PAN AFRICAN UNIVERSITY

Adoption of Climate-Smart Improved Sorghum *[Sorghum bicolor (L.) Moench]* Varieties and Its Impact on Smallholder Farmers' Income in Karat Zuria District of Konso Zone, Southern Ethiopia

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Adoption of Climate-Smart Improved Sorghum *[Sorghum bicolor (L.) Moench]* Varieties and Its Impact on Smallholder Farmers' Income in Karat Zuria District of Konso Zone, Southern Ethiopia.

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DEDICATION

I dedicated this Thesis to my lovely Wife Kaylote Kalita Karata for her love, courage and sincere support.

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BIOGRAPHICAL SKETCH

The author was born to his father Kassu Sagara, and his mother Katana Ayano, in Busso *kebele* of Karat Zuriya district, Konso zone, SNNPR, Ethiopia, on February 2, 1993. From 1998/99 to 2003/04, he had his elementary education at Busso Elementary School (grades 1 to 5), then joined Konso Primary and Secondary High School in 2004/05 and completed grade 6. He then shifted to Karat Elementary and Primary School in 2005/06 and studied grade 7 to 8 and completed his grade eight in 2007/08 and again joined Konso Secondary and Preparatory School and studied from grade 9 to 12 from 2008/09-2011/12, respectively.

He joined Arba Minch University in November 2012 and graduated on June 25, 2015, with a Bachelor of Science degree in Rural Development and Agricultural Extension (RDAE). In October 2015, the author was hired by former Konso Woreda Rural Youth Job Opportunity Creation Affairs and worked for six months as an expert in Gellabo Cluster until February 2016. After that, he joined South Ethiopia Agricultural Research Institute (SEARI), formerly called Southern Agricultural Research Institute (SARI), Jinka Agricultural Research Center (JARC) on May 23, 2014, formerly as a junior Pre-Extension Demonstration (PED) of Agricultural Technology researcher and now Agricultural Technology Transfer and Communication (ATTC) Assistance Researcher-I and had worked for three consecutive years up to August 2019. During his stay at JARC, the author published more than five research articles in reputable journals and also four proceedings, and has got principal and co-authorship.

He then joined Haramaya University in October 2019 up to January 2023 to pursue a Master of Science degree in RDAE specialization in Agricultural Communication and Innovation for Development (ACID). Immediately after graduating from Haramaya University, he was again awarded PAU Scholarship and joined PAUWES to pursue his second Master of Science in Climate Change Policy from May 2023 to April 2025.

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ABBREVIATIONS AND ACRONYMS

AE	Adult Equivalent
AU	African Union
AARC	Arba Minch Agricultural Research Center
ATT	Average Treatment Effect on the Treated
CIA	Conditional Independence Assumption
CSISVs	Climate Smart Improved Sorghum Varieties
ETB	*Ethiopian* Birr
EU	European Union
FGDs	Focused Group Discussions
GPS	*Generalized* Propensity Score-matching
HH	Household Head
KII	Key Informant Interview
KZDANaRO	Karat Zuria District Agriculture and Natural Resource Office
PSM	Propensity Score Matching
SNNPRS	Southern Nations, Nationalities and Peoples Regional State
SPSS	Statistical Product and Service Solutions
STATA	Statistical Data
TLU	Tropical Livestock Unit

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ABSTRACT

Ethiopia is among the most vulnerable countries in East Africa to the variability of climate change due to its inhabitants' reliance on rain-fed agriculture. Sorghum is among the popular cereal crops of major economic importance in Ethiopia. The Ethiopian government is attempting to increase household income by promoting the adoption of climate-smart improved sorghum varieties. In the Karat Zuria district, however, there is no solid evidence for the adoption and impact of climate-smart improved sorghum varieties on the total annual income of smallholder farmers. As a result, the research was carried out to determine the factors that influence smallholder farmers' adoption of improved sorghum varieties and to assess their impact on smallholder farmers' income in the study area. A multi-stage sampling technique was used to select 384 representative sample households (184 adopters and 200 non-adopters) for this study. A semi-structured interview schedule, focus group discussions, and key informant interviews were used to gather primary data. The secondary data were gathered via reviewing a variety of documents. A probit model was used to analyze the data and determine the factors that influence the adoption of improved sorghum varieties. Age, sex, education level, family size, farm land size, access to non/off-farm activities, membership of farmers cooperatives, distance to the nearest market, access to credit, access to varieties information from research center and irrigation access were among the 14 independent variables that influence the adoption of improved sorghum varieties. To estimate the average treatment effect on the treated in this study, an endogenous switching regression model was used. According to the findings, the adoption of improved sorghum varieties had a substantial favorable average effect on total annual income of 0.7681, of treatment over control with positive transitional heterogeneity of 0.1257. These results imply that adopting climate-smart improved sorghum varieties increases the average annual household income of adopters by 12.57%. Contents identified major challenges and opportunities of climate smart improved sorghum varieties. It revealed that, adoption of climate smart improved sorghum varieties is crucial in improving farmers' income. As a result, the study recommends that the local government and other key stakeholders should promote climate smart improved sorghum varieties to help non-adopting smallholder farmers in the study area.

Keywords: Adoption, Climate-smart improved sorghum varieties, Endogenous switching regression model, Impact, Karat Zuria district, and Total household income.

Kebede Kassu Sagara

Adoption of Climate Smart Improved Sorghum [Sorghum bicolor (L.) Moench] Varieties and Its Impact on Smallholder Farmers' Income in Karat Zuria District of Konso Zone, Southern Ethiopia.

1. INTRODUCTION

1.1. Background of the Study

Ethiopia is among the most vulnerable countries in East Africa to the variability of climate change due to its inhabitants' reliance on rain-fed agriculture (Erekalo & Yadda, 2023; Palmer et al., 2023). Agriculture is the most susceptible sector in Ethiopia due to its excessive dependence on climatic conditions (Abdulrahaman et al., 2020; Gebre, 2021). Climate-induced shocks not only cause hunger and income deprivation but also lead to a loss of assets that hamper the long-term income opportunities of small farmers (Makate et al., 2022; Tofu et al., 2022). It is challenging to avoid climate change influences with mitigation actions, as most Ethiopian farmers depend on rain-fed agriculture, which is climate-sensitive (Destaw & Fenta, 2021; Moges & Bhat, 2021; Zerssa et al., 2021). Climate-smart agriculture (CSA) is a sustainable form of agriculture that aims to increase productivity, improve adaptation, and reduce greenhouse gas emissions into the atmosphere (Gashure et al., 2022). Ethiopia's agricultural sector is negatively affected by extreme climatic events such as flooding and droughts (Kassaye et al. 2021; Yang et al. 2020).

In 2020, out of the whole grain crop space enclosed by breakfast cereal, i.e., 10.2 million hectares, 14.97% (1.88 million hectares) was shielded by sorghum, third status following *teff* and maize (Teressa et al., 2021). Similarly, out of the total national grain production, cereals contribute to 87% (253 million quintals), with sorghum shares accounting to up to 16% (47 million quintals) (CSA, 2018). Sorghum production has considerably increased in the last five years by 1.7 million tons of yield production. This was obtained from the adoption and sorghum varieties (Demeke & Di Marcantonio, 2019). Nearly 4.5 million smallholder farmers cultivated sorghum in 2019 (Demeke & Di Marcantonio, 2019) while production in yield and productivity increased from 1.2 loads/ha to 2.5 loads/ha (Amare et al., 2020).

Cereal is a critical component of Ethiopia's current agricultural policy since it may be used to replace imported goods and achieve food security. Sorghum variety improvement policies and strategies in Ethiopia have a lengthy history dating back to more than 50 years, starting in the middle of the 1950s at the Haramaya College of Agriculture with Oklahoma State University's partnership effort (Semahegn & Teressa, 2021). Research has been carried out to advance innovations in food security, cultivation practices, and variety improvement (Feyissa Desiso et al., 2019). In Ethiopia, better sorghum varieties have been issued at the regional and national levels over the past forty years for lowland areas, but adoption of these types has been slow(Ahmed Mumed & Hassen Habib, 2023).

Sorghum is the third most important cereal grain after *teff* and maize in Ethiopia both in area and production. In Ethiopia, sorghum is produced for food, feed, and stalks for fodder and building material. Currently, sorghum is produced by more than 5 million holders and its production is estimated to be 51,692,525 quintals from 1,896,389 hectares of land (Gizaw & Assegid, 2021). The average productivity of the crop is 27.26 quintals per hectare. It covers 14.96% of the total area allocated to grains (CSA, 2018; Solomon et al., 2021).

The three major crops cultivated in Konso are sorghum 80.6%, maize 67.6%, and *teff* 22.5%, respectively (Gashure et al., 2022). Two improved sorghum varieties (*Melkam* and *Teshale)* were demonstrated and/or disseminated in Karat Zuria district of Konso zone by AARC and or its partner SARI. Despite the increasing importance of improved sorghum in Ethiopia, there is inadequate knowledge on improved sorghum varieties adoption and their impact on income, especially in the target area of the study. Against this backdrop, the objective of this study is to assess the impact of climate-smart improved Sorghum varieties (CSISVs) adoption on households' income and determinants of CSISVs adoption in Karat Zuria district.

1.2. Statement of the Problem

Climate-smart agriculture (CSA) is gaining traction as a new paradigm for agricultural adaptation to changing climates and mitigation (Khatri-Chhetri et al., 2020; Pacillo et al., 2022). It is a strategy for agricultural management in the face of climate change (Kifle, 2021), boosts productivity while also increasing farmers' adaptive capacity and resilience to climate change (Eshete et al., 2020; Fentie & Beyene, 2019a) and increasing agricultural productivity in the face of changing climate conditions (Habtewold, 2021; Zerssa et al., 2021).

There are different factors which affect the adoption of CSA practices in Ethiopia (Tadesse & Ahmed, 2023). The adoption of some specific improved varieties significantly rise crop and household income (Manda et al., 2019; Tufa et al., 2019; Wordofa & Sassi, 2020). A large body of well-established empirical literature shows that, adopting agricultural technologies improves food security, leads to an increase in household incomes, raises productivity, gives more opportunities for market access, and leads to an overall increase in social welfare measured by monetary income or expenditure-based approaches (Biru et al., 2020; Manda et al., 2019; Wossen et al., 2019).

Yet there is no robust evidence for the adoption and impact of improved climate-smart improved sorghum varieties (CSISVs) developed and disseminated by AMARC and its partners. The systematic analysis of the adoption on income security impacts of these technologies has been scarce. Studies literature in the study area have looked at the impact of cereal crops (maize, *teff* and sorghum) production (Gashure et al., 2022).

Sorghum (*Sorghum bicolor*), maize (*Zea mays*), and *teff* (*Eragrostis tef*) are the three major cereal crops produced in Konso (Gashure et al., 2022). A field experiment involving seven improved sorghum [*Sorghum bicolor (L.) Moench*] varieties and one local check was carried out at Konso zone Karat Zuria district at *Arfayde, Fuchucha* and *Sorobo* farmers' training center during the 2016-2017 main cropping season to identify the best performing variety for the moisture deficit areas of Konso zone. The seven improved sorghum varieties include (*Melkam, Seredo, Meko-1, 76TI-23, Teshale, Gubiye, Dekeba*) and a local check (Lema, 2020).

Determinants of adoption of climate-smart agricultural technologies were: levels of education, farming experience, contact with extension workers, credit access, access to market information, and total annual income (Geda et al., 2024); farm size, access to irrigated farm, access to extension service, distance to market places, and access to weather information (Kifle, et al., 2022); accessing climate variability information and social group participation (Erekalo & Yadda, 2023; Gashure & Wana, 2023b). Despite that, sorghum varieties adoption is significantly driven by government support, Farmer-Based Organization (FBO) membership, and household size (Abdul-Rahaman, 2023).

Adoption of multiple climate-smart agriculture practices of smallholder farmers in a moist tropical montane ecosystem of Southwest Ethiopia were; improved varieties, crop rotation, raw planting, crop residue management, compost, Soil and water conservation (SWC) and agroforestry (Tadesse & Ahmed, 2023; Teklu et al., 2023; Tilahun et al., 2023b). Limited to specific improved sorghum technologies (Kaliba et al., 2021; Kimbi et al., 2020); crop diversification, terracing, manure, irrigation, and rainwater harvesting (Gashure et al., 2022).

The impact of climate-smart agricultural technology on multidimensional poverty in Ethiopia has been explored in various ways, including its effects on crop production and poverty reduction (Habtewold, 2021; Sedebo, Li, Abebe, et al., 2021), dietary diversity, food, and nutrition security (Teklu et al., 2023; Tilahun et al., 2023b), as well as improvements in calorie and protein availability (Teklewold et al., 2019). Additionally, it has been shown to positively affect per capita consumption (Fentie & Beyene, 2019b), increase grain yield (Adego et al., 2019), and enhance overall crop production (Berhanu et al., 2021; Gashure et al., 2022). It also contributes to improve per capita consumption expenditure (Asrat et al., 2022a) and provides net benefits and a high marginal rate of return (Gezahegn et al., 2019). Welfare indicators such as income, consumption expenditure, and wealth index have been used to measure the impact (Kaliba & Mazvimavi, 2021). However, some studies focus specifically on the impact of climate-smart agriculture on crop income per hectare (Abdul-Rahaman, 2023; Fentie & Beyene, 2019b; Sahara et al., 2023).

Sorghum is the dominant crop in the lowland areas of Southern Ethiopia, especially Konso and South Omo Zones. Its production is increasing in Konso zone of Southern Ethiopia, but there are several production constraints with this crop. Even though the crop is important in the target area, several factors constrain the productivity of sorghum in the target areas. This is associated to the lack of improved varieties related with edaphic and biotic factors that have been appreciated as one of the primary sources of lower sorghum production in the target area. There was no trend of using improved sorghum varieties within the existing production system, hence, these remain a bottleneck within in the study area (Lema, 2020).

Nevertheless, there is limited empirical study in southern Ethiopia regarding the causal effect of CSISVs adoption on households. The scarcity of such empirical investigations has created a knowledge gap on the performance and impact of such CSISVs in the region. This study is initiated to contribute to this debate by producing household-level empirical evidence in Southern Ethiopia, and the researcher was used both qualitative and quantitative methodologies.

In addition, there is scant empirical evidence on the impact and performance of agricultural technologies developed, disseminated, and/or scaled-up by agricultural research and extension and their roles in improving the income of farm households in the study area. Therefore, the study would help to bridge the gap through systematic investigation of the impact of CSISVs adoption on farm households' income in Karat Zuria district of Konso zone, Southern Ethiopia.

1.3. Objectives of the Study

1.3.1. General objective

The general objective of the study was to analyze the adoption of climate-smart improved sorghum varieties and their impact on smallholder farmers' income in Karat Zuria district of Konso Zone, Southern Ethiopia.

1.3.2. Specific objectives

1) To identify factors influencing the adoption of Climate-Smart improved sorghum varieties in the study area.
2) To analyze the impact of Climate-Smart improved sorghum varieties adoption on smallholder farmers' income in Karat Zuria district.
3) To identify challenges and opportunities to adopt Climate-Smart improved sorghum varieties in the study area.

1.4. Research Questions

In light of the above gaps, the study was intended to empirically answer the following research questions.

1) What are the determinants of Climate-Smart improved sorghum varieties adoption decision?
2) To what extent does the adoption of Climate-Smart improved sorghum varieties impact smallholder farmers' income in Karat Zuria district?
3) What are the challenges and opportunities of Climate-Smart improved sorghum varieties adoption among the farming households in the study area?

1.5. Significance of the Study

The study was expected to analyze the adoption of climate-smart improved sorghum varieties and their impact on smallholder farmers' income in Karat Zuria district of Konso Zone, Southern Ethiopia. It would benefit and improve the knowledge base for understanding the impact of climate-smart improved sorghum varieties adoption on smallholder farmers' income. Understanding determinants of climate-smart improved sorghum varieties adoption in the study area would help sorghum farmers to make an appropriate plan that may address households' need. Besides, it would provide information on challenges and opportunities of climate-smart improved sorghum adoption in the study area. Further, the findings of the research work would also provide information for researchers, DAs, NGOs, GOs, development planners, other stakeholders, and students interested in a similar research theme for further investigation in other areas.

1.6. Scope and Limitation of the Study

The study was focused on the analysis of the adoption of climate-smart improved sorghum varieties and their impact on smallholder farmers' income in Karat Zuria district of Konso Zone, Southern Ethiopia. It is limited to Karat Zuria district of Konso Zone, Southern Ethiopia. In addition, the study was limited to the impact of climate-smart improved sorghum varieties adoption on smallholder farmers' income even though the remaining technologies are usually recommended as a package in the Karat Zuria district. Also, it only considers cross-sectional data. The study was also limited to 4 out of the 18 rural kebeles of the district from which a total sample of 384 households was drawn. Therefore, the result of this study did not representing the whole population of the district. The study was only looked at the impact of climate-smart improved sorghum varieties adoption on the income of smallholder farmers in the study area. However, there are other technologies disseminated in the areas which have not been accounted for in the study area, by so doing, the researcher was able to ascertain the real income impacted by most of the rest of the technologies adopted in the area, hence limiting the study.

2. LITERATURE REVIEW

2.1. Definitions and Concepts

2.1.1. Definitions and concepts of adoption, CSA, impact, and income

Adoption: Individuals or groups are important for the adoption of innovation within a social system. Adoption could be defined as the long-term integration of innovation into farmers' normal farming activities (Feder et al., 1985).

Climate-smart agriculture (CSA): is currently promoted as an approach intended to increase sustainable agricultural productivity, enhance household resilience, and reduce greenhouse gas emissions (Tilahun et al., 2023b).

Impact: It implies the changes in people's lives, which are expected to happen due to the adoption of improved sorghum Varieties. It may occur over the long term and affect farmers at the household level, including economic (income) changes and food security. Such changes have positive or negative effects on identifiable population groups, directly or indirectly, intended or unintended (Omoto, 2003).

Income: It is the total amount of money received in exchange for labor, including payments for commodities, services, and capital gains, including farm and non-farm/off-farm income, during a period (Christopher, 2012).

2.1.2. Sorghum production and its importance in Ethiopia

Ethiopia is the largest producer of sorghum in Africa after Nigeria and Sudan and the second after Sudan in the Common Market for Eastern and Southern Africa member countries (Habte et al., 2020). Sorghum is a major staple food crop that ranks second after maize in total production, as well as the third-largest crop in productivity after wheat and maize and area coverage after *teff* and maize (Mengistu et al., 2019). The crop is one of the most widely grown cereal crops in a wide range of agro-ecologies between 400m and 2500m altitudes (Gebregergs & Mekbib, 2020) and a staple food crop for millions of poor Ethiopians whose food insecurity is rampant (Sisang & Lee, 2023; Tasie & Gebreyes, 2020).

Sorghum in Ethiopia is grown in three major agro-ecologies. It is the major crop in the dry lowland environment which accounts for more than 60 % of the cultivated land (CSA 2018). As it is grown in diverse environments, the productivity of sorghum is constrained by several biotic and abiotic factors. The major constraints in the dry lowlands are drought, striga, low yield, and insects (Tesfahunegn, 2012). In Ethiopia, considerable achievements have been obtained in developing early maturing and drought tolerant sorghum varieties and production management practices (Solomon et al., 2021).

