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College of Development Studies

Center of Environmental Studies

Thesis on:

Assessment of Determinants of Climate Smart Agriculture Practice Adoption in Gozamin District, North West Ethiopia

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A thesis Submitted to the Center of Environmental Studies, College of Development Studies, Addis Ababa University in Partial Fulfillment for the Requirement of MA Degree in Development Studies (Environment and Sustainable Development).

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Addis Ababa, Ethiopia

DECLARATION

I BelaynehYerssie, Registration NumberGSR/8955/12, do hereby declare that this thesis is my original work and that it had not been submitted partially; or in full, by any other person for an award of degree in any other University.

Submitted by:

Full Name…………………………………….. Signature……….…… date………………..

Approved by:

This thesis has been submitted for examination with my approval as University supervisor.

Name of Advisor ………..……………………. Signature ……………… date…………….

APPROVAL

I undersigned certify that they have read and hereby recommend to Addis Ababa University to accept the thesis submitted by BelaynehYerssie and entitled “Assessment of determinants of climate smart agriculture practice adoption in Gozamin district, North West Ethiopia” in partial fulfillment of the requirements for the award of a Master of Arts Degree in Development Studies (Environment and Sustainable Development)

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Name of Head of Department…………………… Signature………………date ……...…….

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Acronyms

CSA	Climate Smart Agriculture
CSAT	Climate Smart Agricultural Technology
FDRE	Federal Democratic Republic of Ethiopia
FAO	Food and Agricultural Organization
GDP	Gross Domestic Product
GDoFED	Gozamin District Office of Finance and Economic Development
IFAD	International Food and Agriculture Development
KM	Kilo-Meter
UNEP	United Nation Environment Program
WFP	World Food Program

Abstract

Climate change impacts on production are expected to translate into economic impacts at various scales. At farm level, climate change will cause reduced income for households which will limit the capacity to acquire assets. However, the existing empirical literature shows different factors contribute for the adoption of climate smart agriculture practice. The purpose of this study was to identify the factors of assessment of determinants of climate smart agriculture practice adoption in Gozamin district, North West Ethiopia*. This study used a cross sectional survey research design. Structured interview questionnaire with 323 sample respondents were held to collect primary data from the sample respondents, who were selected using probability sampling technique supplemented by key informant interview. Descriptive statistics and binary logistic regression model were used to identify demographic, socio-economic and extension service determinants that determine the assessment of climate smart agricultural practices adoption in the study area. The result show that 43.34% of the household heads adopted climate smart agriculture. The resulting distribution show that, climate smart agriculture practices: crop rotation (25.53%), inter-cropping (20.57%), soil and water conservation (16.31%), organic fertilizer (15.6%), agroforestry (8.51%), mulching (4.96%), improved grazing (4.26%), improved seed (2.13%) were adopted by the respondents in the study area. The study found that, variables such as sex, educational status, access to extension service, credit and training are significantly and positively affects the assessment of climate smart agriculture practice adoption in the study area. Whereas, land size significantly and negatively affects the adoption of climate smart agriculture practice in the study area. Thus, in the process of adoption of climate smart agriculture, these variables should be considered by the agriculture sector decision makers, donor agencies at different level and individual farm household heads.*

Key Words: Adoption, Climate Smart Agriculture, Gozamin, Logit Regression Model

1. INTRODUCTION

1.1. Background and Justification of the Study

Climate change has become a global threat as its impacts are noticeable in all sectors in general and the agricultural sector is more sensitive to climate change in particular. Almost all or most of the communities in developing counties are agrarian. The effect of climate change is pervasive especially in Africa and sub-Saharan Africa (FAO, 2016).

Agriculture in Africa must undergo a major transformation in the coming decades in order to meet the intertwined challenges of achieving food security, reducing poverty and responding to climate change without depletion of the natural resource base. Although agriculture looms large in the economy of Africa, employing more than 60% of the population and contributing 25-34% of the GDP, productivity is low and food insecurity is high. Reviewing the different dimensions of food insecurity around the world (FAO, IFAD and WFP, 2014).

