)	$F_1Cr_0I_1$ N=62 Mean (SD)	All sample Mean (SD)	F-value
Age	47.29 (10.89)	48.52 (10.83)	44.67 (10.09)	47.79 (11.26)	51.44 (9.33)	48.07 (10.64)	3.13**
Education	1.49 (1.07)	3.65 (1.43)	7.04 (3.12)	5.33 (1.16)	5.18 (1.24)	4.82 (2.44)	59.07***
Farm size	2.60 (0.97)	2.48 (1.02)	3.18 (1.13)	2.95 (0.39)	3.04 (0.697)	2.88 (0.88)	6.11***
AE	4.63 (1.31)	4.71 (1.50)	4.78 (1.41)	4.76 (1.47)	4.97 (1.56)	4.79 (1.46)	0.38
Non/off-farm income	5060.86 (1814.7)	5672.12 (1808.8)	9376.36 (2271.9)	7655.22 (1856.1)	7380.65 (2141.1)	7226.13 (2451.3)	34.84***
Extension	1.26 (0.89)	1.50 (0.92)	2.42 (0.60)	1.82 (1.03)	2.13 (0.76)	1.88 (0.93)	14.10***
TLU	2.96 (2.69)	4.01 (2.20)	6.42 (2.34)	4.29 (2.41)	4.51 (2.62)	4.55 (2.65)	12.52***

Source:Own survey results . Note: ** and *** mean significant at 5% and 1%, respectively. The numbers in the parenthesis are the standard deviation (SD).

4.5. Food Security Status of The Household

4.5.1. Household dietary diversity

To evaluate the food security status of the farm households, Household Dietary Diversity Scores and Household Food Consumption Scores (HFCS) were also used as stand-ins for farmers' food security.These WFP-developed instruments are frequently used as stand-ins for food access(WFP, 2009).

The Household Dietary Diversity Score (HDDS), which counts the number of food types ingested during a given reference period, was one of the primary food security metrics used in this study. The HDDS was determined in this study using a 24-hour dietary recall approach that included 12 food groups. According to the findings, the average HDDS for the entire sample was 5.67, with a 1.71 standard deviation . When disaggregated by adoption categories, the mean HDDS values were as follows: 4.67 for non-adopters ($F_0Cr_0I_0$), 5.09 for crop rotation-only adopters ($F_0Cr_1I_0$), 7.04 for respondents who adopted all CSA packages ($F_1Cr_1I_1$), 5.61 for adopters of organic fertilizer and crop rotation ($F_1Cr_1I_0$), and 5.56 for adopters of organic fertilizer and improved seed ($F_1Cr_0I_1$).

At the 1% significance level, the statistical analysis employing the F-test (F = 16.34) verified that the mean HDDS of the various adoption groups differed statistically significantly. According to these results, CSA practices—especially the whole package (F1Cr1I1)—are linked to a more varied diet, which supports the idea that CSA tactics might increase family food security.

4.5.2. Household food consumption score

The HFCS is a weighted score that takes into account the nutritional significance of the food groups ingested, food frequency, and dietary diversity. A household's HFCS is determined by multiplying the frequency of foods ingested over a seven-day period by the weight of each of the food groups. The WFP assigned weights to food classes based on their nutritional density (Bickel & Cook, 2019), (Jayawardena et al., 2013).

Accordingly, the mean HFCS for the total sampled respondents was 41.53 with a standard deviation of 13.33. When disaggregated by adoption categories, the mean HDDS values were as follows 26.54,32.65,57.39,43.23, and 41.52 for nonadopters ($F_0Cr_0I_0$), Only crop rotation adopters ($F_0Cr_1I_0$), Respondents adopted all packages ($F_1Cr_1I_1$), organic fertilizer and crop rotation adopters ($F_1Cr_1I_0$), and respondents adopted organic fertilizer and improved seed ($F_1Cr_0I_1$), respectively. Additionally, 12.9 % of the sampled respondents were found to have an FCS of 0 to 21 which is ranked poor,19.19 % of the respondents were between 21.5 to 35 which is considered as borderline, and the remaining 67.9% of the households had an FCS of more than 35 which could be regarded as acceptable. At the 1% significance level, the statistical analysis employing the F-test (F = 788.71) verified that the mean FCSHH varied statistically significantly among the various adoption groups.

Table 8: Descriptive results for the outcome variables of the sampled household.

	Adoption of a possible combination of CSA practices						
Variables	$F_0Cr_0I_0$ N=35	$F_0Cr_1I_0$ N=52	$F_1Cr_1I_1$ N=55	$F_1Cr_1I_0$ N=67	$F_1Cr_0I_1$ N=62	All sample	F-value
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	
HDDSHH	4.67 (1.43)	5.09 (1.47)	7.04 (1.94)	5.61 (1.49)	5.56 (1.33)	5.67 (1.71)	16.34***
FCSHH	20.54 (11.00)	32.65 (7.66)	57.39 (9.28)	43.23 (10.23)	41.52 (7.33)	41.53 (13.33)	78.71***

Source: Own constructed from Survey 2025. Note: *** means significant at 1%. Numbers in the parenthesis are standard deviation (SD). HDDSHH and FCSHH mean household dietary diversity and household food consumption score.

4.6. Determinants of Combination of Climate-Smart Agriculture Practices Choices

The Variance Inflation Factor (VIF ≥ 10) was used to assess multicollinearity among the explanatory variables prior to generating the MNL model. This is important because severe multicollinearity may lead to low t-ratios and estimated regression coefficients with erroneous signs, which could result in conclusions that are not accurate (Kim & Maddala, 1992). The results of the VIF analysis indicate that there are no notable multicollinearity issues with any of the explanatory variables used. The Breusch-Pagen test was also used to look for heteroscedasticity in the data. According to Appendices Tables 4, the test findings show no evidence of heteroscedasticity (p = 0.3541).

The criteria that home farmers considered when choosing among several CSA packages were assessed using the MNL selection model. The baseline for comparison was farm households (F0Cr1I0) that did not adopt any CSA techniques. Table 9 displays the marginal effects derived from the MNL model, which illustrates the expected change in the probability of a certain choice based on a unit change in an independent variable (Baiyegunhi, 2024).

According to the model results, the null hypothesis's likelihood ratio test (LR) was rejected [chi2 (52) = 420.42, p > chi2 = 0.0000]. At a significance level of less than 1%, this rejection shows that the null hypothesis which holds that all regression coefficients of all equations are simultaneously zero is rejected. This demonstrates that the independent variables have a significant impact on farm households' selection of CSA packages and validates the model's goodness-of-fit.

The findings show that a range of farm and family characteristics, institutional concerns, and economic variables all have a substantial impact on the decisions made by families when it comes to the factors influencing the selection of various CSA package combinations. This is followed by a discussion of the important variables.

Age of household head (Age): Although the significance levels vary, the MNL model's results show that age has both positive and negative relationships with the adoption of certain CSA activities. Adoption of better seed and organic fertilizer is positively correlated with age (F1Cr0I1), with a marginal effect of 0.0078 and a coefficient of 0.05 that is significant at the 5% level. This implies that farmers are more likely to use this combination every year as they get older by 0.78%. One explanation for this positive correlation could be because older farmers are more likely to embrace these methods because they have greater experience and knowledge about managing soil fertility and the advantages of enhanced seeds. However, age exhibits a weak or negative correlation with other CSA adoption combinations. For instance, in the case of non-adopters ($F_0Cr_1I_0$), all CSA adopters ($F_1Cr_1I_1$), and organic fertilizer and crop rotation adopters (F1Cr1I0), the coefficients are 0.002, 0.004, and 0.02, respectively, with marginal effects of -0.0042, -0.006, and -0.003, none of which are statistically significant. This implies that younger farmers may be less likely to adopt CSA practices, possibly due to limited access to resources and experience. Additionally, younger farmers may be more focused on short-term economic gains rather than long-term sustainability, reducing their likelihood of adopting CSA practices. The findings suggest that while older farmers benefit from their experience, younger farmers may require more targeted training and incentives to engage in climate-smart agricultural practices.

