ADOPTION OF CLIMATE SMART AGRICULTURE PRACTICES AND ITS IMPACT ON FOOD SECURITY OF SMALLHOLDER COFFEE FARMERS: A CASE OF YEKI WOREDA, SOUTH WEST ETHIOPIAN PEOPLES REGIONAL STATE

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Adoption of Climate Smart Agriculture Practices and Its Impact on Food Security of Smallholder Coffee Farmers: A Case of Yeki Woreda, South West Ethiopian Peoples Regional State

By

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DECLARATION

Hereby I declare that this thesis is my original research work and has not been presented for a degree in any other University or any other award. Appropriate credit has been given where reference has been made to the work of others.

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ACRONYMS

AE	Adult Equivalent
AI	Adoption Index
ATT	Average Treatment Effect
CC	Climate Change
CSAPs	Climate Smart Agriculture Practices
DDS	Dietary Diversity Score
EMI	Ethiopian Meteorology Institute
ESR	Endogenous Switching Regression
FAO	Food and Agricultural Organization
FCS	Food Consumption Score
FGD	Focus Group Discussion
GACSA	Global Alliance for Climate Smart Agriculture
HH	Household Head
HFIAS	Household Food Insecurity Access Scale
ICO	International coffee organization
IFPRI	International Food Policy Research Institute
IPCC	Intergovernmental Panel on Climate Change
KII	Key Informant Interview
MoFAN	Ministry of Foreign Affairs of Netherland
PSM	Propensity Score Matching
SD	Standard Deviation
SSA	Sub Saharan Africa
SWEPRS	South West Ethiopia Peoples Regional State
TLU	Tropical Livestock Units
TNSRC	Teppi National spice Research center
UNDP	United Nations Development Programme
WB	World Bank
WFP	World Food Program
WMO	World Meteorology Organization

WAEPCO Woreda Agriculture Environmental Protection and Cooperative Office

BIOGRAPHICAL SKETCH

The author was born to his mother, Wudinesh G/Medhin, and his father, Tefera Bekele, on October 21, 1993, in Shisho-Ende Woreda, Kaffa Zone. He attended his primary education at Dimbira Primary School. Then, he completed his secondary education at Shishinda Secondary and Preparatory School in 2011. In 2012, the author joined the Gonder University faculty of agriculture and graduated with a BSc degree in Rural Development and Agricultural Extension in 2014. After one year of graduation, he was employed in the Chena woreda environmental protection and climate change office as an environmental protection officer and served for two years. Since February 2018, he has been employed at the Ethiopian Institute of Agricultural Research as an agricultural extension and communication researcher. He joined Jimma University's Postgraduate Program in 2022 for his MSc degree in Rural Development and Agricultural Extension, with a specialization in Rural Development.

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ABSTRACT

*Adopting climate-smart agriculture practices (CSAPs) is a viable strategy to improve smallholder coffee producers' ability to adapt to changing climate conditions and to increase their level of food security. This study offers valuable insight into evaluating the adoption of CSAPs and its impacts on the food security of smallholder coffee households in Yeki Woreda, Sheka Zone. The study used cross-sectional data collected from a randomly selected sample of 307 with a three-stage sampling technique in 2023. Both qualitative and quantitative data from the primary and secondary sources was collected through face-to-face interviews, FGDs, KIIs, and field observation and reviewing written and unwritten materials. Descriptive statistics, the binary probit model, PSM, and ESR were the tools used in data analysis. The adoption index was also used to determine the adoption status of CSAPs. The study confirmed that the climate change is reality. The paper identified that using improved coffee varieties, planting multipurpose shade agroforestry, intercropping, mulching, using organic fertilizer, stumping, and using cover crops were the CSAPs adopted by smallholder coffee farmers in the study area. 49.19% of respondents were adopters, while non-adopters accounted for 51.81%. The findings of a probit model revealed that the likelihood of adoption of CSAPs was positively influenced by sex, education level, household size, on-farm income of the respondents, membership in a group, and frequency of contacts with extension agents, and adversely influenced by the age of the respondents. The result of the average treatment effect on treated subjects exhibits positive significance and consistency across the estimation techniques. The effect of the treatment ranges from 27.2% to 30% in PSM estimation and 30% in ESR. In conclusion, it has been noticed that farmers who implement CSAPs consume a wider variety of foods than farmers who do not. Thus, local farmers, the government, policymakers, and global donors must unite to improve the uptake of CSAPs in a coordinated way to thereby enhance and safeguard farmers' socio-*ecological systems *along with associated local, landscape, and global benefits.*

***Key words**: climate change, probit, Propensity score matching, endogenous switching regression*

CHAPTER ONE

1. INTRODUCTION

1.1. Background

Climate change is the most pressing challenge facing the global community. It is highly exacerbating in African countries due to its high dependency on rain-fed production systems and limited adaptive capacity (Abegunde *et al.*, 2022). East Africa's agricultural industry suffers from climate variability, which is predicted to get worse in the future (Aryal et al., 2018). Ethiopia's agriculture sector is found to be very susceptible to the adverse impacts of climate change because of its geography, reliance on nature, and limited ability for adaptation (FAO, 2016). In the upcoming decades, agriculture must feed the continent and Ethiopia in particular, serve as the engine of growth, and adapt to climate change. Climate-smart agriculture (CSA), which simultaneously pursues improved production and resilience for food security while supporting mitigation when appropriate, places these factors at the heart of a paradigm shift in agriculture (FAO, 2013).

The concept of Climate-smart Agriculture (CSA) has emerged as a holistic approach to ensure food security and promote sustainable development while addressing climate change issues (FAO, 2010). It integrates the three dimensions of sustainable development (economic, social and environmental) by jointly addressing the food security, ecosystems management and climate change challenges. CSAPs are a set of agricultural practices and technologies that have three main pillars: sustainably increasing agricultural productivity and incomes; adapting and building resilience to climate change; and reducing and/or removing greenhouse gas emissions, where possible (FAO, 2013).

CSAPs are not a prescribed practice or a specific technology that can be universally applied. It is an approach that requires site-specific assessments of the social, economic and environmental conditions to identify appropriate agricultural production technologies and practices (Williams, *et al*., 2015). A key component of CSA is integrated landscape approach that follows the principles of ecosystem management and sustainable land and water use. CSAPs are an integrated approach to managing landscapes—cropland, livestock, forests and fisheries--that address the interlinked challenges of food security and climate change (World Bank, 2018). Practices are considered climate smart if they maintain or achieve increases in productivity as well as at least one of the other objectives of climate-smart agriculture (adaptation and mitigation) (FAO, 2013). .

Various development partners have ramped up their financial and technical support for effective scaling of CSA in Africa. For instance, between 2016 and 2018, the World Bank approved CSA projects worth US$3.8 billion to support 30 African countries in their pursuit to increase climate resilience and on-farm livelihoods of almost 5 million farmers (World Bank, 2018). Through small-scale on-the-farm pilot CSA projects and large-scale investments by development partners and the private sector, the African Union Development Agency envisions that by 2025 at least 25 million farming families will have adopted CSA (Shilomboleni, 2022).

The transition of African smallholder farmers to using CSAPs requires identification and profiling of context- and commodity-specific practices based on the principles of climate-smart agriculture. Coffee (Coffea L.) is a widely consumed beverage, and the world's second-most traded agricultural product grown in over 80 tropical nations requires the implementation of CSAPs. This is due to the fact that temperature changes and shifting rainfall patterns have severely disrupted its productivity, making areas unsuitable for growing and encouraging the spread of pests and diseases (Muslihah et al., 2020; Davis e*t al*., 2019; Läderach *et al*., 2017).

Due to its transnational nature, climate change also poses a serious threat to Ethiopia's smallholder coffee industry (Moat *et al*., 2017b), which is vital to the nation's economy and provides a living for millions of people (Worku, 2019). This is due to its reliance on the more climate change-prone Arabica coffee species, in addition to its nature based production system and limited ability for adaptation. As a result, smallholder coffee production are experiencing decreased yields, decreased quality, and the occurrence of pests and diseases (Läderach *et al*., 2017; Chemura *et al*., 2016; Bunn *et al*., 2015). Moreover, suitability of areas for coffee production is predicted to decrease by 39–59% by the end of this century due to climate change (Moat *et al*., 2017b). This would have substantial adverse impacts on the national economy as well as the livelihood of smallholder farmers, particularly in the study area, which is known for its lowland coffee production, if CSAPs are not potentially adopted.

Enabling smallholder coffee farmers' adoption of climate-smart agriculture assists farmers in modifying their farming practices in order to boost their harvests, strengthening their ability to withstand shocks related to climate change, and reducing their impact on the environment. For every agro-ecological setting and crop and livestock commodity in Ethiopia, there is, however, a lack of well-developed or documented climate smart agriculture profiles that provide an overview of the challenges posed by climate change, the CSAPs to be adopted in response, and the ways in which these CSAPs help farmers adapt to and mitigate climate change. Downscaling the results of global models to regional, national, and watershed scales is not readily appropriate (Williams, *et al*., 2015). This because climate smart agriculture is context specific. The lack of information, lack of research-based evidence as well as limited institutional capacity impedes the adoption of CSAPs at local farm level. Identifying adaptation and mitigation measures that the smallholder farmers can adopt is critical to the protection and support of their livelihoods in the face of climate-related hazards.

Thus, an exhaustive identification of site-specific CSAPs, and understanding of farmers' adoption behavior, as well as the potential effects on food security status are important in informing stakeholders in enhancing the adoption and effectiveness of CSA practices in smallholder coffee production systems. This study can assist experts and policymakers in developing and implementing evidence-based programs and policies facilitating the adoption of CSAPs. The study can also improve knowledge on climate change and variability in the study area and shed light on the factors causing difficulties in implementing CSAPs by smallholder coffee farmers.

1.2. Statement of the Problem

Climate-smart agriculture practices (CSAPs) encompasses a range of practices and technologies that are tailored to specific agro-ecological conditions, crops and livestock commodities and socio-economic contexts including the adoption of climate-resilient crop varieties, conservation agriculture techniques, agroforestry, precision farming, water management strategies, and improved livestock management (FAO, 2013). The studies show that CSAPs can be more successfully up scaled if they are able to contextualize the specific agro-ecological zones and existing farming systems (Williams, *et al*., 2015). Despite the fact that assessment of CSAPs tailored to specific context and commodity enhances the adoption of CSAPs by local smallholder farmers, there are insufficient studies undertaken in relation to CSAPs in coffee farming. Studies by Schmidt & Bunn, 2021; Salad et al., 2021, identified IVs, soil and water management, pest and disease management practices, shade trees, mulching, and cover crops as CSAPs.

Numerous studies have undertaken on adoption of climate smart agriculture in Ethiopia across the country (Belay *et al.*, 2023; Abiyan, 2020; Tekeste, 2019; Bewketu, M., 2017; Lakachew, 2017; Melaku et al., 2016). However, studies still need to identify and promote viable adaptation and mitigation practices (CSAPs) specific to each context and each commodity in order to facilitate adoption CSAPs by smallholder farmers.

Though there is a growing body of literature on the adoption of CSAPs in Ethiopia, the dearth of research on the adoption of CSAPs in coffee production impedes the implementation of CSAPs by smallholder coffee farmers. This study sought to fill this research gap by identifying site-specific and compliant CSAPs and factors affecting farmers' adoption behavior, as well as the effects of adoption on households' food security status. Further, decision-makers, smallholder coffee farmers, and private investors would have adequate access to information on the impacts of climate change on smallholder coffee production and the viable CSAPs to prioritize investments and efforts for future scaling out of CSAPs.

1.3. Objectives

1.3.1. General objective

The aim of this study was to evaluate the adoption of CSAPs and its impacts on food security of smallholder coffee households in Yeki Woreda, SWEPRS.

1.3.2. Specific objectives

- To assess the perception of smallholder farmers on trends of climate change in the study area
- To identify the existing CSAPs and its status of adoption among smallholder coffee farmers in the study area.
- To analyze the factors that affect adoption of CSAPs among smallholder coffee farmers in the study area.
- To evaluate the impact of the adoption of CSAPs on the food security status of smallholder coffee households.

1.4. Research Questions

- What are the perception of respondents on trends of climate change and its impacts in the study area?
- What are the major CSAPs that have been practiced by smallholder coffee farmers in the study area?
- What are the factors affecting the decision of CSAPs among smallholder coffee farmers?
- Does the adoption of CSAPs have a significant effect on the dietary diversity status of smallholder coffee-based households?

1.5. Significance of the Study

The current CSAPs being used by smallholder coffee farmers were revealed in this study, along with the variables affecting their utilization in the study area. So, this paper is sought to serve as baseline information for further enhancement of smallholder climate-smart coffee production systems. The results of the study are expected to contribute to the existing body of literature on the existing CSAPs in coffee farms and factors that influence the adoption of CSAPs among smallholder coffee farmers in the lowland parts of Ethiopia, with specific reference to Yeki woreda. The findings of the study are also expected to help smallholder coffee farmers and private investors have adequate access to information on the most important and viable CSAPs.

1.6. Scope of the Study

This study was limited in scope, both geographically and in subject matter. Geographically, the study was limited to one woreda, which was purposefully selected based on its high potential for lowland coffee production in southwest Ethiopia. The study was focused on four randomly selected kebeles, with a sample size of 307 drawn from the selected sample kebeles. In terms of the subject matter, this study was focused on the identification of the major existing CSAPs undertaken by smallholder coffee farmers and the major predicators of adoption CSAPs. It was also evaluated for the impacts of the adoption of the CSAPs on the food security of smallholder coffee households in the study area.

1.7. Limitation of the study

The major limitation of this study was that the findings may not be applicable to all farmers in all environmental settings. This is because the findings focus only on lowland coffee farmers, sampled from four kebeles. The food security status estimation was based on the previous one-week consumption data only recorded once at a point in time, which might not accurately represent typical household consumption patterns. Since the collected data was not time series data, there is a high probability of temporal inconsistency in the results.

1.8. Organization of the Paper

Chapter one deals with the introduction (background, statement of problem, aims of the study, significance of the study, scope of the study, limitations of the study). Chapter two discusses a literature review. Chapter three discusses the methods through which the study was undertaken. This section covered a description of the study area, research design, types and sources of data, methods of data collection, sampling techniques and sample size determination, and data analysis. Chapter four exhaustively displays the findings of the study. Finally, the conclusion and recommendation are unveiled in Chapter 5.

CHAPTER TWO

2. LITERATURE REVIEW

2.1. Concepts and Definition of Terms

Smallholder farmer: A smallholder farmer is characterized by a farmer who has small subsistence farms of less than 2 ha, is time and labor intensive, has much dependence on family, and has a low asset base (FAO, 2016).

Climate-Smart Agriculture Practices (CSAPs): refers to agricultural activities that sustainably and efficiently increase agricultural productivity and incomes, reduce or remove greenhouse gas emissions, and enhance the achievement of national food security and sustainable development goals (FAO, 2010). It is not a modern system of agriculture; instead, it is a tactic to identify suitable farming operations employed by farmers to respond to the changing climate (FAO, 2013).

Climate: Climate can be narrowly described as the typical weather or, more precisely, as the statistical representation of the relevant quantities' mean and variability over time periods, ranging from months to millions or thousands of years (IPCC, 2007b). The World Meteorological Organization (WMO, 2020) defines 30 years as the traditional term for averaging these variables.

Climate Change: is a shift in the climate's condition that lasts for a long time, usually decades or longer, and can be detected (e.g., using statistical tests) by variations in the mean and/or variability of its attributes (IPCC, 2007b).

Climate Information: refers to observations, data, and analysis of past, present, and future forecasts of average characteristics of weather in a particular area that are relevant for mitigation, adaptation, and risk management (IPCC, 2021).

Climate Impacts: Impacts describe the consequences of realized risks on natural and human systems, where risks result from the interactions of climate-related hazards (including extreme weather and climate events), exposure, and vulnerability (IPCC, 2007b).

Adaptation: The process of taking the required steps to manage the risks or uncertainty brought on by erratic extreme weather events, such as droughts and floods, with an impact on agriculture (IPCC, 2021).

Adoption: adoption is defined as the integration of an innovation into farmers' normal farming activities over an extended period of time. According to Rogers (2003), adoption is a decision to make use of CSAPs as the best course of action available, and rejection is a decision not to adopt CSAPs. In the case of this study, adoption is defined as the decision of smallholder coffee farmers to use CSAPs at more than the cut-off point of the adoption index, and rejection is if usage of CSAPs is below the cut-off point of the adoption index of CSAPs.

2.2. Theoretical Review

2.2.1. Theory of diffusion of innovation

This study was supported by the diffusion of innovation (DoI) theory of Rogers M. Everett. This hypothesis is predicated on the idea that good communication influences potential users' decisions to accept and spread a particular technology (Rogers, 2003). Diffusion is the process by which an innovation (CSAPs in our case) spreads over time among the members of a social system through certain routes, according to Rogers (2003). The four main elements of the dissemination of innovations, or CSAPs, are innovation, communication channels, time, and the social system, as stated in this description.

Rogers (2003) described the innovation-decision process as an information-seeking and information-processing activity where an individual is motivated to reduce uncertainty about the advantages and disadvantages of an innovation (CSAPs). According to Rogers (2003), the innovation-decision process involves five steps: (1) knowledge, (2) persuasion, (3) decision, (4) implementation, and (5) confirmation. These stages typically follow each other in a time-ordered manner. This process is shown in Figure 2.1.

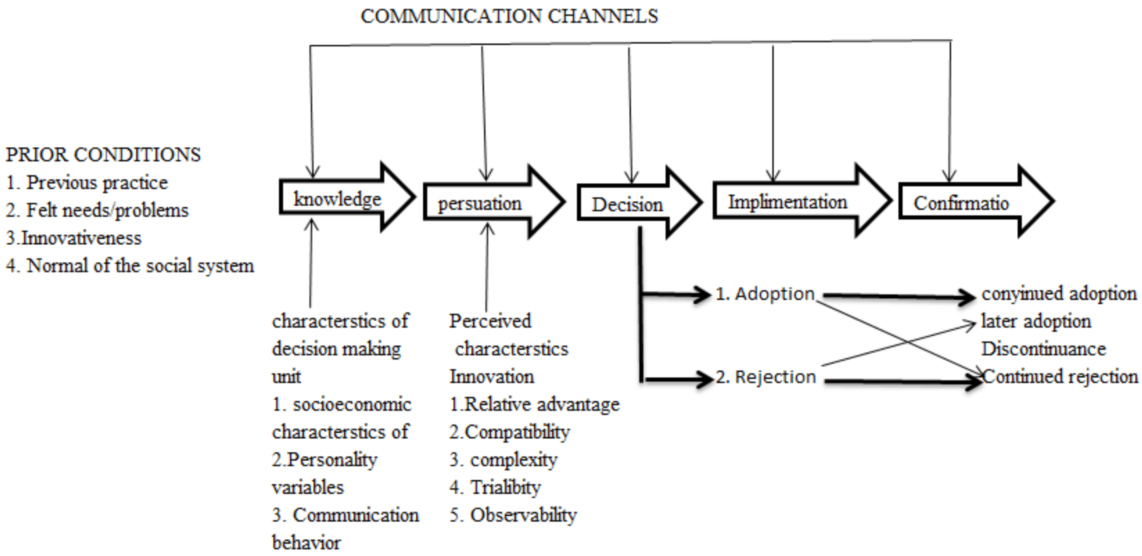

Figure 2.1. Five stage Innovation-Decision Process

Source: Diffusion of Innovations, Fifth Edition by Everett M. Rogers (2003, p.165).

This study sought to establish the relationship between socio-economic factors, farm household characteristics, extension contact and access to weather information in the process of adoption of CSAPs by smallholder coffee farmers. The inception of this study was be premised on the ideas put forward by this theory to prompt an understanding of how CSAPs have been adopted by the smallholder coffee farmers in the study area.

2.2.2. Technology Acceptance Theory (TAT)

The TAT model is based on two main beliefs that explain adoption: perceived usefulness and perceived ease of use. In his work, Davis (1989) defined them as “the degree to which a person believes that using a particular system would enhance his or her job performance” and “the degree to which a person believes that using a particular system would be free of effort,” respectively.

Based on this theory, farmers are expected to adopt a given CSAP if they perceive its importance in enhancing the adaptive capacity of their coffee farm and productivity, and if it is easy to use based on their capacity. Therefore, how farmers perceive the usefulness and ease of use of the CSAPs in adapting to climate change influences their adoption.