According to (Alemu et al., 2023; Solomon et al., 2021) since the establishment of the sorghum program more than 50 sorghum varieties have been released and the number of farmers growing improved lowland varieties reached 28 percent. The low level of improved sorghum variety adoption is attributed to the low availability of farmer preferred varieties in sorghum variety generation and dissemination endeavors (Beshir & Sime, 2013). To enhance the adoption of improved sorghum varieties, large-scale demonstration of improved Sorghum varieties has been conducted in collaboration with agricultural extension research process and agricultural office of the potential sorghum producer areas of the country (Solomon et al., 2021).

2.2. Theoretical Reviews of Adoption and impact of adoption

According to Feder et al., (1985), adoption is defined as the integration of an innovation into farmers' normal farming activities over an extended period. Similarly, adoption is defined as a decision to apply an innovation and to continue to use it over a reasonably long period of time (Van den Ban & Hawkins, 1996). Adoption can be considered as a variable representing behavioral changes that farmers undergo in accepting new ideas and innovations in agriculture anticipating some positive impacts of those ideas and innovations. It further noted that adoption is not a permanent behavior. An individual may decide to discontinue the use of an innovation for a variety of personal, institutional, or social reasons, one of which might be the availability of an idea or practice that is better in satisfying his/her needs.

As noted by Feder et al., (1985), a complete analytical framework for investigating adoption process at the farm level should include farmer's decision-making model. The model determines the extent and intensity of use of a new technology at each point throughout the adoption process and a set of equations of motion describing the time pattern of parameters that affect the decision made by farmer. Final adoption at farm level of the individual farmer is defined as the degree of use of a new technology in the long-run equilibrium when the farmer has full information on potentials of a new technology (Feder et al., 1985).

In most of the sub-Saharan Africa, agriculture remains large, and the bulk of the poor are smallholders who benefit from it directly through increased agricultural profits or indirectly through increase in nominal income from other sources other than own agricultural production (WDR, 2008). Agricultural growth is widely considered as the most effective means of addressing poverty in the developing world. Growth in agricultural production can reduce food insecurity by increasing the amount of food available for consumption. This is particularly important for rural consumers whose food entitlement is mainly based on their own production (Adekambi *et al*., 2009).

Agricultural production can be increased through extensive resource use, expansion of farmlands or intensification by using more inputs and technologies per unit of land. However, relying on extensive resource use is not a sustainable approach to boost agricultural production in many food-insecure countries, where high population pressure is a major challenge. In areas with limited land, intensification focused on investing in modern inputs and technologies offers a more effective strategy to increase agricultural output and alleviate food insecurity. New agricultural technologies and improved practices play a key role in increasing agricultural production (and hence improving national food security) in developing countries. Where successful, adoption of improved agricultural technologies could stimulate overall economic growth through inter-sectoral linkages while conserving natural resources (Sanchez et al., 2009).

Agricultural research can contribute to poverty reduction in three major ways. First, agricultural research helps in developing yield-increasing technologies contributing to an increase in the supply of food on which the poor spend a considerable share of their income. The development of high-yielding varieties, which boost food production both by increasing yields per unit of land per cropping season and by facilitating multiple cropping. Second, agricultural research helps to conserve natural resources since the poor lack alternative means to intensify agriculture except forced to overuse or misuse the natural resource base to meet basic needs. Third, because the poor tend to reside in marginal agricultural areas, research should aim at developing suitable improved technologies (Lipton & Longhurst, 2010). However for these, it is widely argued that research often neglects the marginal areas, thereby worsening poverty in them by reducing market prices of grains without improving technology (Lipton & Longhurst, 2010).

2.3. Empirical Review of CSISVs' Adoption and Impact on Income

2.3.1. Factors Determining the Adoption of Climate-Smart Improved Sorghum Varieties (CSISVs)

The literature on adoption of CSISVs in developing countries points towards several factors operating in quite complex and interactive ways that condition the adoption decision of farmers. Identifying the determinants of adoption of CSISVs is an important intervention to enhance the adoption, which finally results in agricultural development. There are many studies in Africa, particularly in Ethiopia, on the determinants of adoption of CSISVs.

Kimbi et al. (2020) examined factors underlying the adoption of improved technologies among sorghum farmers in Tanzania and evaluated the profitability of grain production. Data were analyzed using descriptive statistics, probit regression model, and gross margin analysis. Probit estimates indicated that age, sex, number of years in school, group membership, and farm size, availability of free seeds, seed accessibility, grain market accessibility, and grain market price were the significant factors influencing adoption of these technologies. Adopters obtained higher profitability (822,288 Tshs/ha) than non-adopters (374,363 Tshs/ha) of improved varieties (Kimbi et al., 2020).

Chavula & Turyasingura (2023) assessed climate-smart agricultural practices adopted by smallholder sorghum producers in Rubanda District, Uganda. The study also evaluated the level of sorghum utilization among smallholder farmers and the contribution to household income. The study revealed 88.3% of smallholder farmers' households produced sorghum and 11.7% produced other crops from the sampled households. Smallholder farmers 41.7% reported growing Rukutu local sorghum variety followed by Magune 31.7%, Kyatanombe at 20%, and Buhuri at 13.3% respectively. In this study, farmers also reported the crop to enhance food security and household nutrition. Furthermore, 76.7% of smallholder farmers earned income from sorghum sales. Sorghum production has a potential to boost income gains from crop production as compared to maize and other cereal crops (Chavula & Turyasingura, 2023).

The study in Oromia region of Ethiopia by (Degefa et al., 2023) using OLS regression were used to analyze factors affecting sorghum productivity. The regression model revealed that variables including sex, age, education, improved variety, soil slope and fertility, Tropical Livestock Unit (TLU), and extension services affected sorghum productivity positively and significantly. In the study areas, most of the farmers used the local sorghum variety. Only 17.89% of sample households used improved sorghum varieties, including *lalo, chemeda*, and *gemedi* varieties. The attributes of the improved sorghum varieties were better performance than the local variety.

In this era of changing climatic conditions, agricultural technology developers continue to promote suitable innovations to cushion and improve the resilience of smallholder farmers against adverse effects and shocks. These improved varieties contribute towards the attainment of household and national food security (Mwangi et al., 2021). This paper aims to understand what influences households' decision to adopt, speed of uptake, and extent of use of improved sorghum varieties (ISVs). Data were analyzed using Double Hurdle and Duration models. Study revealed that consumption expenditure levels, income, and TLU are important determinants of three households' adoption decisions. Access to agricultural credit, distance to administration centers and adoption intensity depict unexpectedly a priori. The findings also show that households are credit constrained and use their own or neighbor's home saved seeds to expand the use of ISVs (Mwangi et al., 2021).

By using multivariate probit (MVP) model Erekalo & Yadda, (2023) analyzed determinants of the adoption of multiple CSA practices by focusing on crop production in Gamo, Gofa and Konso zones of Southern Ethiopia. Crop diversification, irrigation, drought-tolerant and early maturing crop varieties, integrated soil fertility management, and integrated pest management were prominent CSA practices to improve crop productivity, increase adaptive capacity, and mitigate the adverse climate change effects in the study area. The MVP result reveals that farmers' adoption decisions for CSA practices are highly interdependent, indicating that farmers adopt two or more adaptation and mitigation strategies as mutual CSA practices. Furthermore, the regression result reveals that the education level of farmers, extension contact, accessing climate variability related information, access to irrigation facilities, and social group participation were similar underlying factors that affected the adoption decision of CSA practices.

As discussed above, the empirical evidence on the adoption and its determinants in Ethiopia generally indicates that the adoption of climate-smart agricultural technologies was relatively low with considerable personal and spatial heterogeneities. They suggest that the rate and intensity of adoption of agricultural technologies is notably influenced by socioeconomic factors such as livestock holding, farm size, active family member, and so on, and other organizational factors such as access to credit, input and output markets, agricultural extension services, etc. Even though there are many adoption studies throughout Ethiopia, there is a clear bias towards major cereal crops or key cash crops within the geographic scope of the crops' ideal agro-ecologies. Unlike previous studies, this study focuses on estimating the determinants of CSISVs adoption in the Karat Zuria district of Southern Ethiopia. In addition, most of the studies above were undertaken in locations with entirely different socio-economic and biophysical features compared to Konso zone, Karat Zuria district.

2.3.2. Impact of improved crop technology adoption on farm households' income

Studying the impact of CSISVs adoption has a great advantage for a country like Ethiopia where the agriculture sector drives the entire economy. Technological improvement of farming systems and its adoption has a positive impact on the economic development of a country. According to literature on the impact of adoption of agricultural technologies, improved varieties and other accompanying technologies have positive contributions towards income of farm households. The following symmetric reviews of literature also confirm the positive correlation of CSISVs adoption on household income.

The study by Sisang & Lee (2023) evaluated the impacts of the adoption of certain improved varieties in the western highland agro-ecological zones of the Northwest and West Regions. Propensity score matching complemented by endogenous switching regression modeling was applied to ensure unbiased estimation. The results from both econometric approaches were consistent and indicated a positive and significant increase in both the productivity of rice and the income of farmers adopting them. Overall, adopting improved varieties accounted for a

24.4% increase in rice productivity and a 50.4% increase in farmers' income. Notably, non-adopters are expected to witness significant increases in productivity and income should they decide to adopt improved varieties (Sisang & Lee, 2023).

Using data from a household survey in Ghana's Upper East region, Abdul-Rahaman, (2023) applied an endogenous treatment effects model to account for both observable and unobservable selection biases in households' adoption decisions. The study examined the effects of adopting improved sorghum varieties on smallholder farm performance and household welfare, focusing on key outcomes such as farm input expenditure, farm output, farm net returns, and household consumption expenditure per capita.The results also show increased farm performance and better welfare associated with improved sorghum variety adoption. In particular, adopters incur 12.87% input expenditure, generate 6.95% farm output, 6.39% farm net returns, and 9.88% household consumption expenditure per capita, relative to non-adopters.

Asrat et al. (2022) analyzed the impact of Awash irrigation on the welfare of rural smallholder farmers in Asiyta district, Ethiopia. This study employed an endogenous switching regression model to control for endogeneity problems associated with adoption decision. Accordingly, the correlation coefficient result proved the existence of self-selection and endogeneity. Results indicated, irrigation users' per capita consumption expenditure and income were 16 % and 35 %, respectively, higher compared to non-irrigation- users significantly. Endogenous switching regression model further identified amount of own land cultivated, education status, number of extension contacts, livestock holding, nearest market distance, access to non-farm job, and nearest canal distance significantly determine irrigation participation (Asrat et al., 2022).

Fentie & Beyene (2019), studied on the impact of a climate-smart agricultural practice (row planting) on the welfare of rural households in Gubalafto woreda of Amhara region in Ethiopia. The study employed PSM and a Semi-parametric Local Instrumental Variable (LIV) version of the generalized Roy model. The results from the PSM model revealed that adoption of row planting technology has a positive and significant impact on per capita consumption and crop income per hectare. Covariates are well balanced and the impact estimate is insensitive to unobserved selection bias indicating that the estimates are a pure effect of the row planting technology. Marginal benefit of row planting is increasing with higher propensity of the farmer to adopt the climate smart planting technology (Fentie & Beyene, 2019).

Wordofa *et al*. (2021) studied the adoption of improved agricultural technology and its impact on household income in Eastern Ethiopia. The research employed the PSM procedure to establish the causal relationship between adoption of improved crop and livestock technologies and changes in farm income. Econometric analysis shows that households using improved agricultural technologies had higher annual farm income compared to those households not using such technologies. The findings highlight the importance of promoting multiple and complementary agricultural technologies among rural smallholders. So, technology generation, dissemination and adoption interventions are strengthened. Moreover, the linkage among research, extension, universities, and farmers needs to be enhanced through facilitating a multi-stakeholders innovation platform (Wordofa et al., 2021).

The study by Tadesse & Ahmed, (2023) assessed factors affecting CSA adoption and its impact in Ethiopia. The study revealed that the CSA implemented in Ethiopia were agronomic practices, integrated soil fertility management, conservation agriculture, agroforestry systems, and irrigation. The factors that affect CSA in Ethiopia were age of the family head, sex, household size, education level, distance to farm land, farm size, farming system, farm income source, off-farm income, access to irrigation, market access, access to agricultural credit, access to extension service, membership to organizations, farmers' perceptions of rainfall shocks, crop yield, access to climate information, access to agricultural inputs, slope, agro ecology, change in precipitation, tenure security and livestock ownership. The impact of CSA practices improves soil fertility status, increased crop yield, per capita nutrition consumption and dietary diversity, increased income of smallholder farmers, hence reducing poverty.

Study by Beyadegie, 2019 reported the impact of the adoption of Kabuli chickpea varieties on income and consumption expenditure of rural households in West Belesa district, Ethiopia. PSM was utilized through the treatment and control group approach. Kernel 0.25 matching algorism was the best selected match algorithm used to estimate ATT. By producing Kabuli chickpea varieties, the farmers had got additional income from crop production Birr 13281.15 per year over the control and the treated household got additional income from animal production Birr 12941.65 per year. Kabuli chickpea producer households spent additional expenditure Birr 771.31 and 163.71 per year for household food and non-food consumption respectively. So Kabuli chickpea varieties producer had a positive and significant impact on agricultural income and consumption expenditure. So, to improve farmer's household income Kabuli chickpea varieties should be disseminated for all chickpea producer areas.

The study in Central and Northern Tanzania anlyzed the impact of adopting improved seeds on consumption expenditure, income, and wealth index among small scale sorghum producers. In this study, quantified the welfare effects of adopting improved sorghum varieties in Tanzania using a doubly robust estimator that adjusts for self-selection bias and cofounding effect. It also notably used the inverse probability treatment weighting with regression adjustment to estimate the impact of adoption on farmers' welfare. The welfare indicators included income, consumption expenditure, and wealth index at the household level. The main results indicate that the distribution of some variables in the adopter group was systematically different compared to the non-adopter group. Also, the adoption of improved sorghum seeds substantially increased all welfare indicators. The adoption of improved sorghum varieties has the potential to reduce both food insecurity and poverty. The impact, however, varied by region and among household groups (Kaliba & Mazvimavi, 2021).

Simlarly the study by Kaliba et al., (2021) measured the Impact of adopting improved seeds on access to broader food groups among small-scale sorghum producers in Tanzania used double-robust estimators (i.e., inverse probability weighting and inverse probability weighting with regression adjustment) to quantify the effect of adopting climate-adaptive improved sorghum varieties on household and women dietary diversity scores. The results from the study showed that, the adoption of improved sorghum seeds has a positive effect on both household and women dietary diversity scores, improves nutritional status, food security adequacy, and general welfare of small-scale farmers.

The studies revealed the significant and promising effect of CSA technologies on the general wellbeing of farm households. However, most of the studies focus only on politically or financially important crops. Therefore, it is important to evaluate the impact of climate smart improved sorghum adoption in addition to adoption status of households.

2.3.3. Challenges and opportunities of Sorghum production in Ethiopia

The production of sorghum is mainly constrained by multitudes of factors such as climate change effects, poor agronomic practices, poor fertility management practices, poor pest and disease management, lack of ready markets, lack of organized market infrastructure, poor research- extension- farmer linkages and access to credit facilities as well as poor sorghum processing and value addition technologies (Kazungu et al., 2023). Despite that fact, sorghum producers face several challenges including limited access to agricultural inputs, land scarcity, and limited access to credit institutions that would boost sorghum production (Chavula & Turyasingura, 2023). Sorghum national average productivity in Ethiopia is 2.1 tons/ha which is far below the global average of 3.2 tons/ha due to the problem of drought, striga, insect pest (stalk borer, midge, and shoot fly), diseases (anthracnose and smut), soil fertility decline, inadequate adoption of existing improved varieties, lack of high yielding and good quality sorghum varieties. On the other hand as the opportunity, the Ethiopian government is pursuing a strategy of improving Sorghum productivity primarily through agricultural intensification, involving an increased use of inputs, including seeds of improved crop varieties and involved sorghum plant breeding since 1976 with different objectives and released many improved sorghum varieties (Kinfe & Tesfaye, 2018).

2.4. Impact Evaluation Methods

According to (Baker, 2000), there are two main approaches in impact assessment. These are randomized (experimental) designs and quasi-experimental (non-randomized) designs.

2.4.1. Experimental (randomized) method

In a randomized experiment, the treatment and control samples are randomly drawn from the same population. In other words, in a randomized experiment, individuals are randomly placed into two groups, namely, those that receive the program or intervention and those that do not get the program service or intervention. This allows the researcher to determine program impact by comparing the outcome variable for the two groups.

According to (Ezemenari et al., 1999), a random assignment of individuals to treatment and non-treatment groups ensures that on average any difference in outcomes of the two groups after the intervention can be attributed to the intervention. The main advantage of a randomized experiment is its ability to avoid problem of selection bias, which arises when participation in the program by individuals is related to their unobservable or unmeasured characteristics (like motivation and confidence), which in turn determine the program outcome. Obviously, randomization must take place before the program begins.

2.4.2. Quasi-Experimental (non-randomized) Method

The quasi-experimental method consists of constructed (matched) control where individuals to whom the intervention is applied are matched with an “equivalent” group from whom the intervention is withheld (Ezemenari et al., 1999).

According to (Jalan & Ravallion, 2003), a quasi-experimental method is the only alternative when neither a baseline survey nor randomizations are feasible options. The main benefit of quasi-experimental designs is that they can draw on existing data sources and are thus often quicker and cheaper to implement, and they can be performed after a project has been implemented. The most frequently used quasi-experimental design methods available for evaluating development programs include PSM, difference in differences (DD), regression discontinuity design (RDD), and instrumental variables (IV) (Nguyen & Bloom, 2006).

Difference-in-Differences: Method in which one compares a treatment and comparison group outcome before and after a project for a sample of participants and nonparticipants. Program only around the cut-off point for eligibility and nothing can be said of individuals far away from it (Caliendo & Kopeinig, 2008).

Instrumental variables or statistical control: In this method, one uses one or more variables that affect participation but not outcomes given participation. It is used to identify the exogenous variation in impact only due to the program, recognizing that the program is purposively placed rather than randomized. The instrumental variables are used to predict program participation first and then analyze how the outcome indicator varies with the predicted values (Baker, 2000).

Propensity Score Matching (PSM**)**: It is one of quasi-experimental methods to estimate causal treatment effects: The method tries to create the observational analogue of an experiment in which everyone has the same probability of participation. The difference is that in PSM it is the conditional probability P(X) that is intended to be uniform between participants and matched comparators, while randomization assures that the participant and comparison groups are identical in terms of the distribution of all characteristics whether observed or not. Hence there are always concerns about remaining selection bias in PSM estimates (Ravallion, 2007). The PSM is the best method to impact evaluators with time constraint and working in the absence of baseline data in that it can be applied with a single cross-section data. But PSM makes only the use of observable characteristics in a sampled unit to generate a control group that is comparable to the treated group following exogenous characteristics.

The Endogenous Switching Regression (ESR): The ESR model has been identified as a model that can correct for selection bias that could arise from both observed and unobserved variables within a dataset. This model is recommended by the works such as Maddala, 1983; (Sisang & Lee, 2023; Wole et al., 2014). So, in the case of this study, the impact of climate smart improved sorghum varieties adoption 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 improved variety, the second stage estimates two outcome equations from two regimes, representing both adopters and non-adopters of the CSISVs.

2.5. Analytical Framework of CSA Practices Adoption and Its Impact

Programs might appear potentially promising before implementation yet fail to generate expected impacts or benefits. The obvious need for impact evaluation is to help policy makers decide whether programs are generating intended effects; to promote accountability in the allocation of resources across public programs; and to fill gaps in understanding what works, what does not, and how measured changes in well-being are attributable to a particular project or policy intervention (Shahidur *et al*., 2010).