Sex of household (SexHH): At a 5% significance level, the MNL model results (Table 9) demonstrate a positive correlation between the household head's sex and crop rotation adopters (F0Cr1I0) of CSA, suggesting that female household heads are less likely to implement crop rotation. Furthermore, with a coefficient of 2.056 and a marginal effect of 0.15 at the 5% significance level, sex significantly and favorably influences the adoption of crop rotation alone. This suggests that crop rotation is 15% more common among male farmers than among female farmers. The results of the MNL model also show that some CSA adoption categories are adversely correlated with sex.. For instance, in the adoption of all CSA practices (F1Cr1I1), organic fertilizer and crop rotation (F1Cr1I0), and organic fertilizer and improved seed (F1Cr0I1), the coefficients are 0.61, 0.59, and 0.55, respectively, with marginal effects of -0.0046, -0.065, and -0.077, though not statistically significant. This suggests that female farmers are less likely to adopt these CSA combinations than male farmers. The negative correlation could be attributed to several factors, including limited access to agricultural inputs, credit, and extension services faced by female-headed households.

Education of household head (Education): Education plays a significant role in the adoption of climate-smart agriculture (CSA) practices, with both positive and negative associations observed. The results indicate that education is positively correlated with the adoption of all CSA practices ($F_1Cr_1I_1$), organic fertilizer and crop rotation ($F_1Cr_1I_0$), and organic fertilizer and improved seed ($F_1Cr_0I_1$). Specifically, the coefficient for education in the adoption of all CSA practices ($F_1Cr_1I_1$) is 3.78, with a marginal effect of 0.157, significant at the 5% level. This means that an additional year of education increases the probability of adopting all CSA practices by 15.7%. Similarly, for organic fertilizer and crop rotation adopters ($F_1Cr_1I_0$), the coefficient is 3.42, with a marginal effect of 0.062, while for organic fertilizer and improved seed adopters ($F_1Cr_0I_1$), the coefficient is 3.43, with a marginal effect of 0.058, both significant at the 5% level. This suggests that education enhances farmers' ability to understand the benefits of CSA, access relevant information, and implement improved agricultural techniques effectively. The positive association can be attributed to the fact that educated farmers are more likely to adopt innovative agricultural practices, interpret climate information, and make informed decisions regarding soil fertility management and crop diversification.

However, in some cases, education might have a negative or insignificant effect on CSA adoption due to competing priorities. Educated farmers may have better opportunities for non-farm employment, leading to reduced engagement in agricultural activities, which can negatively impact the adoption of labor-intensive CSA practices. Additionally, the availability of alternative income sources might reduce their reliance on agriculture as a primary livelihood, limiting their interest in adopting new farming techniques.

Notwithstanding these possible disadvantages, the general pattern indicates that education plays a significant role in the adoption of CSA, highlighting the necessity of laws that improve farmers' access to agricultural training, education, and extension services in order to optimize the advantages of CSA practices.The findings support the claims made by (Belachew et al., 2020) and (Teklu et al., 2023)that education is essential to Ethiopia's acceptance of innovations (new CSA).

Household size (AE): household size measured in terms of adult equivalent (AE) has both positive and negative associations with different CSA adoption choices. For adopters of organic fertilizer and improved seed ($F_1Cr_0I_1$), family size has a positive and significant impact, with a coefficient of 0.81 and a marginal effect of 0.0498, significant at the 1% level. This suggests that larger households are more likely to adopt this combination, possibly due to increased labor availability, which facilitates labor-intensive CSA practices like organic fertilizer application. However, for other CSA adoption categories, the relationship is not statistically significant. The negative marginal effects observed in other CSA combinations (e.g., crop rotation-only adopters, $F_0Cr_1I_0$, with a coefficient of 0.55 and a marginal effect of -0.022) suggest that larger family sizes may create economic constraints, limiting the ability of households to invest in certain CSA practices. In such cases, the burden of providing for more family members might shift the focus toward short-term food security rather than long-term sustainable practices. The mixed findings highlight that while larger families may benefit from additional labor, they may also face financial limitations that influence their ability to adopt specific CSA practices.(Atinkut & Mebrat, 2016),(Belachew et al., 2020), and (Kifle et al., 2022), observed a positive correlation between household size and CSA practices in various regions of Ethiopia, which was in agreement with this conclusion. Large families, however, are less likely to adopt some and complete combination packages of CSA practices, according to the unfavorable connections between some and full combination packages.

Table 9: Determinants of climate-smart agriculture practice adoption: result of MNL selection model

	Adoption of alternative combination of CSA practices							
Variables	$F_0Cr_1I_0$		$F_1Cr_1I_1$		$F_1Cr_1I_0$		$F_1Cr_0I_1$	
	Coef. (SE)	ME	Coef. (SE)	ME	Coef. (SE)	ME	Coef. (SE)	ME
Sex	2.056 (1.85)	0.15**	0.61 (2.08)	-0.0046	0.59 (1.86)	-0.065	0.55 (1.87)	-0.077
Age	0.002 (0.052)	-0.0042	0.004 (0.06)	-0.006	0.02 (0.06)	-0.003	0.05 (0.06)	0.0078**
Education	2.53 (0.71)	0.14***	3.78 (0.75)	0.157**	3.42 (0.74)	0.062**	3.43 (0.74)	0.058**
AE	0.55 (0.41)	-0.022	0.56 (0.46)	-0.0036	0.62 (0.44)	-0.024	0.81 (0.42)	0.0498*
Farm size	-0.73 (0.56)	-0.113**	0.02 (0.67)	0.0039	-0.08 (0.61)	0.011	0.16 (0.63)	0.098**
Extension	0.23 (0.52)	0.062*	1.59 (0.65)	0.031**	0.40 (0.55)	-0.069	0.84 (0.56)	0.099**
Credit	2.64 (1.09)	-0.002	4.44 (1.31)	0.046**	2.71 (1.18)	0.023	2.47 (1.19)	-0.066
Trai_CSA	1.47 (1.15)	0.19**	4.11 (1.14)	0.045**	2.22 (1.22)	0.079	3.08 (1.23)	0.221***
Climate_information	0.88 (1.24)	0.074	1.26 (1.60)	0.101*	1.15 (1.46)	0.242**	0.11 (1.42)	-0215
Ln_NFIH	-1.71 (1.0)	-0.34***	3.81 (1.61)	0.113**	0.90 (1.24)	0.307**	-0.047 (1.198)	0.1215**
TLU	0.68 (0.23)	0.011	1.14 (0.27)	0.012**	0.72 (0.25)	-0.010	0.76 (0.25)	0.0093
Labor	-0.04 (0.97)	-0.059	0.30 (1.19)	0.0012	0.81 (1.09)	0.194**	-0.077 (1.073)	0.137
Cooperative member	1.78 (0.88)	0.083	4.11 (1.37)	0.108***	1.07 (0.95)	0.092	1.023 (0.96)	0.099
Constant	-0.59		-65.03***		-30.22***		-24.55***	
Number of obs = 271			LR chi2(52) = 420.42 Prob > chi2 = 0.0000 Pseudo R2 = 0.4886					
Log likelihood = -220.06054								

Source: Own constructed from the survey, 2025. ***, **, and * means significance at 10%, 5%, and 1%, ME and SE represent marginal effect and standard error, respectively. $F_0Cr_0I_0$ is the base category.

Farm size: Farm size exhibits both positive and negative associations with different CSA adoption choices. The MNL model results indicate that farm size negatively affects the adoption of crop rotation alone ($F_0Cr_1I_0$), with a coefficient of -0.73 and a marginal effect of -0.113, significant at the 5% level. This suggests that a 1-hectare increase in farm size reduces the probability of adopting crop rotation by 11.3%.