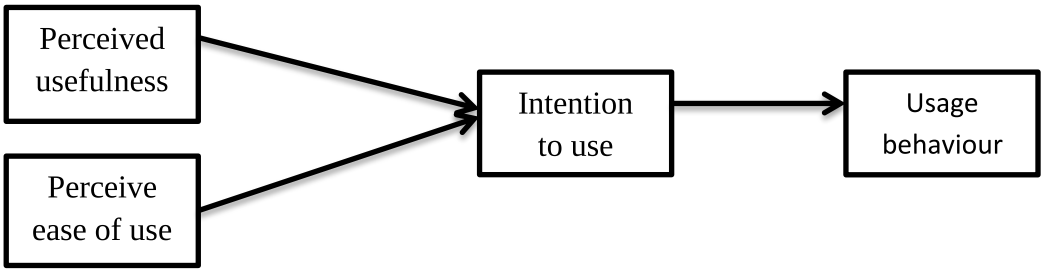

Figure 2. 2.Technology acceptance model

Source: technology acceptance model (Davis, 1989)

2.3. Climate Change Trends in Ethiopia

Ethiopia's mean annual temperature increased by 1.3°C between 1960 and 2006, at a rate of 0.2°C to 0.28°C each decade (Mcsweeney *et al*., 2010). According to projections, the temperature will rise by 3.1°C in 2060 and 5.1°C in 2090 (FAO, 2010). Due to climatic unpredictability, the nation has seen completely absent seasonal rain in some years and unexpected rain in others (MoFAN, 2018). By 2080, temperatures are forecast to rise by 1.4–4.1 ◦C, and the Rift Valley's mean annual rainfall is predicted to fluctuate from −40% to +10% (Kassie *et al*., 2014). It is anticipated that in north-western Ethiopia, the mean maximum and minimum temperatures will increase by 1.55–6.07 °C and 0.11–2.81 °C, respectively, in the 2080s compared to the base period considered (1979–2008) (Ayalew *et al*., 2012).

For the majority of the watersheds in Ethiopia's central and southwest Rift Valleys, there has been a notable decline in Kiremt (June–September) rainfall, according to a trend study of annual and seasonal rainfall for over 134 stations over 13 watershed zones (Cheung *et al*., 2008). According to Asfaw *et al.* (2018), a time series analysis of temperature and rainfall amounts in northern Ethiopia revealed an increasing trend during drought years and a declining trend for both Belg and Kiremt rainfall patterns.

2.3.1. Impacts of climate change on Ethiopian agriculture

Increased temperature, erratic rainfall patterns, frequent floods, and droughts are events that increase uncertainty and risk in agricultural production (Eshete *et al*., 2020), and the food security of Ethiopia's smallholder farmers. For example, the primary rainy season failure in 1983–84 caused a 9.7% decline in GDP and a 21% decrease in agricultural output. Furthermore, the El Nino-caused drought in 2015–16 left 10 million people without access to food (USAID, 2016). By 2045, climate change is predicted to have a 10% negative impact on Ethiopia's GDP (USAID, 2016). This is due to a number of factors, including the nation's heavy reliance on rain-fed agriculture, its low adoption of improved agricultural technologies and practices needed to meet the demands of a changing environment for production, its topography, which severely degrades land, and its limited ability to adapt to the negative effects of climate variability and change (World Bank, 2010).

2.3.2. Impact of climate change on coffee production

By altering temperature and rainfall patterns, global warming has an impact on coffee production by rendering some regions unusable (Djufry *et al*., 2022). Robusta is of inferior quality but harder and more productive around 22–28 °C, while Arabica, which is typically used in specialty coffees, grows best at 18–22 °C (Magrach & Ghazoul, 2015). Rising temperatures above these ideal ranges and erratic rainfall patterns mess with plant phenology, reduce yields and quality, and encourage the growth of pests and diseases (Jawo *et al*., 2023; Djufry *et al*., 2022; Magrach & Ghazoul, 2015). Rising temperatures cause complex, stressed plant growth with atypical leaves and stems, a decrease in photosynthetic capability, and accelerated coffee berry ripening. On the other hand, prolonged dry spells weaken trees and increase their susceptibility to pests, while heavy rains and winds cause damage to trees and increase fruit fall (Djufry *et al.*, 2022).

The suitability of areas for coffee growing is predicted to be significantly impacted by climate change as well (Jawo *et al*., 2023; Bunn *et al*., 2015; Magrach & Ghazoul, 2015; Ovalle-Rivera *et al*., 2015). The following is how Ovalle-Rivera *et al.* (2015) recorded the decline of Arabica coffee growing area in the future worldwide: Tanzania (22%), Uganda (25%), Brazil (29%), and Mexico (29%) would significantly reduce the number of presently coffee-growing areas by 2050.

2.3.3. Ethiopian coffee sector and climate change

Ethiopia's temperate highland regions are mostly known for producing coffee, which is a significant cash crop that provides household income in the area (Richardson *et al*., 2022). The majority of coffee is grown in humid (wet) evergreen forests, which are primarily found between 1200 and 2100 meters above sea level (Moat *et al*., 2017b). Ethiopia's five main coffee-growing zones are the North, South West, Rift, South East, and Harar. The main coffee-producing areas in Ethiopia include Wellega, Illubabur, Jimma-Limu, Kaffa, Bench-Maji, and Tepi in the south-west coffee zone (Moat *et al*., 2017b). Four distinct production strategies are used in Ethiopia to produce coffee: forest coffee (10%), semi-forest coffee (35%), garden coffee (35%), and plantation coffee (15%) (Degarege and Lovelock, 2021).

Ethiopian regions that grow coffee have been seeing the effects of climate change. Due to climate change, some of Ethiopia's coffee-growing regions are now unsuitable for producing coffee and will remain so in the future (Moat *et al*., 2017b).Due to a general decrease in rainfall and an increase in drought near the end of the dry season, particularly in areas between 1700 and 2000 meters above sea level, coffee output has generally decreased in the Wellega coffee area (Moat *et al*., 2017b).Some regions have already lost their suitability, like the Central Eastern Highlands, Arsi, and Harar; by 2040, the Northern Rift Valley and Bale are predicted to lose their suitability as well. Conversely, the Eastern and Rift Valleys are quite vulnerable (Moat *et al*., 2017b).

The additional coffee growing regions will become available to highland because to the upslope shift in coffee growing suitability from lower altitude areas to higher altitude areas (e.g., above 2000 m) (Moat *et al*., 2017b).The recommended method to produce coffee in the face of climate change is to relocate coffee estates to highland areas of south-western Ethiopia, as these locations are expected to have a good combination of mild temperature and sufficient rainfall (Moat *et al*., 2017a; Davis *et al*., 2012). Even though new, higher-altitude areas may benefit coffee production, Ethiopia's negative effects will probably be felt more keenly because lowland coffee production areas are no longer suitable, highland areas have a high population density, and land is allocated for various economic activities.

2.4. Concept of Climate Smart Agriculture Practices

Aiming to achieve sustainable increases in food production and income, build adaptability and resilience to climate variability, and mitigate, reduce, and/or remove greenhouse gas emissions from agricultural practices in order to curtail climate change challenges, the concept of CSAPs was first introduced in 2010 at the Hague Conference on Food Security (FAO, 2010). By concentrating on the possible trade-offs and synergies between the three pillars of climate-smart agriculture—agricultural productivity and food security, adaptive capacity, and mitigation benefits—the concept of CSAPs offers a range of strategies for reorganizing and transforming agricultural systems to support food security in the face of climate change (FAO, 2013).

Through lowering greenhouse gas emissions and boosting soil carbon absorption, CSAPs aim to decrease agriculture's impact on climate change, boost farmers' resistance to it, and raise production in a way that is both socially and environmentally sustainable (FAO, 2010; World Bank, 2010). In order to accomplish short and long-term agricultural development goals that integrate the three facets of sustainable development—economic, social, and environmental—and concurrently address issues related to food security and climate change, the CSAPs aim to transform agriculture systems (Branca *et al*., 2011).

Improved seed varieties, crop rotation, intercropping, cover crops, integrated soil fertility management (organic fertilizer and efficient use of inorganic fertilizer), conservation tillage and residue management (tillage and crop residue management and incorporation of crop residues), water management (irrigation, bunds, terracing, contouring, and water harvesting), integrated pest management (combination of biological, chemical, and cultural control), agro-forestry (intercropping crops and trees, live fencing), and other climate-smart agricultural practices are the following categories (Branca *et al*., 2011; FAO, 2013; Saguye, 2017).

2.5. Common CSAPs in Ethiopia

Integrated watershed management, integrated soil fertility management, sustainable land management, conservation agriculture, mulching, composting, intercropping with legumes, agroforestry, integrated pest and disease management, crop rotation, integrated crop-livestock management, aquaculture, and early warning systems are among the agricultural practices that Ethiopia considers to be CSAPs that help adapt to and mitigate the effects of climate change (Eshete *et al*., 2020; Chandra *et al*, 2018; FAO, 2016; Melaku *et al*., 2016). The requirement for site-specific assessments to determine appropriate agricultural production practices is a fundamental component of the CSAPs. Area closure, the use of inorganic fertilizers, the application of manure, the application of decomposed coffee husk, conservation tillage, intercropping, cover cropping in coffee, the use of improved fodder, crop rotation, and soil and water management techniques are some of the main CSAPs that have been implemented in Ethiopia's coffee-producing regions (Samuel *et al*., 2022).

2.6. Empirical Review

2.6.2. Climate smart agricultural practices in coffee farming

Variations in temperature and precipitation frequency are positively and significantly correlated with an increased likelihood of putting at least one climate change adaptation strategy into practice (Zuluaga *et al*., 2015). Many studies have identified various CSAPs that, if implemented effectively and on time, might make coffee producing systems more resilient to climate change. Salad *et al*. (2021) and Chengappa *et al.* (2017) identified planting shade, intercropping, mulching, soil and water conservation practices, cover crops, and stumping as major CSAPs in smallholder coffee production system through their study on adoption intensity of CSAPs in Arabica coffee production in Bududa District in Uganda. Adoption of CSAPs by smallholder coffee growers is therefore anticipated to improve resilience and adaptation to the impacts of climate change, decrease or eliminate greenhouse gas emissions, and boost productivity in a sustainable manner (FAO, 2013).

Intercropping: is the practice of growing two or more crops concurrently on the same field. By intercropping coffee with other tree crops, producers can diversify their revenue streams, ease cash flow restrictions, and lessen competition for land until latex production starts. By enhancing the ideal microclimate for coffee growth, intercropping coffee with other crops like bananas or ensets may also help with climate change adaptation. Bananas have two benefits: they provide shade, regulate stomata closure in severe water shortages, and minimize transpiration, which keeps bananas well-hydrated in drought conditions (Van Asten *et al*, 2015). The coffee canopy's air temperature is lowered by more than 2°C when banana shade is present (Mugagga, 2017).The reduction of overpowering in coffee grown under banana shade often results in larger and heavier cherries, acting as a buffer against changes in coffee production every two years. As a result, farmers can get paid more and the processed product has a better taste (GACSA, 2015).

Improved varieties: To maintain high coffee productivity in a changing environment, one crucial strategy is to adopt enhanced coffee types that are resistant to significant disease risks or tolerant of abiotic stress (Bunn *et al*., 2019).

Organic fertiliser: Applying organic fertilizer (compost) to croplands is one agricultural practice with significant potential to improve soil health and reduce greenhouse gas emissions. By diverting organic waste from landfills that create methane, smallholder farmers can obliquely contribute to the decrease of greenhouse gas emissions (Gravuer, 2016). Composting enhances soil microbial and plant biomass, which sequesters carbon into long-term, stable organic matter fractions. Composting also directly stimulates biological activities in the soil (Gravuer, 2016). Utilizing the fractions of decomposed organic matter in crop land improves soils' ability to retain water and nutrients, acting as a reservoir of nutrients for plants. It also enhances aeration, improves water infiltration, lowers soil erosion, and supports a variety and abundance of soil organisms, all of which can enhance plant health (Bravo-Monroy *et al*., 2016).

Mulching: Mulching is the process of covering the topsoil with organic residues in order to retain moisture, lower the temperature of the surface soil, and shield the soil from erosion brought on by heavy rains. Mulching, which is widely employed during dry seasons to conserve moisture and give the ideal temperature for crop growth, also entails covering plants with dried straw (Subedi, 2019). It also aids in the suppression or control of weeds. It is marketed as one of the climate-smart techniques that helps soil retain water, reduces evapotranspiration, and regulates soil temperature fluctuations, all of which help to create an environment that is conducive to plant growth (FAO, 2013).

Agroforestry: Planting temporary or permanent shade on coffee farmland is known as agroforestry. Its goals are to preserve coffee plants from the effects of climate change, increase household income, and improve food security. It is employed in the control of soil fertility, preservation of biodiversity, sequestration of carbon, and microclimate adjustment (Ehrenbergerova *et al*., 2017). It is well known to be an effective tactic for developing nations to deal with food insecurity and climate change (Meragiaw, 2017). Ehrenbergerova *et a*l. (2017) claim that by addressing unfavorable weather extremes and a nutritional imbalance, coffee shadow agroforestry lessens the stress on coffee. Shade trees are excellent for Arabica coffee plants because they control temperature and can lower it by up to 4 °C (Abaynesh, 2020).

Soil and Water Conservation Practices (SWCPs): In Ethiopia, various physical, biological, and agronomic SWCPs have been used in response to drought, nutrient depletion, and soil erosion. Since the 1980s, the Ethiopian government has worked with the local community and several donors to promote soil and water conservation (SWC) throughout the nation (Beshah, 2003). Stone bunds, soil bunds, fanya juu, tied-ridging, minimum tillage (minimum soil disturbance without crop residue), and mulching are examples of SWC methods.

Cover crops: Cover crops offer agricultural producers a natural and inexpensive climate solution through their ability to capture atmospheric carbon dioxide (CO2) into soils. But cover crops don't just remove CO2 from the atmosphere; they also make soil healthier and crops more resilient to a changing climate (Gloria, 2022). Cover crops also trap excess nitrogen – keeping it from leaching into groundwater or running off into surface water – releasing it later to feed growing crops. This saves costs on inputs like water and fertilizer and makes crops more able to survive in harsh conditions (Gloria, 2022).

Stumping: is the technique of bringing coffee trees back to life by pruning older and less productive trees down so that they stimulate the growth of new sprouts within a few months that develop into new branches. Stumping significantly increases production, improves livelihoods, and helps farmers adapt to climate change. Stumping is a key practice in reducing forest emissions while also dramatically increasing farmers' incomes and reducing the need for farmers to shift to other crops that deplete the soil of nutrients (World Bank, 2021). It also produces healthier trees that are better able to withstand pests, disease, and the erratic weather that comes with a changing climate (World Bank, 2021).

Farm diversification: it refers to a strategy to lower greenhouse gas emissions while raising yields and enhancing the standard of living for smallholder farmers (Hailemariam *et al*., 2013). Dessie *et al.* (2019) have provided evidence that cropping system diversity in Ethiopia's northwest is an effective approach for mitigating risks and enhancing food security. In order to diversify the farming system, coffee must be integrated with livestock, permanent crops, and seasonal crops (Djufry *et al*., 2022).

2.6.3. Factors influencing adoption of CSAPs among small scale farmers

It has been demonstrated that a variety of factors, such as household, institutional, socioeconomic, and farm characteristics, influence the adoption of CSAPs. Age, gender, education level, head of household, asset endowment, household income, farm size, farming experience, access to agricultural extension agents, loan availability, and availability of climate change information are some of these factors (Malefiya, 2017; Wekesa, 2017; Mulwa *et al*., 2017; Tekeste, 2019; Girma *et al*., 2020).

In order to evaluate the adoption of various climate smart technologies among farmers, Aryal *et al.* (2018) used multivariate probit and ordered probit models. The results showed that the following factors significantly influenced farmers' adoption of climate smart technologies in the Gangetic plains of Bihar, India: gender, educational attainment, access to social and economic capitals, farmland features, market accessibility, extension visits, access to training, and climate risk awareness.

Using the multivariate probit method, Faleye and Afolam (2020) in Nigeria found that the adoption of the various CSAPs had a negative impact on sex, age, years of education, use of credit, access to an extension service, and membership in a farmer association, while positively influencing radio information, farm size, volume of credit, farming experience, number of contacts with an extension agent, and membership in a cooperative society.

According to Mbwambo *et al*. (2021), smallholder coffee farmers' perceptions of several aspects of climate change were influenced by their educational background, farming experience, and access to climate information. According to Mbwambo *et al*. (2021), the findings of their study suggest that improving the timely and accurate distribution of weather information can aid farmers in understanding the effects of climate change and increase their adoption of CSAPs.

The MNL model calculated by Ahmed (2019) revealed that while gender and age of household members demonstrated a significant and negative correlation with the adoption of CSAPs, ownership of livestock, income, access to weather information, and the education level of household heads have a positive influence on the adoption of CSAPs.

Muluken *et al*. (2021) used 120 households to analyze the results of MNL regression, which showed that the adoption of structural soil and water conservation measures in Eastern Ethiopia was significantly predicted by factors such as education, farming experience, plot area, plot's distance from the dwelling unit, the number of economically active household members, and extension contact.

Girma *et al.* (2020) conducted a survey with 240 smallholder farmers in Jimma Zone and found that the decision of coffee growers to adapt to climate change is influenced by various factors such as the availability of weather forecasts and formal extension services, education level, age of the household head, farm size, income from coffee, and agro-ecological setting.

2.6.4. Impact of CSAPs on food security

At the home level, the idea of food security has been widely applied as a welfare indicator. If every member of the home always has physical and financial access to enough wholesome food that satisfies their dietary needs and food preferences while also being safe and nutritious, then the household is said to be food secure (FAO, 2013). According to (Wekesa, 2017), the CSAP is a strategy for changing agricultural systems to promote global food security and the fight against poverty. CSAP adoption by smallholder farming households, however, offers a "triple-win" benefit: increased productivity or food security, improved adaptation, and decreased greenhouse gas emissions or mitigation (Abegunde *et al*., 2022).

According to research by Abegunde *et al*. (2022), in the King Cetshwayo District, South Africa, farming households studied would have a higher likelihood of food security if they participated in the adoption of CSAPs. According to research conducted in the Teso North sub-county of Kenya by Wekesa *et al.* (2018), farmers who embraced CSAPs saw higher levels of food security than those who did not. A farm household will gain more from CSA adoption, according to Dooley and Chapman's (2014) study on climate-smart agriculture and REDD+ implementation in Kenya, partly because CSAPs include benefits related to adaptation, food security, and mitigation.

Adoption of CSAPs lowers farmers' vulnerability to crop failure and downside risks while also improving farm net returns in a favorable and significant way (Shahzad *et al*., 2021). At the macro level, the widespread adoption of CSAPs by smallholders will promote food security, poverty alleviation, and economic growth by raising agricultural revenue and production in a sustainable way and enhancing resistance to climate change. By putting CSAPs into practice, a smallholder plantation-based coffee production system that is sustainable can be established (Djufry *et al.*, 2022).

Hasan *et al.* (2018) found a positive correlation between household food security and the adoption of CSAPs in their study on the effect of climate-smart agriculture adoption on the food security of coastal farmers in Bangladesh. Adoption of CSAPs and innovations can enhance the results of household livelihood indirectly through increasing the supply of food staples, which leads to improved access to food through the markets due to affordability, and directly through increasing crop and livestock productivity, which improves food and nutrition security (Radeny *et al*., 2018).

CSAPs are defined as agricultural practices that meet the requirements of the climate-smart agriculture profile. Practices include agro-forestry, using organic manure, mulching, using wetland, crop rotation, crop diversification (cereal and legume intercropping), planting cover crops, drought- and heat-tolerant crops, improved grazing, effective manure management, and improving animal diets (Abegunde *et al.*, 2022).

Crop rotation, fertilizer application, insect resistance, high yielding, drought and short-season variety tolerance, and post-harvest technologies that enhance food security components are all included in the adoption of CSAPs, according to Tekeste (2019).

2.7. Methods of Measuring Household Food Security

According to the 1996 World Food Summit, food security is defined as a state that exists when all people have physical and economic access to enough safe, nutritious food that satisfies their dietary needs and preferences for an active and healthy life (WFP, 2009).