Ethiopia is a vulnerable to the adverse effects of climate change mainly due to its high dependence on rain-fed agriculture, low adaptive capacity and a higher reliance on natural resources base for livelihood, among others (EPCC, 2015).

The agriculture of Ethiopia is characterized by low productivity (FAO, 2016). In developing countries, where the economy is heavily relay on agriculture, development of the agricultural could be the most efficient poverty reduction measure. Yet, agricultural expansion for economic development which comes at the expense of soil, water, biodiversity and forest conflicts with the nation's green economy development goals, and often compromises production and development in the longer term. Ethiopia has initiated Climate-Resilient Green Economy initiative to protect the country from the adverse effects of climate change to realize its ambition of reaching middle income status in 2025 (FDRE, 2011).

Persistent land fragmentation and declining farm size that seriously leading to land degradation, deterioration of soil fertility, low agricultural productivity and undermine the sustainability of the agricultural sector in the study area. Consequently, farmers have started cultivating steep slopes and communal grazing lands, clearing forests and endangering biodiversity which is a means for climate change induced problems. Soil acidity, soil fertility and soil erosion are major production constraints in the study area (setotaw et al.2020).According to Alemayehu (2019) smallholder farmers in the study area produce crops on marginal lands and live in areas with poor access to markets and technical assistance in the form extension service and rural credit.

The existed literatures show that adoption of climate smart agriculture is negligible in most of the rural areas. This implies that if the problem is not solved, it is difficult to maximize agricultural productivity in particular and to achieve sustainable development in general. Therefore, this study is aimed to identify the determinants that affect the climate smart agriculture practice adoption in Gozamin district, North West Ethiopia.

1.2. Statement of the Problem

Climate change impacts on production are expected to translate into economic impacts at various scales. In a farm level, climate change will cause reduced income for households which will limit the capacity to acquire assets and meet their social cost (Belay and Getaneh, 2016).

Agriculture remains vital to the economy of Ethiopia and its development has significant implications for poverty reduction (FAO and UNEP, 2015). Climate change increasingly affects agriculture and results in socio-economic consequences for national economies and individuals. However, the adoption of climate smart agriculture is not well studied, especially in a rural agricultural area, including the study area.

Global warming, drought and extreme weather are frequently fluctuating yields and quality of crops produced (Arman et al, 2016). To fulfil the Climate Resilient Green Economy target, Climate Smart Agriculture practices are needed. In the national appropriate mitigation actions, the planned mitigation technologies and practices by agriculture sector is presented practicing composting 80000 KM^2 of cropland and agroforestry on 261840 square kilometers (FDRE, 2011).

Melaku et al. (2016) asserted there is a lack of specific and adequate research findings on climate smart agriculture practices in Ethiopia for the various agro-ecology, soil type, rainfall pattern, farming system, temperature and moisture ranges. A study conducted at national level in Ethiopia has identified that the adoption rate of CSA practices is low and there is a gap in research at local level regarding CSA scoping study. Williams et al. (2015) confirmed that there is no as such a climate smart agriculture practice but the natural, bio-physical, socioeconomic, institutional and development situation of the local area determines the context with in which the climate smartness is evaluated and recommended.

On the other hand, previous Studies found that different variables determine the adoption of CSA practice in different area. Francis Maguza-Tembo et al (2017) found that age, sex, location, farmer type, off-farm participation, land ownership, climate variability knowledge and credit are among the factors. Whereas Zakari S., (2019) argues that access to training, membership of an organization, source of income, family size and livestock ownership are the determinants to adopt climate smart agriculture.

Abegunde V., (2019) in his study identified farming experience, farm size, agricultural extension, media, membership of an agricultural association and perception of climate change determines adoption CSA. AryalP., et al (2018) focus on demographic and socio-economic characteristics. Saha K., et al (2019) found occupation, family size, farm size, farming experience, cattle ownership, annual income, market difficulty, access to farm information, training, organization affiliation and perception of climate change are determinant variables of adoption of climate smart agricultural technology.