A possible explanation is that larger farms may prioritize monocropping or cash crops over rotational cropping. Conversely, farm size has a positive and significant effect on the adoption of organic fertilizer and improved seed ($F_1Cr_0I_1$), with a coefficient of 0.16 and a marginal effect of 0.098, significant at 5%. This implies that a 1-hectare increase in farm size increases the likelihood of adopting organic fertilizer and improved seeds by 9.8%. This positive relationship could be due to larger farms having the financial capacity and land availability to invest in multiple sustainable practices.Larger farms may have more resources to execute input-intensive CSA systems, whereas smallholders may rely on crop rotation due to land limits, according to the mixed results. This result is in line with the findings of (Belachew et al., 2020) and (Kassa & Abdi, 2022), who contended that farmers can diversify their livestock and crops and implement innovative agricultural techniques to reduce productivity risks when they have more land.

Access to extension service (Extension): The impact of extension services on adopting climate-smart agriculture (CSA) practices is positive and statistically significant across multiple adoption categories. Specifically, for farmers who adopted all CSA practices ($F_1Cr_1I_1$), the coefficient is 1.59 with a marginal effect of 0.031, significant at the 5% level. This indicates that access to extension services increases the probability of adopting all CSA practices by 3.1%. Similarly, for those adopting organic fertilizer and improved seed ($F_1Cr_0I_1$), the coefficient is 0.84 with a marginal effect of 0.099, also significant at the 5% level, suggesting that extension services improve the likelihood of adoption by 9.9%. In the case of farmers adopting crop rotation only ($F_0Cr_1I_0$), the coefficient is 0.23, with a marginal effect of 0.062, significant at the 1% level, implying that extension services enhance adoption probability by 6.2%. However, Extension service has a negative association with organic fertilizer and crop rotation combination of CSA and is statistically insignificant. farmers who receive extension support are more likely to embrace superior agricultural practices, according to the positive correlation shown between extension services and CSA adoption. There are multiple reasons for this: First, extension services give farmers the technical know-how and fundamental information they need to successfully implement CSA practices. Second, they ensure that farmers have access to the most recent knowledge by acting as a liaison between them and new agricultural technologies. Finally, extension services may facilitate farmers' access to financing and inputs, reducing their financial stress and promoting the use of sustainable agricultural practices. According to other studies by (Atinkut & Mebrat, 2016 ; (Fantay Gebru et al., 2019 ; (Negera et al., 2022; and Teklu et al., 2023), extension services had a positive and significant influence on Ethiopia's adoption of CSA techniques. This result is consistent with those findings.

Access to credit (Credit): Access to credit is essential for increasing the uptake of climate-smart agriculture (CSA) techniques. With a coefficient of 4.44 and a marginal effect of 0.046, the results demonstrate that credit availability has a positive and significant impact on the adoption of all CSA practices ($F_1Cr_1I_1$). This effect is significant at the 5% level. According to this, farmers with financing availability are 4.6% more likely than those without to implement a complete set of CSA practices. The positive relationship can be explained by the fact that CSA adoption often requires financial investment in improved seeds, organic fertilizers, and other sustainable farming technologies. Farmers with access to credit can afford these inputs, making them more capable of implementing CSA techniques. The absence of a significant effect on other CSA combinations (F1Cr1I0, F1Cr0I1, and F0Cr1I0) might indicate that partial adopters either rely on traditional financing mechanisms or that credit availability is not specifically directed toward CSA-related investments. Strengthening rural financial systems and ensuring targeted credit programs could further boost CSA adoption. This is consistent with study by (Kifle et al., 2022), who discovered that financing facilities are a major factor in encouraging farmers to implement CSA practices like feeding animals.

Training on CSA practices (Training): Training in climate-smart agriculture significantly influences the adoption of various CSA practices. The results indicate that CSA training has a positive and significant effect across multiple adoption categories. For full adopters ($F_1Cr_1I_1$), the coefficient is 4.11, with a marginal effect of 0.045, significant at the 5% level, meaning that CSA training increases the probability of adopting all CSA practices by 4.5%. Similarly, for farmers who adopt only organic fertilizer and improved seed ($F_1Cr_0I_1$), the coefficient is 3.08, with a marginal effect of 0.221, significant at the 10% level, indicating that training increases adoption probability by 22.1%. For crop rotation-only adopters ($F_0Cr_1I_0$), the coefficient is 1.47, with a marginal effect of 0.19, significant at the 5% level, showing that training increases adoption by 19%. These findings suggest that training enhances farmers' technical knowledge, confidence, and ability to implement CSA strategies effectively.

The stronger effect on $F_1Cr_0I_1$ adopters (compared to $F_0Cr_1I_0$ & $F_1Cr_1I_1$) might be due to the specificity of training programs that focus more on crop rotation, organic fertilizers, and improved seeds rather than on a fully integrated CSA package. The implication is that expanding and refining CSA training programs to cover a more holistic approach to CSA could further improve overall adoption rates. This result is consistent with previous studies by (Mulugeta, 2020)as well as (A. Belay et al., 2024), which found that training and Conservation Agriculture (CSA) practices—such as improved crop varieties and soil and water conservation measures—were positively correlated in the South Wollo Zone of Ethiopia and Northeast Ethiopia, respectively.

Access to Climate/weather information: The adoption of climate-smart agriculture (CSA) methods is positively and significantly impacted by access to climate information, albeit the impact varies depending on the specific CSA combination. At the 1% level, the coefficient for farmers implementing all CSA techniques ($F_1Cr_1I_1$) is 1.26 with a marginal effect of 0.101. According to this, farmers who have access to climatic data are 10.1% more likely than those who do not to implement every CSA package practice. Similarly, for those adopting organic fertilizer and crop rotation ($F_1Cr_1I_0$), the coefficient is 1.15, with a marginal effect of 0.242, significant at the 5% level, meaning that climate information increases adoption probability by 24.2%. This strong positive relationship indicates that better access to weather forecasts, climate trends, and agronomic advisories enables farmers to make more informed decisions, reducing production risks and enhancing resilience to climate variability. However, for farmers adopting organic fertilizer and improved seed ($F_1Cr_0I_1$), the relationship is negative and not statistically significant, suggesting that the impact of climate information may be more relevant for CSA practices that involve crop diversification strategies and organic fertilizer rather than improved seed alone. According to (Negera et al., 2022), there was a positive relationship between meteorological data and the adoption of CSA activities, such as improved agronomic practices, drought-tolerant high-yielding crop varieties, and soil water conservation techniques, in Ethiopia's Bale-Eco region.

Off-farm participation (Off-farm): According to the results of the MNL model the relationship between non-farm income (Ln_NFIH) and CSA adoption is mixed, indicating both positive and negative associations depending on the CSA combination. For farmers adopting all CSA practices ($F_1Cr_1I_1$), the coefficient is 3.81, with a marginal effect of 0.113, significant at the 5% level, suggesting that an increase in non-farm income raises the likelihood of adopting all the packages of CSA practices by 11.3%. Similarly, for those adopting organic fertilizer and crop rotation ($F_1Cr_1I_0$), the coefficient is 0.90, with a marginal effect of 0.307, also significant at the 5% level, meaning that higher non-farm income increases adoption probability by 30.7%. For organic fertilizer and improved seed adopters ($F_1Cr_0I_1$), the coefficient is -0.047, but the marginal effect is 0.1215, significant at the 5% level, indicating a 12.15% increase in adoption likelihood. These positive associations suggest that non-farm income enables farmers to invest in CSA practices by alleviating financial constraints.

On the other hand, the coefficient is -1.71 for farmers that simply use crop rotation ($F_0Cr_1I_0$), with a marginal effect of -0.34 which is significant at the 10% level. This implies that an increase in non-farm income reduces the probability of adopting crop rotation alone by 34%. This indicates that farmers with higher non-farm earnings may shift their focus away from agriculture or invest in less labor-intensive farming techniques, making crop rotation less attractive. These findings highlight the dual role of non-farm income—it can either facilitate CSA adoption by improving financial capacity or discourage engagement in specific CSA practices if alternative income sources reduce the reliance on agricultural productivity. According to this finding, farm households with an off-farm source of income are more likely to engage in CSA than those without one, according to (Assen & Ashebo, 2018)and (Kifle et al., 2022) .