2.7.2. Household food consumption score

Based on dietary diversity, frequency of consumption, and the relative nutritional significance of the different food groups consumed by households, the Food Consumption Score (FCS) is a composite score (WFP, 2009). The World Food Program (WFP) created the HFCS tool, which estimates the dietary diversity score weighted by frequency using the record of the food items consumed prior to the previous seven days. This serves as a proxy indicator of household food security (WFP, 2009). Using a standard seven-day food dataset, the household food consumption score (HFCS) is generated by first classifying food items into groups and then adding the frequency of consumption of each group's member foods. The consumption frequency of eight distinct food groups—main staples, legumes, vegetables, fruit, meat and fish, milk, sugar, and oil—is used to calculate the HFCS (WFP, 2009).

According to WFP (2009), there are two different ways of determining the cut-off points. 1) FCS is classified as ≤ 28, between 28.5 and 42, and ≥ 42.5 for poor, borderline, and appropriate consumption groups, respectively, when sugar and oil are components of food groups that are regularly consumed. 2) Households with FCS of < 21, between 21.5 and 35, and > 35 are characterized as poor, borderline, and acceptable consumption groups, respectively, for consumption patterns where oil and sugar are of infrequent frequency.

2.7.3. Household dietary diversity score (HDDS)

This is the most commonly used method which measures food security by applying a 24 hour recall basis (Swindale & Bilinsky, 2006). Households will be required to keep records or recall the foods consumed within the last 24 hours. This method is advantageous as it measures the food availability, access and actual consumption/utilisation aspects of food security. This method also addresses the caloric and dietary quality concerns using food frequency questionnaire. This method also addresses caloric and dietary quality concerns using a food frequency questionnaire. The disadvantage of this method is that it is based on short memory, typically a 24-hour recall time without frequency information or weighted category cut-offs, which could lead to substantial bias as some information may be lost.

2.7.4. Household food insecurity access scale (HFIAS)

The HFIAS is a tool designed by FANTA to evaluate households' food access issues over the course of a 30-day recall period. It attempts to reflect the degree of food insecurity families experience as a result of a scarcity or lack of resources for food access and to record changes in food consumption habits. It is composed of nine questions, and these questions relate to three different domains of the access component of food insecurity: anxiety and uncertainty about household food access, insufficient quality, and insufficient food intake (Swindale & Bilinsky, 2006). Each question has four response options: never, rarely, sometimes, and often, which are coded as 0, 1, 2, and 3 in order of increasing frequency. Responses to these nine questions are summed to construct a food insecurity score, with a maximum score of 27 indicating most food insecure households. The disadvantage of this method is that its longer reference periods result in less accurate information due to imperfect recall.

2.8. Conceptual Framework

A conceptual framework shows the connections between the response variable, the outcome variable, and the explanatory factors. The adoption of CSAPs and the food security of smallholder coffee farmers are anticipated to be impacted by the effects of CC, which include temperature increases, erratic rainfall patterns, and outbreaks of pests and diseases. Farmers who realized that climate change was happening and that it would have an impact on coffee production planned to implement various tactics to improve their ability to adapt and continue growing coffee in spite of the difficulties brought on by the changing climate. It was expected that the adoption of CSAPs by smallholder coffee farmers would be influenced by institutional features, socioeconomic factors, and household characteristics. It is anticipated that when CSAPs are successfully put into practice, smallholder coffee production would become more resilient and adaptive, as well as sustainable in terms of production and productivity. This expected to boost farm income and enhance family food consumption.

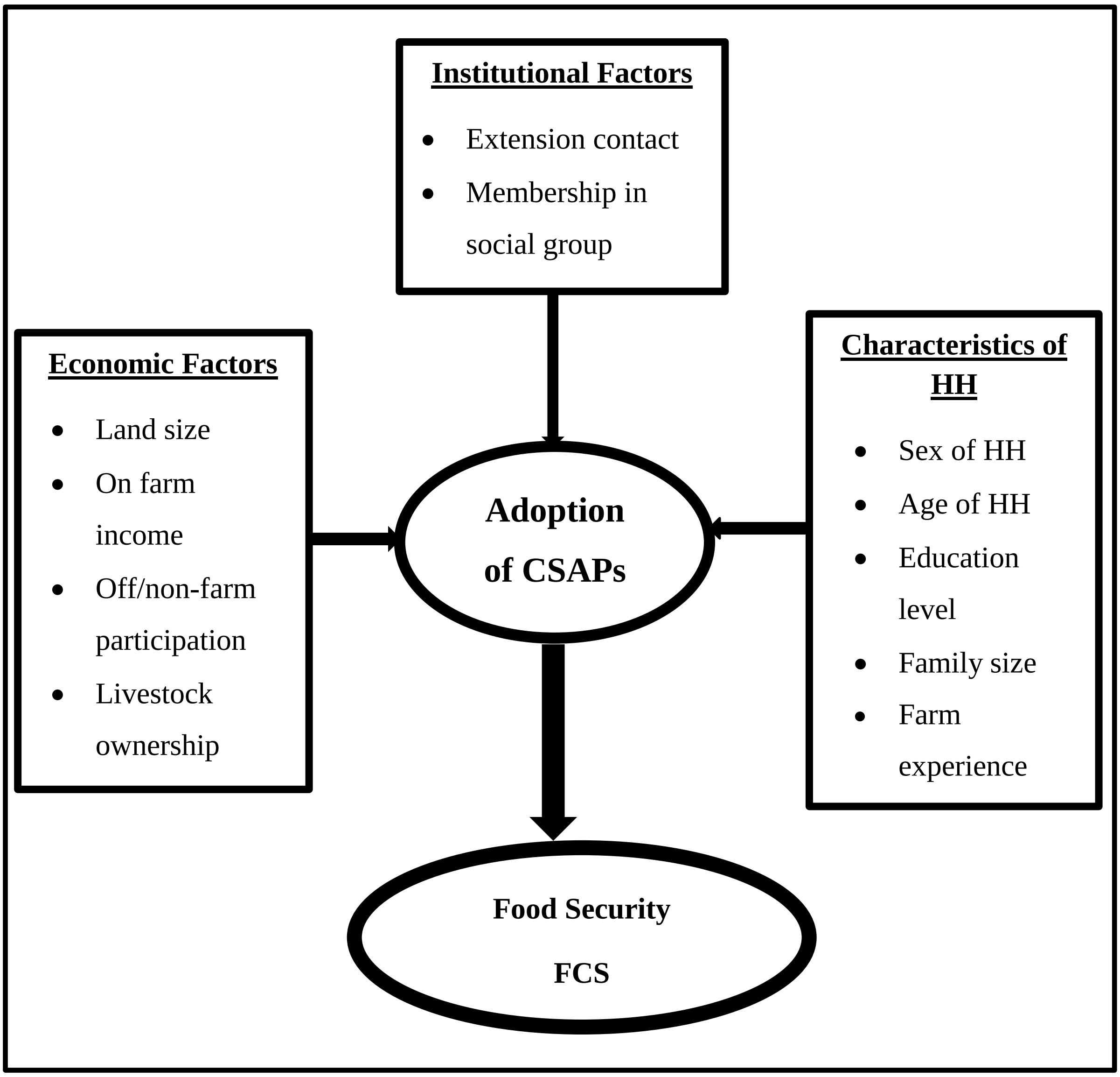

Figure 2. 3. Conceptual framework of the study

Source: Own constructed (2024) after thorough review of various literatures.

CHAPTER THREE

3 METHODS AND MATERIALS

3.1. Description of Study Area

The study was conducted in Yeki woreda, Sheka Zone. The lowland coffee production potential of the research area was deliberate in its selection, as was the possible impact of climate change. The Andracha woreda borders it on the north, the Benchi-Sheko zone borders it on the south, the Kaffa zone borders it on the east, and the Gambella Region borders it on the west. The study area is situated 600 kilometers away from Addis Ababa, with coordinates of $7^0 10'0''$ N to $7^0 20'0''$ N and $35^0 20'0''$ E to $35^0 40'0''$ E (TNSRC, 2015). The research area, which has twenty-two rural kebeles with a total population of 161,419—of which 84,468 are male and 76,951 are female—covers an area of 590.035 km^2, according to data from WAEPCO (2022).

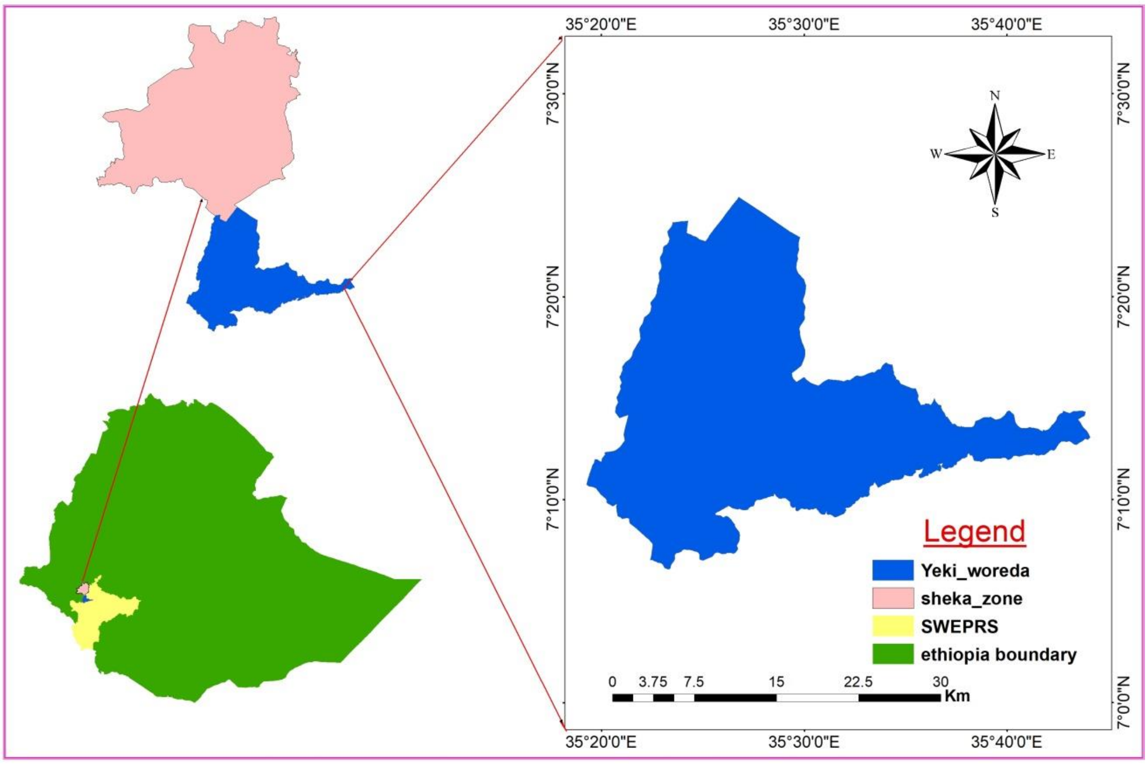

Figure 3. 1. Map of study area

Source: Own computed, 2024

Climate

At an elevation of 1200 meters above sea level, the research area experiences maximum and minimum temperatures of 35 °C and 15 °C, respectively. The area is in a hot to humid lowland agro-ecology with an average annual rainfall of 1488.05 mm (TNSRC, 2015). Rising temperatures, irregular rainfall, and extended dry seasons lasting from December to May have all been seen in the study area (WAEPCO, 2022). The region is referred to as a "green hot and dry zone."

The land cover composition

Perennial agriculture (35,916.5 hectares), annual agriculture (7,877.75 hectares), natural and manmade forests (9,485 hectares), wetland (762.6 hectares), grazing land (644.5 hectares), and other land cover compositions (4317.54 hectares) make up the land cover composition of the study area (WAEPCO, 2022). The sizes of landholdings vary from 0.25 ha to 10 ha. The study area's forest cover dropped dramatically as a result of the growth of agricultural areas, communities, and coffee farms, from 73% in 1973 to 32% in 2010. As a result, during the past forty years, the terrain has shifted from being dominated by forests to being less so (WAEPCO, 2022).

Livelihood activities

Agriculture is the primary source of income, and it is the backbone of small-scale, non-mechanized economic activity. The study area's main income crops are coffee, spices (ginger, turmeric, and black pepper), and maize and sorghum, which are also the area's main yearly staple crops. The potential for fruits, primarily bananas, avocados, and mangos, is well known in the research area. 165,805 cows, 5,107 horses, mules, and donkeys, ruminants (sheep 23,725 and goats 14,570), and poultry (93,800) make up the study area's livestock population (WAEPCO, 2022).

Coffee

There is a high potential for low-land coffee cultivation in the study area. Smallholder farm households that produce coffee cultivate roughly 28,668 hectares of land, whereas private investors grow coffee on about 7,000 hectares of land. Smallholder coffee growers held minimum and maximum holdings of 0.125 and 5 hectares, respectively, with an average production of 0.6 tons per hectare (WAEPCO, 2022). Small holdings that use relatively little enhanced technology—mostly high-yielding, improved and adaptable varieties, and improved agronomic techniques—account for about 80% of the study area's coffee production.

3.2. Research Design and Approaches

Cross-sectional research was used in this study. This is due to the fact that it saves resources without sacrificing accurate results. In order to gather information and analyze the findings of both quantitative and qualitative research at the same time, a mixed-methods research strategy was used. The sampling units were drawn using a three-stage random sampling approach. The instruments utilized in the data gathering process were a semi-structured questionnaire, field observations, focus group discussions (FGD), and key informant interviews (KII).

3.3. Sampling Techniques and Sample Size Determination

All of the small-scale coffee producers in the study area made up the study's population. The process of selecting respondents involved three stages of sampling. In the first stage, Yeki woreda in the Sheka zone was purposefully chosen from three woreda due to its great potential for lowland coffee cultivation. In the second stage, four kebeles were chosen at random. Using simple random sampling based on probability proportional to size and the Yamane (1967) formula for sample size determination at a 95% confidence level and 5% level of precision, 307 sample respondents were selected from the sampling frame in the final step, as indicated below.

$$s = \frac{N}{1 + N(e)^2} = \frac{1323}{1 + 1323(0.05)^2} \cong 307 \qquad (1)$$

where s is the sample size, N is a total number of sample Kebeles household heads, e is the precision level, or sampling error. Sample households from each kebele were selected using the proportionality factor stated as follows:

$$H_{no} = \frac{X}{Y} \times s \qquad 2$$

Where:

H_{no} = the number of households to be sampled from each kebele

x = the total number of households in the given kebele

y = the sum of the total number of households in all the four kebeles

S = total sample household used for the analysis.

Table 3. 1. Proportion of sample size per each kebeles

Sample kebeles	Total number of households	Number of sample households	Proportion of sample Household head (%)
Selam Ber	325	75	25%
Beko	336	78	25%
Addis Birhan	349	81	27%
Fide	313	73	23%
Total	1323	307	100%

Source: own computed based data from (WAEPCO, 2022).

Target groups were chosen in accordance with predetermined eligibility criterions. The selected target groups in this study are people who are residents of the sample kebele, those who have been producing coffee for more than five years, those who are older than eighteen, and those who are not experiencing natural problems such as sickness, funerals, and other ceremonies.

3.4. Data Type and Sources

Both qualitative and quantitative forms of data collected from primary and secondary sources were analyzed in this study in accordance with its goals. Primary data directly collected from respondents include socio-economic data, trends of climate change, impacts of climate change, and CSAPs. Additionally, secondary data was gathered from already-existing sources, such as books, research reports, dissertations, woreda annual and quarter reports, and published and unpublished literature, including peer-reviewed journals.

3.5. Tools of Data Collection

This study employed a variety of data collection techniques to gather accurate and legitimate data from primary and secondary sources. Thirty randomly chosen respondents participated in the pretesting of the instruments before the real data collection. Then, with regards to the suitability and clarity of each instrument, the chosen respondents were asked for any recommendations or critiques. As a result, there were no significant problems that required changing the data collection instruments. Interview schedules, FGDs, KIIs, and field observation were employed as methods in the research to gather primary data and examine written sources for secondary data. These instruments are covered in the section below.

3.5.1. Face to face interview

A semi-structured questionnaire was used along with an interview schedule that the researcher and five trained enumerators used to gather both quantitative and qualitative data from sample households. Researchers and professional enumerators helped with the interview schedule to make it easier to communicate with respondents. Data on household characteristics, socioeconomic factors, institutional features, biophysical variables, and the current CSAPs were gathered using this technique.

3.5.2. Key informant interview (KII)

Purposively chosen people who were deemed to be extremely knowledgeable about the topic under investigation, as well as the socioeconomic context of the study area, trends in climate change, practices used in coffee production, and current CSAPs among smallholder coffee farmers, participated in key informant interviews (KIIs). KIIs used to gather more qualitative data on climate change trends and their effects on coffee production; they also embraced CSAPs and their effects on food security. Ten key informant interviews were carried out with four development agents, four model farmers, and two experts from the woreda agriculture, environmental protection, and cooperative offices.

3.5.3. Focus group discussion (FGD)

FGDs were conducted with participants who were specifically chosen based on their experience and level of awareness regarding the implications of climate change, as well as their implementation of various response strategies. FGDs included youth coffee farmers, women-headed households, elders, and model farmers who had been producing coffee for a long time and were using various CSAPs. Each focus group had eight participants overall, for a total of 32 people. FGDs were conducted in an effort to learn more about participants' opinions of climate change trends, impacts on coffee production brought on by climate change, and their awareness of and perceptions of CSAPs and their effects on food security.

3.5.4. Field observation

In order to generate data that could be utilized to triangulate data gained through other techniques, field observation was employed as a supporting approach. In order to support and improve the information gathered using additional primary and secondary data collection methods, the researcher conducted field observation to comprehend the biophysical and socioeconomic characteristics of the places.

3.6. Data Analysis

3.6.1. Descriptive statistics

Descriptive statistics such as frequency, mean, standard deviation, and percentage were used to describe the socio-economic characteristics of the respondents, CSAPs usage, and institutional characteristics. A t-test for independent samples was used to determine the mean difference between the two groups. The chi-square test is also used to examine the association between two categorical variables. Narrative analysis and conceptual generalization were used to assess the qualitative data obtained from focus group discussions, key informant interviews, and observation.

3.6.2. Adoption index

In Chapter 4, every practice currently used by smallholder coffee producers was thoroughly enumerated and made transparent. In order to classify families as adopters or non-adopters, the extent of adoption is anticipated to be known following the identification of the current CSAPs carried out by smallholder coffee producers. An adoption index (AI) was used in this study to determine the degree of CSAP acceptance among smallholder coffee farmers. Using the formula adapted from Tiamiyu (2010), the adoption index was computed to ascertain the degree of CSAPs adoption among individual farmers, in accordance with the protocols of Salad et al. (2021); Teshome (2021); and Olumide & Atanda (2020).

$$AI_i = \sum \left[\left(\frac{AP_i}{RP_i} \times WP_i \right) \right] \tag{2}$$

Where AI= CSAPs adoption index of the i^{th} smallholder coffee farmer, AP_i=actual level of practice adopted by i^{th} farmer (area under practice P_i by i^{th} farmer), RP_i=the recommended level of practice P_i need to be adopted by i^{th} farmer, WP_i=proportion of score (weight) for each practice.

As a result, weights determined through discussions with experts and farmers based on how frequently farmers use the practices were used to create the adoption index, which indicates the extent to which the respondent farmer has embraced the entire set of CSAPs (Olumide & Atanda, 2020). The position of a particular smallholder coffee producer household in relation to the grand mean adoption score is then used to identify it. A farmer is classified as an "adopter" if their score is higher than the grand mean; otherwise, they are classified as "non-adopters" (Ogunya *et al*, 2017).