Estimating the impact of the participation in this case adoption of improved sorghum varieties requires separating its effect from participating factors, which may be correlated with the outcomes. This task of “netting out” the effect of the program from other factors is facilitating if control groups are introduced. “Control group” consists of a comparable group of individuals or households who were not involved in the program but have similar characteristics as those participating in the program, called the “treatment group”. In theory, evaluators could follow three main methods in establishing control and treatment groups: randomization/pure experimental design; non-experimental design and quasi-experimental design. In practice, in the social sciences, the choice of a particular approach depends, among other things, on data availability, cost and ethics to experiment. In what follows, brief descriptions of the main impact evaluation methods mentioned above are given.

Experimental method and Non-Experimental methods

Experimental method is randomized method, where the treatment and control samples are randomly drawn from the same population. In other words, in a randomized experiment, individuals are randomly placed into two groups, namely, those that are involved in the program or those that are not involved in the program. This allows the researcher to determine the participation impact by comparing the outcome variable for the two groups. In the contrary, non-experimental approach is used in cases where program placement is intentionally located. Non-experimental methods are frequently used in practice either because program administrators are not too keen to randomly exclude certain parts of the population from an intervention or because a randomized approach is out of context for a rapid-action project with limited time to conduct an experiment.

Generally, randomized evaluations seek to identify a program's effect by identifying a group of subjects sharing similar observed characteristics (say, across incomes and earning opportunities) and assigning the treatment randomly to a subset of this group. The non-treated subjects then act as a comparison group to mimic counterfactual outcomes. This method avoids the problem of selection bias from unobserved characteristics. However, the quality of impact analysis depends ultimately on how it is designed and implemented. Often the problems of compliance, spillovers, and unobserved sample bias hamper clean identification of program effects from randomization. In such cases, researchers then turn to non-experimental methods. The basic problem with a non-experimental design is that for the most part individuals are not randomly assigned to programs, and as a result, selection bias occurs in assessing the program impact (Shahidur *et al*., 2010).

The essential idea of the before and after estimator of an impact evaluation approach is to compare the outcome of interest variable for a group of individuals after participating in a program with outcome of the same variable for the same group or a broadly equivalent group before participating in the program and to view the difference between the two outcomes as the estimate of average treatment effect on the treated. Cross-section estimators use non-participants to derive the counterfactual for participants in which case it becomes quasi-experimental method.

A quasi-experimental method is the only alternative when neither a baseline survey nor randomizations are feasible options (Wole et al., 2014). The main benefit of quasi-experimental designs is that they can draw on existing data sources and are thus often quicker and cheaper to implement, and they can be performed after a project has been implemented, given sufficient existing data. The principal disadvantages of quasi-experimental techniques are that the reliability of the results is often reduced as the methodology is less robust statistically; the methods can be statistically complex and data demanding; and there is a problem of selection bias.

Propensity Score Matching (PSM): PSM is one of the quasi-experimental methods, which constructs a statistical comparison group that is based on a model of the probability of participating in the treatment, using observed characteristics. Participants are then matched based on this probability, or propensity score, to nonparticipants. The average treatment effect of the program is then calculated as the mean difference in outcomes across these two groups. The validity of PSM depends on two conditions: (a) conditional independence (namely, that unobserved factors do not affect participation) and (b) sizable common support or overlap in propensity scores across the participant and nonparticipant samples. Different approaches are used to match participants and nonparticipants based on the propensity score. They include nearest neighbor (NN) matching, caliper and radius matching, stratification and interval matching, kernel matching and local linear matching (LLM). Regression-based methods on the sample of participants and nonparticipants, using the propensity score as weights, can lead to more efficient estimates.

PSM is not without its potentially problematic assumptions and implementation challenges. First, PSM requires large amounts of data both on the universe of variables that could potentially confound the relationship between outcome and intervention, and on large numbers of observations to maximize efficiency (Bernard et al., 2010). Second, related to the previous point one can never be entirely sure that it has included all relevant covariates in the first stage of the matching model and effectively satisfied the conditional independence assumption (CIA). Furthermore, PSM is non-parametric: that does not make any functional form assumptions regarding the average differences in the outcome. Although the first stage involves specification choices - e.g., functional forms like logit and probit, empirical analyses tend to find impact estimates that are reasonably robust to different functional forms. Moreover, if unobservable characteristics also affect the outcomes, PSM approach is unable to address this bias (Ravallion, 2005).

Due to their shortcomings of the above models, ESRM model was employed to evaluate the impact of adoption (as a binary treatment variable) on the income of household because it is very appealing to evaluators with time constraints and working without the baseline data that it can be used with a single cross-section of data and avoids hidden bias.

2.6. Conceptual Framework

The identification of the driving factors for adopting new climate smart agricultural technologies is the first step in developing a conceptual framework for the CSISVs adoption and its impact on farm household income. These include household demographic characteristics (age, sex, education level, farm experience, and family size); socio-economic factors (total farmland holding, total livestock ownership, access to non/off-farm activities, and membership in farmers cooperatives); and institutional factors (distance to the nearest market, access to credit service, frequency of extension contact, access to irrigation, and access to market information). The use of climate smart improved sorghum varieties is then expected to have a significant economic advantage in terms of increased yield, increased farm household marketable surplus, and, eventually, improve farm income.

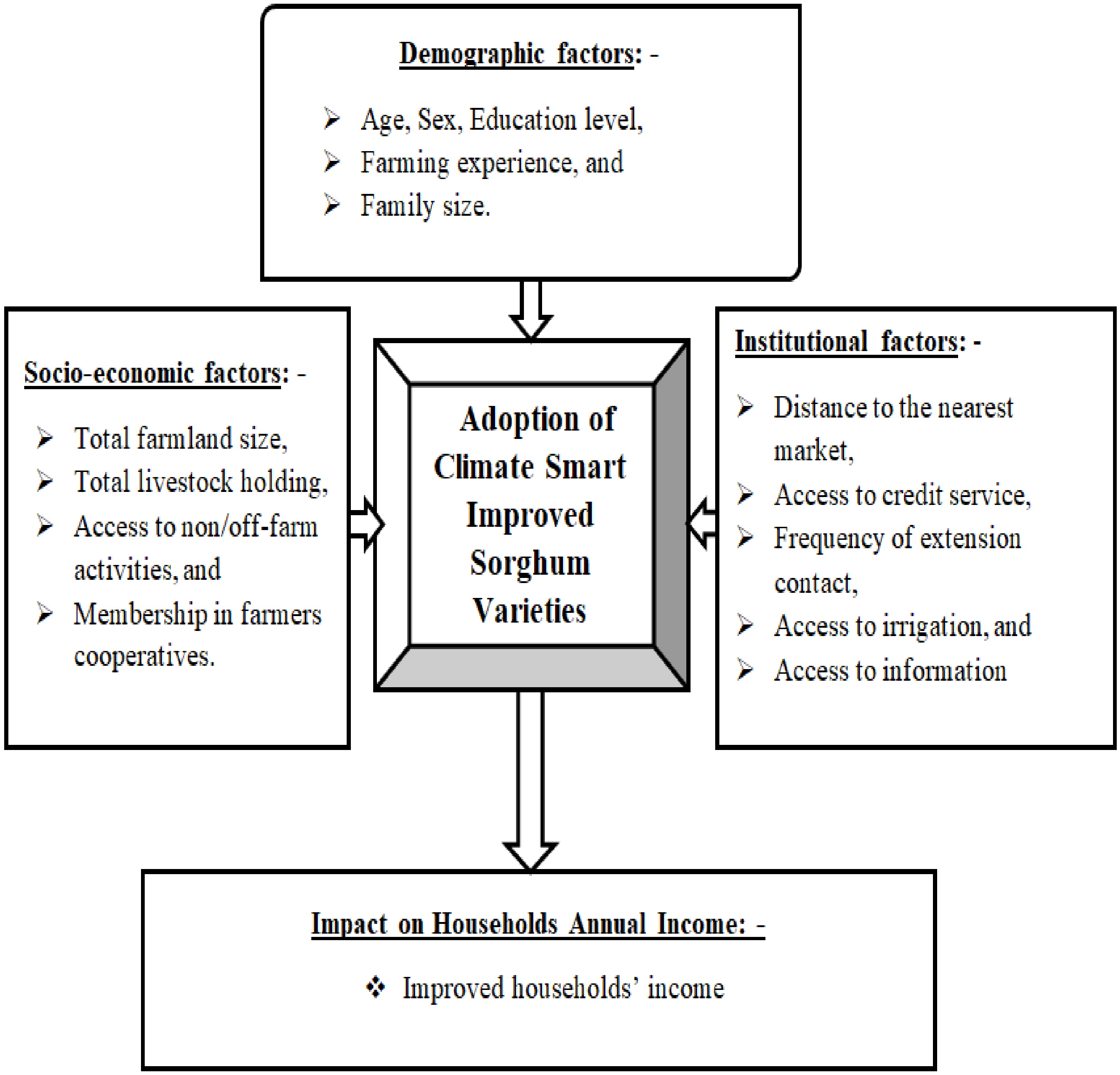


Figure 1: Conceptual framework of CSISVs adoption and its impact on household income

Source: Own design from the literature (2025)

3. RESEARCH METHODOLOGY

3.1. Description of the Study Area

The study was conducted in Karat Zuria district of Konso zone, South Ethiopia Regional State. Konso zone is located 522 km south of Addis Ababa in the Great Rift Valley and bordered on the south by the Oromia region, on the west by the South Omo zone, on the northwest by the Alle Zone, on the north by Gardula, on the northeast by Amaro Zone, and on the east by Burji Zone. The Sagan River, which flows south then west to join the Weyto, defines part of the Zone's boundary with Burji and the entire length of the boundary with the Oromia Region. The administrative center is Karat. The native Konso traditionally practices a distinct and sustainable form of agriculture that involves the building and maintaining of stone terraces and fertilizing the fields with manure. A central feature of their fields is the endemic tree crop, *Moringa stenopetala*. The main crop is sorghum, *teff*, and maize (Gage & Suntebo, 2023).

Astronomically, it is located between 5° 12'−5° 40' Nand 37° 01'−37° 43' E (Figure 1). Topographically, the Konso cultural landscape has rugged surfaces of varied elevations characterized by mountainous terrain intersected by ravens and valleys. According to the traditional agroecological zone (AEZ) classification, 80 % of the Konso landscape is semiarid (*Kolla*), with elevations ranging from 500–1500 m, and 20 % is subhumid (*Woynadega*), with elevations ranging from 1500–2300 m. The primary rainy season in Konso is spring (*Belg*), which is also the main crop production season. The average annual temperature in Konso is 23 degrees Celsius and the average yearly rainfall is 801.96 mm. Konso's total populations is 277,964 and 55,673 households (Central Statistical Agency 2017) population projection. The community's livelihood is mainly based on livestock and crop production, with sorghum serving as a staple food staple food (Gashure & Wana, 2023a).

Konso people of Ethiopia have been using stone terracing for distinctive farming technology for more than 400 years. By using this indigenous technique, they sustainably and successfully turn their sloppy hills and terrains into fruitful agricultural fields by growing crops on steep, erosion-prone areas. The terracing system is an essential part of the Konso people's cultural legacy because it not only demonstrates their inventiveness but also helps in conserving water and preserve soil. The Konso Cultural Landscape was recognized by UNESCO as a World Heritage Site in 2011, emphasizing the value of conserving the Konso people's agricultural practices and cultural identity in the face of contemporary issues like climate change and environmental degradation (Assen, 2024).

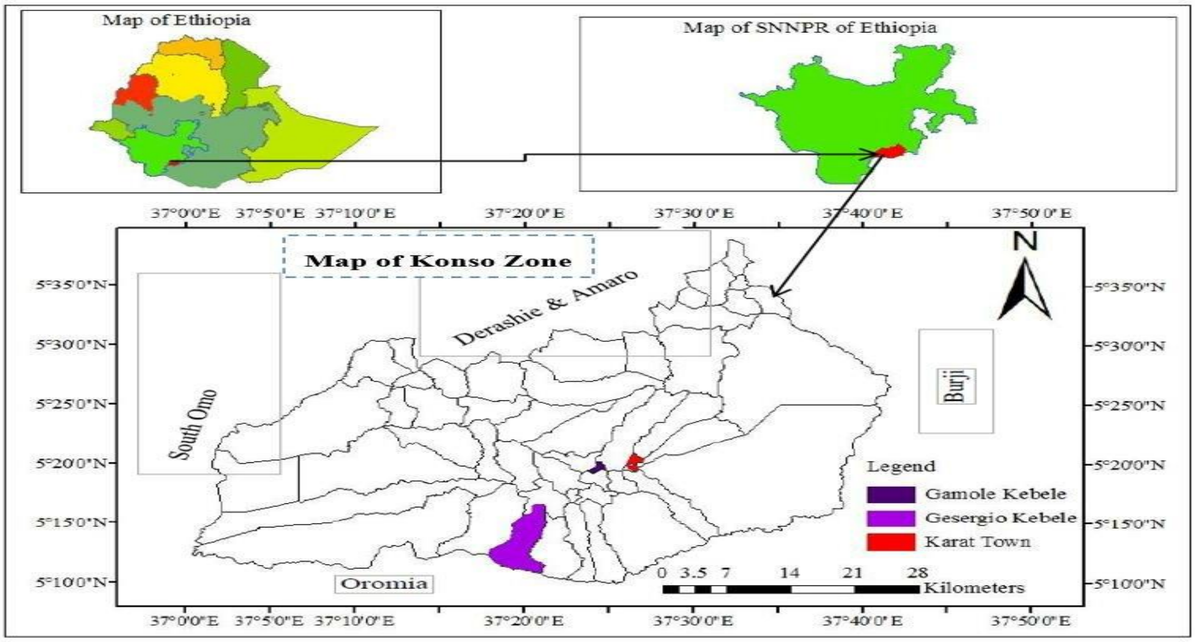


Figure 2: Map of district and Konso zone in South Ethiopia Region

Source: (ARC GIS computation, 2025)

3.2. Research Design

The study is designed to investigate the adoption of climate-smart improved sorghum varieties and its impact on smallholder farmers' income in Karat Zuria District of Konso Zone, Southern Ethiopia. Cross-sectional data were generated to achieve the objectives of this study. Cross-sectional data involves data collection from sample of population at one specific time as opposed to longitudinal method which gathers data on a factor over time. Its advantage is that it is an efficient way to identify possible group differences because one can study them at one point in time. Here, it was used to describe determinants of climate-smart improved sorghum varieties adoption decision and impacts on income of farm households in the study area. To address the stated objectives both quantitative and qualitative approaches were used.

Cross-sectional data were used to describe and explain the current situation of challenges and opportunities of climate-smart improved sorghum varieties adoption and factors affecting production in the study area. It is also chosen because it was helpful in obtaining pertinent and precise information on impact of introduced climate smart sorghum varieties on smallholder farmer's income by concerned stakeholders and to draw valid conclusions about the events of the sample population.

3.3. Sampling Techniques

Multi-stage sampling technique was used for the representative sample selection. First, the major sorghum growing district (Karat Zuria district) is selected purposively based on the potential and promotion of the climate-smart improved sorghum varieties, South Ethiopian Agricultural Research Institute (SEARI) and Arbaminch Agricultural Research Centre (AARC) arrangements and directions and the researcher is relatively familiar with the district; second, 4 representative *kebeles* due to researcher's convenience, out of 16 improved sorghum producers of 20-rural *kebeles* of the district is selected randomly via simple random sampling technique. In the third stage, sample households were selected by stratifying the household respondents into two groups in each kebele, *i.e.,* adopters and non-adopters of climate-smart improved sorghum varieties (CSISVs). Also, a comprehensive list of both households is prepared with the assistance of experts from the agricultural office of the district, chiefs/chairpersons and DAs from administrative *kebeles'* who provides farm households' lists as a sample frame. Finally, a representative sample farm household is selected using simple random sampling technique from each stratum based on the proportion to sample size of study population on the spot from each *kebele*.

3.4. Sample Size Determination

Due to heterogeneity, infinite size, and/or vast population, the researcher employed the (Cochran, 1977) formula to select the representative sample from the study population. Due to a lack of resources, the sample size from each of the four sample *kebeles* is estimated by applying the proportionality formula to their sample size. The value of P is assumed to be as follows for the purpose of computing sample size. There are two circumstances to consider when determining the sample size for a proportion. First, the formula can be applied with an approximate value of P (for instance, one from a previous study). Second, one should choose P=0.5 if an approximation of P is unknown. If there has not been any prior research in the field, a pilot survey was advised because it was given the data needed to determine P's value. As a result, this figure provides a sample size large enough to ensure a precise prediction (Ott & Longnecker, 2009). In this study, the pilot survey's P value of 0.5 is used (Sigei et al., 2014); regrettably, the p value is consistent with the researcher's findings. The following criteria were used to determine the sample size: -

$$\boldsymbol{n0} = (\boldsymbol{z}\hat{}\boldsymbol{2} * (\boldsymbol{p})(\boldsymbol{q}))/\boldsymbol{e}\hat{}\boldsymbol{2} \qquad (1)$$

Where, n_0 is the sample size.

z = denotes the standard deviation of the normal distribution (1.96 for a 95% CI-confidence interval)

p = due to unknown variability, p = 0.5 (the proportion of the population who adopted improved sorghum varieties, which is 50 percent),

q = 1-P =0.5. (50 percent),

e = required level of precision, in this case (0.05)

$n_0 = \frac{z^2 * (p)(q)}{e^2}$ =>$n_0 = \frac{(1.96)^2 * (0.5)(0.5)}{(0.05)^2} => \mathbf{384}$.

To get a sample from each of the four sample *kebeles*, a proportionality sampling technique was used, with the formula determined by equation (2).

$$n_i = \frac{Ni(n_0)}{\Sigma Ni} \qquad (2)$$

Wheren_i =the sample to be selected from i's *kebele*

Ni = The total population of a particular *kebele, Σ*= is a summation symbol

ΣNi= is the total number of people in the sixteen *kebeles* that were selected

n_0 = total sample size

As elaborated in (*Section 3.3*), the probability proportional to sample size approach was then used to calculate the sample size for each *kebeles*, as shown in *Table 1* below:

Table 1. Sample size distribution across the four selected *Kebele*

No	Name of Sample *Kebeles*	Total number of HHs	Sample selected				Total sample
			Adopters		None-adopters		
			Total	Sample	Total	Sample	
1	*Jarso*	1453	668	67	785	72	139
2	*Sorobo*	675	308	30	367	34	64
3	*Arfayide*	744	330	33	414	38	71
4	*Abaroba*	1152	537	54	615	56	110

Total	**4024**	**1843**	**184**	**2181**	**200**	**384**

Source: (Own calculation, 2025)

3.5. Data Types and Sources

The study employed both quantitative and qualitative data from primary and secondary sources. The primary data were collected from the sample respondents of both adopters and non-adopters on different characteristics such as demographic, socioeconomic and institutional characteristics of households by using a semi-structured interview schedule. Furthermore, different secondary data were used for this study from reports, books, journals articles, working papers, and reports from Karat Zuria district agriculture and Natural Resource office.

3.6. Methods of Data Collection

Household survey, FGDs and KIIs, were employed as methods of data collection. For the household survey, a semi-structured interview schedule was first prepared in English language, and then translated into *Affa Xonso* language to facilitate the interview process. The interview schedule was pre-tested at the local level and employed for gathering data. Focused Group Discussions and KII were employed for gathering qualitative data from the sample respondents. Focused Group Discussions guide and KII checklist were developed for gathering data from the sample respondents.