However, there are still inconsistencies in variable and in significance as well. Some of them used descriptive statistics and others used different models for data analysis. Therefore, this gap initiated to undertake this study which aims to assess the determinants of Climate Smart Agriculture practice adoption in Gozamin District, North West Ethiopia to fill the existing knowledge gap and to contribute to the existing limited literature.

1.3. Basic Research Questions

- What is the adoption level of climate smart agriculture practice in the study area?
- What are the determinant factors affecting the adoption of climate smart agriculture practice in Gozamin District?

1.4. Objectives of the Study

1.4.1. General Objective

The general objective of this study was to Assess the Determinants of Climate Smart Agriculture Practice adoption in Gozamin District, North West Ethiopia.

1.4.2. Specific Objectives

- To assess the adoption level of climate smart agriculture practice among household heads.
- To identify the determinants of adoption of climate smart agriculture practice in a study area.

1.5. Significance of the Study

Climate change is a major threat for agricultural sector and the high vulnerability of the sector demands adoption of climate smart agricultural practices to keep sustainability. On the other hand, identification of the determinants to adopt climate smart agriculture is the most crucial for agriculture and climate change sector policy makers, decision makers and to those future researchers on this cross-cutting issue.

1.6. Scope of the Study

The study would be made to have spatial and thematic delimitation. Spatially, the study was conducted in Gozamin District of North West Ethiopia. The primary focus of this research was on the climate smart agricultural practice adoption. Thematically, the study was delimited to examine the adoption status of climate smart agriculture in the study are and to identify the major determinants that affect climate smart agriculture practice adoption in the rural context.

1.7. Limitations of the Study

Some of the limitations in this study are described as follows: the findings of this study cannot necessarily represent all factors determining the adoption of climate smart agriculture. Therefore, it is suggested that other researchers to include more factors which are expected to have effect on the adoption of climate smart agriculture. The other limitation of this study is that, the result is not generalized to other districts with different agro-ecology zone. Despite these limitations, the researcher has paid due attention to ensure the reliability and validity of the collected data.

CHAPTER TWO: LITREATURE REVIEW

In this chapter, the researcher reviewed some theoretical and empirical works on the adoption of climate smart agriculture practice, which have received a great deal of attention in development literature and national plans of many countries. Thus, this chapter contains the conceptual and theoretical frameworks, empirical works conducted on the adoption of climate smart agriculture and finally the conceptual framework is included.

2.1. Theoretical Literature

Climate-smart agriculture, a concept developed by Food and Agricultural Organization (FAO), is an approach to developing the technical, policy and investment conditions to achieve sustainable agricultural development for food security under climate change (FAO, 2013).

The emerging of CSA can be note to have started after the Hague conference where countries met to discuss the adverse effect of climate change and how to mitigate the effects. This conference led to a number of actions and policies to be implemented in order to achieve its objectives (FAO, 2015).

Lipper and Zilberman (2018) however noted that the term "CSA" was widely adopted before the development of a formal conceptual framework and tools to implement the approach, leading to considerable variation in meanings applied to the term, hence some controversies in the use of the term. At the same time, the aforementioned authors argue that no specific guidance was provided by the FAO on how to define a CSA practice, or prioritize amongst objectives, to develop site specific CSA solutions.

In the broader Ethiopian context, climate smart agriculture practices (CSA) and technologies are being implemented within the framework of integrated watershed management, which incorporate a wide range of practices in crop and livestock production including agroforestry, crop rotation and intercropping as well as soil and water conservation measures such as soil/stone bunds, terracing, infiltration ditches, and tie ridges among others (FAO, 2016).

CSA is being promoted for the adaptation and mitigation of climate change and variability in many places. In terms of outputs, the concept of CSA has been well articulated. CSA should help to improve farm productivity, increase resilience to weather extremes and decrease greenhouse gas emissions wherever possible (FAO, 2010; Steenwerth et al., 2014).