3.7. Impact Estimating Strategy

The concept of evaluating the impact of the adoption of CSAPs is based on farmers' decisions to adopt or not to adopt, guided by both observable and unobservable factors. The variables influencing households' adoption decisions of CSAPs were initially investigated using a binary probit model. Farmers' adoption or non-adoption decisions are based on unobservable utility (Y_1), which is influenced by the explanatory variables in such a way that the higher the utility (Y_1), the higher the likelihood of adoption of CSAPs by smallholder farmers. As a function of an observable vector of variables (N), the utility gain from adopting CSAPs (Y_i^*=$Y_1 - Y_0$) can be stated in the selection equation approximated as follows (Issahaku & Abdulai, 2020):

$$Y_i^* = \beta N_i + \mu_i \quad Where\ Z_i = \begin{cases} 1 & if\ \beta N_i + \mu_i > 0 \\ 0 & otherwise \end{cases} \qquad 3$$

Wherein; N_i was a vector of exogenous variables influencing the adoption decision; Z_i represents the treatment variable with a binary function of 1 if the farmer adopted and 0 if the farmer didn't adopt, β is a vector of parameters to be estimated, and $\mu_i$is a random error term assumed to be normally distributed.

It is anticipated that the decision to adopt CSAPs would have an impact on outcome variable at the household level. The outcome variable is assumed to have a linear function with a vector of exogenous variables N_i and with endogenous adoption decisions of the practices Z_i. This relationship is represented as follows;

$$Y_i = \alpha N_i + \sigma Z_i + \varepsilon_i \qquad 4$$

Where in; Y_i represents the outcome variable, Z_i represents the treatment variable with a binary function of 1 if the farmer adopted and 0 if the farmer didn't adopt α and σ stands for parameters to be estimated by the model, ε_i represents the random error term.

However, estimating the impact of the adoption of CSAPs on the food security of smallholder coffee producers using ordinary least squares might produce biased estimations (overestimation or underestimation) caused by self-selection bias and endogeneity resulting from heterogeneity in observed and unobserved household characteristics. Thus, propensity score matching (PSM) and endogenous switching regression (ESR) models are utilized to obtain unbiased and trustworthy findings.

3.7.1. Endogenous switching regression (ESR) model

The fundamental idea behind the ESR model is that, in addition to the factors that are observed, there can be unobserved characteristics of households that could affect both the adoption of CSAPs and food security. The adoption decision of CSAPs could be endogenous in the outcome equation, and estimating the outcome variable without correcting for the potential endogeneity could result in biased estimates. The ESR model is thus used to address endogeneity-selection bias that could arise from both observed and unobserved factors Maddala (1983) and Lee (1983). In the context of this study, the impact of adoption of CSAPs on food security is estimated in two stages. While the first stage of the impact estimation dwells on the decision by farmers to adopt or not to adopt the CSAPs, as was seen in equation (3), the second stage estimates two outcome equations from two regimes, representing both adopters and non-adopters of the CSAPs. The outcome equations of two regimes are given as follows:

$$\begin{cases} Regime\ 1.\ Y_{1i} = \alpha_1 N_i + \varepsilon_{1i} \quad if \quad Z_i = 1 \quad (Adopters) & 5a \\ Regime\ 2.\ Y_{2i} = \alpha_2 N_i + \varepsilon_{2i} \quad if \quad Z_i = 0 \quad (Non\ adopters) & 5b \end{cases}$$

where Y_1 and Y_2 represent the outcome variable respectively for adopters (regime 1) and non-adopters (regime 2); N_i represents the vector of covariates of farmer i; α_1 and α_2 are parameters to be estimated; and ε_{1i} and ε_{2i} are errors terms associated with the outcomes variables. According to the ESR framework, it is assumed that the error terms in equations 3, 5a, and 5b have a trivariate normal distribution with a zero mean and a covariance matrix that looks like this:

$$cov\ (\mu, \varepsilon_1, \varepsilon_2) = \Omega = \begin{bmatrix} \delta_\mu^2 & \delta_{\mu1} & \delta_{\mu2} \\ \delta_{\mu1} & \delta_1^2 & . \\ \delta_{\mu2} & . & \delta_2^2 \end{bmatrix} \qquad 6$$

where δ_μ^2 is the variance of the error term in the selection $equation\ 3$; δ_1^2 and δ_2^2 are the variances of the error terms in the outcome $equations\ 5a\ and\ 5b$; $\delta_{\mu1}$ and $\delta_{\mu2}$ are the covariances of $\mu, \varepsilon_{1i},\ and\ \varepsilon_{2i}$. Covariance between $\varepsilon_{1i}\ and\ \varepsilon_{2i}$ is not defined since Y_1 and Y_2 are not observed simultaneously (Maddala, 1983). The expected values of $\varepsilon_{1i}\ and\ \varepsilon_{2i}$ conditional on the sample selection are non-zero, because the error term of equation 3 is correlated with the error terms of the outcome $equations\ 5a\ and\ 5b$.

The inverse Mills Ratios computed from $equation\ 3$ with $\lambda_{1i} = \frac{(\phi(Z_i\alpha))}{(\Phi(Z_i\alpha))}$ and $\lambda_{2i} = \frac{(\phi(Z_i\alpha))}{(1-\Phi(Z_i\alpha))}$ were included in $equations\ 5a\ and\ 5b$ to correct for selection biases resulting from unobservable factors. Therefore, the outcome equations of two regimes (adopter and non-adopter) corrected for endogenous adoption are given as:

$$\begin{cases} Regime\ 1. Y_{1i} = \alpha_1 N_i + \delta_{\mu1}\lambda_{1i} + \eta_{1i} \quad if \quad Z_i = 1 \quad (Adopters) & 7a \\ Regime\ 2. Y_{2i} = \alpha_2 N_i + \delta_{\mu1}\lambda_{1i} + \eta_{2i} \quad if \quad Z_i = 0 \quad (Non\ adopters) & 7b \end{cases}$$

By construction, the expected values of the error terms η_{1i} and η_{2i} are both zero due to the inclusion of the inverse Mills ratio terms in equations (7a) and (7b1), so that OLS estimation of these equations yields unbiased estimates of α_1, α_2, $\delta_{\mu1}$, and $\delta_{\mu1}$.

Perhaps the more important issue in the estimation of the ESR model is the stability and reliability of the estimation. Identification of the instrumental variables affecting the selection variable but not the outcome variable in order to confirm the stability and consistency of the estimation is the main concern in the ESR model (Kassie *et al.,* 2014; Di Falco and Veronesi, 2013; Bourguignon *et al*., 2007). Social group membership and the frequency of extension contact were used as instrumenting variables affecting the adoption decision but not the outcome variable, although it is acknowledged that getting a true instrument is empirically challenging. A falsification test was used to verify the validity of these instruments (Di Falco and Veronesi, 2013). Consequently, the results of the falsification test conducted on the chosen instrumental variables, which are presented in Appendix Table 1, indicate that these variables together significantly influence the decision to adopt CSAPs (in selection equation: X^2 =88.40; P-value=0.001), but not the outcome variable (F (2) =2.21, P-value=0.113) for adopters and (F(2) =0.92, P-value=0.4) non adopters.

Conditional expectations and treatment effects

The structure of the expected conditional and average treatment effects under the actual and counterfactual scenarios given in Table 3.2 is specified as follows:

$$(a)\ \ E[Y_{1i}|N, Z_i = 1] = \alpha_1 N_{1i} + \delta_{1\mu}\lambda_{1i} \quad \text{((Adopters)} \qquad 8a$$

$$(b)\ \ E[Y_{2i}|N, Z_i = 0] = \alpha_2 N_{2i} + \delta_{2\mu}\lambda_{2i} \quad \text{(Non} - \text{adopters)} \qquad 8b$$

$$(c)\ E[Y_{2i}|N, Z_i = 1] = \alpha_2 N_{1i} + \delta_{2\mu}\lambda_{1i} \ \text{(Adopters had they decided not to adopt)}\ 8c$$

$$(d)\ E[Y_{1i}|N, Z_i = 0] = \alpha_1 N_{2i} + \delta_{1\mu}\lambda_{2i} \ \text{(Non adopters had they decided to adopt)}\ 8d$$

From these results, one can compute the effects of unbiased treatments using equations 8a through 8d. Equations 8a through 8d define the expected outcomes that were used to compute the heterogeneity effects. Equations 8c and 8a were used to compute the base heterogeneity for adopter families (BH_1), and Equations 8d and 8b were used to calculate the base heterogeneity for non-adopter households (BH_2). In order to comprehend the effect of the usage of CSAPs on food security, transitional heterogeneity (TH) was finally calculated as the difference between ATT and ATU (Table 3.2). The following were the equations for the adopted and non-adopted groups' expected conditional and average treatment effects:

$$\begin{aligned} ATT = a - c &= E[Y_{1i}|N, Z_i = 1] - E[Y_{2i}|N, Z_i = 1] \\ &= N_{1i}(\alpha_1 - \alpha_2) + \lambda_{1i}(\delta_{1\mu} - \delta_{2\mu}) \qquad 9 \end{aligned}$$

Similarly, the average effect on the untreated households (ATU), or the anticipated change in the food security status of the household non-adopters had they chosen to adopt CSAPs, is provided as follows:

$$\begin{aligned} ATT = d - b &= E[Y_{1i}|N, Z_i = 0] - E[Y_{2i}|N, Z_i = 0] \\ &= N_{2i}(\alpha_1 - \alpha_2) + \lambda_{2i}(\delta_{1\mu} - \delta_{2\mu}) \qquad 10 \end{aligned}$$

where N_1 and N_2 are set of explanatory variables affecting food security in regime 1 and 2, respectively. α_1 and α_2 are parameters to be estimated.

Despite the fact that these households are adopting CSAPs, it's possible that unobservable factors that could potentially affect the status of household food security caused the households that adopted CSAPs to have a better food security status than the households that did not. We can also characterize the impact of base heterogeneity on households in accordance with Carter and Milon (2005) as follows:

$$BH_1 = a - d = \alpha_1(N_{1i} - N_{2i}) + \delta_{1\mu}(\lambda_{1i} - \lambda_{2i}) \quad for\ adopters \qquad 11a$$

$$BH_2 = c - b = \alpha_2(N_{1i} - N_{2i}) + \delta_{2\mu}(\lambda_{1i} - \lambda_{2i}) \quad for\ non\ adopters \qquad 11b$$

Table 3. 2. Conditional expectations, treatment, and heterogeneous effect

Sub-Samples	Decision Stage		Treatment effect
	To adopted	Not to adopted	
Adopters	$(a)\ E[Y_{1i} \mid N, Z_i = 1]$	$(c)\ E[Y_{2i} \mid N, Z_i = 1]$	ATT
Non adopters	$(d)\ E[Y_{1i} \mid N, Z_i = 0]$	$(b)\ E[Y_{2i} \mid N, Z_i = 0]$	ATU
Heterogeneous effects	BH_1	BH_2	TH

Note: (a) and (d) are observed outcomes; (b) and (c) are the hypothetical unobserved outcomes (expected situations). Z_i = 1 if households adopted CSAPs; Z_i = 0 if households non-adopter of CSAPs. Y_{1i} & Y_{2i} are food security indicators (FCS) of adopter and non-adopter. ATT & ATU: average treatment effect on treated and untreated. BH: is the effect of base heterogeneity for households that adopted (Z = 1) and did non-adopted (Z = 0). TH: Transitional heterogeneity = ATT–ATU.

3.7.2. Propensity score matching (PSM)

The estimation of ESR may yield findings that are sensitive to the model assumption or the choice of instrumental variables. It is believed that using the PSM approach would be essential to confirming the reliability of the estimated treatment effect data that were obtained from the ESR. Introduced in 1983 (Rosenbaum and Rubin, 1983), the PSM method is a quasi-experimental technique that uses observable features in a sampling unit to create a control group that is similar to the treated group in terms of external variables. Rosenbaum and Rubin (1983) state that in order to guarantee the validity of the matching process, the PSM model is based on the assumptions of unconfoundedness (conditional independence) and a common support condition (satisfactory overlap).

According to the conditional independence assumption (CIA), given a set of observable covariates (N) that are unaffected by treatment (adoption decision), the potential outcome of adopters and non-adopters is independent of treatment assignment (i.e., independent of how adoption decisions are made by households) (Khandker *et al*., 2009; Rosenbaum & Rubin, 1983). CIA's written as:

$$Y_{i1}, Y_{i0} \perp {}^{D_i}/_{N_i} \qquad 12$$

Where: $\perp$ indicates independence; N_i is a set of observable characteristics, Y_0 is the outcome of an individual on control and Y_1 is the outcome of an individual on treatment. As a result, for Z = 1 and Z = 0, the mean of the possible outcome is comparable, $E\ (Y_0|Z\ =\ 1, X) = E\ (Y_0\ |Z =\ 0, X)$, after accounting for observable differences.

Another assumption is the common support or overlap condition: In order to identify suitable matches, the common support assumption states that there must be a substantial overlap in the traits of the treated and untreated units (Bryson et al., 2002). For every value of N, there is a positive probability of receiving treatment as well as not receiving treatment.

$$0 < p\left(Z = {}^{1}/_{N}\right) < 1 \qquad 13$$

Because an individual falling outside of this region would not be eligible for treatment, this restriction means that the balancing property check would only be performed on observations whose propensity score falls within the common support region of the propensity score of the treatment and control groups (Becker & Caliendo, 2007). This assumption ensures that people with the same observable traits have an optimistic possibility of belonging to both groups in the propensity score distribution. According to Caliendo & Kopeinig (2005), the PSM was implemented using five steps, as discussed below.

Step 1: Estimating the Propensity Score

Equation 3 states that CSAPs adoption is empirically regressed on a vector of observable characteristics (N). Using a probit estimator, propensity scores (which range from 0 to 1) are produced from the regression (Rosenbaum and Rubin, 1983). As a result, the propensity scores (adoption probability), which are utilized to match adopters to non-adopters in the sampled data set, are provided as:

$$P(X) = Prob\ (Z_i = 1|N_i) \qquad 14$$

Step 2: Matching estimators/algorithm

In PSM, many algorithms are employed to match samples. Adopters and non-adopters are matched using each of these distinct and specialized matching techniques (Caliendo and Kopeinig, 2008). In PSM, the most commonly used matching estimators are kernel, radius, and nearest neighbor matching.

Following the generation of the propensity scores, an investigation is conducted into the covariate balancing property and the overlap over the determined common support. Adopters and non-adopters can receive similar treatment because of the overlap assumption. The zone of shared support was identified by comparing the minima and maxima of the propensity score between the two groups. As a result, if an observation's propensity score fell between the minimum and maximum, it was eliminated, and all observations in the other group were eliminated (Caliendo & Kopeinig, 2008).

Step 4: Testing the matching quality

Distributing relevant features, or variables, equally between adopter and non-adopter groups is the primary objective of PSM. The quality of covariates in the match can be examined using a variety of methods. The smallest standardized bias of each covariate utilized in the matching, the number of variables that remain insignificant after matching, and the smallest pseudo-R2 after matching are the methods used to verify the balancing quality of the covariates in this study (Caliendo & Kopeinig, 2008).

Step 5: Calculating average treatment effect on treated

ATT estimation is the last step in the PSM estimation process. The PSM estimator examines what would have happened to a household's food security status if the homes that adopted CSAPs had decided not to do so. It is accepted that $Y_i(Z = 1)\ and\ Y_i(Z_i = 0)$ cannot be seen simultaneously in the same household. Furthermore, it is not possible to estimate the impacts of individual treatments; instead, one must estimate the population's average treatment effects. The average treatment effect on the treated (ATT), which is defined as follows, is the most often used average treatment effect estimation, as explained in Caliendo & Kopeinig (2008).

$$ATT = E(T|Z = 1) = E[Y(1)|Z = 1] - E[Y(0)|Z = 1] \quad 15$$

Where T_i is treatment effect (effect due to adoption of CSAPs), Y_i is the outcome variable (food security) i, Z_i is an adoption decision for the CSAPs.

3.8. Definition and Measurement of Variables and Working Hypothesis

3.8.1. Dependent variables

The decision made by farmers to implement the CSAPs on their coffee fields served as the study's dependent variable (Y).

3.8.2. Outcome variable

The state of food security (measured in FCS) for smallholder coffee households in the study area served as the study's outcome variable. The Household Food Consumption Score (HFCS), a stand-in for farmer food security, was utilized to gauge the respondents' level of food security. It is a composite score that incorporates dietary diversity, food frequency, and the relative nutritional importance of different food groups consumed by a household. For the calculation of the FCS, data are collected on the 7-day recall of the frequency of consumption of different food items, and food items are grouped into 8 specific food groups, with each group given a weight representing the nutrient density of that food group (see Appendix Table 6 for classification and their corresponding weights). The value of FCS ranges from 0 to 112, with a higher FCS representing a higher dietary diversity and/or frequency of consumption and a higher nutritional value of a household's diet, and vice versa. FCS was calculated using the subsequent formulas:

$$FCS = \sum [f \times w]$$

Where w = weighted value indicating the nutritional value of chosen food categories; and f = frequency of food consumption. Food consumption ranges from 0 to 28, from 28.5 to 42, and > 42 for poor, borderline, and acceptable consumption, respectively.

3.8.3. Independent variables

The regression model's explanatory (independent) variables result from the interaction of several variables, including the demographics of the household, the socioeconomic background, and the institutional setting. Based on the evaluation of relevant empirical literature and prior findings, 11 explanatory factors were found and included in this study; they are shown in Table 3.3.

Sex of household head (SEXHH): This variable is a dummy variable, taking the value 1 if male and 0 if female. It is hypothesized that male-headed households are better off than female-headed households in adoption CSAPs. This is because women are culturally designated for domestic pursuits and have restricted access to crucial resources like finances, the labor force, and land, which oftentimes undermines their capacity to venture into labor-demanding farm enterprises. Waaswa (2021) showed that male-headed households are found to be more likely to adapt to climate change.

Age of household heads (AGEHH): Age is a continuous variable that indicates the length of time that a household head has existed and is measured in years. According to certain research, farmers' adoption of CSAPs was significantly hampered by their advanced ages (Zakaria et al., 2020; Wekesa, 2017). Ageing is associated with a decline in physical ability, an increase in risk-averseness, and a short-term planning horizon. Thus, in this study, the age of household heads is hypothesized to have a negative effect on the adoption of CSAPs.

Education level of the household head (EDUHH): It is a continuous variable measured in the number of years spent in school by the household head. Different scholars revealed that education level has a positive influence on the adoption of CSAPs (Abiyan, 2021; Wamalwa, 2017). A possible explanation is that educated farmers tend to have better access to new technologies and to update information about the risks associated with climate change and adaptation strategies to climate change. Therefore, it is expected to have a positive influence on the adoption of CSAPs in the study areas.

Family size (FAMSZ): This is a continuous variable measured in adult equivalent that refers to the total number of family members in the household at the time of study. Household size as a proxy for labor availability may influence the adoption of a new technology positively as its availability reduces labor constraints (Lakachew, 2017;

Awoke, 2018). This is plausible because smallholder farmers in the county mostly use family labor for their agricultural operations. Hence, the study expected that the size of the family could affect the adoption of CSAPs to climate change positively.

Farmland Size (LANDSZ): Farmland size refers to the arable land available to an individual farm household and is continuous and measured in hectares. There is a positive and significant relationship between farm size and the adoption of CSAPs (Ahmed, 2019; Bewketu, 2017; Lakachew, 2017). Therefore, the variable is expected to positively influence the choice of CSAPs.

On-farm Income (FAMINC): It is a continuous variable and measures the amount of annual income a given household obtains from the sale of coffee products, measured in Ethiopian Birr. An increase in annual farm income increases the chance of uptake of CSAPs (Abiyan, 2020; Waswa, 2021). Farm income is, therefore, predetermined to drive the CSA adoption level in a positive direction.

Non/off-farm participation (OFFARM): It is considered a dummy variable and takes the value 1 if the respondent has participated in off-farm or non-farm activities and 0 otherwise. Waswa (2021) indicated a negative relationship between off-farm participation and the practice of CSAPs. Indulging in off-farm vocations usually disinclines farmers from committing themselves to farm work due to the triggering nature of off-farm revenue from many off-farm activities (Waswa, 2021). Engaging in off-farm activities diverts time and effort away from on-farm agricultural activities. In this study, therefore, it is expected to negatively affect farmers' adoption decisions of CSAPs.

Livestock size (LIVESTK): It refers to the amount of livestock owned by the household. This is a continuous variable and is measured in tropical livestock units (TLU). Farmers who have a large number of livestock in TLU are less likely to respond to climate change using CSAPs as an adaptation strategy (Bewketu, 2017). The larger number of livestock owners is predicted to substantially hamper adoption of CSAPs.