Structures of the Household Interview: Based on related literature and investigators' knowledge, semi-structured survey questions were constructed to collect data from sampled household heads. The respondents were asked to recall total annual income of the year during the interview. The household interview schedules are comprised of household demographic, socio-economic characteristics, institutional factors, and other issues related to determinants of climate smart improved sorghum varieties adoption and its impact on income.

Six enumerators, all diploma holders, who speak the local language *Affa Xonso* were selected and recruited based on their adequate knowledge about the area, prior exposure to similar work, and well acquainted with the culture and language. The necessary theoretical and practical training was given to enumerators about the methods of data collection and content of the interview schedule for one day by the researcher. Before official implementation, the survey questions were pre-tested on 19(5 % (N=384)) farmers outside the sample *kebeles* as a pilot in the study district. In doing so, ambiguous questions were omitted and replaced by valued questions.

Key Informant Interviews (KIIs): Key Informant Interviews (KIIs) were conducted to gather in-depth and diverse qualitative data on the challenges and opportunities related to the adoption of climate-smart improved sorghum varieties. A total of 11 KIIs were held with key informants at various levels, ranging from community to district levels. The informants were selected based on their knowledge and experience, with community leaders providing guidance in the selection process. Two Development Agents (DAs) were chosen from each sample *kebele,* one male and one female. At the district level, one expert from agricultural extension and one field crop specialist were selected.

Key informants were selected purposively based on experience and expertise in climate-smart improved sorghum production as well as involvement in support provisions to sorghum producing farmers. Climate-smart improved sorghum adoption and its impact on income and other data related to the study subject were collected. Thus, the data were used to enrich information gained from the household survey and FGDs. The KII was used to identify and refine challenges and opportunities of climate-smart improved sorghum production adoption for income improvement in the study area.

Focused Group Discussions (FGDs): Focused group discussions are sources of qualitative data, which were used to support and cross-examine information obtained from the survey respondents about the impact of climate-smart improved sorghum varieties adoption, and was used to triangulate the information generated from the structured interview method and KIIs. The size of FGD participants were decided according to the proposition of (Hennink et al., 2019), who argues a group should consist of 6-8 participants for the advantage of easy management, smooth interaction, rich details and equal opportunity to share insights. Therefore, four FGDs were undertaken in selected *kebeles* consisting of 6-8 discussants per group; they were from non-sample households but aware of the local setting. The discussants were selected purposively by the consultation of informed local elders, and based on gender, education level, and wealth status to have a broader viewpoint from the diverse social segments.

Furthermore, the researcher intentionally included old, middle, and young farmers to get a diverse age spectrum. The participants of the focus groups for four sites were heterogeneous, composed of household heads: youth, old people, religious leaders. The interactive discussion was organized on climate-smart improved sorghum varieties production adoption, marketing, land holding situation, access to extension service and access to market and farming employment (off/non-farming activities); major challenges and opportunity to adopt the improved sorghum technology and obtain income. In all FGDs the researcher was played an active role in organizing, moderating, and controlling the whole discussion processes.

The qualitative data collected from FGD discussants were general information about the impact of climate- smart improved sorghum adoption on smallholder farmers' income in Karat Zuria district and other facts related to the study. Each FGD was conducted by a researcher who served only as a moderator and note taker. All FGDs and KIIs were recorded by a digital voice recorder with the permission of discussants and/or respondents to write out notes about production and adoption of CSISVs, factors affecting their adoption, challenges and opportunities of CSISVs adoption and were translated into English.

3.7. Methods of Data Analysis

Both descriptive and econometric models were used to analyze the empirical data that were collected through various tools. Descriptive statistics such as mean, standard deviation, frequency, and percentage were used to determine the demographic, socio-economic, and institutional characteristics of the rural household. Also, analysis of challenges and opportunities of climate-smart improved sorghum varieties production adoption were identified by narrating in the study area. The descriptive statistics output was presented using tables and graphs; inferential statistics; *T-tests* were used to compare the mean variances of the continuous explanatory variables between climate smart improved sorghum varieties adapters and non-adapters sample households and chi-square (χ^2) tests were employed to compare the association between some qualitative characteristics dummy and/or discrete explanatory variables for improved sorghum varieties adapters and non-adapters sample respondents.

In the econometric part, the research used *probit* and endogenous switching regression models to quantify important empirical results of determinants of climate-smart improved sorghum varieties (CSISVs) adoption in the study area, and analyze the impact of CSISVs adoption on smallholder farmers' income respectively. The quantitative data were analyzed using the Statistical Product and Service Solutions (SPSS) version 25 and STATA version 15 software.

Qualitative data from KII and FGDs were analyzed through thematic analysis. Thematic analysis is a method of analyzing qualitative data. It is usually applied to a set of texts, such as interview transcripts. The researcher closely examines the data to identify common themes topics, ideas and patterns of meaning that come up repeatedly (Braun et al., 2017). There are various approaches to conducting thematic analysis, but the most common form follows a six-step process: familiarization, coding, generating themes, reviewing themes, defining and naming themes, and writing up that the research were employed in the study.

3.7.2. Econometric models specification

3.7.2.1. Binary probit model

The dependent variable is dichotomous taking two values, 1 if the event occurs as adopter and 0 if it doesn't. Estimation of this type of relationship requires the use of dichotomous dependent variables. In this regard, linear probability, straight forward logit and probit model are the possible alternatives. Although linear probability and straight forward logit models are the simplest methods, it is not logically attractive models in that they assume that the conditional probability increases linearly with the value of explanatory variables. Thus, straight forward logit model is not appropriate to test the statistical significance of estimated coefficients (Green, 1991; (Gujarati, 2009). Therefore, the probit regression model was used to identify determinants of CSISVs adoption in this study.

The Probit model is suited to estimate CSISVs' adoption decisions since the response dependent variable is a binary one. The model assumes that farmers' decisions whether to adopt CSISVs or not depend on unobservable utility index (or a latent variable) that is determined by farmer-specific factors such as the explanatory variables indicated in this study. Studies on the adoption of climate-smart agricultural innovations have applied limited dependent variable models such as the probit or logit function. These distributions are very similar to each other and in most cases their applications have given similar results (Maddala, 1986). In this study, the probit model is used to analyze farmers' adoption decision because it is an appropriate econometric model for the binary dependent variable as the error term is assumed to be normally distributed (W. H. Greene, 1994; Gujarati, 2009; Wooldridge, 2009).

The probit model of CSISVs adoption derived from an underlying latent variable model, which is expressed as:

$\mathbf{Yi^*} = \boldsymbol{\beta 0} + \boldsymbol{\beta ijXij} + \mathbf{ei}$, ………………………………………………………………. (1)

where $\mathbf{Yi^*}$ – an underlying index reflecting the difference between the utility of adopting and not adopting CSISVs; $\boldsymbol{\beta 0}$ – the intercept; $\boldsymbol{\beta ij}$ – is a vector of parameters to be estimated; $\mathbf{Xij}$ – are independent variables which explain CSISVs adoption; $\mathbf{ei}$ – the standard normally distributed error term that is independent of $\mathbf{Xj}$ and is symmetrically distributed about zero.

Given the assumptions from the latent variable model, the model for a farmer's adoption of CSISVs is derived as:

$\mathbf{P}\ (\mathbf{Yi^*} = \mathbf{1}|\mathbf{x}) = \mathbf{F}\ (\boldsymbol{\beta 0} + \boldsymbol{\beta ijXij})$, ……………………………………………………. (Eq. 2)

where F – a cumulative distribution function, the function that ensures the likelihood of adopting CSISVs, and it lies strictly between zero and one. Therefore, a farmer adopts CSISVs if $Yi^* > 0$, and otherwise, if $Yi^* \leq 0$. Therefore, the model to estimate the probability of observing a farmer adopting the CSISVs can be explicitly stated as:

$\mathbf{P}\ (\mathbf{Yi^*} = \mathbf{1}|\mathbf{x}) = \mathbf{F}(\boldsymbol{\beta X}) = \int \mathbf{1}\ \sqrt{\mathbf{2\pi}}\ \boldsymbol{\beta X} -\infty\ \mathbf{exp}\ (-\ \mathbf{z}\ \mathbf{2/2})\ \mathbf{dz}$ ………………………….…. (Eq. 3)

where P – the probability that the i^{th} farmer adopted CSISVs and 0 otherwise; X – the K by 1 vector of the independent variables; z – the standard normal variable, i.e.; $Z \sim N(0,\sigma 2)$; β – the K by 1 vector of the coefficients to be estimated; F(βX) – the cumulative distribution function of the standard normal distribution which is the integral of the probability density function.

The parameter estimates were obtained by maximum likelihood estimation (MLE) procedure using STATA-15 econometric software (W. H. Greene, 1998). The summaries of variables that determine farmers' adoption decision are shown in Table 2.

Regression analyses are usually aimed at estimating the marginal effects of an independent variable on the dependent variable, while holding the effects of other independent variables constant. But in the probit model, parameter estimates cannot be interpreted as marginal effects. Therefore, the marginal effect of an independent variable is obtained by calculating the derivative of the outcome probability with respect to an independent variable. The marginal effect associated with a continuous explanatory variable X_k on the probability P (Yi =1 | X), holding the other variables constant, can be derived as follows:

$\boldsymbol{\partial Pi / \partial \chi ik} = \boldsymbol{\phi}\ (\mathbf{Xi}\ \boldsymbol{'\beta})\ \boldsymbol{\beta k}$ ……….……………………………………………..……..... (Eq. 4)

Where $\boldsymbol{\phi}$ =Cumulative distribution function for the standard normal random variable; $\boldsymbol{\beta k}$ =Coefficient of k^{th} explanatory variable. (Xi´β) = product of the k by 1 vector of the coefficients to be estimated, and transpose of a row vector of values of k repressors for the i^{th} sorghum farmer; ∂Pi/∂Xik = partial derivative of probability of adoption of pesticide with respect to specified explanatory variable. Scholars showed detailed mathematical derivation of the normal probability distribution of the error term of the probit model (W. Greene, 2008; Stock & Watson, 2012).

3.7.2.2. Test of multicollinearity

Before taking the selected variables into the probit model, it is compulsoryto check for the existence of multicollinearity among the continuous variables and verify the degree of association among discrete variables. The reason for this is that the existence of multi-collinearity affects the parameter estimates. The Variance Inflation Factor (VIF) was used to test for the existence of multicollinearity between continuous explanatory variables. It shows how the variance of an estimator is inflated by the presence of Multicollinearity (Gujarati, 2009). If R^2 of the multiple correlation co-efficient that results when the explanatory variable, Xi, is regressed against all the other explanatory variables, VIF is computed as follows:

VIF (Xi) $= (1 - R^2)^{-1}$

As R^2 Approaches 1, the VIF approaches infinity. That is, as the existence of collinearity increases, the variance of the estimator increases, and in the limit, it can become infinite. If there is no collinearity between regressors, the value VIF was 1. As a rule of Thumb, Values of VIF greater than 10 is often taken as a signal for the existence of a multicollinearity problem in the model (Gujarati, 1995).

Similarly, there may also be interaction between two qualitative variables, which can lead to the problem of multi-collinearity or association. To detect this problem, coefficients of contingency were computed from the survey data. Contingency coefficient is a chi-square (x^2) based measure of association. A value of 0.75 or more indicates a stronger relationship (Healy, 1984). The contingency coefficients were computed as follows:

$$C = \sqrt{\frac{x^2}{1 + x^2}} \tag{5}$$

Where C = coefficient of contingency, x^2= chi-square test and N=Total sample size

3.7.3.1. Specifications of Endogenous Switching Regression Model

Different econometric models were used for estimating the impact of CSISVs adoption on the income of households. For instance, propensity score matching (PSM), which tries to compare the difference between the outcome variable of adopters and non-adopters with similar inherent characteristics, is used. However, it cannot correct unobservable bias because the propensity score matching only controls for observed variables (Ahmed & Mesfin, 2017). The basic problem (for both experimental and non-experimental studies) is that everyone has two potential outcomes: the observed (actual) and unobserved (counterfactual), i.e., each individual faces two regimes. In randomized experiments, the average impact of the treatment can be obtained by computing the differences of mean values of outcome variables for treatment and control groups. However, impact analysis in non-experimental studies is still difficult since the causal effect obtained by comparing treatment groups with non-experimental control groups could be biased due to self-selection (non-random assignment) of the treatment (Shiferaw et al., 2014).

Since unobservable characteristics are unavoidable in the CSISVs' adoption decisions and income, matching helps control only for observable differences, not unobservable differences (Mojo et al., 2017). Accurate impact measurement requires controlling for both observable and unobservable characteristics through random assignment of individuals into treatments (Adego et al., 2019). In the absence of random assignments, selection bias may persist as observed and unobserved characteristics of individuals may affect the likelihood of receiving treatments as well as outcome indicators (Wossen et al., 2017). To overcome these biases, the endogenous switching regression (ESR) is the best model since unobservable factors simultaneously affect the CSISVs adoption decision and the income of farmers (Ma & Abdulai, 2016).

To estimate the decision to adopt CSISVs and their impact on income, two stage ESR, which accounts for both the observed and an observed heterogeneity effect was used. In the first stage of ESR, farmers' decision to adopt improved sorghum varieties is modeled and estimated using a probit model. Following a random utility maximization theory, which coincides with empirical literatures (Jaleta et al., 2018; Shiferaw et al., 2014; Tilaye et al., 2023) farmers adopt CSISVs if the perceived benefit from adoption of CSISVs is greater than its counterpart. Consider the k^{th} farm households' decision to adopt or not. Let U_0 represent the expected benefits from non-adoption of CSISVs, and let U_k represent the benefit generated from adoption of CSISVs. Assume that the latent variable K_i^* (U_{k-U0}) represents the utility (the benefit from adoption), the farmer adopt improved technology if $K^*_i = U_k - U_0 > 0$. The net benefit (K^*_i) cannot be observed and is a latent variable, which is a function of observed characteristics (zi) and the error term (εi):

$$K_i^* = z_i\alpha + \varepsilon_i \qquad \text{With } K_i = \begin{cases} 1 \text{ if } K_i^* > 0 \\ 0 \text{ otherwise} \end{cases} \tag{1}$$

Were Ki being a binary indicator variable (latent variable) that takes a value 1 if a farmer is an adopter of CSISVs and zero otherwise and α is a vector of parameters to be estimated in this study; adoption is defined as farmers who used any of the CSISVs, either newly purchased from primary cooperatives or reuse of CSISVs from previous year production. In the second stage, conditional on the selection equation, the outcome variables can be written as the switching regime following (Lokshin & Sajaia, 2004) as follows:

$$\text{Regime 1}: \; y_{1i} = \beta_1 X1i + \eta_{1i}, \; if \; K = 1 \tag{2A}$$

$$\text{Regime 2}: \; y_{2i} = \beta_2 X2i + \eta_{2i}, \; if \; K = 0 \tag{2B}$$

Where y_{1i} and y_{2i} are outcome variables for adopters and non-adopters of CSISVs, X_i is Vector of observed socioeconomics and farm-level characteristics; β is a vector of parameters to be estimated. For the ESR model to be identified, it is important to apply exclusion restrictions as a selection instrument that directly determines the selection equation or the decision to adopt, but not the outcome equation. In this study, access to information was used as an instrumental variable for the impact of CSISVs adoption on the outcome variables of interest for this study. Adoption characteristics of smallholder farmers can be determined by the availability of different information sources and those information sources are from the market and used as a tool for facilitating dissemination process of agricultural technologies. Similarly, the area of farm land size influences the area of production of improved varieties and determines farmers to adopt improved technologies (Jaleta et al., 2018; Shiferaw et al., 2014).

A simple falsification test following (Jaleta et al., 2018) was used to test the validity of the instruments, which significantly determines the selection equations or adoption decisions but not the outcome variable among farm households that do not adopt CSISVs, as shown in (*Appendix table 2*). Which would be shown as in the Appendix part of the supporting information for total annual income, which clearly illustrate that, access to information known by farmers were used as valid selection instruments for ***t*** outcome variable used for this study: they are jointly statistically significant in the selection equation (*χ2*; *p*) but not for the outcome equation for the farm households that do not adopt CSISVs. (F-stat, p-value) for the total annual income outcome variable, which verifies the validity of the instruments used for this study. The stochastic terms in *Eqs (1)* and *(2)* are assumed to have a tri-variate normal distribution with mean zero and non-singular covariance matrix specified as:

$$\operatorname{cov}(\varepsilon, \eta_1, \eta_2) = \begin{bmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon 1} & \sigma_{\varepsilon 2} \\ \sigma_{1\varepsilon} & \sigma_1^2 & . \\ \sigma_{2\varepsilon} & . & \sigma_2^2 \end{bmatrix}, \tag{3}$$

Where; $\sigma_\varepsilon^2 = \operatorname{var}(\varepsilon), \sigma_1^2 = \operatorname{var}(\eta_1), \sigma_2^2 = \operatorname{var}(\eta_2), \sigma_{\varepsilon 1} = \operatorname{cov}(\varepsilon, \eta_1), \text{and } \sigma_{\varepsilon 2} = \operatorname{cov}(\varepsilon, \eta).$.
It is plausible that the variance of δ^2_ε is assumed to be equal to 1 because the ***β*** coefficients in the selection model are estimable up to a scale factor. The covariance between η1 and η2 is not defined since y_1 and y_2 are not observed simultaneously (Lokshin & Sajaia, 2004). The expected values of η_1 and η_2 conditional on the sample selection are non-zero because the error term in the selection *Eq (1)* is correlated with the error terms in *Eqs (2A)* and *(2B)* respectively. The expected value of the error terms in *Eqs (2A*) and *(2B)* can be expressed as follows:

$$E(\eta_{i1} | K_i = 1) = \sigma_{1\varepsilon} \frac{\phi(z_i \alpha)}{\Phi(z_i \alpha)} \qquad = \sigma_{1\varepsilon} \lambda_{i1} \quad \text{And,}$$

$$E(\eta_{i2}|K_i = 0) = -\sigma_{2\varepsilon}\frac{\phi(z_i\alpha)}{1-\Phi(z_i\alpha)} \qquad = \sigma_{2\varepsilon}\lambda_{i2}$$

Where ϕ (.) is the standard normal probability density function, ϕ(.) is the standard normal cumulative density function, $\lambda_{i1} = \frac{\phi(z_i\alpha)}{\Phi(z_i\alpha)}$ and $\lambda_{i2} = \frac{\phi(z_i\alpha)}{1-\Phi(z_i\alpha)}$. Where λ_{i1} and λ_{i2} are the Inverse Mills Ratios (IMR) estimated from the selection equation and then were incorporated in *Eqs (2A)* and *(2B)* to correct for selection bias in a two-step estimation procedure (ESR) use *conditional expectations, treatment and heterogeneity effects*. The above framework can be used to estimate the average treatment effect on the treated (ATT) and the average treatment effect on untreated (ATU) by comparing the anticipated values of the outcomes for adopters and non-adopters in actual and counterfactual scenarios following (Di Falco et al., 2011) defined as follows:

Adopters with adoption of ITVs (observed scenario)

$$E(y_{i1}|K = 1; x) = x_{i1}\beta_1 + \sigma_{1\varepsilon}\lambda_{i1} \tag{4A}$$

Non-adopters without adoption (observed scenario)

$$E(y_{i2}|K = 0; x) = x_{i2}\beta_2 + \sigma_{2\varepsilon}\lambda_{i2} \tag{4B}$$

Non-adopters had they decided to adopt (counterfactual scenario)

$$E(y_{i2}|K = 1; x) = x_{i1}\beta_2 + \sigma_{2\varepsilon}\lambda_{i1} \tag{4C}$$

Adopters had they decided not to adopt (counterfactual scenario)

$$E(y_{i1}|K = 0; x) = x_{i2}\beta_1 + \sigma_{1\varepsilon}\lambda_{i2} \tag{4D}$$

The average treatment effect on the treated (ATT) is estimated as the difference between (4a) and (4c), which is the impact of adoption of ITVs on the outcome of interest for adopters.

$$ATT = E(y_{i1}|K = 1, x) - E(y_{i2}|K = 1, x) = x_{i1}(\beta_1 - \beta_2) + \lambda_{1i}(\sigma_{1\varepsilon} - \sigma_{2\varepsilon}) \tag{5}$$

Similarly, the expected change in non-adopter’s food security, the effect of the treatment on the untreated (ATU) is computed as the difference between (4d) and (4b)

$$ATU = E(y_{i1}|K=0,x) - E(y_{i2}|K=0,x) = x_{i2}(\beta_1 - \beta_2) + \lambda_{2i}(\sigma_{1\varepsilon} - \sigma_{2\varepsilon}) \quad (6)$$

The heterogeneity effect is the difference *between Eqs (4A)–(4D)* Following (Carter & Milon, 2005), the base heterogeneity effect (BH1) for farmers that decided to adopt CSISVs is estimated as the difference of *Eqs (4A)* and *(4D),*

$$\begin{aligned} BH_1 &= E(y1i|Ai=1) - E(y1i|Ai=0) \\ &= (X1i - X2i)\beta_{1i} + \sigma 1\eta(\lambda 1i - \lambda 2i). \end{aligned} \quad (7)$$

In the same manner, the base heterogeneity (BH_2) for farmers that decided not to adopt the

CSISVs is the difference between *Eqs (4C)* and *(4B)*, BH2

$$\begin{aligned} &BH_2 = E(y2i|A_i=1) - E(y2i|Ai=0) \\ &= (X1_i - X_2i)\beta_{2i} + \sigma 2\eta(\lambda 1i - \lambda 2i). \end{aligned} \quad (8)$$

Lastly, the transitional heterogeneity (TH) is the difference between *Eqs (5)* and *(6)*.