Ethiopia signed and ratified many of the international conventions and protocols related to climate change and land degradation including the united-nations framework convention on climate change, the convention on biological diversity and the United Nations (UN) convention to combat desertification. In Ethiopia there are policies and strategies relevant to CSA includes the climate resilient green economy strategy, national adaptation program of action, Ethiopian program of adaptation to climate change, nationally appropriate mitigation actions, rural development policy and strategies, growth and transformation plan, Ethiopia's Agricultural Sector Policy and Investment Framework, Environmental Impact Assessment Proclamation, Environmental Policy of Ethiopia (Melaku et al., 2016).

About 48% of Africa's population or approximately 450 million people live in extreme poverty, on less than US$1.25 per day, with 63% of the continent's poor living in rural areas depending on agriculture for their livelihoods (World Bank, 2015).

Lehmann et al. (1998) climate smart agricultural technologies have potential in addressing loss of soil fertility and land degradation. Climate smart agriculture technologies including agroforestry, use of organic manure and conservation agriculture have emerged as a sustainable land management practice.

Thangata et al. (2007) found that many smallholder farmers are in a state of poverty and cannot afford to purchase industrial inputs to improve yields therefore climate smart agricultural technologies play an important role to improve yields. Climate-smart agriculture include proven practical techniques like; mulching, intercropping, conservation agriculture, crop rotation, integrated crop livestock management, agroforestry, improved grazing, and improved water management. These technologies involve innovative practices such as better weather forecasting, more resilient food crops and risk insurance.

Fischer et al., (2002) and Boko et al., (2007) indicate that climate change will cause a wide-ranging decline in most of the crops such as sorghum, maize, millet and groundnuts in several countries such as Sudan, Ethiopia, Eritrea, Zambia, Ghana and Gambia. Yields from crops that rely on rainfall could drop by 50% by 2020 and dwindle 16 net revenues from crops by 90% by

2100 in some countries, worsening food insecurity and putting millions of persons at risk of starvation, with Africa expected to account for the majority by 2080s particularly small-scale farmers.

Adaptation in agriculture has increasingly gained attention with its application taking different dimensions such as transformation of whole farming systems, modifications of existing systems and adoption of practices such as soil and water conservation, agroforestry (Meridian Institute, 2011).

2.2. Empirical Literature

Temesgen et al. (2014) Ethiopia is vulnerable to climate variability and change, and it frequently faces climate related hazards, commonly drought and floods. The variability of rain fall and the increasing temperature were a cause for frequent drought and famine, and putting disastrous impact on the livelihood of the peoples.

Francis M., et al (2017) conducted a study on determinants of climate smart agriculture technologies adoption in the Drought Prone Districts of Malawi using a Multivariate Probit Analysis. The study reveals that gender, age, location, farmer type, level of education, livelihood status/off-farm participation, land size and ownership, household income, household expenditure, anticipated weather pattern, climate variability knowledge, access to credit affects the adoption decision of Climate Smart Technologies significantly.

ZakariS., et al (2019) undertake a study and their econometric models revealed that access to credit service, access to training, membership of an organization, source of income, family size and ownership of animal of traction influence significantly and positively the adoption of these climate smart agriculture technologies and practices.

Pagliacci F., et al, (2020) in their study findings highlight that non-financial factor should be considered in order to design more effective schemes to prompt farmers to adopt and continue such practices over the long run. Their finding also stresses the need to complement financial support with proactive information-based instruments.

Tran N., et al (2019)in their study showed that gender, age, number of family workers, climate-related factors, farm characteristics, distance to markets, access to climate information, confidence on the know-how of extension workers, membership in social or agricultural groups and attitude toward risk were the major factors affecting the decision to adopt climate smart agriculture technologies. However, the effects of these factors on the adoption of climate smart agricultural technologies varied across three provinces. These technologies when adopted tend to increase NRI but the increase is much greater when these are combined.