Total Livestock Holdings (TLU): Total Livestock Holding (TLU) is positively associated with the adoption of all CSA practices packages ($F_1Cr_1I_1$) with a coefficient of 1.14 and a marginal effect of 0.012, significant at the 5% level. This suggests that an increase in livestock holding enhances the likelihood of CSA adoption by 1.2%. Similarly, for farmers adopting organic fertilizer and improved seed ($F_1Cr_0I_1$), the coefficient is 0.76 with a marginal effect of 0.0093, though not statistically significant. In contrast, for organic fertilizer and crop rotation adopters ($F_1Cr_1I_0$), the coefficient is 0.72, but the marginal effect is negative (-0.010), indicating a weak and insignificant relationship. For those practicing only crop rotation ($F_0Cr_1I_0$), the coefficient is 0.68, with no significant impact on adoption. The positive relationship in most cases could be attributed to the fact that livestock serves as a financial asset that facilitates investment in CSA technologies. Farmers with higher livestock holdings may have greater financial flexibility to invest in organic fertilizers and improved seed varieties, thereby improving soil fertility and productivity. However, the weak or negative impact in some cases might be due to competing labor and resource demands, as farmers with large livestock holdings might prioritize livestock-related investments over crop-related CSA practices.This result was consistent with (Berhanu, 2016) , who found a positive and significant effect of TLU on adopting CSA practices in Ethiopia.

Access to Labor: According to the results of the MNL model Access to labor presents mixed effects on CSA adoption. For adopters of organic fertilizer and crop rotation ($F_1Cr_1I_0$), labor has a significant positive effect with a coefficient of 0.81 and a marginal effect of 0.194, significant at the 5% level. This implies that households with higher labor availability are 19.4% more likely to adopt this combination of CSA practices. In contrast, for adopters of all CSA practices ($F_1Cr_1I_1$), labor has a coefficient of 0.30 with an insignificant marginal effect of 0.0012. Similarly, for those adopting only crop rotation ($F_0Cr_1I_0$), labor shows a negative but insignificant association with a coefficient of -0.04 and a marginal effect of -0.059. For organic fertilizer and improved seed adopters ($F_1Cr_0I_1$), labor is negatively associated (coefficient = -0.077) but not significant. The positive impact of labor on the adoption of organic fertilizer and crop rotation can be explained by the labor-intensive nature of these practices, which require significant human effort for soil preparation, manure application, and rotational planting. However, the absence of a strong positive association for the adoption of all CSA practices or certain combinations could be due to labor constraints, where households with limited labor may prioritize less labor-intensive practices or mechanized farming methods. This outcome was in line with the findings of (Murray et al., 2016), who discovered that labor access had a favorable and noteworthy impact on Ethiopian adoption of CSA methods.

Cooperative membership: One of the most important factors influencing farmers' adoption of climate-smart agriculture (CSA) practices is cooperative membership. The results show that cooperative membership and the probability of using CSA techniques are significantly and favorably correlated across various combinations. Specifically, for farmers who adopt all CSA practices ($F_1Cr_1I_1$), cooperative membership has a coefficient of 4.11 with a marginal effect of 0.108, significant at the 10% level. This suggests that being a cooperative member increases the probability of adopting this combination of CSA practices by 10.8%. The significant positive effect for farmers adopting all CSA practices ($F_1Cr_1I_1$) implies that those who are part of cooperatives are more likely to have access to multiple support mechanisms, making them more inclined to adopt a comprehensive set of CSA interventions. Similarly, for those adopting organic fertilizer and crop rotation ($F_1Cr_1I_0$) and those adopting organic fertilizer and improved seed ($F_1Cr_0I_1$), the coefficients are 1.07 and 1.023, respectively, with marginal effects of 0.092 and 0.099, though not statistically significant. Meanwhile, for farmers practicing crop rotation only ($F_0Cr_1I_0$), the coefficient is 1.78 with a marginal effect of 0.083, showing a positive but not strongly significant relationship.

The positive association between cooperative membership and CSA adoption can be attributed to several factors. First, cooperatives provide farmers with access to critical agricultural inputs such as improved seeds, organic fertilizers, and credit facilities, which enhance their capacity to implement CSA practices. Second, cooperatives serve as a platform for knowledge sharing and training, allowing members to learn about the benefits and technical aspects of CSA from extension agents and fellow farmers. Third, cooperatives often facilitate access to extension services, market linkages, and climate information, reducing the barriers to adoption. This outcome aligns with earlier research conducted by (Zerssa et al., 2021a), who identified a positive relationship between Cooperative membership and Smart agriculture practice (CSA) practices.

4.7. Impact of Combined Climate-Smart Agriculture Practices on Household Food Security

The results of the Multinominal Endogenous Switching Regression model, which illustrate the projected impacts of a combination of CSA packages on food consumption score and household dietary diversity, are shown and discussed in this section.

(Di Falco & Veronesi, 2013) State that selection tools are necessary to ensure the identification of the result equation. These technologies directly affect the adoption decision, even though they don't change the outcome variables. Contact with agricultural extension and instruction in CSA processes served as the study's instruments. While training on CSA techniques gives farmers advice on how to implement new agricultural practices, the agricultural extension agent is the main source of information on these practices. Adopting CSA techniques is essential to having a causal influence since farmers are more likely to adopt new technology and practices when they have the required training and are aware of the advantages of agricultural extension agents (Baiyegunhi & Hassan, 2025). The validity of the instruments was assessed using a falsification test. As shown in Appendix Table 7, the outcomes demonstrated the reliability of the chosen variables as instrumental factors.

Consequently, the results show that the instrumental factors selected have a significant impact on the adoption of CSA techniques without significantly changing the outcome variables (welfare outcome variables). Furthermore, the Variance Inflation Factor (VIF) was employed before the execution of the MESR model to ascertain whether a significant multicollinearity issue existed among the explanatory variables (Table 14).

Table 10: displays the results of the multicollinearity test for the variance inflation factor (VIF).

Variables	VIF(variance inflation factor)	1/VIF
Education	1.44	0.696593
ln_NFIHH	1.37	0.732210
TLU	1.18	0.845206
Extension	1.15	0.867984
Erosion	1.16	0.862314
Train_CSA	1.16	0.862474
Farm size	1.10	0.909404
Credit	1.10	0.909804
Cooperative	1.08	0.926722
CSA training	1.08	0.927135
Climate information	1.07	0.933777
Age	1.07	0.937729
Labor	1.07	0.937956
AE	1.05	0.956834
Sex	1.04	0.959432
Mean VIF	1.14	

Source: Own constructed from the survey, 2025

When at least one of the independent variables is a linear combination of the others, there is a problem with multicollinearity. There was no explanatory variable eliminated from the estimation model because the VIF results revealed no major multicollinearity problems. As previously stated, the factors in the model were believed to affect households' participation in CSA practices as well as their total income, income from crop production, total income from animal husbandry, and calorie acquisition. Thus, a measure of multicollinearity associated with the variance of the inflation factor is defined as:

$$VIF(Xi) = \left(1 - Ri^{2)-1}\right)$$

The multiple correlation coefficients between the explanatory variables are denoted by Ri^{2}. There is multicollinearity among the variables (Xi) since the value of VIF (Xi) increases in parallel with the value of Ri^{2}. It was determined that the variables' VIF values were moderate, or less than 10. The VIF result indicates that multicollinearity is not a significant issue with the data. Consequently, every explanatory variable was kept and used in the research.

To assess the causal impact of CSA activities on farm household food security, the average adoption effects are computed by comparing the actual results with the expected results in a counterfactual scenario. Thus, Table 11 displays the average treatment effects of CSA package adoption based on MESR on the outcome variables under real and counterfactual situations.

Table 11 illustrates the considerable difference between the actual values and the counterfactuals of the outcome variables. The real data shows that households with alternative CSA packages score higher on nutritional variety and food intake than households without such packages. Consequently, the ATT analysis demonstrates that when farm households adopted different combinations of agricultural techniques, their HDDS and FCS grew dramatically.