The validity of the ESR requires an exclusion restriction that is correlated with CSISVs adoption status, while it does not affect the income of adopters (Mojo et al., 2017; Wossen et al., 2017). This requires at least one additional variable as an instrument (IV) in *Equation (2)* that correlates with the treatment status but not with outcome indicators. Thus, the information set of variables as selection instruments (selection variables) can be used. The researchers argue that access to variety of information from research centers and access to non/off farm activities are critically important in determining the adoption of CSISVs. So, access to variety information from the research center was considered as IV.

3.8. Definition of Variables and Working Hypotheses

3.8.1. Dependent and treatment variables

Adoption of climate smart improved sorghum Varieties: as (Feder et al., 1985), and Doss (2006) stated, adopters of climate-smart agricultural technologies are the ones who adopt a component or more of a technology and continue using it, whereas non-adopters are those who never tried it. It is a dummy variable. Here the adopting households are the ones who have tried the climate smart improved sorghum varieties and kept on using them in the last two years (Beyadegie, 2019; Degefu, 2016) and they are coded as 1. The rest of the households are considered as non-adopters, and they were coded as 0.

For ESRM model: Adoption status of climate smart improved sorghum varieties, representing households that have been producing climate smart improved sorghum varieties continuously for the last two years.

3.8.2. Outcome variable

Total income is a continuous variable in Birr that can be monitored. It refers to the household's total annual income, which is computed by adding money from crop sales, animal sales, animal products sales, and income from on-farm and off-farm activities.

3.8.3. Explanatory variables

The following explanatory variables include demographic (age, sex, education level, farming experience, and family size); socioeconomic (total farmland size, total livestock holding, access to non/off-farm activities, and membership in farmers cooperatives); and institutional (distance to the nearest market, access to credit, frequency of extension contact, access to irrigation, and access to variety information from research center) factors are hypothesized to determine the adoption of climate smart improved sorghum varieties in the study area.

1. Age of the HH: represents a continuous variable that refers to the HH's age in years completed or obtained at the time of the survey. It is hypothesized to have a positive impact on the adoption of climate-smart improved sorghum varieties (CSISVs) because older farmers are expected to make adoption decisions ahead of younger farmers due to their collective wealth of knowledge in crop production management. Furthermore, older households have more access to land and other assets than younger households. They have also worked in social and physical settings, including weather forecasting and risk mitigation (Tadesse & Ahmed, 2023). However, as the age of the HH approaches the point where the farmer gets older and unable to contribute to farming activities, decisions on adopting climate smart improved varieties may take a long time and slow down. In comparison to the older and weaker HHs, younger and more energetic HHs are required to cultivate larger farms (Asrat et al., 2022b; Gashure & Wana, 2023b). It also affects a household's ability to seek and receive off-farm income, an area where younger households typically excel. As a result, the predicted impact of households on the adoption of CSISVs and income could vary, being either positive or negative, depending on the household's age.

2. Sex of the HH: Male or female biological characteristics are represented by this symbol. It's a dummy variable that represents HH's gender. If the household head is male, the score is 1; otherwise, if the household head is female, the score is 0. Being male household head had an impact on the adoption of new and improved technologies (Abdul-Rahaman, 2023; Tadesse & Ahmed, 2023; Tilahun et al., 2023a). It was discovered that there was a correlation between male HHs and the adoption of new climate-smart technologies. According to these studies, male HHs are more likely than their female counterparts to adopt CSISVs. As a result, it was hypothesized that the HH's sex was positively associated with CSISVs adoption, increasing the likelihood of an income increase.

3. Education level of HH: This variable represents the total number of years an individual has had formal schooling. Almost all agricultural studies have included education as an essential explanatory factor that influences households' decisions to participate in and practice innovations. Education provides people with the required knowledge about how to best utilize their limited resources to obtain the best results and is thus linked to adoption. Farmers' capacities to perceive, evaluate, and adjust to novel events and technologies in a risky environment were anticipated to benefit from households with higher educational levels. By raising the farmer's awareness of how to obtain, process, and apply information linked to the climate smart technology adoption, education is measured as a continuous variable in this study and was projected to have a favorable impact on adoption of CSA technologies (Abdul-Rahaman, 2023; Geda et al., 2024; Tadesse & Ahmed, 2023). Farmers' adoption of climate smart agriculture technology, and thus household income, was thought to be more likely if they had higher education.

4. Farming experience: It is a continuous variable. It suggests that compared to farmers with less farming experience, farmers with greater agricultural competence are more likely to adopt climate-smart enhanced sorghum cultivars. For instance, (Geda et al., 2024) reported a positive relationship between farming experience with adoption. Furthermore, it is believed that the HH's personal experience with adoption is positively correlated with their level of agricultural experience. Therefore, it makes sense to assume that more farming experience would have a positive impact on CSISVs' adoption and raise the likelihood of a rise in total annual income.

5. Family size of the household: It is a continuous variable that refers to the total number of individual members living in the same household; this includes the HH, spouse, children, relatives, housemaids, and employed workers who all live under one roof and contribute to the HH measured in adult equivalents (AE). Larger households are typically associated with more work, allowing farmers to complete a variety of climat-smart agricultural practices. Because of labor shortages at peak seasons, farm households with a bigger pool of labor are expected to adopt new varieties and employ them more intensively. Adoption is positively correlated with household size. According to (Erekalo & Yadda, 2023; Tadesse & Ahmed, 2023), there is a strong link between family labor supply and adoption, unlike the finding of (Geda et al., 2024). As a result, it is expected that this variable would have a positive impact on adoption of CSISVs, increasing the probability of getting more income.

6. Total farmland size of HH: It is a continuous variable that refers to the total size of farmland owned by the household in a hectare (whether farmed or rented out). Farmers with greater land holdings can pay the costs of new agricultural technologies and are willing to take the risk of crop failure. For example, studies conducted by (Abdul-Rahaman, 2023; Geda et al., 2024; Kifle, et al., 2022; Tadesse & Ahmed, 2023; Tilahun et al., 2023a) examined determinants of CSA practices adoption and found that farm size had a positive and significant impact on adoption. This indicates that farmers with greater farm sizes are more likely to adopt CSISVs, whereas farmers with smaller farms are less likely to do so. As a result, it is hypothesized that this variable would have a positive impact on CSISVs adoption, resulting in increased income.

7. Total livestock holdings of HH: It is a continuous variable that measures HH's livestock holding in TLU (Storck et al., 1991) as shown in the (*Appendix Table 1*). Livestock ownership is significant not only as a source of income but also as a savings alternative or proxy for physical assets and risk management mechanisms in the household. Livestock serves as a source of food, buffer stock, and draught power for crop cultivation in Ethiopian agriculture, manure, and monetary income from the sale of milk, butter, eggs, skins and hides, and live animals, among other things. The adoption of more sustainable CSA technologies for crop production is increasing, as is the ownership of livestock (Sedebo, Li, Etea, et al., 2021). As a result, it is hypothesized that this variable would have a positive impact on CSISVs adoption, increasing the probability of increased income.

8. Access to non/off-farm activities: is a dummy variable that returns "1" if any family member earns non/off-farm income (non-farm earnings, salaries, pensions, transfers, remittances, and interest; may include petty trade, traditional mining, smith, tailor, handcraft, renting a home, and so on), and "0" otherwise. It is expected to have a positive impact on adoption because participating in non-farm activities might help overcome financial issues (Tadesse & Ahmed, 2023). Off-farm activities, on the other hand, may not have a positive influence in all circumstances of adopting CSA technologies. Where the production crop is labor-intensive, it hurts adoption by diverting labor away from cultivation (Asrat et al., 2022b). As a result, it is hypothesized that non/off-farm activities would have a positive or negative impact on improved sorghum varieties adoption, as well as increase or lessen the probability of income.

9. Membership in farmers' cooperatives: It's a dummy variable that states "1" if the HH is a member and "0" if he or she is not. Farmers' cooperatives are built on the common interests of their members and are supposed to supply production input at a reasonable price and in a better market for members to increase their bargaining power (Abdul-Rahaman, 2023; Tadesse & Ahmed, 2023). Cooperative membership facilitates households' access to services provided by the cooperative and serves as a form of social participation. As a result, this variable is predicted to have a favorable impact on HH engagement in CSISVs adoption decisions that would increase the likelihood of farmers' income.

10. Distance to the nearest market: This is a continuous variable with kilometers as the unit of measurement. It's the distance between the household and the nearest market. Access to the market and other public infrastructure may open more revenue alternatives by allowing for diversified methods such as non-farm and/or off-farm work, easy access to input, and transportation. In the estimation of learning linkages, as stated by (Kifle, et al., 2022), it is critical to keep track of all potential sources of information (adoption of improved sorghum varieties). Therefore, it's critical to consider the household's proximity to a town with greater infrastructure, information access, and market integration. The closer farm households are to the market, the more market information they acquire and, as a result, higher prices for their products (owing to lower marketing transaction costs) (Abdul-Rahaman, 2023). Proximity to market centers provides households with non-farm employment opportunities, allowing them to earn more money (Asrat et al., 2022b; Gashure & Wana, 2023b; Geda et al., 2024). Households that are closer to the market center have a higher probability of accessing non-farm jobs. As a result, this variable is assumed to have a negative or positive association with CSISVs adoption decision of HH, which also determines the income of the households.

11. Access to credit service: is a dummy variable that takes the value "1" if the household has credit and has used it previously and "0" otherwise. Credit is extremely beneficial for purchasing inputs such as improved seeds and other necessary inputs. Farmers who do not have access to funds or credit may find it challenging to obtain and purchase modern technologies (Geda et al., 2024; Kifle, et al., 2022; Tadesse & Ahmed, 2023). As a result, it is hypothesized that access to finance would have a positive impact on CSISVs' adoption decisions, increasing the likelihood of increased income.

12. Frequency of extension contact: This refers to the number of times the household contacted extension agents during the year. Exchange visits, participation in demonstrations and field days, and any other consultation and advice during the year are all examples of this. Extension professionals provide guidance and information to rural residents on how to adopt CSA technologies, which increases farmers' yield and productivity (Asrat et al., 2022b; Erekalo & Yadda, 2023; Kifle, et al., 2022; Tadesse & Ahmed, 2023). As a result, it is hypothesized that extension service would be positively correlated with farmers' decision to adopt improved sorghum varieties, increasing the chances of income improvement.

13. Access to irrigation: is a dummy variable that takes a value of "1" if the household has irrigation access and "0" if it does not. Climate-smart agricultural practices are more likely to be adopted by rural households who participate in irrigation. Irrigation access allows households to plant a variety of income and domestic crops, which improves sorghum production (Kifle, et al., 2022; Tadesse & Ahmed, 2023). As a result, it is hypothesized that having access to irrigation would enhance CSISVs adoption and, as a result, can increase income.

14. Access to varietal information from research center: This variable is a dummy variable that takes the value "1" if the HH has information access about the sorghum varietal traits issue, and "0" otherwise. This can be stated as follows: varietal information, such as improved variety production and variety parameters including productivity, earliness, disease and pest resistance, lodging behavior, and other variety traits information, allows farmers to gain from the production of improved technologies. Farm households with higher varietal information access had a much higher rate of improved agricultural technology adoption (Kamara *et al*., 2022; Tiruneh & Wassie, 2020). If the HH does not have any information on the sorghum varieties, they may be discouraged from producing because they do not know whether production would result in a high yielding or a loss. One of the most critical factors in increasing CSA technologies adoption and improving household income has been identified as varietal information access from research center. It is expected that having access to information would be positively linked to the adoption of CSISVs as a result.

Table 2 Summary of description, measurement, and hypothesis of variables

No	Variables	Description of variables	Measurement of variables	Hypothesized signs
A.	**Dependent variable**			
1	Adoption of CSISVs	"1" if Adopter and "0" if Non-adopter	Dummy	(+)
B.	**Outcome variable**			
1	Total income of HH	Total annual income level of HH in ETB	Continues	(+)
C.	**Explanatory variables**			
1	Age of the HH	Age of the HH in years	Continuous	(+/-)
2	Sex of the HH	It is HH sex takes the value "1" if male and "0" otherwise	Dummy	(+)
3	The educational level of HH	Total number of years of education of the HH in school	Continuous	(+)
4	Farm experience	It measures the sorghum farming experience in number of years	Continuous	(+)
5	Family size of household	Total number of household members; measured in (AE)	Continuous	(+)
6	Total farmland size	The total size of farmland owned by the HH in ha	Continuous	(+)
7	Total livestock holdings of HH	Total livestock holding owned by HH in (TLU)	Continuous	(+)
8	Access to non/off-farm activities	"1" if any member of the family has access and "0" otherwise	Dummy	(+/-)
9	Membership in farmers' cooperatives	"1" if the HH is a member and "0" otherwise	Dummy	(+)
10	Distance to the nearest market	It is the distance from HH's residence to the nearest market in kilometers	Continuous	(-)
11	Access to credit service	"1" if the HH has access and "0" otherwise	Dummy	(+)
12	Frequency of extension contact	The no of interactions the HH had with extension agents during the year.	Continuous	(+)
13	Access to irrigation	"1" if the HH has access and "0" otherwise.	Dummy	(+)
14	Access to information from research center	"1" if the HH has access and "0" otherwise	Dummy	(+)

Source: Own definition based on extensive review, 2025.

4. RESULT AND DISCUSSIONS

This chapter is dedicated to a discussion of the survey results as well as secondary data for both qualitative and quantitative analysis. As a result, it covers a descriptive analysis of farm household characteristics, factors influencing climate-smart improved sorghum varieties adoption, and its impact on smallholder farmers' total annual income. Finally, the chapter discusses the challenges and opportunities of CSISVs production in the study area.

4.1. Descriptive Analysis of Sample Household Characteristics

4.1.1. Demographic, socioeconomic, and institutional characteristics of households

4.1.2. T-test of sample households (*for continuous variables*)

The descriptive statistics for the variables of the sample households examined in the study are offered in Table 3. It demonstrates that the t-value was computed for all continuous variables and was found statistically significant for Age, education level, family size, farmland size, TLU, and market distance at a 1% significance level, and also farming experience at a 10% significance level. This suggests that there was a significant difference in all these factors between adopters and non-adopters.

Table 3. T-test of sample households (*for continuous variables*)

Continues variables	Non-Adopters (N=200)		Adoption (N=184)		Total Households (N=384)		T-Value
	Mean	SD	Mean	SD	Mean	SD	
AGE	48.5	11.5893	45.5272	9.6620	47.0755	10.7982	2.7175***
EDUL	2.24	0.9417	2.8207	0.9667	2.5182	0.9959	-5.9592***
FRMEXP	11.285	8.4135	12.7446	8.5004	11.9843	8.4757	-1.6899*
FAMSAE	4.48	2.0102	5.2446	2.5543	4.8464	2.3157	-3.2728***
FRMLSIZ	2.855	2.3028	4.1902	2.7314	3.4948	2.6012	-5.1925***
TLU	4.9701	3.8671	6.9457	5.0196	5.9167	4.5591	-4.3397***
MARDIS	6.18	3.5013	4.4538	3.2826	5.3528	3.5019	4.9727***
FEXNCOT	2.925	1.6101	3.1304	1.5415	3.0234	1.5789	-1.2748

Source: Own survey result (2025)

Note: *** ($P<0.01$), *($p<0.1$) denote significant at 1% and 10% probability level respectively

Age of the HH: The age of the HH was one of the hypothesized variables that can influence the adoption of climate-smart improved sorghum varieties. In terms of age, the average age of the sample respondents was 47.0755 years. The average age of adopters and non-adopters was 45.53 and 48.5 years old, respectively. The t-test analysis showed that had a significant mean difference between adopters' and non-adopters' categories at a 1% level of significance (*Table 3*). The descriptive analysis of the adoption of CSISVs showed a significant difference in HHs' ages between adopters and non-adopters. Adopters had younger than non-adopters, according to the findings.

Education level of HH: The respondents' average education level was 2.5182 years of schooling. Adopters and non-adopters had average education levels of 2.8207 and 2.24, respectively. At a 1% level of significance, the t-test analysis revealed that education level had a significant mean difference between adopters and non-adopters (*Table 3*). In CSISVs adoption, the descriptive analysis revealed a significant difference in HH education between adopters and non-adopters. Non-adopters had a lower level of education than adopters, according to the findings.

Farm experience of HH: With a standard deviation of 8.4757, the average farm experience of sample households was 11.9843. Adopter households had a mean farm experience of 12.7446 with a standard deviation of 8.5004, whereas non-adopter households had a mean farm experience of 11.285 with a standard deviation of 8.4135. At a 10% probability level, the t-test result for the differences in farm experience between the two groups was significant t = -1.6899 (*Table 3*). As it can be observed that, the average farm experience of the non-adopter households appears lower than the adopters.

Family size of HH in AE: The mean family size of sample respondents was 4.8464 ha, while the average land size of the adopter and non-adopter farmers was 5.2446 and 4.48 ha, respectively. At a 1% significance level, the independent sample t-test revealed a statistically negligible difference in family size between adopter and non-adopter sample respondents.

Farmland size of HH: The average farmland size of sample respondents was 3.4948 ha, while the average land size of the adopter and non-adopter farmers was 4.1902 and 2.855 ha, respectively. At a 1% significance level, the independent sample t-test revealed a statistically negligible difference in farmland size between adopter and non-adopter sample respondents.