Farming experience (FARXP): continuous denotes the number of years the respondent has been involved in coffee production. Some studies revealed that the farm experience of household heads has a positive and significant relationship with the adoption of CSA practices (Zakaria et al., 2020; Mugagga, 2017). The more farming experience there is, the higher the likelihood of the accumulation of physical and social capital. The accumulation of physical and social capital and technical know-how over time can offer farmers better exposure and capacity to adopt CSAPs. In this study, farming experience is hypothesized to drive the CSA adoption level in a positive direction.

Group membership (GROUPM): It is a dummy variable represented by 1 if the respondent is a member of any farm group and 0 otherwise. Membership in social groups promotes the adoption of agricultural technology (Tekeste, 2019). Membership in social groups is anticipated to have a positive correlation with the decision to adopt CSAPs.

Extension Contact (EXTCON): It is a continuous variable measured in the number of contacts between extension agents and farmers annually. Extension contact positively and significantly influences the extent of adoption of climate-smart agriculture practices (Salad et al., 2021; Tekeste, 2019). Therefore, extension contact is expected to have a positive effect on selected adaptation strategies.

Table 3. 3. Operationalization of variables and working hypothesis

Variable	Description of Variables	Type	Value and unit of measurement	Effect on adoption
SEXHH	Sex of household head	Dummy	1=Male, 0=Female	+
AGEHH	Age of household head	Continuous	year	-
EDUHH		Continuous	Years of schooling	+
FAMSZ	Family size of	Continuous	Adult equivalent	+
FAREXP		Continuous	Years spent in coffee farming	+
LIVESTK	Livestock owned	Continuous	TLU	-
LANDSZ	Land size	Continuous	Hectares	+
FARINC	Income from coffee	Continuous	Ethiopian Birr	+
OFFARM	Off/non-farm participation	Dummy	1= participant 0=non-participant	-
GROUPM	Membership of HH in social group	Dummy	1=member 0=non member	+
EXTCON	Frequency of contacts with extension agents	Continuous	Number of contacts	+

Source: Author's computation after thorough review of literature, 2023

3.9. Ethical consideration

Before the questionnaires, FGDs, and KIIs were administered, the study's purpose was explained to the respondents, and it was made clear that participation was entirely voluntary. The principles of integrity, impartiality, transparency, respect for research subjects, observance of intellectual property, secrecy, informed consent, faithfulness, and honesty were all used in the study's conduct. The information gathered was just used for the study; it wasn't used for any other purposes. Moreover, consent from local authorities was sought. The researcher did not knowingly engage in or take part in any malicious activity that could have compromised the privacy of research subjects.

CHAPTER FOUR

4. RESULT AND DISCUSSION

This chapter includes a discussion of the results for the three specific objectives. Subsection one explains the socioeconomic traits and how they relate to the adoption of CSAPs. Subsection 2 deals with the perceptions of respondents about the trends of climate change and its impacts. Subsection 3 displays the findings from the first objective, which looked at the particular CSAPs utilized by smallholder coffee growers in the field. Subsection 4 describes the food security level of smallholder coffee households. Subsection 5 addressed the second and third objectives. Propensity score matching (PSM) analysis and the endogenous switching regression model (ESR) were used to evaluate how CSAPs affected farmers' food security status, and a probit regression analysis was used to identify the factors influencing the adoption decisions of CSAPs mentioned in the section.

4.1. Descriptive and Inferential Statistics of Demographic and Socio-economic Characteristics of the Sample Households

4.1.1. Descriptive statistics of categorical variables

Sex of household head

According to the survey results displayed in Table 4.1, 79.80% of the sampled had a male head, while the remaining 20.20% had a female head. Of the adopters' households, 85.97% were adopters male headed. The result of chi-square tests revealed that there is a significant difference in the adoption of the CSAPs between households headed by women and men at significance level of 5% (X^2=5.04, p<0.05). This is consistent with the finding of Lakachew (2017) and Abiyan (2020), who revealed that male-headed households are more likely to adopt CSAPs compared to female-headed households. In addition, the participants in the focus group discussion and key informant interview noted that women's involvement in farm operations is restricted in the field due to household responsibilities that keep them occupied all day. They also emphasized how cultural norms restrict women's ability to make decisions in the economy and their ownership rights over fixed assets.

Membership in social groups

The survey results in Table 4.1 demonstrated that 73.29% of sample households were members of social groups, while just 26.71% did not belong to any farm groups. According to Table 4.1's chi-square test result, there was a significant difference in the participation of non-adopters and adopters of CSAPs in different farmers' groups at a significance level of 1% (x2 = 34.80, p-value = 0.001). The more the respondents participate in different social groups and networks, the more likely they are to adopt CSAPs. This is because agricultural practices, by nature, are labor-intensive and require social network. This culture plays a great role in the adoption of CSAPs. Participants in the FGDs argued that the culture of working together in participating farm groups like ‘debo’, 'wonfel', and ‘idir’ helped them perform various labor-intensive agricultural practices easily. The find is consistence with works of (Awoke, 2018; Abiyan, 2020)

Off farm and/or non-farm participation of respondents

Based on the survey results demonstrated in Table 4.1, 56.68% of sampled households participated in non-farm or/and off-farm activities in addition to their coffee farm activities, while the remaining 43.32% did not. The results of the chi-square test (x^2 = 0.03, p = 0.86) revealed that involvement in non-farm or off-farm activities made no discernible difference in the adoption of the CSAPs. On the contrary, the findings of Abiyan (2020) stated that there was a significant difference between households that were participating in off-farm activities and households that were not in the adoption of CSAPs.

Table 4. 1. Descriptive statistics of categorical variables

Variables		Non adopters		Adopters		Total		X^2
		Freq.	%	Freq.	%	Freq.	%	
Sex of household head	Female	39	25.32	23	15.03	62	20.20	5.04**
	Male	115	74.68	130	84.97	245	79.80	
Off/non-farm participation	No	66	42.86	67	43.79	133	43.32	0.03
	Yes	88	57.14	86	56.21	174	56.68	
Group membership of household head	No	64	41.56	18	11.76	82	26.71	34.80***
	Yes	90	58.44	135	88.24	225	73.29	

Source: own survey result, 2004
***, **indicates statistical significance at less than 1% and at 5% respectively

4.1.2. Descriptive statics of continuous variables

Age of the respondents

According to the results of the independent sample t-test shown in Table 4.2, the age of household heads ranged from 37 to 58 years, with a mean age of 45.67 and a SD of 4.46. The mean age of the adopters was 44.67, which was 2 years lower than the mean age of the non-adopters, who had an average age of 46.67 years. The mean age difference between two groups was statistically significant at significance level of 1% (t (305) = 4.04, $p < .001$). The finding is in line with the finding (Awoke, 2018; Lackachew, 2020) revealed the age negatively correlated with adoption of CSAPs. In the study area adopters of CSAPs were younger households than non-adopters. The fading is also supported by FGDs. Participants in FGDs were agreed that performing agricultural practices for old aged individuals are difficult. They were reasoned out as agricultural practices are labor intensive and tedious which are mainly energy consuming.

Family size

In terms of family size, the sampled households' mean family size was 5.02 measured in adult equivalents (AE) with a standard deviation of 0.87; the biggest family size was 6.86, while the smallest was 3.12. According to the survey results displayed in Table 4.2, the mean family size (AE) of adopters (M = 5.39, SD = 0.80, N = 153) was found to be significantly greater than that of non-adopters (M = 4.64, SD = 0.79, N = 154), according to the independent samples t-test (t (305) =-8.39, p<0.001). The adoption of CSAPs and the size of a respondent's family are strongly correlated, as shown by the t-test result in Table 4.2. The findings is consistence with (Tekeste, 2019; Wekesa, 2017). Issues raised while FGDs also consistence with statistical findings. The participants discussed that performing agricultural activities are easy for households with many children.

Education status

According to the survey results displayed in Table 4.2, the mean year of schooling of the sample respondents was 2.73. The adopters had a higher mean year of schooling (3.56) than the non-adopters (1.89). The t-test for independent samples revealed that the mean difference in schooling between adopters and non-adopters was significantly different at a significant level of 1% (t (305) =-7.69, p<0.001). This implies that the respondent head of household is more likely to embrace the CSAPs the longer they attend school. This is consistent with the works of Ahmed (2019) and Tekeste (2019), who stated that the higher the year of school spent, the higher the likelihood of adoption of CSAPs. Regarding education, participants in FGDs had different views. The majority of participants in the FGDs argued that accessing formal education helps people access and use different information and technologies easily. On the contrary, some of the participants in FGDs also argued that spending years in school is senseless because many educated youths are jobless. This is because, as they said, the education system today is not practically what makes youth love farming.

Farm experience

As the survey result demonstrated in Table 4.2, the sample households' mean year spent in coffee farming was 14.98 with a standard deviation of 3.02. The highest year of experience was 20, and the lowest was 7. The mean farming experience of the adopters was 16.20, which was significantly higher than that of non-adopters, with 13.77 at a significant level of 1% (t (305) = 5.71, $p<0.001$). This is because the more time the farmers spend on coffee farming, the more they know about their coffee plants current situations, and in turn, the more they apply different practices to improve their coffee production. This is consistent with Waaswa's (2021) result that the adoption of CSAPs is significantly and favorably connected with agricultural experience.

Livestock holding

With the assumption that households with a high number of TLUs would be less likely to adopt CSAPs in the study area, livestock ownership was taken into consideration in this study. As the survey result demonstrated in Table 4.2, the mean number of livestock owned measured in TLU was 4.80, with a standard deviation of 1.22. The adopter sample households had a mean TLU of 4.43, which is significantly lower than non-adopter households with a 5.17 TLU at a significance level of 1% (t (305) =5.65, $p<0.001$). The findings revealed that increasing the number of livestock in TRL, decreases the likelihood of adoption of CSAPs by smallholder coffee farmers. This is because the farmers having many livestock intended to allocate land for grazing. This is finding is supported by the works of (Tekeste, 2019; Lakachew, 2017).

Land size

It was proposed that respondents with larger land holdings would be more inclined to embrace CSAPs than respondents with smaller land holdings. The mean land size of the sample households in the study area was 1.58 hectares, with a standard deviation of 0.56 hectares. According to the survey results displayed in Table 4.2, adopters had a mean land size of 1.68 hectares, which is substantially higher than that of non-adopters with 0.57 hectares at a significance level of 1% ($t(305) = -3.16$, $p<0.001$). This result implies that, in comparison to HHs with smaller land sizes, respondent HHs with larger land sizes are more likely to implement CSAPs. This is because land is a crucial asset that motivates farmers to adopt CSAPs. This result is supported by the finding of Awoke (2o18), who stated that an increase in farm size increases the probability of adopting crop production.

On farm income

It was hypothesized that respondents who profit greatly from coffee sales are more likely to embrace CSAPs than respondents who profit less from such sales. According to the findings of the survey demonstrated in Table 4.2, the mean coffee sales income of the respondent households was 53804.56, with a standard deviation of 9500.39. The independence sample t-test result indicated that the mean income of adopters was substantially higher than that of non-adopters at a significance level of 1% ($t(305) = -4.13$, $p<0.001$). Households that gain a significant amount of money from the sale of coffee are more likely to adopt CSAPs. This is because money has motivational power. The results of Abiyan (2020) and Lakachew (2017) corroborate the finding.

Extension contact

Agricultural Extension is an unofficial educational program aimed at helping rural farmers solve their problems by providing information and advice. The findings of the independent sample t-test displayed in Table 4.2 indicate that the mean number of extension contacts with the sample households was 4.49, with a standard deviation of 2.85. The mean number of extension contacts for adopters was 3.09, which is substantially less than for non-adopters, 2.47, at a significance level of 1% ($t(305) = -9.94$, $p<0.001$). This result implies that, in comparison to the respondent who interacted with extension agents less frequently, the one who interacted with them more frequently was more likely to adopt CSAPs. This is because frequent interaction between extension agents and farmers exposes farmers to new practices and persuades them to practice them. This is consistent with the work of Wekesa (2017) and Waaswa (2021), who stated that frequent contact of extension agents with farmers increases the likelihood of adoption of CSAPs.

The majority of FGD participants argued that extension agents are their sources of information and know-how about agricultural technologies. They said, ‘‘…extension agents train us practically on the demonstration field, visit our field, disseminate technologies, advise...’’.

Table 4. 2. Descriptive statistics of continuous variables

Variable	Adopters (N=153)		Non adopters (N=154)		Total sample (N=307)		t-test
	Mean	SD	Mean	SD	Mean	SD	
Age HH in year	44.67	3.85	46.67	4.80	45.67	4.46	4.04***
Education level (year)	3.56	1.95	1.89	1.83	2.73	2.06	-7.69***
Family size in AE	5.39	0.79	4.64	0.78	5.02	0.87	-8.39***
Farm experience (year)	16.20	2.85	13.77	2.67	14.98	3.02	-7.68***
Land holding (ha)	1.68	0.54	1.48	0.57	1.58	0.56	-3.16***
On farem Income (ETB)	55993.46	9724.32	5162.87	8776.04	53804.56	9500.32	-4.13***
Livestock (TLU)	4.43	1.16	5.17	1.16	4.80	1.22	5.65***
Extension contact	5.91	2.47	3.09	2.49	4.49	2.85	-9.94***

*** indicates statistical significance at 1%; Source: Author’s survey result, 2024

4.2. Perception of Respondents on Trends of Climate Change in the Study Area

4.2.1. Perceptions of respondents on CC and its impacts

As per the survey results presented in Figure 4.1, 99.35% of the respondents stated that throughout the past 20 years, there has been climatic change in the research area. Conversely, just 0.65% reported that they have not noticed any change in the environment.

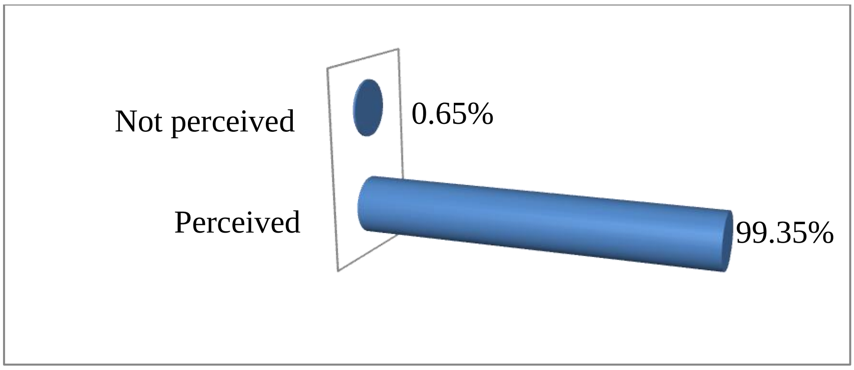

Figure 4. 1. Perception of respondents on occurrence of CC in the last 5-20 years

Source: Field survey result, 2023

Perceptions of respondents on observed climate change incidents

When the sample HHs were questioned about the factors and CC-related incidents that occurred in the study area over the previous five to twenty years, they concluded that there had been a shift in the climate and that CC had an impact on coffee farming. Fig.4.2 ("a" through "d") shows the results. As a result, the research area's temperature conditions over the previous 20 years were reported by 94%, 4%, and 2% of the respondents surveyed as "increasing," "decreasing," and "I do not know," respectively (Figure 4.2 (a)). 49%, 26%, and 25% of the respondents gave the following answers when asked about the distribution of rainfall in the research area over the last 20 years: "erratic," "no change," and "I do not know" (Fig. 4.2 (b)). 59%, 24%, 11%, and 6% of the respondents indicated that there had been "increasing," "decreasing," "no change," and "I do not know" in relation to the research area's dry season patterns during the previous 20 years (Fig. 4.2 (c)). The perception report shown in Figure 4.2 generally indicates that there is an uneven distribution of rainfall, a periodic increase in temperature during the dry season, and other factors that are making agricultural activities in general and coffee producers in particular in the study area more difficult.

Furthermore, participants in the focus group discussions (FGDs) in the study area highlighted the occurrence of climate change during the past two decades, which has been characterized by rising temperatures and an uneven distribution of rainfall. According to certain participants in FGDs, the irregular distribution pattern makes it challenging to forecast trends in rainfall. The participants of FGDs that “Rainfall can arrive early and disappear early, arrive late and disappear late, cause flooding, and then dry out for a period”. They also brought up the fact that producing coffee would be complicated by extremely heavy rain or protracted dry periods during the floweing and fruit set. During the discussions, a few FGD participants brought up the issue of unexpected rains during harvest, which caused difficulties in drying coffee and consequent losses during and after harvest. In general, they claimed that the seasons are erratic and that it is today hard to distinguish between the Kiremit and Belg seasons. These findings unequivocally demonstrated that temperature and rainfall patterns were the primary aspects of the local climate that had changed. The changes that the experts at the IPCC expected were supported by these data (IPCC, 2007b).

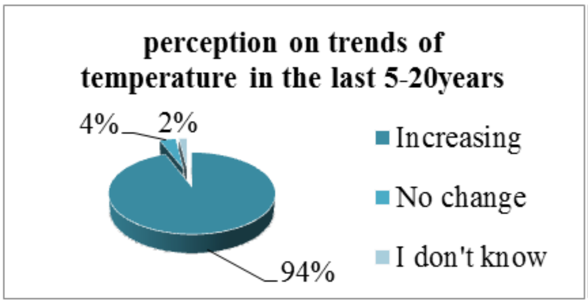

Figure 4.2 (a)

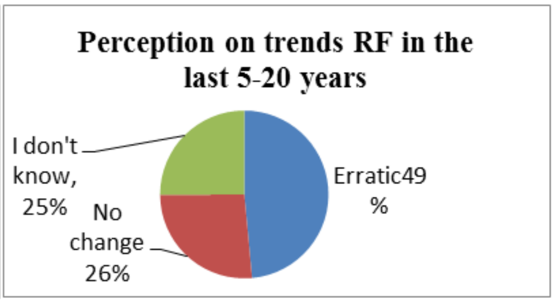

Figure 4.2 (b)

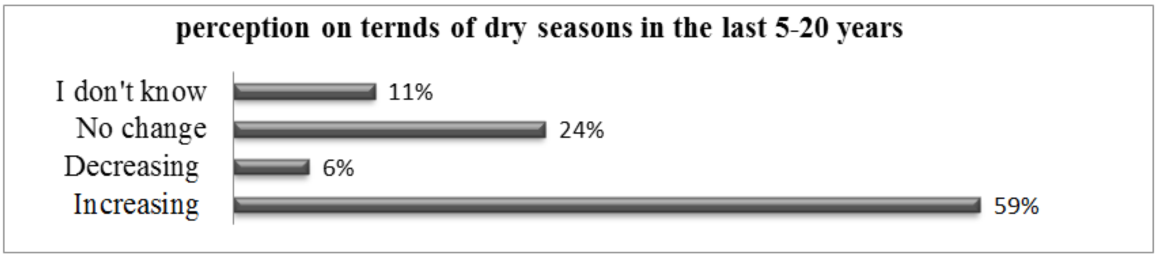

Figure 4.2 (c)

Figure 4. 2. Perception on trends of CC events occurrence for last 5-20 years

Source: Author's field survey result, 2023

Throughout the last 20 years, CC incidents have been reported in the research area by key informants also. This was demonstrated by altered rainfall patterns, an increase in the highest temperature, extended dry spells from the customary January to April, a reduction in the length of the previous April–August rainfall season, an alteration in humidity levels, and the appearance of new diseases and pests over a two-decade period.

4.2.2. Metrological data based trend analysis of climate change (2000-2020)

4.2.2.1.Trends of temperature

The research area's temperature distribution was typified by yearly variations as well as general patterns of higher temperature. The research area's maximum and minimum yearly temperatures for the previous 20 years have varied between 26.1ºC and 35ºC and 9.4ºC and 17.9ºC, respectively, according to data retrieved from EMI. The study area's yearly average minimum temperatures for the previous 20 years varied from 13.51 °C to 16.43 °C, while its average maximum temperature varied from 29.36 °C to 30.53 °C, indicating a high degree of temperature variability. The highest temperature (35 ^{o} C) and lowest temperature (9.4 ^{o} C) for the past 20 years (2000–2020) were recorded in 2017, and 2005, respectively. The maximum and minimum temperatures in the study area increased steadily over the 20 years between 2000 and 2020, as shown in Fig. 4.3. In the studied area, the average annual minimum and maximum temperatures in 2000 were 14.75 and 30.55, respectively, whereas in 2019 they were 15.05 and 31.05, respectively. The mean annual maximum and minimum temperatures in the study area have increased by roughly 0.1 ºC and 0.3 ºC over the previous 20 years, as shown in Fig.4.3.