4.7.1. Household dietary diversity score and food consumption score

Only Crop Rotation Adopter ($F_0Cr_1I_0$): The outcomes from the MESR Model in (Table 11) show that, For the Household Dietary Diversity Score (HDDSH) under the Crop Rotation Adopter Only ($F_0Cr_1I_0$) category, the results indicate that households who adopted crop rotation had a significantly higher dietary diversity score compared to their hypothetical scenario if they had not adopted the practice. The actual mean HDDSH for adopters was 5.096 (SE = 0.41), while their estimated score if they had not adopted crop rotation would have been 3.019 (SE = 0.23), leading to a significant ATT (Average Treatment Effect on the Treated) of 2.077 (SE = 0.26), which is statistically significant at the 1% level. This suggests that crop rotation adoption positively influences dietary diversity by expanding access to a variety of food items, likely through improved soil fertility and diversified crop production. On the other hand, the ATU (Average Treatment Effect on the Untreated), which estimates the potential impact on non-adopters had they chosen to adopt crop rotation, was 3.660 (SE = 0.49), showing an even larger potential gain in dietary diversity compared to their actual mean of 4.657 (SE = 0.15). The higher ATU compared to ATT indicates that non-adopters could benefit even more from adopting crop rotation, suggesting significant room for policy interventions encouraging its adoption to enhance household dietary diversity.

The results demonstrate a positive and significant impact of crop rotation on food consumption patterns for the Household Food Consumption Score (FCSHH) under the Crop Rotation Adopter Only (F0Cr1I0) category. The actual mean FCSHH for adopters was 32.654 (SE = 0.66), while their estimated score if they had not adopted would have been 28.129 (SE = 1.027), leading to a significant ATT of 4.525 (SE = 1.22), statistically significant at the 1% level. This indicates that crop rotation enhances household food security by ensuring better food access, variety, and nutritional quality. The ATU, which measures the effect of potential adoption on non-adopters, was 9.507 (SE = 1.618), which is substantially higher than ATT, revealing that non-adopters could gain even more if they chose to implement crop rotation. Their actual mean FCSHH was 26.542 (SE = 1.337), significantly lower than the expected score of 36.049 (SE = 0.911) if they had adopted crop rotation. This suggests that promoting crop rotation among non-adopters could lead to significant improvements in food consumption scores, reinforcing its role in enhancing food security and dietary adequacy at the household level.

Improved Seeds and Crop Rotation Adopter ($F_1Cr_1I_0$): Under the scenario where improved seeds and crop rotation were adopted ($F_1Cr_1I_0$), the results indicate a substantial impact on household dietary diversity. Households that adopted these practices had an average HDDSH of 5.612, whereas if they had not adopted them, their score would have dropped significantly to 1.426. This difference, represented by the Average Treatment effect on the Treated (ATT), is 4.186 and is statistically significant at the 1% level, confirming a robust positive effect of these climate-smart practices on dietary diversity among adopters. Similarly, for non-adopters, the hypothetical impact of adoption is even greater. The non-adopters actual HDDSH is 4.657, but if they had adopted, their score would have surged to 9.864, yielding an Average Treatment effect on the Untreated (ATU) of 5.207, also statistically significant at the 1% level. This suggests that improved seeds and crop rotation adoption could dramatically enhance dietary diversity for non-adopters, possibly even more than for current adopters, highlighting a significant potential benefit for those yet to adopt these climate-smart strategies.

Table 11: Impacts of climate-smart practices on households’ food security

Packages	Decision stage(Adopters)		Effects	Decision stage(Non-adopters)		Effects
	Adopters(actual)	If they do not adopt	ATT	If they would adopt	Non-adopters(actual)	ATU
	Mean. (SE)	Mean (SE)	Mean (SE)	Mean (SE)	Mean (SE)	Mean (SE)
Household dietary diversity (HDDSH)						
$F_0Cr_1I_0$	5.096 (0.41)	3.019 (0.23)	2.077*** (0.26)	8.317 (0.47)	4.657 (0.15)	3.660*** (0.49)
$F_1Cr_1I_0$	5.612 (0.097)	1.426 (0.15)	4.186*** (0.17)	9.864 (0.47)	4.657 (0.15)	5.207*** (0.49)
$F_1Cr_0I_1$	5.564 (0.078)	1.416 (0.16)	4.148*** (0.18)	9.698 (0.37)	4.657 (0.15)	5.041*** (0.399)
$F_1Cr_1I_1$	7.037 (0.15)	0.150 (0.23)	7.187*** (0.28)	12.138 (0.33)	4.657 (0.15)	7.481*** (0.37)
Household Food Consumption Score (FCSHH)						
$F_0Cr_1I_0$	32.654 (0.66)	28.129 (1.027)	4.525*** (1.22)	36.049 (0.911)	26.542 (1.337)	9.507*** (1.618)
$F_1Cr_1I_0$	43.231 (0.565)	35.075 (0.997)	8.156*** (1.146)	42.942 (1.012)	26.542 (1.337)	16.400*** (1.677)
$F_1Cr_0I_1$	41.524 (0.572)	36.353 (1.079)	5.171*** (1.222)	39.393 (0.825)	26.543 (1.337)	12.850*** (1.571)
$F_1Cr_1I_1$	57.391 (0.877)	34.023 (0.989)	23.368*** (1.322)	46.615 (1.733)	26.543 (1.337)	20.072*** (2.189)

Own constructed from the survey, 2025. Note :ATT and ATU donate the average treatment for treated and untreated conditions, respectively. *** Means significant at 1% and Numbers in parenthesis are standard error (SE).

For the Household Food Consumption Score (FCSHH) under the same adoption scenario ($F_1Cr_1I_0$), the impact is also highly significant. Adopters of improved seeds and crop rotation have an actual FCSHH of 43.231, whereas their counterfactual scenario—if they had not been adopted—would have resulted in a significantly lower score of 35.075. This yields an ATT of 8.156, statistically significant at the 1% level, demonstrating that adoption enhances food consumption scores considerably. For non-adopters, the effect of potential adoption is even more striking. Their current FCSHH is 26.542, but if they were to adopt, their score would increase dramatically to 42.942, leading to an ATU of 16.400, also significant at the 1% level. This highlights that non-adopters stand to gain more from adoption than current adopters have, suggesting a strong potential for improving food security through these climate-smart practices. The results underscore that improved seeds and crop rotation adoption meaningfully enhances both dietary diversity and overall food consumption, reinforcing the importance of encouraging broader uptake among farming households.

Organic Fertilizer And Improved Seed Adopters ($F_1Cr_0I_1$): According to the result from (Table 11) for Household Dietary Diversity Score (HDDSH) under the category of organic fertilizer and improved seed adopters ($F_1Cr_0I_1$), the results indicate a substantial positive impact of adoption. The actual mean HDDSH for adopters is 5.564, whereas, had they not adopted, their mean score would have been significantly lower at 1.416. At the 1% level, this leads to a statistically significant Average Treatment effect on the Treated (ATT) of 4.148. This implies that households' food diversity significantly increases as a result of using organic fertilizer and improved seeds . Similarly, the Average Treatment effect on the Untreated (ATU) is also significantly positive at 5.041, implying that non-adopters would experience a notable increase in their dietary diversity if they were to adopt. Their actual mean HDDSH is 4.657, but if they adopted it, their score would rise to 9.698. The high statistical significance of these effects ($p < 0.01$) underscores the strong link between adopting organic fertilizer and improved seeds and improved dietary diversity, suggesting that these agricultural practices are critical in enhancing food security at the household level.

Regarding the Household Food Consumption Score (FCSHH) for organic fertilizer and improved seed adopters ($F_1Cr_0I_1$), the findings also reveal a significant positive impact. The actual mean FCSHH for adopters is 41.524, whereas had they not adopted, their mean score would have been 36.353, resulting in an ATT of 5.171, which is highly significant at the 1% level. This demonstrates that adoption contributes notably to an improved food consumption score, meaning households have greater food security and dietary quality due to adopting organic fertilizer and improved seeds.The real mean FCSHH for non-adopters is 26.543; however, if they adopted, their score would increase dramatically to 39.393, resulting in an

ATU of 12.850, which is likewise significant at the 1% level. The relevance of these farming methods in guaranteeing improved food consumption and nutrition security is highlighted by the notable difference between the actual and counterfactual means for both adopters and non-adopters. The findings unequivocally imply that increasing the usage of organic fertilizer and better seeds may be essential to reducing food insecurity and improving the nutritional value of food in farming households.