Total livestock holding of HH in TLU: With a standard deviation of 4.5591, the average total livestock holding of sample households was 5.9167. Adopter households had a mean livestock holding of 6.9457 with a standard deviation of 5.0196, whereas non-adopter households had a mean livestock holding of 4.9701 with a standard deviation of 3.8671. At a 1% probability level, the t-test result for the differences in livestock holding between the two groups was significant t = -4.3397 (*Table 3*). As it can be observed that, the average livestock holding of the non-adopter households appears lower than the adopters.

Distance to the nearest market of HH: As the farm households' characteristics in the study area was related to CSISVs adoption, this variable was analyzed across the area. This variable serves as a proxy for transaction costs. According to the descriptive analysis, the mean walking market distance for the total sample homes in the study area was 5.3528 km, and the non-adopters mean walking market distance was 6.18 km, while the adopters was 4.4538 km. At a 1% significance level, the descriptive analysis revealed a significant difference in the distance of the market from household residence between adopters and non-adopters in CSISVs adoption. The non-adopter category has a greater market distance than the adopter category.

4.1.3. Chi-square test of sample households (*for dummy categorical variables*)

The findings revealed that the chi-square test was figured for the categorical and dummy variables, and it was found that there was a statistical association between adoption decisions and significance for the access to non/off farm income, membership of farmers cooperatives, access to credit, access to information; sex of the household head and access to irrigation at a 1%, and 5% significant level in these variables (*Table 4*).

Sex of HH: Between the CSISVs adopters, the technology was adopted by 51.58% of sample respondents who are male-headed HH, whereas the technology was adopted by 48.44% of farmers who have female-headed HH. Being male-headed HH increases the likelihood of being the adopter of CSISVs. The chi^2-test indicated that, there was a statistically significant difference in adopting CSISVs between credit users and non-credit users at a 5 % probability level.

Table 4. Chi^2-test of sample households (*for dummy categorical variables*)

Dummy categorical variables		Non-Adopters (N=200)	Adopters (N=184)	Total (N=384)	χ 2 -Value
		f (%)	*f (%)*	*f (%)*	
SEX	Female	107 (53.5)	79(42.93)	186(48.44)	4.2831**
	Male	93 (46.5)	105(57.07)	198(51.58)	
ANOFI	No	113 (56.5)	75 (40.76)	188(48.96)	9.5001***
	Yes	87 (43.5)	109(59.24)	196(51.04)	
MFCoop	No	80 (40)	47 (25.54)	127(33.07)	9.0484***
	Yes	120 (60)	137(74.46)	257(66.93)	
ACCRDT	No	96 (48)	62 (33.70)	158(41.15)	8.0975***
	Yes	104 (52)	122(66.30)	226(58.85)	
ACCMI	No	112 (56)	67 (36.41)	179(46.61)	14.7743***
	Yes	88 (44)	117(63.59)	205(53.39)	
ACCIRR	No	162 (81)	132 (71.74)	294(76.56)	4.5803**
	Yes	38 (19)	52 (28.26)	90(23.44)	

Source: Own survey result (2025)

Note: *** (P<0.01), *(p<0.5) denote significant at 1% and 5% probability level respectively

Access to non/off farm income: Among the climate smart improved sorghum varieties adopters, the technology was adopted by 51.04% of sample respondents who have access to non/off farm income, whereas the technology was adopted by 48.96% of farmers who have no access to credit. Having access to credit increases the likelihood of being the adopter of CSISVs. The chi^2-test indicated that, there was a statistically significant difference of adopting CSISVs between having non/off farm income access and not having non/off farm income access at a 1 % probability level.

Membership in farmers' cooperatives: Being a cooperative group member increases the probability of being adopter 66.93%. On the other hand, the majority of non-cooperative group 33.07% did not join the adopters group. At a 1% probability level, there is a statistically significant difference in the adoption of CSISVs between membership in cooperative organizations and their counterparts. As a result, almost 74.46% adopters of improved sorghum varieties were members of farmers' cooperatives, which was much greater than the non-adopters.

Access to credit Service: Among the CSISVs adopters the technology was adopted by 58.85% of sample respondents who have access to credit, whereas the technology was adopted by 41.15% of farmers who have no access to credit. Having access to credit increases the likelihood of being the adopter of CSISVs. The chi^2-test indicated that, there was a statistically significant difference of adopting CSISVs between credit users and non-credit users at a 1 % probability level.

Access to market information: Market information access on input and output pricing was examined between adopter and non-adopter sample households in the adoption of CSISVs. In all, 46.61 % of households lack information on input and output pricing, compared to 53.39 % of sample households accessing market information. At a 1% level of significance, the chi-square value suggests that, there was a significant difference in the adoption of CSISVs between having market information accesses and non-accesses on input and output pricing of CSISVs.

Access to irrigation: Majority of sample respondents 76.56% have no access to irrigation. There were considerable differences in terms of access to irrigation by adopters and non-adopters of improved sorghum in the study area. Among adopters, majority 71.74% had no access to irrigation. While low proportion 28.26% has access to irrigation. There was statistically significant difference between adopters and non-adopters which was at 5% probability level in terms of access to irrigation.

4.1.4. Sample households' THI and lnTHI description

Table 5 shows, the descriptive statistics of sample households based on their THI and lnTHI scores. Households were asked about agricultural products and by-products mainly produced for sale and or not for sale, as well as farm and non-farm wage labor, and so on, to analyze the levels of total household annual income between the two groups. As a result, total income is the sum of all agricultural and non-agricultural incomes.

Table 5. T-test of sample households (*for Outcome variable*)

Continues variables	Non-Adopters (N=200)		Adoption (N=184)		Total Households (N=384)		T-Value
	Mean	SD	Mean	SD	Mean	SD	
THI	23129	14852.32	60144.57	38308.62	40865.62	34039.05	-12.6700***
lnTHI	9.8845	0.5808	10.8158	0.6372	10.3307	0.7657	-14.9832***

Source: Own survey result (2025)

Note: *** (P<0.01) denote significant at 1% probability level

The average annual household income of the sampled respondents was 40,865.62 ETB, with a standard deviation of 34,039.05. Adopters and non-adopters households had total average incomes of 60,144.57 ETB and 23,129 ETB, respectively, with standard deviations of 38,308.62 and 14,852.32. At a 1% probability level, the statistical test of the mean difference in incomes between adopter and non-adopter groups reveals a statistically significant difference. The sample households' overall lnTHI was 10,337, with a standard deviation of 0.7657. The findings showed that the adopting families received a 10.8158 score with a standard deviation of 0.6372. Non-adopter households, on the other hand, had a mean overall lnTHI score of 9.8845 with a 0.5808 standard deviation. At a 1% probability level, the mean difference between the two groups was statistically significant, according to the statistical T-test result (*Table 5*).

4.2. Econometric Results

4.2.1. Factors determining farmers' adoption decision of *CSISVs*

A detailed discussion of the main characteristics of sample households and their relationship with the adoption of improved sorghum varieties were presented in the preceding section. However, examining the relationships and associations between those factors is insufficient to draw any conclusions. As a result, the results and discussions from an econometric model analysis presented that show how numerically the independent variables influenced each other in the course of their interactions with the dependent variable. In order to determine the impact of several explanatory variables on the adoption of climate-smart improved sorghum varieties, the probit model was employed.

Before running the model analyses normality test of the data were analyzed by employing the Shapiro-Wilk test shown in (*Appendix Table3*) and also, Variance Inflation Factor (VIF) for continuous/discrete explanatory variables and Contingency Coefficients (COC) for dummy categorical explanatory variables were also used to check for the presence of serious multicollinearity among independent variables for all continuous and discrete variables. The VIF values in (*Appendix Table 5*) reveal that none of the continuous explanatory variables have a major multicolinearity problem, and the contingency coefficient values were similarly minimal, as shown in (*Appendix Table 6*). Two multicollinearity problem tests were included in the respective models based on the value of this. The respective models contained the hypothesized continuous/discrete and dummy variables.

Under this section, determining factors affecting climate improved sorghum varieties of adopter farmers which were hypothesized was analyzed. However, before analyzing the data, the contingency coefficient and variance inflation factor were used to assess the multi-collinearity effect of the dummy and continuous independent variables. Gujarati (2003) discovered that a larger value of the variance inflation factor (typically equal to 10 or higher) indicates a serious multicollinearity issue, whereas a contingency coefficient of 0.75 or higher indicates a stronger relationship between explanatory variables and the presence of multicollinearity. Accordingly, there is no multicollinearity problem in dummy/categorical independent variables. As a result, no explanatory variable was removed from the estimation model because there was no concern with multicollinearity (*Appendix Table 5* and *6*).

4.2.2. Probit Model Output

The parameter estimates of the probit model were estimated via the maximum likelihood approach. The LR chi-square value indicates how the fitted model fits. Accordingly, the chi-square value showed that the model fitted to analyze the data. The binary probit model shows the factor variables that affect the farmers' decisions to adopt CSISVs. On the other hand, the parameter estimates of the binary probit model do not represent the actual magnitude of change or the probabilities; rather, they simply show the direction of the effect of explanatory factors on the dependent variable (Wooldridge, 2010). As a result, the marginal effect was calculated to represent the expected change in the likelihood of varietal exchange in explanatory variables, and the predicted probabilities were better explained using the probit model's marginal effects.

Eleven of the fourteen hypothesized explanatory variables were found to be determinants of farmer adoption of climate-smart improved sorghum cultivars. Age, sex, education level, family size, farm land size, access to non/off-farm activities, membership of farmers cooperatives, distance to the nearest market, access to credit, access to variety information from research center and irrigation access were identified as determining factors influencing farmers' CSISVs adoption decisions.

Table 6. Determinants of CSISVs adoption decision

Independent variables	Coef.	Std. Err.	z	P>|z|	Marginal effect (dy/dx)
AGE	-0.0205273 **	0.0080138	-2.56	0.010	-0.0081721
SEX	0.3027284**	0.1508603	2.01	0.045	0.1200249
EDUL	0.3111602***	0.0779802	3.99	0.000	0.1238762
FRMEXP	0.0064482	0.0107883	0.60	0.550	0.0025671
FAMSAE	0.0921742***	0.0307921	2.99	0.003	0.0366955
FRMLSIZ	0.1018821***	0.0327411	3.11	0.002	0.0405603
TLU	0.029782	0.0206291	1.44	0.149	0.0118565
ANOFI	0.3191278**	0.1567496	2.04	0.042	0.1264857
MFCoop	0.5534868***	0.1634427	3.39	0.001	0.2153767
MARDIS	-0.0759421***	0.0224574	-3.38	0.001	-0.0302334
ACCRDT	0.3356105**	0.1537703	2.18	0.029	0.1326776
FEXNCOT	0.0588302	0.0510399	1.15	0.249	0.0234209
ACCMI	0.508136***	0.1562903	3.25	0.001	0.1999013
ACCIRR	0.5532425***	0.1799417	3.07	0.002	0.2172099
_Cons	-1.99733	0.000	0.5676663	-3.52	
Log pseudo likelihood = -195.89161		Number of obs = 384 Wald chi2(14) = 85.40		Prob > chi2 = 0.0000 Pseudo R2 = 0.2631	

Source: Own econometric result (2025), Note that *** and ** indicate significance at the 1%, and 5% probability levels, respectively.

Age of household heads (AGE): The model result shows that the age of the HHs had a positive and significant impact on the adoption of CSISVs at a less than 5% probability level, which supports the hypothesis. After controlling for other variables, the marginal effect after probit model revealed that a unit (year) increase in the age of the HH decreases the likelihood of the households adopting the CSISVs increased by 0.82 %. As the age of the HH approaches the point where the farmer gets older and unable to contribute to farming activities, decisions on adopting climate smart improved varieties may take a long time and slowdown. In comparison to the older and weaker HHs, younger and more energetic HHs are required to cultivate larger farms which agree with the results of (Asrat et al., 2022b; Gashure & Wana, 2023b) and disagree with the finding of (Tadesse & Ahmed, 2023). This indicates that adopter categories are younger than the non-adopter's category, and this indicates that one's ability to seek and receive off-farm income, which is something that younger HHs does best.

Sex of the HH (SEX): One of the factors influencing farmers' adoption decisions in CSISVs were their sex. Farmers' adoption decisions in CSISVs were likewise found to be highly influenced by this variable, as hypothesized. At a 5% level of significance, it was found to be positively associated with the farmers' decision to adopt improved sorghum varieties. The marginal effect result from the probit model indicates that changing this variable from 0 to 1 (changing from female to male) increases the predicted probability of adopting CSISVs by 12% while keeping all other factors constant. Male-headed households showed higher adoption intensity than female-headed ones which agrees with the result of (Abdul-Rahaman, 2023; Tadesse & Ahmed, 2023; Tilahun et al., 2023a). This is because of women in Ethiopia faces social and cultural discrimination, low education level and constrained resource and service access. In addition male headed households were more likely to get information about new technologies and have more education levels.

Education level (EDUL): As shown in Table 6, the HH's decision to adopt CSISVs was positively and significantly influenced by his or her level of education. The adoption of improved sorghum varieties was influenced by the HH's education level at a 1% level of significance. The explanation for this could be that as one's level of education increases, so does one understands of new varieties, and its benefits increases. As indicated in the table above, as educational level increases by one grade, the probability of HH adopting improved sorghum varieties increases by 12.38 %. The findings of (Abdul-Rahaman, 2023; Geda et al., 2024; Tadesse & Ahmed, 2023) on the factors influencing the adoption of CSA practices are consistent with this result.

Family size in AE (FAMSAE): As depicted in Table 6, family size measured in adult equivalent is one of the determinant factors which determine the adoption decision of CSISVs in smallholder farm households. Family size positively determines the use/adoption of CSISVs. The reason might be CSISVs require more labor during the critical time to implement basic agronomic practices such as plowing, sowing, weeding and harvesting, especially the adoption of improved sorghum varieties absorbs more labor force if farmers practice row planting and fertilizer application and other necessary complimentary packages during sowing. The Probit model affirms that keeping all other variables constant a unit increase in family size results in the likelihood of adopting CSISVs increases by 3.67 %. The result is coinciding with the adoption literature (Erekalo & Yadda, 2023; Tadesse & Ahmed, 2023), there is a positive link between family labor supply and adoption but argue with the findings of (Geda et al., 2024).

Total farm land size in Ha (FRMLSIZ): The cultivated farm land holding size is the determinant factor for climate smart improved sorghum adoption which was positive and significant at 1% significance level (Table 6). The marginal effect of farm land size is also showing that an increase of farm by one hectare increases the probability of adopters than the non-adopters by 4.06%, keeping other variables at their means. Farmers with greater land holdings can pay the costs of new agricultural technologies and are willing to take the risk of crop failure. This outcome was reinforced by the results of (Abdul-Rahaman, 2023; Geda et al., 2024; Kifle, et al., 2022; Tadesse & Ahmed, 2023; Tilahun et al., 2023a) examined determinants of CSA practices adoption and found that farm size had a positive and significant impact on adoption.

Access to non/off-farm activities (ANOFI): One of the factors influencing farmers' adoption decisions in CSISVs were their access to non/off-farm activities. Farmers' adoption decisions in CSISVs were likewise found to be highly influenced by this variable, as hypothesized. At a 5% level of significance, it was found to be positively associated with the farmers' decision to adopt improved sorghum varieties. The marginal effect result from the probit model indicates that changing this variable from 0 to 1 (changing from non-non/off-farm activities participants to non/off-farm activities participants) increases the predicted probability of adopting CSISVs by 31.91 % while keeping all other factors constant. In other words, the probabilities of adopting CSISVs were 31.91 % greater for farmers who had involvement in non/off-farm activities compared to their counterparts. The respondents' reveled their argument that, the production of CSISVs is labor intensive in which adopter households use the money to hire labor and rent land rather than direct involvement and focus on the services such as motorcycle services and shopping activities. Non-farm activities might help overcome financial issues. The researchers (Tadesse & Ahmed, 2023) found the same result and disagree with the result of (Asrat et al., 2022b).

Membership in farmers' cooperatives (MFCoop): It was predicted that farmer cooperative members would have a favorable impact on the adoption of the climate smart improved sorghum varieties. At the same time, the study supports the prediction and demonstrates that, at 1% significance value, farmer cooperatives had a favorable and substantial impact on the adoption of improved sorghum varieties in the studied area. The marginal effect implies that as farm households join farmers' cooperatives, the likelihood of farmers adopting climate smart improved sorghum varieties rises by 21.53%. These findings corresponded with those made by other authors (Abdul-Rahaman, 2023; Tadesse & Ahmed, 2023) who showed that, cooperative membership facilitates households' access to services provided by the cooperative and serves as a form of social participation hence increasing the probability of CSISVs adoption.

Distance to the Nearest Market (MARDIS): At a 1% level of significance, the distance between a farmer's residence and the nearest market center was significantly and negatively related to the CSISVs adoption decision, as expected. Other things remaining constant, the marginal effect revealed that as the distance between a farmer's residence and the nearest market center increases by one kilometer, the likelihood of farmers adopting CSISVs decreases by 3.02 %. This is because, as farmers live far from the nearest market, they must pay high transportation expenses to sell their products and have little market information, both of which can restrict farmers from adopting improved sorghum varieties. Distance to the market has significantly and negatively affected the adoption of improved varieties, according to the findings of (Kifle, et al., 2022; Abdul-Rahaman, 2023; Asrat et al., 2022b; Gashure & Wana, 2023b; and Geda et al., 2024).