Abegunde V., et al, (2019) in their study on the adoption of climate smart agriculture identified that, educational status, farm income, farming experience, size of farmland, contact with agricultural extension, exposure to media, agricultural production activity, membership of an agricultural association or group and the perception of the impact of climate change were found to be statistically significant and positively correlated with the level of CSA adoption. Furthermore, off-farm income and distance of farm to homestead were statistically significant but negatively correlated with the Climate Smart Agriculture level of adoption. They argue that climate change-related education through improved extension contact and exposure to mass media can strengthen integrated farm activities that bolster farm income.

Belay et al, (2017) in their study on climate smart agriculture found that 90% of farmers have already perceived climate variability and 85% made attempts to adapt using practices like crop diversification, planting date adjustment, soil and water conservation and management, increasing the intensity of input use, integrating crop with livestock, and tree planting**.** Their result found that education, family size, gender, age, livestock ownership, farming experience, frequency of contact with extension agents, farm size, access to market, access to climate information and income were the key factors determining farmers' choice of adaptation practice.

Maharjan S., et al (2018) conduct a study on the issue and their finding show significant correlations between multiple Climate Smart Agricultural Practices, indicating that their adoptions are interrelated, providing opportunities to exploit the complementarities. The results confirm that both the probability and intensity of adoption of climate smart agriculture practices are affected by numerous factors, such as demographic characteristics, farm plot features, access to market, socio-economics, climate risks, access to extension services and training. Farmers who perceive high temperature as the major climate risk factor are more likely to adopt crop diversification and minimum tillage. Farmers are less likely to adopt site-specific nutrient management if faced with short winters; however, they are more likely to adopt minimum tillage in this case. Training on agricultural issues is found to have a positive impact on the likelihood and the intensity of climate smart agricultural practices adoption.

NdambiriH., et al (2019)in their study on climate smart agriculture practice found that, social factors (age and sex) were found to significantly relate to adoption of climate smart agriculture. Land size and income facilitate the adoption of CSA practices. Land ownership increases the likelihood of farmers adopting strategies that capture the returns from their investment. Most of the training that they have received has been mainly through workshops, field day and group training.

SuruguM., et al (2019) studies the determinants of Climate Smart Agriculture (CSA) Adoption among Smallholder Food Crop Farmers in the Techiman Municipality, Ghana. The results indicate that the CSA practices implemented by most of the farmers include using personal experience to predict weather events, reliance on radio/television to access weather information, minimum tillage, use of organic manure and forestation. Economic, environmental, socio-cultural and institutional factors influenced CSA adoption.

Saha K., et al (2019) investigates factors affecting to adoption of climate-smart agriculture practices by coastal farmers in Bangladesh. Their results revealed that farmers mainly perform CSA practices to cope with the effects of climate change, such as salinity, floods, cyclones, storm surge, and droughts. The practices are saline tolerant varieties, submergence-tolerant varieties, drought resistant varieties, an early variety of rice, Sorjan method, pond side vegetable cultivation, watermelon cultivation, sunflower cultivation, plum cultivation, relay cropping, urea deep placement, organic fertilizer, mulching, rainwater harvesting, and seed storage in plastic bags. The logit model indicates that farmer’s level of education, occupation, family size, cultivated farm size, farming experience, cattle ownership, annual income, market difficulty, access to farm information, training experience, organization affiliation, and perception of climate change, all affect farmers’ selection of adaptation strategies for climate change.

Wamalwa W., (2017) undertake a study on the adoption of climate smart agricultural practices among small scale farmers of kitutu and nyaribarichache in kisii county, kenya. climate smart practices, adoption of climate smart practices was shown to be enhanced by higher income level, educational level, size of the farm, farming experience, knowledge of the practices, weather and climate information based on chi-square test results, which were within the significant level.

Gicheha1 G., et al (ND) conducted a study on advancing climate smart agriculture: adoption potential of multiple on-farm dairy production strategies among farmers in Murang'a County, Kenya. Their findings show interdependence of the strategies with complementarily and substitutionaly relationships among the practices. The interdependence can facilitate the tailoring of suitable packages of strategies which are interrelated to optimize their synergies. Capital, gender, water availability, market access and infrastructure and social networks were found to be the most important determinants of adoption decision as well as the intensity of adoption.