ALL Packages Together (Organic Fertilizer, Crop Rotation, And Improved Seed)($F_1Cr_1I_1$): According to the results of the MESR model presented in (Table 11) the impact of adopting climate-smart agricultural practices on household dietary diversity (HDDSH) is highly significant, particularly for those who adopted organic fertilizer, crop rotation, and improved seeds together ($F_1Cr_1I_1$). The actual mean dietary diversity score for adopters of this package is 7.037, which is significantly higher than the counterfactual mean (0.150) had they not adopted, resulting in an ATT of 7.187 with strong statistical significance at the 1% level. This highlights that adopting all three practices together substantially improves household dietary diversity. Similarly, non-adopters of this package have a much lower actual dietary diversity score of 4.657, but if they were to adopt, their estimated mean score would rise to 12.138, leading to an ATU of 7.481, also highly significant at 1%. This indicates that adoption could lead to an even greater improvement in dietary diversity for non-adopters compared to current adopters. The substantial difference between adopters' actual and counterfactual outcomes, along with the large ATU, strongly suggests that adopting organic fertilizer, crop rotation, and improved seeds together plays a crucial role in enhancing dietary diversity. The magnitude of these effects, compared to other packages, underscores the synergistic benefits of integrating multiple climate-smart practices in improving household food access and consumption patterns.

Regarding the household food consumption score (FCSHH), the impact of adopting organic fertilizer, crop rotation, and improved seeds together ($F_1Cr_1I_1$) is again substantial and highly significant. Adopters of this package have an actual mean FCSHH of 57.391, whereas if they had not adopted, their mean score would have been 34.023, yielding a significant ATT of 23.368 at the 1% level. This implies that the adoption of this climate-smart package significantly enhances household food security, as reflected in their improved food consumption patterns. Similarly, non-adopters currently have a much lower actual mean FCSHH of 26.543, but if they were to adopt, their estimated mean score would increase to 46.615, leading to an ATU of 20.072, which is also statistically significant at the 1% level.

These findings indicate that adopting this package could greatly improve food consumption scores for both current and potential adopters, with even greater potential benefits for those who have yet to adopt. The substantial magnitude of ATT and ATU compared to other packages further reinforces the importance of adopting multiple climate-smart agricultural practices in combination. These results clearly show that organic fertilizer, crop rotation, and improved seeds together provide the highest benefits in terms of food security, emphasizing the need for broader adoption to enhance resilience and nutrition among farming households.

5. SUMMARY, CONCLUSION, AND RECOMMENDATIONS

5.1. Summary and Conclusion

Climate change is making it harder for smallholder farmers in developing countries like Ethiopia, which is negatively affecting their overall well-being and lowering agricultural productivity and revenues. By using Climate-Smart Agriculture (CSA) practices, greenhouse gas emissions are decreased, yields are increased, climate variability resistance is strengthened, and ultimately, farmers' livelihoods are improved. Determining the factors that motivate farmers to embrace alternative CSA techniques was the purpose of this study. The majority of these activities were also identified and categorized using principal component analysis (PCA) to investigate the climate-smart contributions of farmers to household food security in Dejen Woreda, northwest Ethiopia, in terms of FCS and HDDS. Semi-structured questionnaires were utilized by trained enumerators to gather primary data from 271 sample homes. A multinomial endogenous switching regression (MNESR) model calculates the implicit impact of adoption on household welfare, whereas the multinomial logit (MNL) selection model examines the determinants influencing the adoption of CSA practices.

The primary variables influencing farmers in the research area to implement climate-smart agriculture (CSA) practices were identified by the study. Numerous factors, such as labor availability, cooperative membership, financing availability, training accessibility, and climate information, have a significant impact on CSA adoption, according to descriptive statistics. 91.51% of the households surveyed were headed by a man, and these households were more likely to adhere to CSA practices. A statistically significant relationship between CSA adoption and cooperative membership ($\chi^2=47.1$, $p<0.01$), credit availability ($\chi^2=29.9$, $p<0.01$), and training access ($\chi^2=17.92$, $p<0.01$) was revealed by the results of the Chi-square test. Additionally, the factor analysis showed that training accessibility, cooperative membership, and financial availability were important factors in CSA adoption.

The multinomial logit model also indicates that education level, extension services, access to credit, training on CSA, and climate information significantly influence the likelihood of adopting CSA practices. Specifically, a one-unit increase in education level increased the probability of adopting all three CSA practices (organic fertilizer, crop rotation, and improved seeds) by 15.7% ($p<0.05$). Similarly, access to training on CSA increased the likelihood of full CSA adoption by 22.1% ($p<0.01$). Credit availability also played a significant role, increasing the probability of CSA adoption by 4.6% ($p<0.05$). Additionally, farm size had a mixed effect, with a negative influence on adopting some CSA combinations while positively affecting others.

The FCS and HDDS both show a significant improvement in food security outcomes when CSA practices are adopted. The mean HDDS of all sampled households was 5.67, with significant variations across adoption categories: non-adopters (4.67), crop rotation-only adopters (5.09), full CSA adopters (7.04), organic fertilizer and crop rotation adopters (5.61), and organic fertilizer and improved seed adopters (5.56). The F-test ($F = 16.34$, $p < 0.01$) confirmed the statistical significance of these differences. Similarly, the mean FCS was 41.53, with significant disparities among adoption categories: non-adopters (26.54), crop rotation-only adopters (32.65), full CSA adopters (57.39), organic fertilizer and crop rotation adopters (43.23), and organic fertilizer and improved seed adopters (41.52). The F-test ($F = 78.71$, $p < 0.01$) validated these findings.

The conclusions of the study show the range of climate-smart agricultural production methods employed by farmers in Dejen Woreda, Northwest Ethiopia. Techniques such as crop rotation, better seed, organic fertilizer, intercropping, conservation agriculture, and agroforestry are crucial for boosting output and climate change resilience. Farmers are actively seeking methods help lessen the negative consequences of climatic variability and soil deterioration by implementing such measures, thereby showcasing their dedication to sustainable agricultural production. More targeted support in the form of education, awareness, and extension services is necessary, though, as a number of factors influence how successful these strategies are.

The impact analysis using the Multinomial Endogenous Switching Regression (MESR) model further revealed that CSA adoption significantly improved food security. The Average Treatment Effect on the Treated (ATT) for HDDS was highest for full CSA adopters (7.187, $p < 0.01$), indicating that these households consumed a more diverse diet than they would have in the absence of adoption. Similarly, ATT for FCS was highest for improved seed and crop rotation adopters (8.156, $p < 0.01$), demonstrating the positive effect of CSA practices on household food consumption. Furthermore, the Average Treatment Effect on the Untreated (ATU) suggested that non-adopters could substantially improve their food security if they adopted CSA, with potential gains of 16.400 in FCS and 7.481 in HDDS ($p < 0.01$). Generally, all these results underscore the critical role of CSA in enhancing household resilience to food insecurity and climate change.

Implementing CSA techniques, particularly the use of organic fertilizer, crop rotation, and better seeds, resulted in a considerable improvement in both the Household Dietary Diversity Score (HDDS) and the Household Food Consumption Score (FCSHH). In contrast to a counterfactual score of 0.150, households that combined all three strategies showed the highest dietary diversity, with a mean HDDS of 7.037. Similarly, adopters' food consumption score was 57.391, which is far higher than the 34.023 they would have had in the absence of adoption. These findings imply that combining several CSA strategies improves food security and household resilience synergistically. Furthermore, as evidenced by their prospective improvement in HDDS and FCSHH, non-adopters stood to benefit much from CSA adoption as well, highlighting the necessity of policies that encourage broader adoption of these practices.