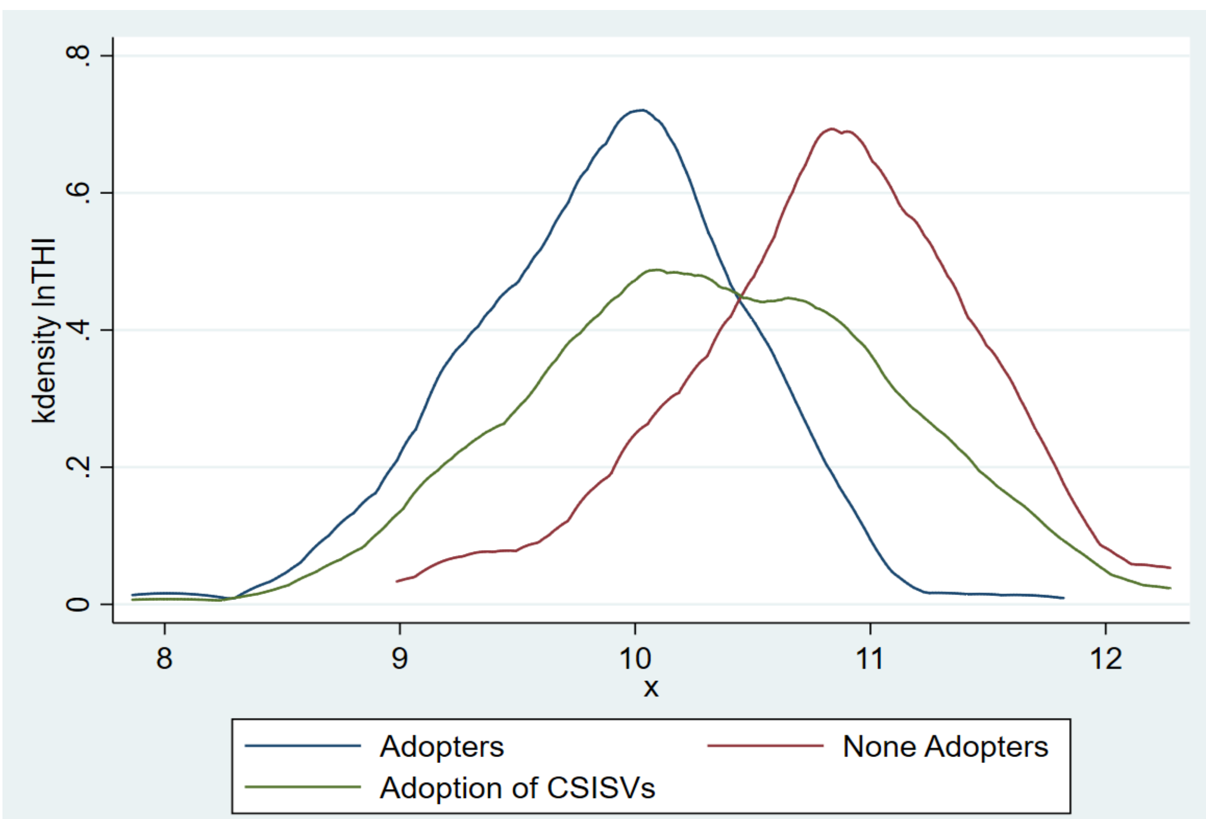
Access to credit service (ACCRDT): One of the variables suggested as a determinant of farmers' adoption decisions in CSISVs was access to credit. Farmers' adoption decisions in CSISVs were likewise found to be influential in this variable, as hypothesized. At a 5 % level of significance, it was determined to be significantly and favorably related to farmers' adoption decisions in improved sorghum varieties adoption. The probit model shows that, for a discrete change in this variable from 0 to 1, the expected chance of adopting CSISVs increases by 13.27% change from non-credit user to credit user. In other terms, it means that farmers who have access to credit have a 13.27% increased probability of adopting CSISVs than farmers who do not. This result is not surprising, considering that farmers in the study area use credit to purchase inputs such as improved sorghum varieties, according to FGD participants. Researchers such as (Geda et al., 2024; Kifle, et al., 2022; and Tadesse & Ahmed, 2023) obtained the same result.

Access to information from research Center (ACCMI): Variety information from development agents and research centers are determinant factors which determine the probability of adopting CSISVs. Availability of information on improved variety production and variety parameters such as productivity, earliness, disease and pest resistant, lodging behavior and other variety traits information from development agents and researchers in the study area had a positive effect on the adoption decision of smallholder farmers CSISVs. Access to information is supposed to make sure confidence on updating the nature of the available technologies and farmers to have a better understanding of the variety trait and encourages adopting improved technologies. At a probability level of less than 1%, the result of the marginal effect of probit model shows that those farm households who have got variety information from research center increases the probability of adopting improved CSISVs by 19.99% more than their counter parts. This result is consistent with the result of (Kamara et al., 2022; Tiruneh & Wassie, 2020).

Access to irrigation (ACCIRR): As it was hypothesized, access to irrigation was positively associated with household CSISVs adoption. Rural households that have access to irrigation have a higher chance of achieving high adoption. This hypothesis is supported by the results of the probit regression study. At a probability level of less than 1 %, having access to irrigation had a positive and significant effect on household adoption of CSISVs. The most likely reason is that having access to irrigation boosts adoption, allowing farmers to produce better as much in a cropping season. This situation may open the path for increased agricultural production and food supply for individual households. When all other factors are held constant, the marginal effect result from pobit analysis shows that, having access to irrigation increases the probability of households adopting CSISVs by 21.72 %. This result is consistent with that of (Kifle, et al., 2022; Tadesse & Ahmed, 2023).

4.2.2. Kernel density of lnTHI for CSISVs adoption

The distribution of the kernel density estimated scores in the households are depicted in Figure 3 below. Treatment households are mostly found on the right side of the distribution, partly in the middle, and partly on the left. The majority of control households, on the other hand, are spread across the distribution, with some in the middle and some on the left. As a result, the figure shows that the predicted kernel density scores distribution of CSISVs adopters (treatment group) and non-adopters (control group) has a sufficient common area.



Source: Own estimation from survey data (2025)
Figure 3. Graph showing Kernel density of lnTHI for CSISVs adopters, non-adopters and total

4.2.3. Impact of CSISVs Adoption on Total Households Income

The results in (*Table-7*) present the main impact assessment and show the expected household income under the two conditions, namely actual and counterfactual. The predicted household income from the endogenous switching regression model was used to estimate the mean household income gap between the adopters when they adopted and had they not adopted, and the non-adopters and if they had adopted. The projected household income for the adopter and non-adopter samples is shown in cells (a) and (b), respectively. While cell (d) shows the expected household income of non-adopters if they adopted, cell (c) shows the expected household income of adopters if they did not adopt.

Table 7: Impact of climate-smart sorghum adoption on THI using ESRM

		Adoption decision		Treatment Effect
Outcome	Sub-Sample	Adopted	Not to adopt	
	Adopters(TT)	(a)= 10.81583 (0.0223984)	(c) =10.0477 (0.0171)	ATT=0.7681*** (0.0282)
lnTHI	Non-Adopters(TU)	(d)= 10.5270 (0.0238)	(b)= 9.8845 (0.0137)	ATU= 0.6425*** (0.0275)
	Heterogeneity Effec(TH)	BH1= 0.2888 (0.0328)	BH0= 0.1632 (0.0217)	TH= 0.1257*** (0.0312)

Source: Own econometric result (2025),

Note that, (TH=Transitional Heterogeneity Effect), (BH1= Base Heterogeneity) =difference between adopter-did not adopted has adopted), and (BH0= Base Heterogeneity) =difference between if adopter did not adopt-not adopt)

The farming households that adopted had an estimated log household income of roughly 10.81583, whereas the farming households that did not adopt had an expected log household income of roughly 9.8845. The households that adopted the climate-smart enhanced sorghum varieties saw a 0.93 gain in household income, or around 93% higher than the farming households that did not adopt, according to the log difference in income. Di Falco et al. (2011) state that this is a basic comparison that might not be sufficient for the researcher to draw the conclusion that, on average, farm households that adopted climate-smart enhanced sorghum varieties made more money than those that did not. Because of this shortcoming, the research employed the heterogeneity effects to take counterfactuals into consideration ((c) and (d)).

The average treatment effects, which illustrate how the adoption affected household income, are displayed in the final column of *Table 7*. The difference between what adopters earned (a) and what they would have earned (c) if they had chosen not to adopt is known as the average treatment impact of the treated (ATT). In addition, the difference between what non-adopters would have earned without adoption (b) and what they would have made had they adopted (d) is known as the average treatment impact of the untreated (ATU).

The adoption of climate-smart enhanced sorghum varieties raised household income by 76.81%, according to the data in the final column of Table 7, which indicate that ATT was beneficial and statistically significant. According to the findings, adopters who choose not to adopt would have lost an average log of 0.7681 of their entire household income. However, if farmers had chosen to use climate-smart improved sorghum varieties, their total annual household income would have increased by 64.25%, according to the results of the ESR of the average treatment effect on the untreated (ATU), which is positive and statistically significant. Thus, the heterogeneity effect (TH), which was 12.57%, is obtained from the difference between the ATT and ATU. According to these findings, adopting climate-smart enhanced sorghum varieties raises adopters' household income by 12.57%. The results of (Wordofa et al., 2021), who came to the conclusion that adopting CSISVs raised adopters' agricultural income in Zambia, are in line with these findings. Fentie & Beyene (2019), found that the climate-smart agricultural practice raised household income on the income of rural households in Gubalafto woreda of Amhara region in Ethiopia.

The outcome variable in Table 7's final row has a highly significant and positive transitional heterogeneity (TH), indicating a systematic difference between the adopting and non-adopting farmers. If farmers who adopted CSISVs had not adopted them, or if farmers who did not adopt CSISVs had adopted them, transitional heterogeneity quantifies the size of the impact of CSISV use (Ngoma 2018). The study's positive TH (=0.1257) suggests that adopting CSISVs was more important and advantageous for the adopting farming household than for the non-adopters. These findings concur with those of (Abdul-Rahaman, 2023). According to the study's importance of TH, farmers who adopted in the counterfactual scenario (c) would have much higher incomes than those who did not. This importance of TH demonstrates that, whether or not adopters choose to use climate-smart modified sorghum varieties, there are certain pertinent sources of variability that benefit adopters and increase their incomes relative to non-adopters. This result supports research by (Sisang & Lee, 2023; Kaliba & Mazvimavi, 2021; Kaliba et al., 2021)that found a favorable relationship between household income and agricultural technologies.

4.3. Challenges and Opportunities to Adopt CSISVs

In Karat Zuria district of Konso zone, there were numerous challenges and opportunities associated with the production of CSISVs. According to the study, KIIs, and FGDs, farmers confront numerous challenges in the production of CSISVs. Apart from the constraints, research indicates that there are also opportunities of CSISVs production. These constraints and opportunities were discussed further below.

4.3.1. Challenges to Adopt Climate Smart Improved Sorghum Varieties

In addition, farmers, FGD discussants, and key informants in the study area identified numerous constraints. These are; lack of awareness and knowledge, limited access to quality, climate variability, cultural and traditional practices, infrastructure challenges, pest and disease management, limited access to credit, and inadequate policy and poor institutional support are some of the major identified challenges.

Lack of awareness and information among farmers was one of the issues raised by the farmers. Regarding the advantages of improved sorghum varieties, it's possible that many farmers are unaware of these benefits or are not aware of the right cultivation methods needed for successful adoption. This lack of understanding may cause reluctance to alter long-standing farming methods that have been handed down through the generations. Farmers who participated in FGD discussions indicated that another significant obstacle is the lack of access to high-quality seeds. Supply chain problems frequently cause farmers to experience irregular availability of improved seeds. The cost of high-quality seeds can be unaffordable for smallholder farmers, which hinders their ability to use these new types. The general economic difficulties that many people in the study area confront exacerbate this budgetary limitation.

Some limitations were disclosed by KIIs from Kebeles, DAs, agricultural specialists (including specialists in plant science and agricultural communication), and local women farmers. As one farmer said, "The adoption of improved sorghum varieties is significantly at risk due to climate variability." Unpredictable weather patterns, such as droughts and excessive rains, can have a negative impact on crop performance in the Karat Zuria district.
Farmers are hesitant to spend money on better seeds that might not flourish under shifting climate conditions because of this uncertainty. A female agricultural expert from the Kebeles who participated in KII noted that "traditional and cultural practices also play a role in hindering adoption." Due to cultural conventions and beliefs, many farmers who are used to conventional agricultural methods may be reluctant to adopt new ones. Therefore, even when improved varieties are available, this can impede the transition.

Farmers who participated in the *Jarso Kebele* FGD discussed infrastructure issues that make matters more difficult. Farmers may be less inclined to invest in enhanced sorghum varieties if they are unable to sell their produce due to limited market accessibility and inadequate transportation infrastructure. The potential advantages of implementing new techniques might not materialize in the absence of dependable market access. Furthermore, controlling diseases and pests is still quite difficult. Better cultivars might still be vulnerable to regional pests and illnesses, requiring efficient management techniques that farmers might not have easy access to. If farmers are worried about possible losses in the study region, this worry may discourage them from using new kinds.

Finally, KII and DAs noted that financial limitations are a widespread problem since they prohibit farmers from investing in better seeds and other agricultural inputs due to limited access to credit and financial resources. Many farmers struggle financially, which makes it hard for them to take the risks involved in implementing innovative farming techniques. Finally, another major obstacle to adoption was a lack of institutional and policy support. In the absence of robust government regulations and incentives that encourage the adoption of better sorghum varieties, farmers might be deterred from making the switch. To promote adoption and assist farmers in overcoming their obstacles, effective policy frameworks are crucial.

4.3.2. Opportunities to Adopt Climate Smart Improved Sorghum Varieties

In the study area, farmers, FGD discussants, and key informants in the study area were identified numerous opportunities. These are increasing awareness and education, access to improved seeds, climate resilience improved sorghum varieties, market opportunities, community engagement, technological advancements, policy support and improving financial access were some of the major opportunities identified in the study area.

Female specialists from the *Kebeles* who participated in KII noted that raising farmer awareness and education is one of the major opportunities. Farmers can be empowered to make knowledgeable selections by putting in place training programs that emphasize the advantages and farming methods of enhanced sorghum varieties. Creating demonstration farms can also highlight effective farming methods, enabling farmers to see the advantages directly and promoting the adoption of these new cultivars. Access to better seeds is yet another important chance. Establishing seed cooperatives can increase farmers' access to high-quality seeds at reduced prices, increasing the viability of smallholder farmers' adoption of better cultivars. More government programs to disperse better seeds can also help in this endeavor, giving farmers the tools they require to be successful.

The potential that impact CSISVs production were highlighted by the FGD discussants; improved sorghum varieties' ability to withstand climate change is a key factor in their uptake. These cultivars frequently have characteristics that increase their resistance to climate change, assisting farmers in sustaining production even in the face of adversity like drought. Furthermore, improved soil health which is critical for overall productivity can result from climate-smart agriculture methods. Additionally, the adoption of enhanced sorghum cultivars opens up a plethora of market options. Processing sorghum into other products has the potential to add value, which might boost demand and boost farmers' profits. Furthermore, enhanced cultivars can satisfy export quality requirements, creating new markets and sources of income for regional farmers.

For these variations to be successfully adopted, community involvement is essential. Participatory breeding programs that involve farmers in the breeding process ensure that the developed varieties meet local preferences and desires. By facilitating resource sharing and increasing their negotiating power, stronger farmer organizations can encourage the adoption of better practices. New developments in technology open up new possibilities. Farmers can gain a great deal from using mobile technology to disseminate information on market access and best practices. Working together with research organizations can result in the creation of sorghum cultivars that are more adaptable and tolerant to regional conditions.

Policy support was cited by participants as being crucial to creating an atmosphere that encourages the adoption of improved varieties. Farmers may be encouraged to adopt these types by government policies that offer financial incentives or subsidies. Additionally, improving access to resources and markets through rural infrastructure investment can help farmers sell their goods more easily. Additionally, enhancing financial accessibility through loan and microfinance programs might enable farmers to make investments in better cultivars and methods. In addition to reducing climate variability risks, the implementation of crop coverage products can offer farmers a profitable safety net program while they adopt new, enhanced climate-smart farming techniques.

5. SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

5.1. Summary and Conclusions

Based on the study's major findings, the following summary and conclusions can be made. The purpose of this study was to look at the impact of CSISVs adoption on smallholder farmers' total annual income in adopters' comparison to non-adopter households. The respondent farmers in the study area were selected using multi-stage sampling techniques. Cross-sectional data from both primary and secondary sources were used in this study. A semi-structured interview schedule was used to gather primary data from 384 respondents (adopters and non-adopter groups). Secondary data were also collected from secondary sources in the study area, such as books, published and unpublished documents, and other governmental office reports.

The probit model revealed that 14 independent variables were identified and included in the model. Eleven of the considered explanatory variables were shown to significantly influence the adoption decision of climate smart improved sorghum varieties in the study area. Age, sex, education level, family size, farm land size, access to non/off-farm activities, membership of farmers cooperatives, distance to the nearest market, access to credit, access to varieties information from research center and irrigation access were among the variables.

Sex, education level, family size, farm land size, access to non/off-farm activities, membership of farmers cooperatives, access to credit, access to varieties information from research center and irrigation access were found to be positively and significantly influencing the adoption decision of CSISVs in the study area. These findings show that households with a male households, higher level of education, a high family size, a high farmland size, access to non/off-farm activities, membership of farmers cooperatives, access to credit and irrigation have a higher likelihood of adopting CSISVs than their counterparts. In the study area, the age and distance to the nearest market were found to have a negative and significant effect on farmers' CSISVs adoption decisions. This means that farm households with older age and who live far from the nearest market are less likely than their counterparts to adopt CSISVs in the study area.

The ESRM of the impact estimation result showed that there was a positive and significant improvement in outcome variable lnTAI of CSISVs adopter's smallholder farm households, which could be attributed to the adoption of CSISVs in the district, using the positive TH (0.1257). Furthermore, the estimated ATT for outcome variable lnTAI was free of falsification test as of the instrumental variable (IV) as shown in (*Appendix table 2*), indicating their insignificant so that, CSISVs should be promoted in the study area.

According to the ESRM findings, households that adopted CSISVs had higher total annual incomes than those that did not. This statistically significant difference suggests that the income of households were all improved by CSISVs adoption. In other words, the outcome demonstrates that, CSISVs adoption led to increased income. The aforementioned finding implies that, better adoption of CSISVs could potentially improve household income. This concludes that, households adopted CSISVs are more likely than those who do not adopted to have higher total annual incomes.

In addition, farmers, FGD discussants, and key informants in the study area identified numerous constraints and opportunities. Lack of awareness and knowledge, limited access to quality, climate variability, cultural and traditional practices, infrastructure challenges, pest and disease management, limited access to credit, and inadequate policy and poor institutional support were among the key constraints identified in the study area. Increasing awareness and education, access to improved seeds, climate resilience improved sorghum varieties, market opportunities, community engagement, technological advancements, policy support and improving financial access were some of the opportunities that might enhance income in the study area. If diverse institutions, governments, and other concerned stakeholders play a vital role, these opportunities can be used to their full potential. As a result, these stakeholders must engage in CSISVs adoption in the study area by minimizing constraints/challenges and improving available enabling factors.

In conclusion, addressing these problems necessitates a multifaceted approach that includes supportive legislation, education, improved access to resources, and infrastructure development. These obstacles must be removed in order to greatly increase the Karat Zuria district's adoption of climate-smart modified sorghum varieties, which will increase local farmers' resilience and agricultural productivity. Leveraging these opportunities can also greatly increase the Konso zone's adoption of climate-smart enhanced sorghum varieties, which will boost local farmers' resilience, livelihoods, and agricultural output.

5.2. Recommendations

On the basis of the study's findings, the following recommendations are made:

Age was found to be negatively connected to the adoption of climate smart improved sorghum varieties; therefore, adult farmers should be supported, and older farmers should be linked to younger farmers to increase improved sorghum varieties adoption by pooling resources.

The education level of the HH was found to be one of the factors and key variables affecting CSISVs adoption in the Karat Zuria district. As a result, farmers should be educated using methods that are appropriate for their circumstances, such as adult education.

Since this variable was identified as one of the key factors influencing the adoption of CSISVs in the Karat Zuria district, it is essential to increase access to credit services in the study area, enabling farmers to use credit for CSISVs production.

To reduce the hurdles to the adoption of climate-smart improved sorghum varieties caused by market distance and access concerns, local market connectivity between producers and small traders, as well as a link to other markets, should be organized near the farm gate if possible. The necessary steps must also be taken by relevant local administrators and authorities to construct marketplaces in more convenient locations or to improve farmers' access to markets through infrastructure development.

The possibility of adopting improved sorghum varieties was found to rise with the access to variety information from the research center. As a result, agricultural research institutions and centers in the study area should put a greater emphasis on improving the DAs' and other agricultural extension practitioners' provision and outreach services by designing and implementing participatory research activities, capacity building, and discussion forums, among many other tasks. Thus, this increases farmers’ adoption of CSISVs and turns improve their income.

One of the factors and major variables determining the adoption of the improved sorghum varieties in the study area was determined to be HHs who has access to irrigation. Therefore, the farmers should be supported by concerned government (office of agriculture and natural resources, irrigation office of the district, AARC), Agricultural Growth Program (AGP-II), and other stakeholders in irrigation that should conserve and manage the existing irrigation schemes, groundwater, and land resources that avail water potential for irrigation in a sustainable manner and turn improves the smallholder farmers' income.