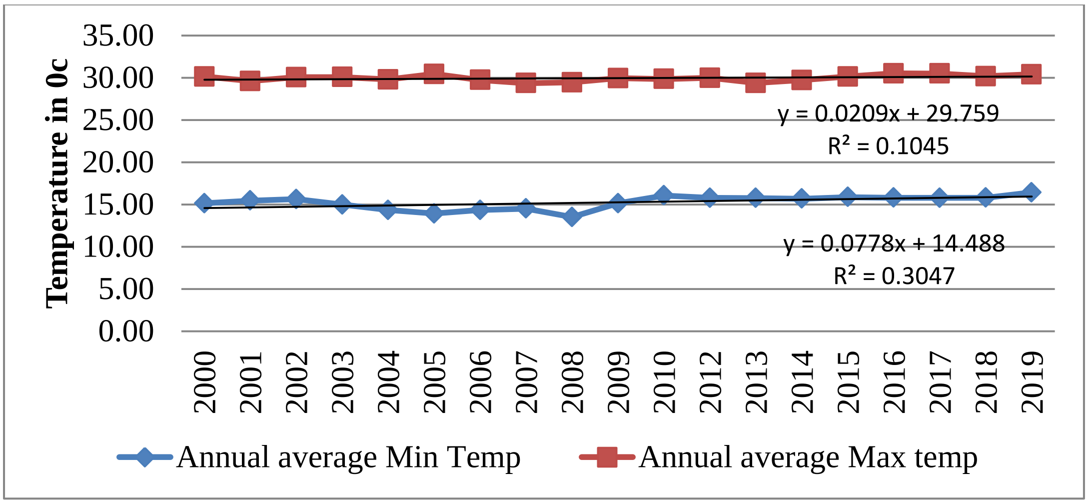

Figure 4. 3. Annual average min and max temperature of the study area (2000–2020)

Source: Authors' computation of temperature data from EMI, 2022

4.2.2.2.Trends of rainfall in the study area

The study area saw an annual rainfall of 1127.3 to 2386.7 mm, with a mean of 1488.05 mm, a standard deviation of 270.67 mm, and coefficient of variation 18 % (Table 4.3).

This suggests that although rainfall varies somewhat, it is not far from high variability. The years with the least and most annual precipitation totals in the region were 2012 and 2008, respectively. The analysis confirms the findings of McSweeney *et al*. (2010), who found that Ethiopia has significant seasonal and yearly rainfall variability. The distribution of yearly rainfall in the research area has shown an irregular trend over the last 20 years, as shown in Fig.4.4, and the seasonal and annual rainfall distribution patterns are still unpredictable.

Table 4. 3. Seasonal and annual rainfall distribution of the study area (2000-20200)

Year	Spring	Summer	Autumn	Winter	Annual Total
2000	484.3	429.5	473.5	90.6	1477.9
2001	452.3	594.4	353.1	131	1530.8
2002	398.8	459.4	319.2	109.8	1287.2
2003	292.3	521.8	434	107.1	1355.2
2004	438.2	403.3	348.9	156.6	1347
2005	337.1	506.9	318.6	43.3	1205.9
2006	484.1	607.7	481.6	141.1	1714.5
2007	445.4	553.6	357.6	121.3	1477.9
2008	511.9	1170.9	545	158.9	2386.7
2009	549.1	356.7	330	126.7	1362.5
2010	463	512.9	444.1	234.6	1654.6
2012	452.7	105.9	452.9	115.8	1127.3
2013	464.2	546	471.1	116.5	1597.8
2014	318.8	496.8	401.8	70	1287.4
2015	503.4	418.1	505.3	34.2	1461
2016	570.5	489.7	291.5	107.8	1459.5
2017	520.8	502.2	545.5	61.2	1629.7
2018	409.4	352.8	321.4	103.4	1187
2019	320.9	418.4	680.2	248.6	1668.1
2020	403.06	500.97	484.48	123.91	1512.42
Min	292.3	105.90	291.5	34.2	1127.3
Max	570.5	1170.9	680.2	248.60	2386.7
Mean	457.5	498.33	427.99	120.28	1488.05
SD	70.64	192.43	99.7	53.29	270.67
CV %	15	39	23	44	18

Source: Author’s computed from EMI (2024)

Based on the results displayed in the Table 4.3, the average amount of rain that fell during the spring was 457.5 mm, with the highest total amount recorded in 2016 at 570.5 mm and the lowest in 2003 at 292.3 mm. With a standard deviation of 70.64 mm and a coefficient of variation of 15%, it suggests that springtime rainfall varies moderately. The average summer rainfall was 498.33 mm, with the highest total rainfall of 1170.9 mm in 2008 and the lowest of 105.90 mm in 2012. The summer rainfall had a high degree of variability (CV of 39%) and little consistency (SD of 192.43 mm). accordingly, It is challenging to forecast the patterns of rainfall distribution in the research area. Because rain-fed agricultural production systems are the only ones used in the research area, this could have a major negative impact on the cropping systems there.

4.2.3. Perception on the observed impacts of CC on coffee farming

The effects of climate change that have been observed on coffee cultivation over the previous 20 years in the research region were assessed through the use of a survey containing appropriate questions. Because of this, the survey results displayed in Table 4.4 demonstrated the different impacts of CC that have been observed on coffee production in the study area throughout the course of the preceding 20 years. The main effects that the respondents in the study area noted were the rise in pests and diseases, the decline in yield, the falling of flowers and fruits, and the failure of coffee trees. In response to questions about the occurrence of pests and diseases in coffee farming, 47.23%, 43%, and 9.77% respondents said they were "strongly agreeing," "agreeing," and "ambivalent," respectively. The sample respondents, comprising 49.19%, 43.32%, and 7.49%, expressed strong agreement, agreement, and ambivalence on the decrease in smallholder coffee producing yield. The falling of fruits and flowers was one of the CC-influenced concerns that smallholder coffee growers in the research area had to deal with; 48.86% and 43.97% respondents said they "strongly agreed" and "agreed," respectively. 14.03%, 28.99%, and 57.98% of the respondents said that they "strongly agree," "agree," and "ambivalently" felt about the failure of coffee trees, respectively.

The participants of FGDs talked about their experiences with harvesting and post-harvest losses due to unexpected rain, fruit falling, and difficulty in drying and storing—all of which degrade coffee quality. This clearly showed how farmers in the research area are starting to recognize the threat that climate change poses.

Table 4. 4. Perception on adverse impacts CC on coffee farm in the last 5-20 years

Occurred impacts	Level of perception					
	Strongly agree		Agree		Ambivalent	
	Freq.	%	Freq.	%	Freq.	%
Occurrence of pests and disease	145	47.23	132	43.00	30	9.77
Decreasing of yield	151	49.19	133	43.32	23	7.49
Falling of flowers and fruits	150	48.86	135	43.97	22	7.17
Failure of coffee trees	40	13.03	89	28.99	178	57.98

Source: Author's field survey result, 2024

4.2.3.1.Perception on extent of impact of CC on coffee production

An appropriate inquiry was given to the respondents in order to find out if the research area's coffee production was being impacted by CC. According to the survey results shown in Table 4.5, 50%, 37%, and 13% of respondents reported that the effect of climate change on coffee has been high, medium, and low throughout the previous 20 years.

Table 4. 5. Perception of impacts of CC on coffee in the last 5-20 years

Perception	Level of perception	Freq.	%	X^2
Extent of impacts on coffee farm	High	154	50	
	Medium	113	37	20.97***
	Low	40	13	

Source: Author's computation of survey data, 2024

4.2.3.2.Perception of respondents on sources of information

Regarding the availability of information on CC and CSAPs, the survey report showed that all respondents had access to information from various sources. Table 4.6 provides a summary on the sources of information that smallholder farmers used to learn about climate variability and CSAPs. Extension agents were the major source of information for smallholder farmers in the study area, followed by neighbor farmers, radio and television, respectively.

Table 4. 6. Information sources about CC and CSAPs

Sources information	'Yes' responses on each sources of information (N=307)		Rank
	Freq.	%	
Extension services	290	94.46	1st
Radio and television	240	78.18	3rd
Neighbor farmer	263	85.67	2nd
Local administrations	45	14.66	4th

Source: Author's computation of survey data, 2024

4.3. Identification of the Existing CSAPs and Its Status of Adoption among Smallholder Coffee Farmers in the study area

Improved coffee varieties: The adoption of improved coffee varieties, such as F-59, Geisha, Catimor (J-19), Catimor (J-21), 7454-5440, and Desu, is the main climate-smart practice adopted by the majority of respondents (67%) in the study area (Fig. 4.4). This was due to a high understanding of the benefits that farmers had gained from the practice, including higher productivity, fewer risks of crop failure, stress tolerance, and disease resistance.

Mulching: Mulching coffee plants with vetivar grass, coffee husk, turmeric residuals, and dry organic grass is one of the most climate-smart practices (63%) adopted in the study area (Fig. 4.4). It helps in maintaining soil moisture, reduces soil temperature, reduces emissions from the uncovered soil surface, and reduces the risk of crop loss.

Intercropping: intercropping coffee with banana, enset, black pepper, legumes, yam, and taro is among the most implemented practices by about 57% of respondents in the study area (Fig. 4.4). This is because of its potential to diversify food and income sources, improve nitrogen fixation and soil quality, reduce the risk of total crop failure, and increase carbon sequestration.

Agroforestry is a climate-smart practice adopted by about 44% of farmers in the study area (Fig. 4.4), including the planting of temporary shade (Sasipania, Lucinia, and Gulo) and permanent shade agroforestry (Sesa, Beribera, and Wanza). It helps in diversifying food and income sources, increasing soil fertility, maintaining soil moisture, preventing soil erosion, and resulting in sustainable land use management. It also leads to carbon sequestration and offers environmental services.

Organic fertilizer is a climate-smart practice adopted by about 45% of respondents in the study area. It is climate-smart because it helps increase productivity with low inputs, compensates for declining soil fertility, avoids emissions from the use of raw animal manure, and improves soil carbon sequestration.

Stumping: It is one of the least adopted in the study area due to farmers' risk aversion from loss of income. It is considered climate-smart because it increases productivity by removing older and less productive trees and initiating healthier ones that are able to withstand pests, diseases, and weather stresses.

Cover crops: is the climate-smart practices adopted by about 29% of coffee farmers in the study area. It is known as climate smart because it improves yields by enhancing soil health, preventing soil erosion, conserving soil moisture, and increasing carbon sequestration.

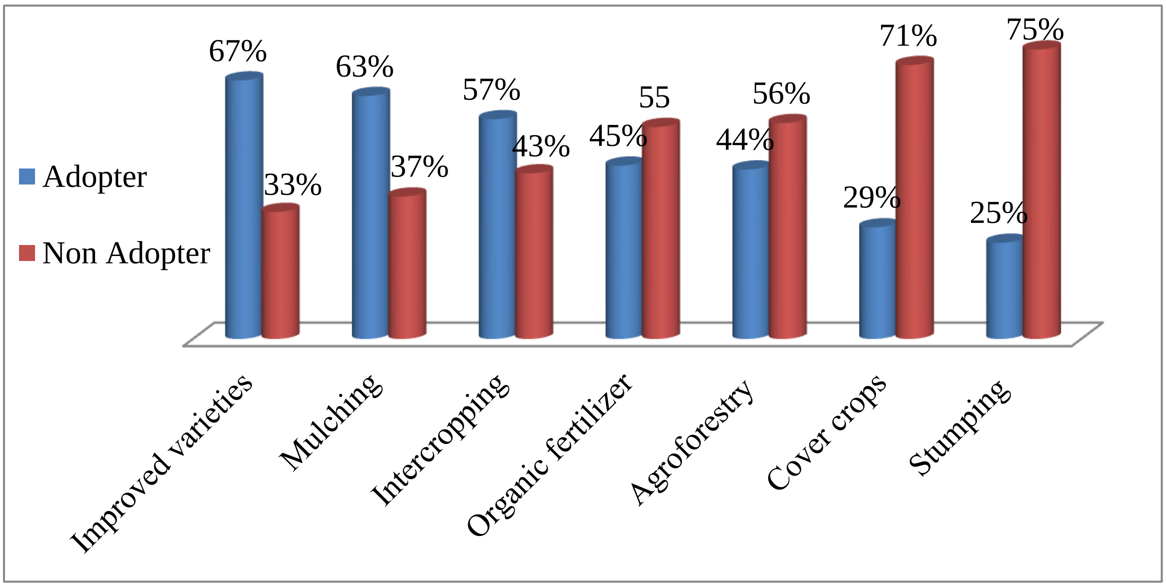

Figure 4. 4. CSAPs adopted by coffee farmers

Source: Author's computation of survey data, 2024

4.3.1. Adoption Status of CSAPs by Coffee Farmers

The adoption index (AI) was used to assess the degree of acceptance of CSAPs among smallholder coffee producers, in accordance with Tiamiyu (2010). Based on the result displayed in Table 4.7, the coffee farm households that participated in the survey had an AI of CSAPs that ranged from 0.3 to 0.83, with a mean of 0.515 and a standard deviation of 0.099. The mean figure of the adoption index was used to divide the respondent households into adopters and non-adopters, in accordance with Ogunya *et al.* (2017).

Table 4. 7. Adoption index among coffee farmers in in the study area

Adoption index	Respondents (n=307)		Non adopters (n=154)		Adopters (n=153)		Cumulative %	T-test
	Freq.	%	Freq.	%	Freq.	%		
<0.515	154	50.16	154	50.16	-		50.16	
>0.515	153	49.84	-	-	153	49.84	49.84	
Min	0.3	-	0.3		0.52			
Max	0.83	-	0.51		0.83			
Mean	0.515	-	0.433		0.595			-25.78***
SD	0.098	-	0.053		0.056			

Note. *** Significant at 1%

Source: Author's computation of survey data, 2024

Based on the value of AI, households with an AI value higher than the grand mean (0.515) were defined as adopters, and households with AI value below the mean were non-adopters. Accordingly, 51.81% of respondents were non-adopters, and the remaining 49.19% were adopters. This indicates that smallholder coffee producers in the research area have not made much progress in adopting CSAPs, indicating that in order to address the issues posed by climate change, more attention should be focused on encouraging all small-scale farmers to accept all available CSAP alternatives.

4.3.2. Major driving and hindrance reasons to adopting CSAPs in the study area

4.3.2.1.Reasons for adopting

The results in Fig.4.5 displayed that the majority of respondents (61%, n = 187) and (23%, n = 71) said that adopting climate smart practices was primarily motivated by the desire to increase productivity and food security, respectively. Only a small percentage of respondents (8%, n = 25) and 5%, n = 15) mentioned improving resilience to climate change and making efficient use of natural resources, respectively. This clearly shows that the majority of respondents' efforts to put CSAPs into practice were motivated more by the desire to boost productivity and food security than by environmental concerns.

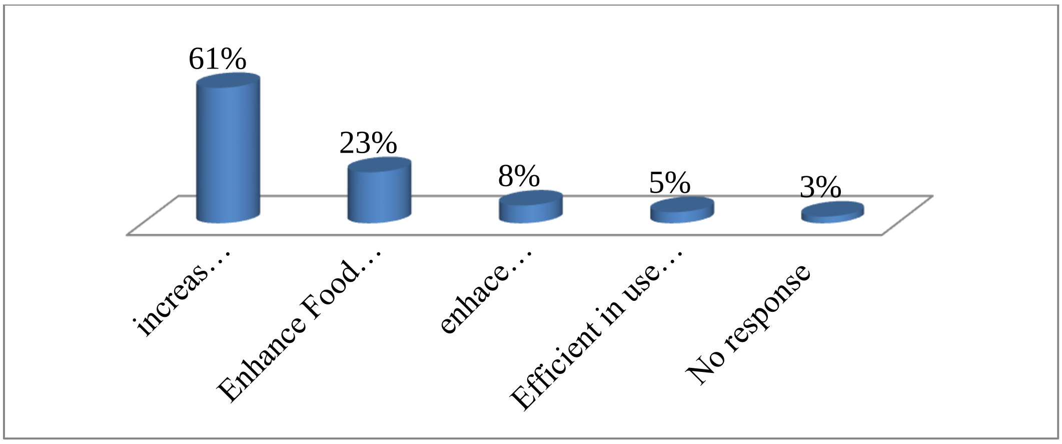

Figure 4. 5. Reasons for adopting CSAPs in the study area

4.3.2.2.Challenges hindering adoption of CSAPs

The primary barriers to adopting CSAPs in the research area were identified by 62%, 46%, and 42% of the respondents, respectively, as a lack of land, a lack of labor, and a lack of awareness, as shown in Fig. 4.6.

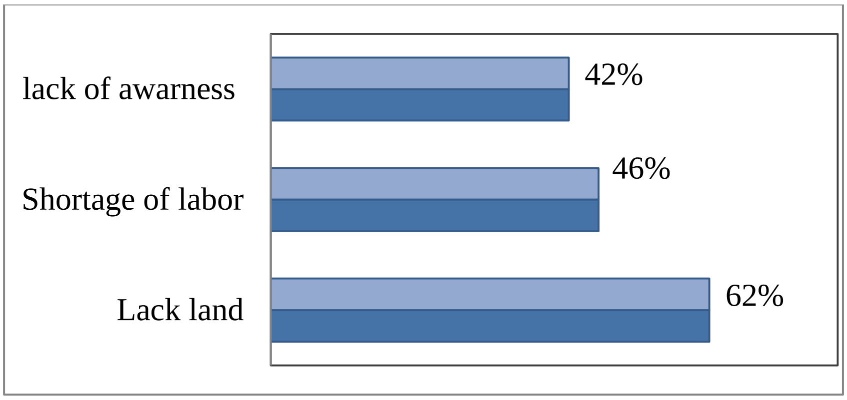

Figure 4. 6. Challenges in adoption of CSAPs

Source: Author’s computation of survey data, 2024

4.4. Factors Influencing Adoption of CSAPs among Smallholder Coffee Farmers

A probit regression model was used to analyze factors influencing the adoption of CSAPs by smallholder farmers in the study area. The relationship between the dichotomous dependent variable (adoption of CSAPs) and 11 explanatory variables was analyzed using a binary probit model. The model appropriately and significantly fit the data at the 1% significance level (chi-square = 125.51, P-value = <0.001). Hosmer and Lemeshow's goodness-of-fit test is another often-used goodness-of-fit test for a binary probit regression model. With a higher p-value of 0.704, the Hosmer-Lemeshow test result indicated that the difference between the observed and predicted frequencies is not statistically significant (Appendix Fig.1). The model appears to have been consistent, fits the data well, and has excellent explanatory power.

The problem of multicollinearity between the explanatory variables was investigated using the variance inflection factor (VIF) and contingency coefficient for continuous and dummy explanatory factors, respectively. The mean VIF value for continuous explanatory variables was 1.67, which was less than 10 (Appendix Fig.2), while contingent coefficient values for the categorical variables were all lower than 0.2, which is less than the tolerable value of 0.75 (Appendix Fig.3). This verified that there was no significant linear relationship among all the proposed explanatory variables. Thus, multicollinearity was not the problem in the model. The model is appropriate since it can resolve the problem of heteroscedasticity and satisfies the assumption of cumulative normal probability distribution.

Missing variable test: In order to determine whether there are any missing variables that could have a substantial impact on smallholder coffee families' adoption of CSAPs, the Ramsey Reset test for omitted variables was computed (Appendix Fig.4). The p-value (prob>F=0.181) is greater than the customary threshold of 0.05 (95% significance), leading us to believe that further variables are not necessary. Consequently, it was determined that the model was the most comprehensive and reliable.

The results of the binary probit regression model are shown in Table 4.8. The sex of households, education level, family size, membership in social groups, farm income, and frequency of extension had a positive and significant effect on the adoption of CSAPs, whereas the age of households had a negative and significant effect.