NyengereJ., (2015) in his study on socioeconomic factors affecting the adoption of use of organic manure as climate smart agriculture technology in Malawi. The findings showed that education, household size and income were significant at 0.05level of significance. Since education, total annual income and size of the household were said to influence use of organic manure then they deserve particular attention in developing plans and implementation of this climate smart agricultural technology.

2.3. Conceptual Framework

Based on the theoretical and empirical literature discussed in the aforementioned paragraphs, climate smart agriculture practice adoption is influenced by a multitude of determinants. To align the conceptual framework with the research objectives, adoption of climate smart agriculture practice is the dependent variable and the mentioned independent variables. The conceptual framework for this study showed in the following figure.

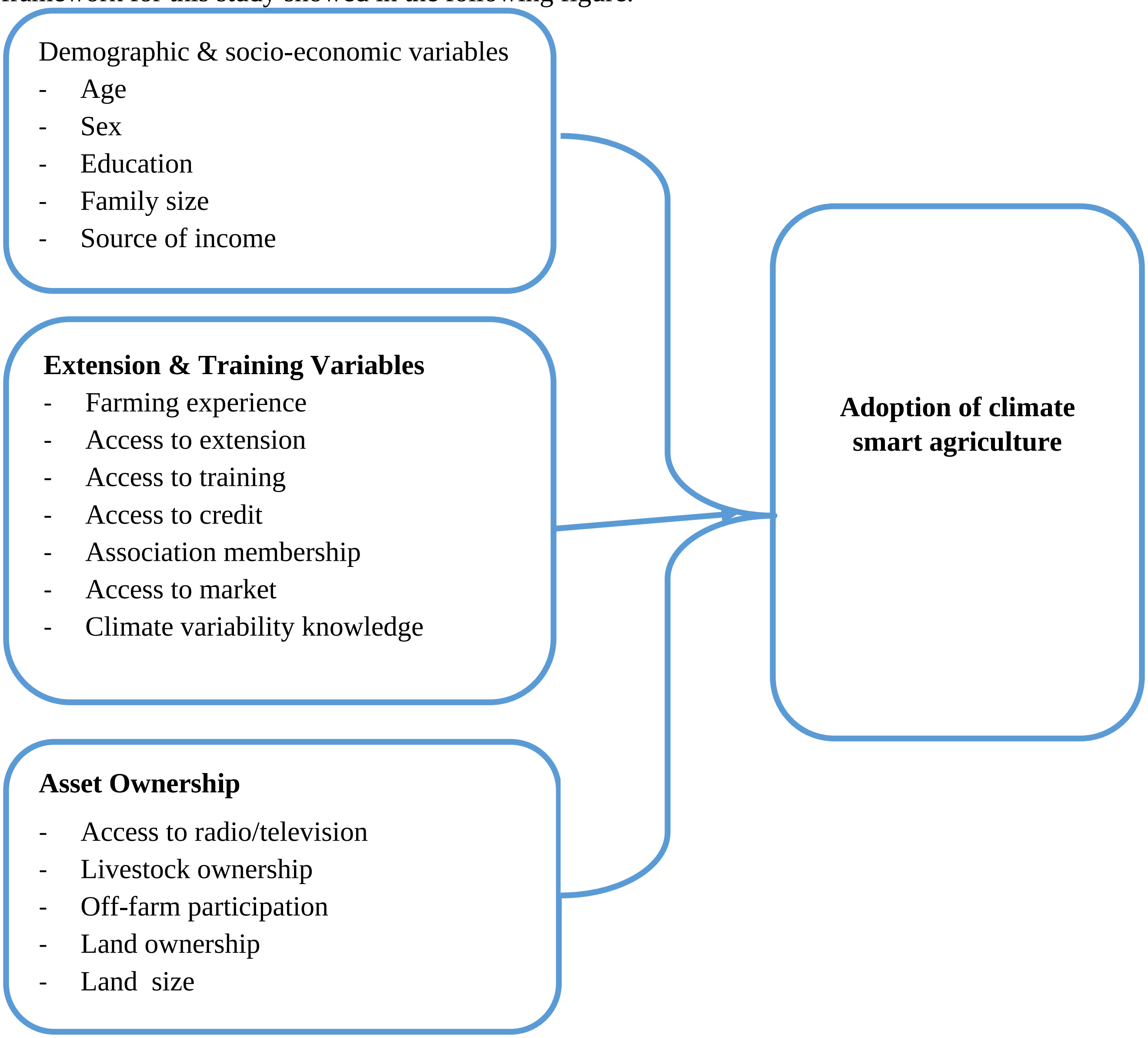


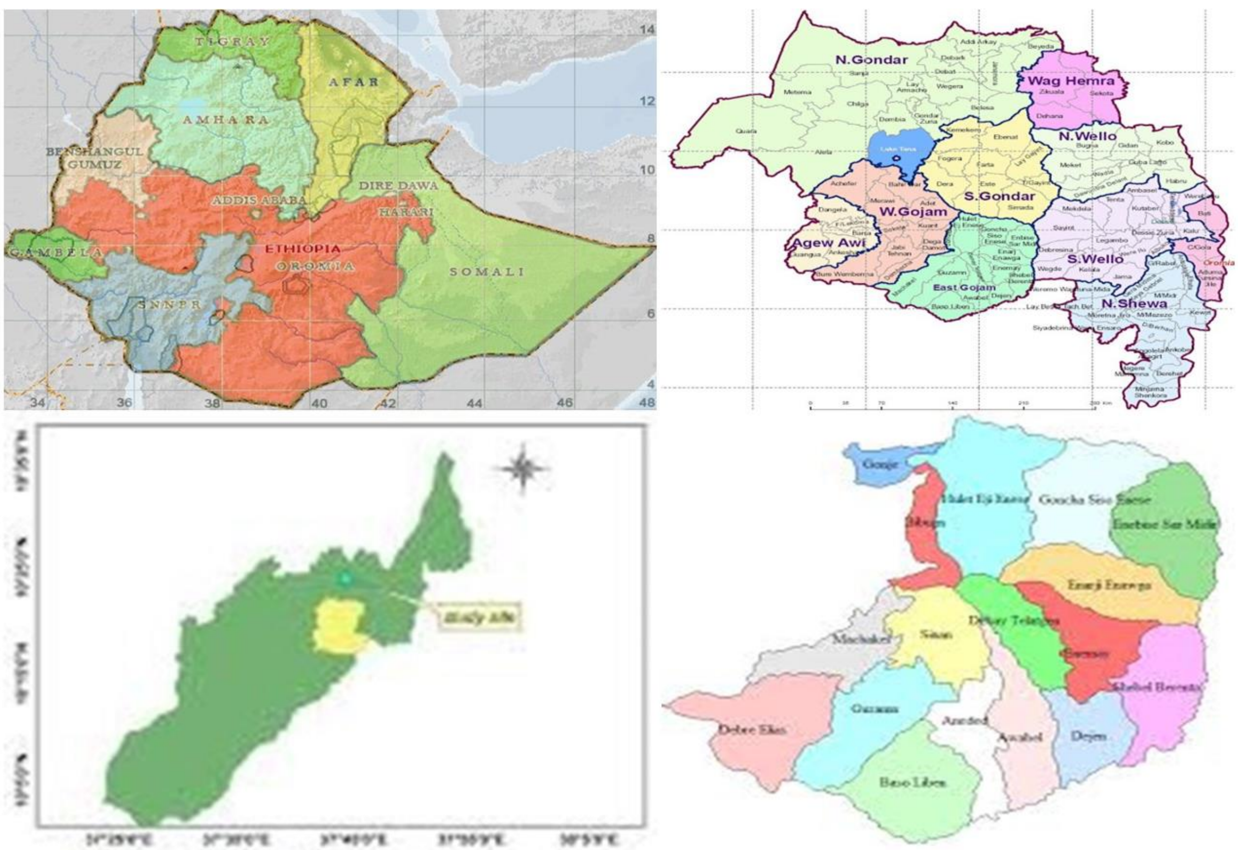
Figure: 2-1 Conceptual Framework Developed by the Researcher, (2021)