According to the findings of this study, the adoption of CSISVs has had a favorable and significant impact on smallholder farmers' TAI in the study area. Hence, the governmental institutions (Arbaminch agricultural research center, Jinka University, offices of agriculture and natural resources), NGOs (EKHC, Save the Children, WSA, SOPDA, AGP), and other concerned bodies in the study area should give attention to smallholder farmers in CSISVs adoption to enhance their income.

Furthermore, all the stakeholders such as input suppliers from the different levels of the region should focus on the constraints and also keep up the opportunities which were indicated by the respondents and take corrective measures to boost uptake of the CSISVs among smallholder farmers, therefore, in turn, improving their total annual income. To address income issues, opportunities to improve income in the study area should be increased.

Finally, this research strongly suggests that future research on the adoption of CSISVs and its impact on household income should be conducted with larger sample size and repeated measures to account for the heterogeneities that are so meaningful in such studies. This study did not look at the spatial and temporal features of adoption, as well as the impact dynamics and intensity of CSISVs. Therefore, further studies should be conducted with accurate and practical recommendations in the study area.

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7. APPENDIX

7.1. Appendix I: Tables in the Appendices

Appendix Table 1. Conversion equivalents of TLU

No	Livestock Type	Conversion factor (TLU)
1	Cow	1
2	Oxen	1
3	Heifer	0.78
4	Bull	1.2
5	Mule/Horse	0.8
6	Calf	0.2
7	Goats	0.2
8	Sheep	0.2
9	Poultry	0.04

Source: ILRI (2013)

Appendix Table 2. Falsification test for the instrumental variable (IV)

Variables	**Regression**			
	Probit ADOPCSISVs ACCI			
ADOPCSISVs	Coef.	Std. Err.	Z/t	P>|Z/t|
ACCI	0.4987188 ***	0.1298518	3.84	0.000
_Cons	-0.3204815	0.0954464	-3.36	0.001
Log likelihood = -258.39284	Number of obs = 384	Prob >chi2 = 0 .0001		
	LR chi2(1) = 14.88	Pseudo R2 = 0 .0280		
lnTHI	Reg lnTHI ACCI If ADOPCSISVs = = 1			
ACCI	0.1135792^{NS}	0.0975266	1.16	0.246
_Cons	10.74361	0.0777691	138.15	0.000
lnTHI	Reg lnTHI ACCI If ADOPCSISVs = = 0			
ACCI	-0.0030102^{NS}	0.082953	-0.04	0.971
_Cons	9.885821	0.0550248	179.66	0.000

Source: Own survey result (2025)

NB: IV=Instrumental Variable; ACCI= Access to variety information from research center; lnTHI=log of THI; ADOPCSISVs = Dependent variable =significant at 1%, probability level and NS=Non-significant

Appendix Table 3. Shapiro-Wilk's normality test

Variable	Obs	W	V	z	Prob>z
lnTHI	384	0.99664	0.892	-0.271	0.60698^{NS}

Source: Own estimation result (2025); Note: NS=Non-significant at a 1% probability level

Appendix Table 4. Conversion factor for adult equivalent (AE)

Age group	Male	Female
Less than 10 0.75	0.6	0.6
10-13	0.9	0.8
>13	1	0.75

Source: (Storck et al., 1991)

Appendix Table 5. Multicollinearity test for the continuous explanatory variable

Variable	VIF	1/VIF
FRMEXP	1.45	0.691048
AGE	1.44	0.696663
FRMLSIZ	1.25	0.797173
TLU	1.24	0.806008
FEXNCOT	1.11	0.898426
EDUL	1.05	0.951270
MARDIS	1.03	0.974250
FAMSAE	1.00	0.995074
Mean VIF	1.20	

Source: Own survey result (2025)

Appendix Table 6. Contingency coefficient for discrete explanatory variables in the model

Independent dummy Variables	SEX	ANOFI	MFCoop	ACCRDT	ACCMI	ACCIRR
SEX	1.0000					
ANOFI	-0.0111	1.0000				
MFCoop	0.1272	0.0202	1.0000			
ACCRDT	-0.1327	0.1656	-0.1491	1.0000		
ACCMI	0.0135	0.1082	-0.1132	0.2159	1.0000	
ACCIRR	0.0073	-0.0115	-0.0292	-0.0121	-0.0499	1.0000

Source: Own survey result (2025)

7.3. Appendix II: Data Collection Tools

UNIVERSITY OF TLEMCEN

PAN AFRICAN UNIVERSITY INSTITUTE OF WATER AND ENERGY SCIENCES INCLUDING CLIMATE CHANGE

CLIMATE CHANGE PROGRAM, POLICY TRACK

MSc. In Climate Change Policy

Semi-Structured Interview Schedule

Dear respondent,

Your responses to this questionnaire will be used to inform the research paper that will be prepared for the thesis proposal entitled "Adoption of Climate-Smart Improved Sorghum *[Sorghum bicolor (L.) Moench]* Varieties and Its Impact on Smallholder Farmers' Income in Karat Zuria District of Konso Zone, Southern Ethiopia" Any information you contribute will be kept strictly confidential and used solely for research purposes. Individual comments will not be identifiable, and the identities of those who respond will not be published or disseminated. Your honesty in responding to the correct answer is critical to the research's reliability. Thank you in advance for your considered cooperation and time commitment.

Sincerely,

Kebede Kassu Sagara (MSc. Scholar at PAUWES)

General Directions

Encircle the choice from the options and or put (x) marks in the space provided for close-ended questions and write respondents' responses on the space provided for open-ended questions.

Part I. Supportive Information

1) Name of the enumerator: __________________ Signature_________________
2) Date of the interview: ____ /____ /2025.
3) Name of respondent: ________________________ ID. Code: ______________
4) Kebele: ________________________ 5) Village (commune): _______________

Part II. Demographic Characteristics

1) The household head's age in years: ____________
2) Sex of household head: 1) Male ☐, 0) Female ☐
3) Education level of household head: 1) Literate ☐, 0) Illiterate ☐
4) If literate what is the total number of household head years of schooling completed: ____

5) Farming experience in producing climate smart improved Sorghum variety in years: ______________

6) List your total family size according to the table below?

No.	**Name of household members** (started with respondent)	**Sex**: 0= Female and 1= Male	**Age:** in years
1)			
2)			
3)			
4)			
5)			
6)			

Part III. Socio-Economic Characteristics

1) Have you produced climate smart improved Sorghum variety for the last consecutive 3years? 1) Yes ☐,0) No ☐

2) Can you please indicate the total size of farmland owned by the household head in hectares accordingly? in the year **2024.**

Total owned land in hectares	Rented in now	Rented out now	Shared in now	shared out now	Grazing land

3) How was the trend of climate smart improved Sorghum varieties production over the last three years regarding:

No	Criterion	Use code* below
1	Your land allocation to climate smart improved Sorghum varieties production?	
2	Your climate smart improved Sorghum varieties yield?	
3	Your income from climate smart improved Sorghum varieties?	

(code* *1. Significantly decreased, 2. Slightly decreased, 3. No change, 4. Slightly increased 5. substantially increased);*

4) Do you have livestock? 1) yes ☐, 0) No ☐

5) If "Yes" how many of the following types of livestock do you have currently?

No	Livestock type	Number (count)	**No**	Livestock type	Number (count)
1	Cow		6	Calf	
2	Oxen		7	Goats	
3	Heifer		8	Sheep	
4	Bull		9	Poultry	
5	Donkay				

Sub Total in TLU				
Grand Total				

6) What is your primary occupation for your source of income? 1) Farming ☐, 2) Part time job ☐, 3) Full time job ☐, 4) Business/self-employment ☐, 5) Farming and job ☐, 6) Remittances (GoE/Family member) ☐, 7) On farm casual labor☐, 8) Other Specify ________

7) Do you have access to non/off-farm activities? 1) Yes ☐, 0) No ☐.If do you have access to non/off-farm income-generating activities fill out the table below: -

No	Types of non/off-farm activities or many transfers	How many family members have participated?	Period of the income?	Annual income (ETB)
1	Sale of hand crafts			
2	Weaving/ spinning			
3	Salaried employment			
4	Sale of local drinks (beverages)			
5	Village shop			
6	Smith			
7	Rented-out oxen for plow			
8	Vehicle (*Motor*/*Bajaj*)			
9	Daily labor(wage)			
10	Tailoring			
11	Livestock trade			
12	Pity trade (grain, vegetables, fruits, etc.)			
13	Sell firewood and grass			
14	Charcoal making			
15	Retail trading			
16	Construction			
18	Service provision e.g Washing, Barber, Shoe shining, posho mill, etc			
19	Food processing			
20	If other specify ________________			
Total				

8) Did you receive any cash or kind in the year **2024** E.C.? 1) Yes, ☐0) No ☐, if "yes" fill the following table?

No	Types of non/off-farm activities or many transfers	Did you obtain income? 1) yes 0) No	Total amount received (ETB)
	Types of income earnings		

1	Remittance		
2	Gov`t transfer (Pension)		
3	Rented-out home		
4	Rented-out farm equipment		
5	Rented-out farmland		
6	Gifts / Received		
7	Relief/ aid		
8	Others Specify		
Total			

NB: if the household received in kind, it must be converted into Birr by the current price of the kind which sells. Also, * If payment is in kind, please convert them to birr at the prevailing price

9) Do you have access to climate smart improved sorghum? 1) Yes ☐, 0) No ☐

10) If "Yes", where did you get and buy climate smart improved Sorghum varieties seeds? 1) Market ☐, 2) multipurpose cooperatives ☐, 3) Agricultural input delivery agents ☐, 4) agricultural research centers ☐, 5) Private enterprises ☐, 6) exchange, gifts... ☐, 7) Konso Development Association (KDA) ☐,8) Others specify ____

11) Do you used inputs for climate smart improved Sorghum varieties production in the last 12 months? 1) yes ☐, 0) No ☐

12) If "Yes" indicate the types and number of inputs used for your climate smart improved Sorghum production in 2024?

Type		The amount used in Kg/ liter	Total Cost in ETB	Source*	The amount harvested in qtl
Sorghum seed	Local				
	Improved				
Fertilizer	NPS(B,Zn)				
	UREA				
Chemicals	Herbicide				
	Fungicide				
	Insecticide				

** 1) Own reserve, 2) Private retailers (purchase from informal suppliers) 3) Relatives, 4) Research institutions, 5) universities, 6) MOA, 7) Primary Coop, 8) Union, 9) Others(specify)______*

13) Do you have a membership to cooperatives 1) yes ☐0) No ☐, If "Yes"?

Experience as a member in years	services obtained	Expression of views and participation in cooperative decisions	you trust the cooperative and its members
	1) input 2) credit service	1) never 2)	1) never 2) sometimes

	3) community service 4) labor Share	sometimes 3) often 4) always	3) often 4) always

14) If "No", what is the most likely reason? 1) No information☐, and 2) No interest,☐ 3) No cooperatives,☐ 4) No credit service☐, 5) Other specify____.

Part IV. On-Farm Income

1) Have you sold any livestock in the past 12 months? 1) yes ☐, 0) No ☐
2) If "Yes" indicate the number of livestock and their products sold in the past 12 months below?

No	Livestock heads	No./amount sold	value in Birr	Annual revenue
1	Cow			
2	Ox			
3	Heifer			
4	Bull			
6	Donkey			
7	Calf			
8	Goats			
9	Sheep			
10	Poultry			
11	Local Beehives-colony			
12	Modern Beehives-colony			
Other	Specify ________			
Animal products	Products	Amount sold in (Kg/Lt)	value in Birr	Annual revenue
	Beef(kg)			
	Mutton (kg or head)			
	Goat (kg or head)			
	Hides/ skins /			
	Milk			
	Butter			
	Yogurt/cheese			
	Chicken (Number)			
	Eggs			
	Honey			
	Dung/Manure-wet/dried			
Other	Specify_______			
Total				

3) What are the major crops produced and income earned in the year **2024**?

Major Crops	Specified crops	Area in ha	The amount produced in (Qntl/Number)	Amount sold in (Qntl/ Number)	Average price/unit (Birr)	Annual revenue
Cereal crops	Sorghum					
	Maize					
	Wheat					
	Barley					
	Other __					
Vegetables	Onion					
	Cabbage					
	Tomato					
	Head cabbage					
	Garlic					
	Irish potato					
	Potato					
	Pepper					
	Lettuce					
	Other __					
Fruits	Mango					
	Avocado					
	Papaya					
	Banana					
	Orange					
	Guava					
	Other __					
Pulse and legume crops	Common bean					
	Faba bean					
	Field pea					
	Chickpea					
	Lentil					
	Other __					
Oilseeds	Groundnut					
	Linseed					
	Sesame					
	Sunflower					
	Other __					
Cash crops	Ethiopian Cardamom (Korarima)					
	Coffee					
	Other __					

Non-food and Other Crops	Animal forage					
	Eucalyptus					
	Condiments					
	Other __					
Root crops	Cassava					
	Taro/*Godere*					
	Yam					
	Enset					
	Other __					
Byproducts						
Total						

Part V. Institutional Factors

1) Do you have market access? 1) Yes ☐, 0) No ☐
2) How far is the distance of nearest Sorghum output market from your residence(farm) in kilometers? ________Km, and or in adult walking time _________hrs.
3) What is your source of market information regarding climate smart improved sorghum varieties (Multiple response possible) 1) Neighbors ☐, 2) Extension agents ☐, 3) Farmer organizations ☐, 4) Input suppliers ☐, 5) Research institutes/Universities ☐, 6) Mass Media (TV, Radio, News Papers) ☐,7) Social-media (Mobile applications…) ☐,8) Merchants☐, 9) Farmer decide themselves ☐, 10) Any other (Specify): _?
4) Where did you sell your climate smart improved sorghum products? 1) On farm (farm gates) ☐, 2) Taking to local market ☐, 3) Through farmers cooperatives ☐, 4) Main market (Gazer) ☐, 5) Retailers☐, 7) processor(s)☐, 8) Central market (Jinka Town)☐, 9) Others specify__________
5) Do you have access to credit in the past 3 years? 1) Yes ☐, 0) No ☐
6) If "Yes", what are your credit sources to fill financial constraints? 1)Cooperative ☐, 2) Micro finance ☐, 3) NGOs☐, 4) local money lender ☐ 5) credit and saving institutions☐, 6) Others specify: ______________.
7) If you have access to credit, what type of credit do you receive? 1) Cash ☐0) In-kind ☐
8) If "cash" how much amount of ETB did you receive? ____if "in-kind" convert to ETB _

9) What is the purpose of the credit? 1) Climate smart improved sorghum seed ▭, 2) other farm inputs ▭, 3) Livestock purchase ▭, 4) HH consumption ▭ 5) Land rent ▭, 6) others specify: ___________.

10) If answer for Qno.5 is "No", why? 1) High interest rate ▭, 2) No need ▭, 3) Lack of Collateral ▭, 4) Fear of inability to repay ▭, 5) No service ▭ 6) others specify: ______________.

11) In your kebele, do you have access to agricultural extension services? 1) Yes ▭0) No ▭

12) If Qno.11 is "Yes" how frequent is your contact with the extension agent in a year? _____

13) Do you have access to irrigation? 1) Yes ▭, 0) No ▭

14) If Qno.13 is "Yes", how much area of your farmland is accessible to irrigation in ha? _____

15) What types of crops are produced by irrigation? 1) Vegetables ▭, 2) Fruits ▭, 3) Root and tuber crops ▭, 4) cereal crops ▭, 5) Perennial crops ▭, 6) Others specify _______________.

Part VI. Constraints and Opportunities of Climate Smart Improved Sorghum Production

1) Identify constraints and opportunities for climate smart improved sorghum production for income improvement in the study area.

No	Constraints	Put (√) mark	Opportunities	put (√) mark
1	Low quality of cultivars,		Increasing demand with increasing population and purchasing power,	
2	Poor seed rate agronomic practices,		Most parts of woredas are accessible to the main asphalt road,	
3	A weak extension system,		Existence of irrigation schemes,	
4	Disease and pests,		Sufficient water and land resources,	
5	Fluctuation of climatic variability		Availability of groundwater potential for irrigation,	
6	Insufficient storage to extend its shelf life;		Existence of Farmer Training Centers,	
7	Poor handling of the products,		Ongoing infrastructure development,	

8	Imperfect price information,		Rural electrification and improved rural roads,	
9	Lack of horizontal cooperation between producers,		Organized farmers as irrigation water user cooperative	
10	Poor market integration (lack of vertical coordination among chain actors),		Availability of wholesale trade	
11	And lack of grades and quality standards		**Other specify __________________**	
12	**Other specify ___________**			

Part VII. Check List for Key Informant Interview

Sir/Madam, good morning or afternoon,

I am carrying out a study on "Adoption of Climate-Smart Improved Sorghum *[Sorghum bicolor (L.) Moench]* Varieties and Its Impact on Smallholder Farmers' Income in Karat Zuria District of Konso Zone, Southern Ethiopia." Thank you for allowing me to have an interview with you. I want to inform you that, as mentioned in my introduction letter, I will respect all ethical research conduct rules.

General information

1) Name of the Interviewee: __________________ Date: ____/____/2025. ID ____
2) What is the Position of the Interviewee: 1) District, 2) Kebele? _________________
3) What is the Sex of the interviewee: 1) Male,0) Female?
4) What is the Profession of the interviewee? ____________________
5) What is the age of the interviewee in Years? ________________

A) Interview Questions

1) What are the constraints and opportunities of climate smart improved Sorghum production for income improvement?
2) What do you think are the root cause of the constraints you mentioned?
3) What actions do you take to solve the constraints? ______________________
4) What are the different types of climate smart improved Sorghum practice which are experienced by the rural households?

5) What do you think about the changes in the production of climate smart improved Sorghum after being a member of climate smart improved Sorghum varieties? 1. Significantly improved, 3. No change, 4. Deteriorated, 5. Significantly deteriorated
6) What do you think about the changes in impact of climate smart improved Sorghum adoption on smallholder farmers' income?

Part VIII. Guide for Focus Group Discussion

Sir/Madam, good morning or afternoon,

I am carrying out a study on "Adoption of Climate-Smart Improved Sorghum *[Sorghum bicolor (L.) Moench]* Varieties and Its Impact on Smallholder Farmers' Income in Karat Zuria District of Konso Zone, Southern Ethiopia." Thank you for allowing me to speak with you. I want to reassure you that, as indicated in my introduction letter, I will adhere to all ethical research norms of conduct.

General information

1) Kebele of FGD group: ________________ Date: ____/____/2025.
2) No of discussants: Male______ Female_____ Total_____. FGD ID: _________

A) Guide information

1) Have you ever produced SORGHUM? If so, what do you know about it?
2) Based on your experience, what have you observed in any changes in your income improvement?
3) What are the constraints and causes of constraints of climate smart improved sorghum varieties production? Put in order of severity?
4) What are the different income sources that are experienced by the rural community?
5) To counteract the constraints of climate smart improved sorghum varieties production, what is expected from whom (what actions and responsibilities)?
6) What are the opportunities for climate smart improved sorghum varieties production? Put in order of importance?
7) What are the positive impacts of climate smart improved sorghum technology on your community?

8) Do you think climate smart improved sorghum technology affects you and your family's income? Why and how?

9) What factors determine the adoption of climate smart improved sorghum varieties in your community?

Thank You for Your Cooperation!!!