Notwithstanding these encouraging results, obstacles including restricted financial availability, training, and cooperative membership still prevent CSA from being widely adopted. To promote the wider adoption of CSA, the study emphasizes the significance of bolstering institutional support, especially through expanded access to extension services and farmer cooperatives. Policymakers and other stakeholders should give priority to focused measures that encourage the adoption of CSA techniques because of their obvious advantages in improving food security. This will help smallholder farmers become more resilient to climatic unpredictability. To create more sustainable farming practices that can be duplicated in comparable agroecological zones, future studies should investigate the long-term economic and environmental effects of CSA adoption. Ultimately, tackling food insecurity and creating a more resilient Ethiopian agriculture sector can be greatly aided by increasing farmers' adaptive capacity through CSA.

5.2. Recommendations

The results of this study are used to make the following policy suggestions.

Since agricultural extension services have a positive and significant impact on farm households' adoption of climate-smart agriculture (CSA) practices, the government should take proactive measures to enhance the standard of extension services in general and expand access to information on alternative CSA techniques. This will ensure that farmers understand how these practices enhance agricultural productivity and sustainability while mitigating the adverse effects of climate change.

Additionally, as education is a major factor in the adoption of CSA techniques, the government and other agricultural extension system stakeholders should educate farmers about CSA practices related to the effects of climate change generally and in a study location particularly. Farmers should use local government extension agents and other communication channels to obtain weather information and information on how climate change affects output and productivity in order to address the issue of climate change, which also encourages the adoption of CSA practices . Credit also encourages farmers to implement more CSA techniques on their farms. Thus, policies and initiatives that aim to increase the use of CSA techniques should generate funds through accessible credit so that farmers can implement a variety of CSA activities and lessen the adverse effects.

Livestock holdings and off-farm involvement were found to be important factors in farm households' adoption of Climate-Smart Agriculture (CSA) methods. Therefore, as a strategic policy intervention, it should be a top priority to guarantee a sufficient supply of agricultural inputs to improve livestock productivity and to promote off-farm employment prospects in rural communities, especially within the study area. By making it easier for CSA techniques to be adopted more widely, this strategy will increase farmers' ability to withstand the negative effects of climate change on food security.

Therefore, farmers in the country as a whole and the research area specifically should be encouraged to use as many different kinds of CSA activities as possible in order to have a bigger impact on welfare and food security status . Household farmers who implemented the full package of organic fertilizer application, crop rotation, and improved seed techniques could attain the best indicators of food security status. Because CSA techniques have enhanced farmer welfare and decreased food insecurity, the government should encourage a broader integration of these practices into sector policies through the Ministry of Agriculture.

Lastly, this study looked into how CSA activities affected food security and household welfare in the near term. The long-term sustainability of CSA practices, particularly their effects on biodiversity, soil health, water resources, and overall farming system resilience, should be the main focus of future studies.

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7. APPENDIX

Appendix Table 1: Conversion factors used to calculate Adult Equivalent (AE)

Age Group (in years)	Male	Female
<10	0.6	0.60
10-13	0.9	0.80
14-16	1.0	0.75
17-50	1.0	0.75
>50	1.0	0.75

Source: Storck, *et al*. (1991)

Appendix Table 2: Conversion factors used to compute tropical livestock units (TLU)

Animal Category	TLU
Cow/Ox	1.0
Calves	0.5
Heifer	0.75
Sheep (young)	0.06
Sheep (adult)	0.13
Horse	1.1
Mule	1.1
Donkey (young)	0.35
Donkey (adult)	0.7
Chicken	0.013

Source: Storck, *et al*., 1991

Appendix Table 3: Breusch–Pagan/Cook–Weisberg test for heteroskedasticity

Assumption: Normal error terms

Variable: Fitted values of CSA practices

H0: Constant variance

chi2 (1) = 0.86

Prob > chi2 = 0.3541

Appendix Table 4: Test the instrumental variables' validity (falsification test).

Food consumption score of household (FCSHH)					
Variables	$F_0Cr_0I_0$	$F_0Cr_1I_0$	$F_1Cr_1I_1$	$F_1Cr_1I_0$	$F_1Cr_0I_1$
Extension	-3.59(2.07)	-0.056 (1.199)	1.776(2.123)	0.42(1.24)	-0.950(1.257)
Train_CSA	3.83 (3.63)	0.164 (2.196)	-3.42(2.966)	-0.803(2.56)	-0.912(2.079)
F-values	F(2, 32)=2.36	F(2, 49)= 0.00	F(2,52)=0.93	F(2, 64)=0.11	F(2,59)=0.36
Prob > F	0.1109	0.9965	0.4029	0.8975	0.7006
Dietary diversity of household (HDDSH)					
Extension	0.1028(0.287)	0.366(0.224)	0.639(0.437)	-0.022(0.179)	0.032(0.228)
Train_CSA	0.311(0.503)	-0.088(0.411)	-0.851(0.61)	0.4098(0.369)	-0.218(0.377)
F-values	F(2, 32)=0.23	F(2, 49)=1.33	F(2,52)=1.85	F(2, 64)=1.63	F(2, 59)=0.18
Prob > F	0.7963	0.2742	0.1676	0.5376	0.8320

The numbers in parentheses show standard errors. Non-adopter ($F_0Cr_0I_0$) is a reference category. $F_0Cr_1I_0$ =adopt only crop rotation practices; $F_1Cr_1I_0$ =adopt organic fertilizer with crop rotation practices; $F_1Cr_0I_1$ = adopt organic fertilizer with improved seed; and $F_1Cr_1I_1$= adopt all together (i.e. Organic fertilizer and crop rotation with improved seed together).

Source: Own constructed from the survey, 2025

Table 5:Food groups in Household Dietary Diversity Score (HDDS)

No	Food groups	Food item	Score
1	Cereals	Any grain-based food, including maize, rice, wheat, sorghum, millet, and others (e.g., bread, *injera, genfo, nifiro, kolo*)	
2	Root and tubers	potatoes, sweet potatoes, yams, cassava, *hamicho, enset*, or more root and tuber-based foods	

3	vegetables	Dark green leafy vegetables, tomatoes, onions, and garlic, as well as wild vegetables	
4	Fruits	Banana, Papaya, Mango, Avocado, and more fruits	
5	Meat, poultry, offal	Meats from the liver, kidney, heart, or other organs of beef, lamb, goat, pork, or chicken.	
6	Eggs	Hens Eggs	
7	Fish	Seafood and fish, whether fresh or dried	
8	Pulses/legumes/nuts	Foods produced from chickpea, common bean, cowpea, pigeon pea, nuts, lentils, and chickpea seeds.	
9	Milk	Milk, cheese, yogurt, and other dairy products	
10	Oil/fat	Food prepared with butter, fat, or oil	
11	Sugar/honey	Honey or sugar, Sweetened beverages, sugary meals like chocolate, candy, cookies, and cakes	
12	Condiments	Various foods, including coffee and tea, alcoholic beverages, and others	
	Total		

Table 6:food groups in Household Food Consumption (HFC) Score

No	Food groups	Number of days (Score)							
		0	1	2	3	4	5	6	7
1	Cereals								
2	Root and tubers								
3	vegetables								
4	Fruits								
5	Meat, poultry, offal								
6	Eggs								
7	Fish								
8	Pulses/legumes /nuts								
9	Milk								

10	Oil/fat								
11	Sugar/honey								
12	Condiments								
	Total								

Table 7:Time Table

Months	**Planned activity**
November	Travel to the study area and begin preparation for the research,
December to January	Start working on the introduction and literature review sections of the research.
January to February	Data collection
February to march	Data analysis and interpretation
March	Write the research paper and complete the final draft.

Questonery

Prepared by: Manaye Asefa

Title: Analysis of Farmers' Climate Smart Contributions to Household Food Security in Dejen Woreda, Northwest part of Ethiopia

Research Questionnaire

INTRODUCTION

The Pan African University Institute of Water and Energy Sciences, including Climate Change (PAUWES), supports this research initiative aimed at assessing the Analysis of Farmers' climate-smart contributions to Household Food Security in the East Gojjam zone, Northwest part of Ethiopia. The main objective of this questionnaire is to collect primary data on households ‘socio-demographic, economic, institutional, and food security-related information that is required to assess the existing agricultural practices and their impacts on household food security.