Sex of household head: Sex was entered into the model as a dummy variable. According to the study, sex was found to positively and significantly influence the adoption of CSAPs at the 1% level of significance (p-value = 0.007) in the study area. The marginal effect result displayed in Table 4.8 indicated that households with a male head taking responsibility for household farming activities were 19.2% more likely to adopt CSAPs as compared to households with a female head taking care of the farming activities, holding other variables constant. The gender differences in the adoption of climate-smart practices were attributed to variances in socioeconomic status. This could be explained by the fact that, in comparison to male farmers, female farmers have less access to extension services, land, and decision-making. In addition, they are risk-averse, consider their family before making decisions about the farm, and prioritize their daily household chores over business endeavors. The results aligned with the findings of Wekesa (2017), who claimed that male-headed households were more likely to adopt CSAPs than female-headed households since men retain the only authority to decide on short- and long-term farm improvements. Participants in focus groups and key informant interviews made it clear that men and women in coffee farming played different roles and had varied technology demands, necessitating different approaches from extension agents.

Age of the household head: It was discovered that there is a negative and substantial relationship between age of the respondents and adoption CSAPs at the significance level of 10% (p = 0.056). According to Table 4.8's marginal effect estimation results, a one-year increase in the respondent's age reduces the likelihood of adoption decisions by 1.4% while keeping all other factors constant. This makes sense because becoming older is linked to a reduction in physical capacity, an increase in risk aversion, and a reduction in planning time, all of which may limit the rate at which CSAPs are adopted. The results support the findings of Wekesa (2017), Zakaria *et al*. (2020), and Chavula *et al.* (2023), who reported that the likelihood of adopting CSAPs declined as farmers' ages increased.

Education level of household head: The education level of the household positively relates to the adoption of CSAPs and is significant at the 5% significance level (p-value=0.026). The marginal effect result in Table 4.8 for education level of household heads reveals that for every additional year spent in formal education, the probability of adoption of the CSAPs increases by 3.1%, regardless of other explanatory variables. In comparison to households without formal education, farmers with formal education had a higher likelihood of implementing CSAPs on their farm, as indicated by the positive coefficient. This is due to the fact that educated HHs have greater access to opportunities and information than uneducated ones, possess the necessary knowledge to comprehend and react to changes that are expected of them, plan ahead more effectively, and can predict future events. The results are in line with the research of Kassa & Abdi (2022) and Ahmed (2015), who discovered a strong and positive correlation between farmers' educational attainment and their use of CSAPs.

Family size of the respondent household: Table 4.8's results demonstrate that family size has a favourable and substantial influence on adoption decision of CSAPs at the 1% level of significance (p-value =0.008). The marginal effect for family size shows that the probability of adoption of CSAPs increases by 9.2% for every extra AE in family size, with all other variables kept constant. This makes sense because most of the county's farmers employ family members to help with agricultural operations. Large family sizes are linked to low labor costs, which allows households to reduce labor barriers needed to implement CSAPs and complete a variety of labor-intensive agricultural tasks. Since the majority of CSAP methods require labor, having a large household size, which is a proxy for family labor resources, may increase the likelihood that farmers will adopt these practices. The results corroborated the claims made by Ahmad (2019), Lakache (2020), and Wekesa *et al.* (2018) that labor availability was ensured by higher household sizes, especially for labor-intensive CSA practices.

On farm income of household: The results displayed in Table 4.8 indicate that on-farm income positively and significantly influences the adoption of CSAPs at a 5% significance level (0.045). The marginal effect result for on-farm income indicates that for every additional unit of income in ETB from the sales of coffee, the probability of adopting CSAPs increases by 0.005%, assuming all other variables are held constant. The finding is consistent with the finding of Abiyan (2020), who stated that farm income significantly determines the adoption of the CCI climate smart option.

Extension contact: Access to agricultural extension services is the major sources of information for smallholders adopting CSAPs. The findings in Table 4.8 show that the frequency of extension contact was shown to have a positive and significant influence on the adoption of CSAPs at the 1% level of significance (p=0.009). The marginal effect estimation shows that, keeping all other variables held constant, one more additional extension interaction between farmers and extension agents increases the likelihood of adoption of CSAPs by 3.3%. The most plausible explanation was that extension agents were the main source of information, technology, and know-how and were working closely with farmers in the study area. Additionally, extension agents play a crucial role in the adoption of CSAPs by increasing awareness and counteracting the negative effects of a lack of formal education in the study area. The finding is in line with research by Abiyan (2020) and Wekesa et al. (2018), which show that CSAP adoption is higher in households with greater access to extension services than in farmers with less access.

Membership of households in social groups: Results in Table 4.8 indicate that social group membership had a positive and significant impact on the adoption of CSAPs at the 5% significance level (P-value = 0.035). Holding all other factors constant, the marginal effect result for group membership indicates that respondents who were members of any social group were 11.9% more likely to adopt CSAPs than non-members. This is because group membership also intensifies informative networking that builds trust among group members and facilitates experience sharing about CSAPs, which creates courage among the persuaded farmers to fully practice CSAPs. Farmers' social groups, like wonfel and debo, serve as a type of social capital that facilitates the execution of various labor-intensive agricultural tasks which also facilitates adoption of CSAPs. The result is in line with the works of Issahaku and Abdulai (2020) and Wekesa *et al.* (2018), which revealed that involvement in farmer-related groups and organizations facilitates the outreach of extension agents to members, lowers the expenses associated with service delivery due to economies of scale, and ensures a greater number of interactions between members and service providers.

Table 4. 8. Probit estimation of adoption of CSAPs

Explanatory Variables	Coef.	St. Error	Z	P>|Z|	dy/dx
Sex of HH (Male)	.697	.257	2.71	.007	.192***
Age of HH	-.050	.026	-1.91	.056	-.014*
Education level	.112	.050	2.22	.026	.031**
Family size	.334	.126	2.66	.008	.092***
Farm experience	.029	.037	.77	.444	.008
Land size	.098	.163	.61	.544	.027
Farm income	.00002	.00009	2.01	.045	.00005**
Off participation (Yes)	-.027	.178	-.15	.878	-.007
Livestock	.132	.094	1.41	.158	.036
Extension contact	.119	.045	2.63	.009	.033***
Group Membership(Yes)	.435	.209	2.08	.038	.119**
_Cons	-3.304	1.519	-2.17	.030**	
Log likelihood =	-150.03732		Num. obs. =	307	
LR chi2(11) =	125.51		Pseudo R2=	0.2949	

***, **, * indicates significance at 1%, 5% and 10% respectively

Source: own computation from the survey (2024)

4.5. Impact of the Adoption of CSAPs on the Food Security of Smallholder Coffee Households

4.5.1. Food security status

The food security status of the sample household was determined based on the consumption score for the previous seven days before the survey. According to the outcome of the independent samples t-test displayed in Table 4.9, the average FCS for adopter and non-adopter households was 44.02 with a 16.71 standard deviation and 34.78 with an 11.38 standard deviation, respectively. There was a statistically significant difference in FCS between the two groups (t = -5.66, p<0.001).

Table 4. 9. Descriptive statistics of food consumption score

Variable	Adopters (N=153)		Non adopters (N=154)		Total sample (N=307)		t-test
	Mean	SD	Mean	SD	Mean	SD	
Dietary diversity in FCS	44.02	16.71	34.78	11.38	39.38	15	-5.66***

*** indicates statistical significance at 1%; Source: Author's survey result, 2024

Fig. 4.7 depicts the percentage of households that fall into various dietary consumption categories. The FCS of 19%, 35%, and 46% of the sample households were laid in the range of 0 to 28, 28.5 to 42, and >42, respectively. About 54% of the adopters' and 28% of non-adopters FCS were laid in the range of 42.5 to 112, respectively.

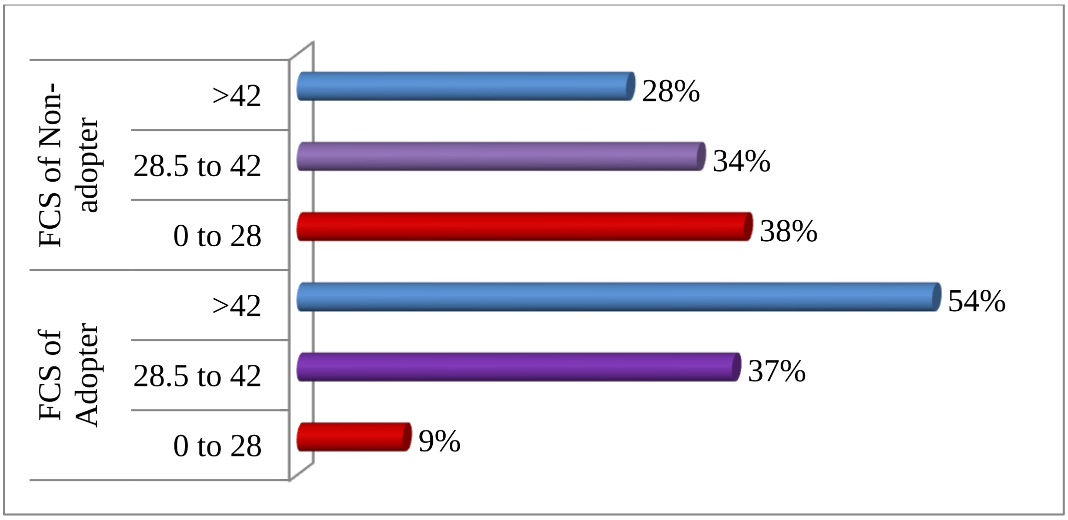

Figure 4. 7. Classification of food security status

Source: Computed from field survey, 2024

4.5.2. ESR model estimation of average treatment effect

The average treatment effect on adopters and non-adopters can be easily estimated with the aid of the ESR model. It generates mean treatment effect on the treated/adopters (ATT) as well as its matching counterfactuals. In a similar vein, the model also yields the mean treatment effect on the untreated/non-adopters (ATU) as well as its counterfactual. The estimated values of the FCS under the actual and counterfactual situations reveal that the treatment effect for adoption of CSAPs on the FCS of smallholder coffee households is positive and significantly different from zero (Table 4.10).

The expected weekly FCS for the adopter households was 44.02. In the counterfactual case, the farm households who adopted the CSAPs would have obtained a dietary consumption score of 30.72, if had they decided not to adopt. In similar vein, the expected FCS of the non-adopter farm households was 36.59, if had they decided to adopt. In the counterfactual case, the non-adopter farm households would have obtained a food consumption score of 34.78, if had they decided not to adopt.

Consequently, adopters' weekly FCS increased by 30% as a result of adopting CSAPs; that is, adopters' food consumption score was 13.3 points higher than the counterfactual. Had non-adopters decided to adopt the CSAPs, their weekly FCS would have increased by 5%. This positive effect on food consumption is expected because adopting all recommended CSAPs would help the coffee farm households have higher productivity, leading to an increase in household income that can be used to increase the household's consumption score.

Table 4. 10. ESR based average treatment effects

Outcome variable	**Household Type and Adoption effects**	**Decision Stage**		**Treatment effect**	**Impact (%)**
		To adopt	Not to adopt		
FCS	Adopter	44.02	30.72	13.30*** (ATT)	30
	Non adopter	36.59	34.78	1.81*** (ATU)	5
	Heterogeneous effects	7.43	-4.06	11.49	

Significant at 1% (***), Source: Author's computation (2024)

The transitional heterogeneity effect is positive and the FCS effect is greater for households that adopt CSAPs. The positive based heterogeneity effect for the FCS implies that CSAPs adopters have higher food security possibly as a result of their decision to adopt CSAPs. The results of ESR revealed that adoption of CSAPs has the strong positive impacts on smallholder coffee farm HHs food consumption status. These results are consistent with other related studies on the impact of agricultural technologies on food security (Fitawek & Hendriks. 2021; Wekesa *et al*., 2018; Jaleta *et al*., 2015).

4.5.3. PSM model based estimation of treatment effect

In addition to the ESR model, this study uses the PSM technique to check the robustness of the results obtained from the ESR model. Propensity scores (the probability of adoption of CSAPs) are estimated using a probit model.

4.5.3.1.Estimation of propensity score and common support region

Estimating of the propensity score and constructing of the common support region is the first step in estimating the treatment effect. A common support condition should be imposed on the propensity score distribution of CSAPs adopters and non-adopters. The estimated propensity scores range between 0.0127 and 0.9465 and 0.0371 to 0.9832 for the non-adopters and adopters, respectively (Table 4.11). The common support region for the estimated score was constructed by using the minima and maxima criteria. The common support region would then fall between 0.0371 and 0.9465 on the propensity score. All observations were fall within the common support region, showing substantial overlap between the two groups. Visual inspection of the distributions of the computed propensity scores for the adopters and non-adopters (Fig. 4.8) further demonstrates that the common support criteria is satisfied. The distribution of propensity scores for adopters is depicted in the upper half of the graph, while non-adopters are represented in the bottom half.

Table 4. 11. Estimated propensity score

Variable		Obs.	Mean	Std. Dev.	Min	Max
Propensity score	Adopter	153	0 .6770	0.2461	0.0371	0.9832
	Non adopter	154	0.3182	0.2335	0.0127	0.9465
	Total households	307	0.4970	0.2994	0.0127	0.9832

Source: Own computation from field survey (2024)

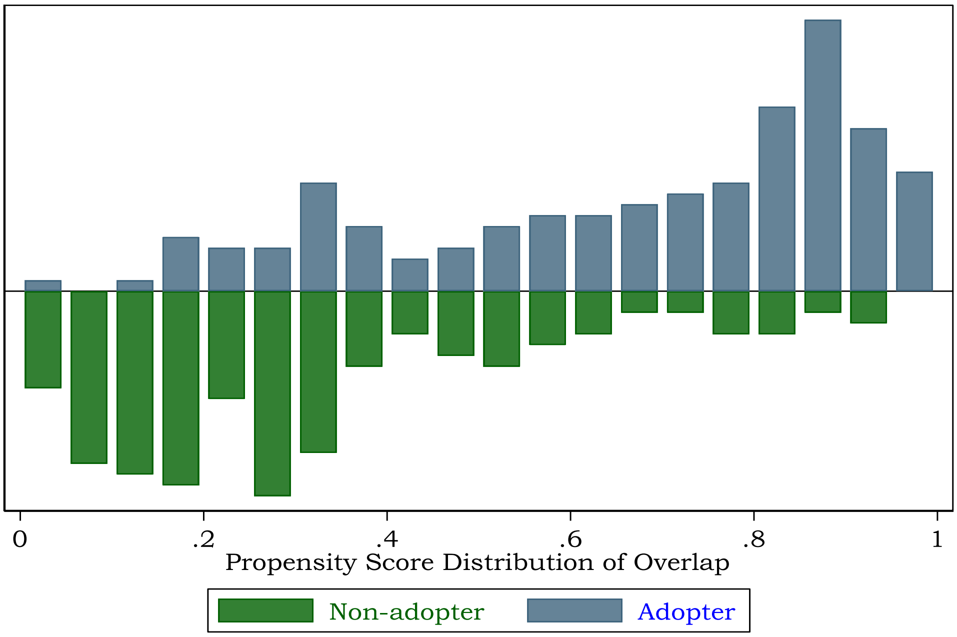

Figure 4. 8. Distribution of estimated propensity for treatment and control groups
Source: STATA output from survey data (2024)

4.5.3.2.Selection of matching algorithms

The decision on the ultimate choice of fitting matching estimators was undertaken based on four principles: the smallest pseudo-R-square value, the lowest standard mean bias, the higher bias reduction, and an insignificant likelihood ratio test after matching (Rosenbaum and Rubin, 1983). Accordingly, the three known matching algorithms in PSM (kernel based matching, nearest neighbour matching and radius matching) were evaluated (Appendix Table 2). Accordingly, kernel based matching with band width (0.1 and 0.25), and nearest neighbour matching (1, 2 and 3) were eligible for treatment effect estimation (Table 4.11).

4.5.3.3.Matching quality

The quality of the matching determines the validity of PSM models. Based on the overall results of the covariate balancing test, as presented in Table 4.12, the standardized mean bias for all covariates was reduced from 68.7% before matching to a range 3.5 to 10.7% after matching. In a similar vein, following matching, the pseudo-R2 dropped from 29.5% to range of 1 to 4.1%. Before matching, the joint significance of all covariates was shown by the likelihood ratio tests (p values) at a probability level of less than 1%; however, after matching, the significance was no longer there. Additionally, matching resulted in a considerable decrease in the total bias within the range of 84 to 95. Therefore, it is evident from these tests that the matching procedure balances the observed characteristics between the control and treatment groups following matching. Therefore, based on this, it can be said that the matching method has a high matching quality.

Table 4. 12. Covariates balancing tests before and after matching

Matching algorithm	Pseudo-R2		LR X2		p>chi2		Mean standardized Bias		Total % |bias| reduction
	U	M	U	M	U	M	U	M	
$KBM^{bw0.1}$	0.295	0.015	125.61	6.20	0.000	0.906	68.7	4.2	94
$KBM^{bw0.25}$	0.295	0.030	125.61	12.83	0.000	0.381	68.7	10.7	84
NNM^1	0.295	0.041	125.61	17.51	0.000	0.131	68.7	9.6	86
NNM^2	0.295	0.023	125.61	9.71	0.000	0.641	68.7	6.6	90
NNM^3	0.295	0.010	125.61	4.45	0.000	0.974	68.7	3.5	95

Source: Own computation from field survey data (20224), where:

$KBM^{bw0.1}$ =Kernel based matching with band width 0.1

$KBM^{bw0.25}$ = Kernel based matching with band width 0.25

NNM^1 = One nearest neighbour matching

NNM^2 = Two nearest neighbour matching two

NNM^3 = Two nearest neighbour matching two

4.5.3.4.PSM Estimation of average treatment effect

The effect of adoption of CSAPs on weekly basis FCS was estimated using nearest neighbour (NNM) and kernel (KBM) matching algorithms of PSM model. Table 4.13 reports the average treatment effect on the treated (ATT). According to the PSM results, the average treatment effect on the treated was consistently positive and significant across all algorithms. Consequently, the average increase in FCS for households following the adoption of CSAPs ranged from 11.97 to 13.34. Stated differently, the effect of the treatment ranges from 27.2% to 30%.

From the results it is noticed that farmers who implement CSAPs consume diverse of foods than farmers who do not. The findings are consistent with those of Belay *et al.* (2023); Abegunde *et al.* (2022); Mossie (2022); Tadesse *et al.* (2021); and Wekesa *et al.*

(2018), who found that farmers who use CSAPs consume more diverse food and yield higher income than non-adopters.

Table 4. 13. Average treatment effects: propensity score matching

Outcome variable	Matching algorithm	Treated	Controls	ATT	S.E	T-stat	Impact (%)
FCS	$KBM^{bw0.1}$	44.02	31.41	12.62***	2.31	5.45	0.287
	$KBM^{bw0.25}$	44.02	32.04	11.97***	2.15	5.57	0.272
	NNM^{1}	44.02	30.67	13.34***	2.80	4.75	0.30
	NNM^{2}	44.02	31.59	12.42***	2.58	4.81	0.282
	NNM^{3}	44.02	31.19	12.83***	2.54	5.06	0.29

Source: Own computation from survey data (2024)

CHAPTER FIVE

5 CONCLUSIONS AND RECOMMENDATIONS

5.1. Summary

The paper assesses the impact of adopting CSAPs on food security smallholder coffee farm HHs in Yeki woreda, SWEPRS. The study utilizes cross-sectional farm household-level data collected in 2023 from a randomly selected sample of 307 in four kebeles. The paper identified that using improved coffee varieties, shade agroforestry, intercropping, mulching, using organic fertilizer, stumping, and using cover crops were the major CSAPs adopted by smallholder coffee farmers in the study area to varying degrees. The findings revealed that the likelihood of adoption of CSAPs was positively influenced by the gender of the household head, household size, education level of HH, on-farm income of households, membership in a group, frequency of annual contacts with extension agents, and adversely influenced by the age of HH. The paper also estimated the causal impact of CSAP adoption through the endogenous switching regression model to control for selection bias and endogeneity due to the respondents' observable and unobservable characteristics and adopted the propensity score matching method to assess the robustness of the estimates of the impacts. The results obtained from the two models were consistent and robust. The results indicate that adoption of CSAPs is positively consistent and significantly affects the food consumption patterns of smallholder farmers in the study area.

5.2. Conclusion

Coffee has immense socio-economic importance in Ethiopia, particularly in the study area, as almost all households make their livelihoods dependent on the coffee value chain. However, the findings indicate that climate change-driven impacts, including rising temperatures, high rainfall variability, prolonged dry seasons, weather extremes, and the occurrence of insect pests and diseases, are found to pose significant risks to smallholder coffee production and the entire coffee value chain in the study area.