Confidentiality and Anonymity

Your participation in this survey is entirely voluntary, and your responses will be kept confidential. No individual's personal information or identity will be disclosed in any research reports or publications resulting from this study. Your anonymity is highly respected and ensured throughout this research process.

Respondent Consent

By completing and submitting this questionnaire, you provide consent for the use of the information provided for research purposes. Your participation is instrumental in understanding the challenges and opportunities surrounding climate-smart agriculture among smallholder farmers. If you choose to discontinue participation at any point or skip any questions, you are free to do so without any consequences.

Section 1: Location Information

1. Woreda (District): ________.
2. Kebele (Sub-district/village): ________.
3. Region: ________.
4. Altitude (if known): ________.

Part II: Household Demographics

1. Name of the household head (optional): ______________________________
2. Gender of household head:

☐ Male

☐ Female

3. Age of household head:

☐ Below 20

- ☐ 21–30
- ☐ 31–40
- ☐ 41–50
- ☐ Above 50

4. The educational level of household head:

- ☐ No formal education
- ☐ Primary education
- ☐ Secondary education
- ☐ Higher education

5.Marital status: 1=Single 2= Married 3= Divorced 4= Widowed

6. Household size (number of members): _____________

	Family size in the household				Total
	0-15	16-30,	31-45	above 45	
Male					
Female					
Total					

7.What is the size of your total land holding in hectares?) _________.

8.Main source of income:

- ☐ Farming
- ☐ Business
- ☐ Employment
- ☐ Other: ______________________________

Part III: Climate-Smart Crop Production Practices employed by farmers in the Crop Sector in the study area

9.Are you aware of Climate-Smart Agriculture (CSA)?

- ☐ Yes
- ☐ No

10. Did you implement CSA practices on your farm?

- ☐ Yes
- ☐ No

11.If you implement, when did you first start practicing CSA? ____________________E.C. (Ethiopian Calendar)

12.What types of crops do you cultivate? (Select all that apply)

- ☐ Cereals (e.g., maize, wheat)
- ☐ Vegetables
- ☐ Fruits
- ☐ Legumes
- ☐ Other: _____________________________

13.Which CSA practice did you implement in the last five years?

S.N	CSA practices Implemented by you and your family	Put Tick Mark (√) on the most applicable ones
	Biophysical/structural Practices	
1	Improved seed	
2	Check dams	
3	Retention reservoirs/rain water harvesting	
4	Hillside terraces	
5	Small scale irrigation	
	Agronomic Practices	
6	Mixed/Inter cropping	
7	Applying organic fertilizer (composting)	
8	Mulching	
9	Crop rotation	

10	Minimal tillage	
11	High yielding crop variety	
12	Use of early maturing crop varieties	
	Agrochemical/Technological Practices	
13	Using pesticides	
14	Applying commercial fertilizers	
15	Using improved post-harvest technology	

14.Have you received any training or support on climate-smart practices?

- ☐ Yes
- ☐ No

If yes, from whom?

- ☐ Government extension services
- ☐ NGOs
- ☐ Community groups
- ☐ Other: ___________________

Part IV: Factors Affecting Climate-Smart Crop Production Practices

15. Do you or your family members work on non-farm activities?

- ☐ Yes
- ☐ No

16. Do you have access to credit?

- ☐ Yes
- ☐ No

17. Do you have access to market information?

- ☐ Yes

☐ No

18. Do you have access to agricultural inputs (fertilizer, seed, agrochemicals, etc.)?

☐ Yes

☐ No

19. How many times did the agricultural development agents visit you last year?

☐ 0 times

☐ 1–3 times

☐ 4–6 times

☐ More than 6 times

20. Do you have access to climate information?

☐ Yes

☐ No

21. Do you have access to labour outside of family labour during peak agricultural season?

☐ Yes

☐ No

22. Do you have any technical or vocational training in agriculture?(not puted in variable view of Spss)

☐ Yes

☐ No

23. Do you have access to irrigation farming?

☐ Yes

☐ No

Part IV: Household Food Security and Coping Mechanisms

24. In the past 12 months, did your household experience food shortages?

- ☐ Yes
- ☐ No

25. If yes, how frequently did food shortages occur?

- ☐ Rarely (1–2 months per year)
- ☐ Sometimes (3–4 months per year)
- ☐ Often (5–7 months per year)

26. During the past month, how many meals per day did your household typically consume?

- ☐ 1 meal
- ☐ 2 meals
- ☐ 3 meals
- ☐ More than 3 meals

27. Do you believe your household has sufficient food to meet nutritional needs?

- ☐ Yes
- ☐ No

28. What are the main reasons for food insecurity in your household? (Select all that apply)

- ☐ Low agricultural productivity
- ☐ Lack of access to markets
- ☐ High food prices
- ☐ Natural disasters (e.g., droughts, floods)

- [ ] Other: ___________________________

29. Over the past month, did your household sell livestock, tools, or other assets to buy food?

- [ ] Yes
- [ ] No

30. How would you rate your household's ability to cope with food shortages?

- [ ] Very effective
- [ ] Effective
- [ ] Neutral
- [ ] Ineffective
- [ ] Very ineffective

30. What support mechanisms do you rely on during food shortages?

- [ ] Government assistance
- [ ] Community/NGO support
- [ ] Borrowing or credit
- [ ] Other: _______

31. What measures do you think could improve your household's food security? (Select all that apply)

- [ ] Access to better agricultural inputs
- [ ] Improved market access
- [ ] Climate adaptation support
- [ ] Financial assistance

☐ Other: ___________________________

32. Over the past month, has your household used any of the following coping strategies due to food shortages?

Coping Strategy	✓ **Yes**	✓ **No**	**Frequencies (rarely, sometimes, often)**
Reducing meal portion sizes			
Skipping meals entirely			
Eating less preferred or cheaper foods			
Borrowing food or relying on relatives/friends			
Selling assets (e.g., livestock, tools)			
Engaging in additional labor or jobs			
Sending household members to eat elsewhere			

Part V: Dietary Diversity and Food Consumption Scores

Objective: To examine the contribution of climate-smart practices to food security using HDDS, FCS, and HFC scores.

A. Household Dietary Diversity Score (HDDS)

33. Over the past **24 hours**, did your household consume any of the following food groups?

No	Food groups	Food item	Score
1	Cereals	Any grain-based food, including maize, rice, wheat, sorghum, millet, and others (e.g., bread, *injera, genfo, nifiro, kolo*)	
2	Root and tubers	potatoes, sweet potatoes, yams, cassava, *hamicho, enset*, or more root and tuber-based foods	
3	vegetables	Dark green leafy vegetables, tomatoes, onions, and garlic, as well as wild vegetables	
4	Fruits	Banana, Papaya, Mango, Avocado, and more fruits	
5	Meat, poultry, offal	Meats from the liver, kidney, heart, or other organs of beef, lamb, goat, pork, or chicken.	
6	Eggs	Hens Eggs	
7	Fish	Seafood and fish, whether fresh or dried	
8	Pulses/legumes/nuts	Foods produced from chickpea, common bean, cowpea, pigeon pea, nuts, lentils, and chickpea seeds.	
9	Milk	Milk, cheese, yogurt, and other dairy products	
10	Oil/fat	Food prepared with butter, fat, or oil	
11	Sugar/honey	Honey or sugar, Sweetened beverages, sugary meals like chocolate, candy, cookies, and cakes	
12	Condiments	Various foods, including coffee and tea, alcoholic beverages, and others	
	Total		

B). Household Food Consumption (HFC) Score

34. How many of the following food groups did your family eat over the course of the last 7 days?

No	Food groups	Number of days (Score)							
		0	1	2	3	4	5	6	7
1	Cereals								
2	Root and tubers								
3	vegetables								
4	Fruits								
5	Meat, poultry, offal								
6	Eggs								
7	Fish								
8	Pulses/legumes/ nuts								
9	Milk								
10	Oil/fat								
11	Sugar/honey								
12	Condiments								
	Total								