The results indicate that the adoption rate of CSAPs among smallholder coffee farmers is still low, with the majority of farmers implementing improved coffee varieties, mulching coffee plants with draw grass cuttings and straws, and intercropping coffee with banana, enset, black pepper, and other root crop practices. This is attributed to smallholder farmers' perceptions of improving coffee productivity and diversifying on-farm income and food sources. Application of organic fertilizers and agroforestry were less commonly adopted practices among smallholder coffee farmers due to their labor-intensive nature and shortage of land, respectively. Stumping or rejuvenation of the old trees and using cover crops were the least implemented practices due to farmers fear of income disruption and the fact that most coffee plots were occupied with old coffee trees, respectively.

Findings indicate that the likelihood of usage of CSAPs was more likely for male-headed households, indicating women's ownership of resources and decision-making are still low in the study area. The findings also indicate that the majority coffee producers in the study area are elderly, indicating that youth participation in agricultural practices is low. The study pinpointed that the adoption of CSAPs is highly correlated with frequent contact with extension agents, as they are the major source of information and advisory providers in close proximity to farmers. The farmers' education level is also significantly correlated with the adoption of CSAPs, as it helps in accessing information and knowledge on CC and the response strategies and helps to understand them from different perspectives. Further findings show that households with a large family size and members of a social group are more likely to adopt CSAPs, as the majority of CSAPs are labor-intensive activities.

Finally, the causal impact estimation from both the ESR and PSM models suggests the adopters of CSAPs have significantly higher FCS (food security status) than the non-adopters.

5.3. Recommendations

Unless concerted efforts are made, the current effects of CC will continue to affect smallholder coffee production in the future. Adoption CSAPs are quite comprehensive as they address a wider spectrum and require a multi-dimensional approach that integrates scientific knowledge, local expertise, and supportive policies.

Jimma and Teppi agricultural research center are responsible to undertake research on in each coffee-growing region and deliver resistant coffee varieties and other CSAPs that are compliant with each coffee-growing zone. The government and NGOs should support and facilitate climate-smart agriculture research projects on smallholder coffee production systems tailored to the peculiar characteristics of specific localities. The government should also modernize the agricultural extension services system, equip extension agents, and improve agricultural information systems.

It was also advised that policymakers design pro-farmer policies that encourage the adoption of CSAPs. Furthermore, women and young people should be encouraged to engage in farming activities by the government and other private organizations.

5.4. Areas of Further Research

Future studies should also concentrate on developing climate-smart ecosystem management strategies, appropriate and sustainable land use policies, and a profile of climate-smart coffee production in all of Ethiopia's coffee-producing zones.

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I. Household Questionnaire

Questionnaire No……………………………

Dear Respondent

My name is Teka Tefera, a post-graduate student at Jimma University pursuing studies for a Masters of Science degree in Rural Development and Agricultural Extension. The purpose of this questionnaire is to gather information on the impact of the adoption of climate-smart agriculture practices (CSAPs) on the food security of smallholder coffee producer households: the case of Yeki woreda, Sheka Zone. You are one of several farmers in this area who have been selected for this study. This is to request that you kindly take a few minutes to reflect and answer the following questions: The information collected will be treated with the utmost confidentiality and will exclusively be used for the sake of this study.

NOTE: This is not a test and only sincere and honest answers are expected

Put a **code** on the appropriate response, or write your response in the space provided.

Thank you for your willingness and time!

Enumerator's name………………………..... Date……………………………...

A. Household Characteristics of the Respondent (Household Head)

AQ1	Gender	**0**	Male				
		1	Female				
AQ2	Age of respondent in years						
AQ3	Education level of respondent in years						
AQ4	Number of members of family living in a household						
AQ5	Age category of members of the household	**Code**	**Age group**	**Male**	**Female**	**Total**	**AE**
		01	<10				
		02	10-13				
		03	14-16				
		04	17-50				
		05	>50				

B. Farm Characteristics

B1. For how long have you been practicing coffee farming? ....years

B2. How many hectares of land do you own? ....hectare

B3. How many hectares of land are under cultivation for coffee?

C. Economic Characteristics

CQ1	Dear respondent! How much is your average annual income from the sales of coffee?			ETB
CQ2	Do you participating in non/off-farm activities?	**0**	No	
		1	Yes	

[illegible] many of the following types of livestock do you have? Please												
Types of livestock	Cow	Ox	Bull	Heifer	Calf	Horses	Donkey	Mule	Camel	Goat	Sheep	Poultry
Head count												

D. Institutional Factors

DQ1	Have you ever informed of CC and its adaptation strategies?	0	No	
		1	Yes	
DQ2	If yes, specify your sources of information from the given options. Please! Use the specified number, 1 for yes and 0 for no	Extension agents	O. No 1. Yes	
		Radio and TV	O. No 1. Yes	
		Neighbour farmers	O. No 1. Yes	
		Local administrators	O. No 1. Yes	
DQ3	How many times do you meet with extension agents per cropping year?			
DQ4	Have you ever received any training on CSA-Ps and its importance?	0	No	
		1	Yes	
DQ5	Are you a member of farmers' group/cooperative association?	0	No	
		1	Yes	

E. Perception on trends of Climate Change

EQ1. Did you perceive that CC has taken place in this area for last 5-20 years?

0) No, I didn't perceived 1) Yes, I perceived

EQ2	If yes [illegible]	Climate variables		
		Temperature	0. Increase 1. decrease 2. no change 3. I don't know	
		Rainfall distribution	0. Erratic 1. No change 2. I don't know	
		Dry season	0. Increasing 1. Decreasing 2. No change 3. I don't know	

EQ3. Are the above mentioned changes in climate variables affecting your farm production negatively? 0) N0 1) Yes

EQ4. If yes, to what level did the CC challenging your farm?

0) Low 1) Medium 2) High

EQ5. Have you observed the following impacts in your coffee farming attributed to CC?

Please! Encircle 1 for ‘Yes’ and 0 for ‘No’.

Occurrence of pests and disease	0. No 1. Yes	
Decreasing of yield	0. No 1. Yes	
Falling of flowers and fruits	0. No. 1. Yes	
Failure of coffee trees	0. No. 1. Yes	

EQ5. Please! Would you indicate the CSAPs you adopted on your coffee farm among the following? Please! Tick on the practices you adopted.

s/n	Types of CSA-Ps	Tick here	Remark
1	Use of improved coffee varieties		
2	stumping,		
3	Organic fertilization		
4	Use of cover crops		
5	Mulching		
6	intercropping		
7	Shade agroforestry		

EQ4. What is/are the driving factor you to attempt these CSAPs? Encircle the possible responses please!

0) Increases productivity 1) Enhances resilience to climate change

2) Efficient in the use of natural resources 3) Enhances food security 4) No response

EQ6. What are the major challenges facing you in adoption of CSAPs? Please! Tick on the challenges you facing.

s/n	Challenges	Tick here	Remark
1	Lack of awareness/training		
2	Poor extension services		
3	Shortage of labour		
4	Others		

F. FOOD SECURITY STATUS

How many days in the last seven days did your household eat any of the food categories in the list below? (Tick appropriately the type of food eaten on each particular day.) Leave blank on each day a particular food was not eaten.

S/N	Food item	7 days ago	6 days ago	5 days ago	4 days ago	3 days ago	2 days ago	Yesterday
Cereals and tubers								
1	Rice							
2	Wheat							
3	Maize							
4	Sorghum							
5	Barley							
6	Teff							
7	Sweet potato							
8	Irish potato							
10	Kocho							
Pulses and nuts								
11	Beans							
12	Peas							
13	Lentil							
14	Other pulses							
Dairy products								
15	Milk							
16	Yogurt							
17	Cheese							
Meat and fish								
18	Meat							
19	Poultry meat							
20	Eggs							
21	Fish							
Vegetables								
22	Dark green vegetables-leafy							
Fruits								
23	Banana							
24	Mango							
25	Avocado							
26	papaya							
Sugar and honey								
27	Sugar, honey							
Oils and fat								
28	Oils							
29	butter							

Thank very much!

II. KEY INFORMANT INTERVIEW GUIDE

Name______________________Position/profession_______________________

A. Perceptions about climate change and its effects on coffee farming

1. Would you say climate change and variability are taking place in this world?
2. If yes, what changes have frequently happened in your world for the last 10–20 years that make you conclude climate change is occurring?
3. Are these changes affecting smallholder coffee production?
4. Would you explain the impacts of climate change on smallholder coffee production?

B. Knowledge about climate-smart practices

5. Do you have enough information on CSAPs?
6. If yes, where did you get this information from?
7. Do you think smallholder coffee farmers are aware of CSAPs? If yes, where did they get this knowledge or awareness from?
8. Are smallholder coffee farmers using CSAPs? If yes, please! Specify the CSAPs they are practicing in your woreda.
9. Do you think adoption of CSAPs is the right way to make agricultural production stable in the face of current climate-changing scenarios?
10. What are the factors affecting the adoption of CSAPs by smallholder coffee farmers?

C. Institutional context with regard to the adoption of climate-smart practices

11. Are the extension workers equipped with the knowledge and skills of CSAPs in your woreda?
12. What is expected from whom to make smallholder coffee production systems more stable in the face of climate change challenges?

Thank very much!

III. **Focus Group Discussion Guide**

Dear Participants!

1. Did you ever hear about CC?
2. If yes, where did you get this information from?
3. Would you say climate change is taking place in this area? If yes, what events have you observed for the last 10–20 years that make you conclude climate change is occurring?
4. Discuss the trends of temperature, rainfall pattern, and dry season in your locality.
5. What are the manifested impacts of CC on agriculture, particularly coffee production?
6. Do you have awareness of CSAPs as response measures for current climate change?
7. CSAPs are location-specific. Please! Discuss the CSAPs that are being practiced by smallholder coffee farmers in your kebele in response to the impact of CC.
8. Discuss the benefits of adopting CSAps for your coffee productivity.
9. What are the factors affecting the adoption of CSAPs by smallholder coffee farmers?
10. What is expected from whom to make the smallholder coffee production system more stable in the face of climate change challenges?

Thank very much!

APPENDIXES

```
. probit ADOPTION SEXHH AGEHH EDUHH FAMSIZ FAREXP  LANDSZ FARMINC OFFARM LIVESTK EXTCONT GROUPM

Iteration 0:   log likelihood = -212.79456
Iteration 1:   log likelihood = -150.36173
Iteration 2:   log likelihood = -150.03744
Iteration 3:   log likelihood = -150.03732
Iteration 4:   log likelihood = -150.03732

Probit regression                               Number of obs     =        307
                                                LR chi2(11)       =     125.51
                                                Prob > chi2       =     0.0000
Log likelihood = -150.03732                     Pseudo R2         =     0.2949
```

ADOPTION	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
SEXHH	.6974543	.2577196	2.71	0.007	.1923332	1.202575
AGEHH	-.050157	.0262729	-1.91	0.056	-.101651	.0013369
EDUHH	.1121956	.0504383	2.22	0.026	.0133383	.2110529
FAMSIZ	.3358552	.126409	2.66	0.008	.088098	.5836124
FAREXP	.0287144	.0375242	0.77	0.444	-.0448317	.1022605
LANDSZ	.0989055	.1629293	0.61	0.544	-.2204299	.418241
FARMINC	.0000183	9.13e-06	2.01	0.045	4.47e-07	.0000362
OFFARM	-.0272578	.1777479	-0.15	0.878	-.3756373	.3211216
LIVESTK	.1323368	.0936796	1.41	0.158	-.0512719	.3159455
EXTCONT	.1195789	.0454957	2.63	0.009	.0304089	.2087489
GROUPM	.4356982	.2097385	2.08	0.038	.0246182	.8467782
_cons	-3.304173	1.519647	-2.17	0.030	-6.282626	-.3257207

```
. estat gof, group(10)

Probit model for ADOPTION, goodness-of-fit test

  (Table collapsed on quantiles of estimated probabilities)

       number of observations =       307
             number of groups =        10
      Hosmer-Lemeshow chi2(8) =         5.49
                  Prob > chi2 =         0.7044
```

Appendix Figure 1.Hosmer and Lemeshow’s goodness-of-fit test

Source: Author’s computation from data, 2024

```
. do "C:\Users\user\AppData\Local\Temp\STD18f8_000000.tmp"

. vif
```

Variable	VIF	1/VIF
EXTCONT	2.31	0.432076
FAREXP	2.03	0.491467
FAMSIZ	1.91	0.522541
LIVESTK	1.86	0.537635
EDUHH	1.63	0.614983
AGEHH	1.32	0.757978
LANDSZ	1.19	0.843468
FARMINC	1.11	0.900557
Mean VIF	1.67	

Appendix Figure 2. . Multicolinearity test for continuous variable (VIF)

Source: Author’s computation from data, 2024

```
. do "C:\Users\user\AppData\Local\Temp\STD18f8_000000.tmp"

. correl ADOPTION SEXHH OFFARM GROUPM
(obs=307)

             | ADOPTION    SEXHH   OFFARM   GROUPM
-------------+------------------------------------
    ADOPTION |   1.0000
       SEXHH |   0.1282   1.0000
      OFFARM |  -0.0094   0.0023   1.0000
      GROUPM |   0.3367   0.1548  -0.0672   1.0000
```

Appendix Figure 3. Multicolinearity test for dummy variables

Source: Author’s computation from data, 2024

```
. ovtest

Ramsey RESET test using powers of the fitted values of ADOPTION
       Ho:  model has no omitted variables
                 F(3, 292) =      1.64
                  Prob > F =      0.1804

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```

Appendix Figure 4. Omitted variable test

Source: Author’s computation from data, 2024

Apendix Table 1. Falsification test for instrumental variables

Variable	Decision to adopt	FCS	
	Coefficient	Adopter	Non adopter
Extension	0.210 (0.030)***	0.639 (0.553)	-0.510 (0.383)
Social group	0.612 (0.192)***	5.827 (4.354)	0.180 (1.932)
_cons	-1.403 (0.188)***	35.118 (4.446)***	36.254 (1.678)***
Number of obs.	307	153	154
X^2	88.40		
p-value	0.000	0.1131	0.4000
F-value		2.21	0.92
Pseudo R2	0.2077		
R-squared		0.0286	0.0121
Adj R-squared		0.0157	-0.0010
Log likelihood	-168.59466		
Root MSE		16.582	11.395

Source: Computed from field survey data (2024)

Appendix Table 2. Matching estimator selection criterion

Matching algorithm	Pseudo-R2		LR X2		p>chi2		Mean standardized Bias		Total % |bias| reduction
	U	M	U	M	U	M	U	M	
$KBM^{bw0.1}$	0.295	0.015	125.61	6.20	0.000	906	68.7	4.2	94
$KBM^{bw0.25}$	0.295	0.030	125.61	12.83	0.000	0.381	68.7	10.7	84
$KBM^{bw0.5}$	0.295	0.073	125.61	30.96	0.002	0.381	68.7	27.2	60
NNM^{1}	0.295	0.041	125.61	17.51	0.000	0.131	68.7	9.6	86
NNM^{2}	0.295	0.023	125.61	9.71	0.000	0.641	68.7	6.6	90
NNM^{3}	0.295	0.010	125.61	4.45	0.000	0.974	68.7	3.5	95
$KBM^{bw0.01}$	0.295	0.289	125.61	84.66	0.000	0.000	68.7	68.7	0
$KBM^{bw0.1}$	0.295	0.289	125.61	84.66	0.000	0.000	68.7	68.7	0

Source: Author's computation from survey data (2024)

Apendix Table 3. Conversion factor for adult equivalent

Age	Adult equivalent	
	Male	Female
<10	0.4	0.2
10-13	0.6	0.6
14-16	0.8	0.75
17-50	1	0.9
>50	0.75	0.5

Source: Storck *et al*. (1991

Apendix Table 4. Conversion factors for livestock

Animals	TLU-equivalent
Camel	1.25
Horse	0.9
Mule	1.1
Ox	1
Cow	1
Heifer /bull	0.75
Calf	0.2
Donkey	0.7
Sheep/goat	0.13
Poultry	0.013

Source: Storck *et al*. (1991)

Appendix Table 5. Food groups for HFCS

No	Food groups	Food Item	Weight
1	Cereals and tubers	bread, rice, maize, barley, wheat, teff, potatoes	2
2	Pulses and nuts	beans, lentils, peas, peanuts, etc.	3
3	Meat and fish	Poultry, eggs, fish and sea food(fresh/dried)	4
4	Dairy products	milk, yoghurt, cheese, other milk's products	4
5	Vegetables	Dark green vegetables-leafy (other vegetables)	1
6	Fruits	Banana, mango, avocado, lemon, orange, papaya et	1
7	Sugar, honey		0.5
8	Oil	Oil, fat, butter	0.5

Source, WFP, 2009

Appendix Figure 5. Pictures captured while FGDs

```
. do "C:\Users\user\AppData\Local\Temp\STD1d00_000000.tmp"

. probit ADOPTION SEXHH AGEHH EDUHH FAMSIZ FAREXP  LANDSZ FARMINC OFFARM LIVESTK EXTCONT GROUPM

Iteration 0:   log likelihood = -212.79456
Iteration 1:   log likelihood = -150.36173
Iteration 2:   log likelihood = -150.03744
Iteration 3:   log likelihood = -150.03732
Iteration 4:   log likelihood = -150.03732

Probit regression                               Number of obs     =        307
                                                LR chi2(11)       =     125.51
                                                Prob > chi2       =     0.0000
Log likelihood = -150.03732                     Pseudo R2         =     0.2949

------------------------------------------------------------------------------
    ADOPTION |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       SEXHH |   .6974543   .2577196     2.71   0.007     .1923332    1.202575
       AGEHH |   -.050157   .0262729    -1.91   0.056     -.101651    .0013369
       EDUHH |   .1121956   .0504383     2.22   0.026     .0133383    .2110529
      FAMSIZ |   .3358552    .126409     2.66   0.008      .088098    .5836124
      FAREXP |   .0287144   .0375242     0.77   0.444    -.0448317    .1022605
      LANDSZ |   .0989055   .1629293     0.61   0.544    -.2204299     .418241
     FARMINC |   .0000183   9.13e-06     2.01   0.045     4.47e-07    .0000362
      OFFARM |  -.0272578   .1777479    -0.15   0.878    -.3756373    .3211216
     LIVESTK |   .1323368   .0936796     1.41   0.158    -.0512719    .3159455
     EXTCONT |   .1195789   .0454957     2.63   0.009     .0304089    .2087489
      GROUPM |   .4356982   .2097385     2.08   0.038     .0246182    .8467782
       _cons |  -3.304173   1.519647    -2.17   0.030    -6.282626   -.3257207
------------------------------------------------------------------------------

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```

Appendix Figure 6. Probit regression estimation

```
. do "C:\Users\user\AppData\Local\Temp\STD1d00_000000.tmp"

. margins, dydx(*)

Average marginal effects                        Number of obs     =        307
Model VCE    : OIM

Expression   : Pr(ADOPTION), predict()
dy/dx w.r.t. : SEXHH AGEHH EDUHH FAMSIZ FAREXP LANDSZ FARMINC OFFARM LIVESTK EXTCONT GROUPM

------------------------------------------------------------------------------
             |            Delta-method
             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       SEXHH |   .1918321   .0682662     2.81   0.005     .0580328    .3256314
       AGEHH |  -.0137955   .0071024    -1.94   0.052    -.0277158    .0001249
       EDUHH |    .030859   .0136006     2.27   0.023     .0042022    .0575157
      FAMSIZ |   .0923757   .0339162     2.72   0.006     .0259011    .1588503
      FAREXP |   .0078978   .0102863     0.77   0.443    -.0122629    .0280585
      LANDSZ |   .0272036   .0447484     0.61   0.543    -.0605016    .1149088
     FARMINC |   5.05e-06   2.46e-06     2.05   0.041     2.17e-07    9.87e-06
      OFFARM |  -.0074972   .0488824    -0.15   0.878     -.103305    .0883107
     LIVESTK |   .0363987   .0255929     1.42   0.155    -.0137625    .0865599
     EXTCONT |   .0328897    .012101     2.72   0.007     .0091721    .0566073
      GROUPM |   .1198371   .0567065     2.11   0.035     .0086943    .2309798
------------------------------------------------------------------------------

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end of do-file
```

Appendix Figure 7. Average marginal effect estimation