CHAPTER THREE: RESEARCH METHODOLOGY

This section elaborates the study area and methodological approaches that the researcher used to achieve the study objectives set in chapter one. Here, the research design as broad blue print that includes sampling procedure, the data source and instruments used, method of data analysis and interpretation, variables and model specification were presented here under in detail.

3.1. Description of the Study Area

According to GDoFED (2020) Gozamin district is found in Amhara national regional state, East Gojjam zone of north western part of Ethiopia, which is 270 km far from the regional capital Bahir Dar and 300 km far from Addis Ababa.



Source: Google Map

Figure: 3.1. Map of the study Area

The agro-climatic zone of the district varies from Kolla, WoinaDega and Dega. The annual rainfall of the Woreda varies from 1000–1510 mm per year. The mean minimum temperature for the district is 8.50C to mean maximum temperature of 300C.According to the census report made by CSA, 1994, the total population size of the district is about 1,700,331. The over whelming majority of the population in the district is living on Agriculture producing varieties of crops such as teff, cereals, oil seeds, pulses and rearing of livestock.

The woreda shares boundary with Debre Elias located to west,Sinan lies to the north, Aneded located to the east and finally Abay River to the south. The geographic location extends from 90 58.4 ½to 100 38 ½ North latitude and 370 24 ½to 370 54.6 ½ East longitude. Gozamin district has an aerial size of 1,800 km^2. The Woreda hosts a topographic variation that extends from 920 m.a.s.l to 3700 m.a.s.l, which forms the Choke Mountain range.

3.2. Research Design

This study used a survey research method since it is based on households' survey as a unit of analysis. Therefore, the study was conducted based on cross-sectional data collected by structured interview with the help of pre-tested questioners to identify assessment of determinants of climate smart agriculture practice adoption in Gozamin district.

3.3. Research Methods

3.3.1. Study Population and Sampling Frame

The study area, Gozamin district is selected purposively among 17 rural districts in East Gojjam Zone, because of my exposure to know the area well. According to GDoFED (2020) the district is divided by 25 rural administrative "kebeles" which has 25,184 households. Households are the smallest sampling units for this study and the heads of each household will be served as a target study population. The district is characterized by three agro-ecological zones (Dega, Woynadega and Kola). Thus, the three agro-ecological zones formed the base for three different clusters of "kebeles." Because, except agro-ecology differences, all rural kebeles of the district has almost similar characteristics in socio-economic and cultural practices. Out of these, one kebele from each agro-ecology cluster (i.e., Gedemala, Enerata and MayAngetam) are selected randomly, considering the time and cost limitations of the researcher. Thus, three kebeles selected randomly from each cluster with 3389 household heads formed the sample frame for this study.

3.3.2. Sample Size and Sampling Techniques

The probability and non-probability sampling techniques were used in this study. Simple random sampling technique was used from the probability sampling techniques to select three "kebeles" with a total of 3389 household heads. According to Yamane (1967) a simplified formula to calculate sample sizes assuming a 95% confidence interval and p = 0.05 level. Thus, the sample size was calculated as:

$$n = \frac{N}{1 + N(e)2} = \frac{3389}{1 + 3389(0.05)2} = 357$$

Where n is the sample size, N indicates the size of population, and e is the level of accuracy.

Since, the target population is less than 10,000 the desired sample size is adjusted using finite population correction formula. Because a given sample size provides proportionately more information for a small population. Thus, the sample size is adjusted as:

$$fn = \frac{n}{1+\frac{n-1}{N}} = \frac{357}{1 + \frac{357-1}{3389}} = 323$$

Where: fn = The adjusted sample size

n = The sample size which is 357

N= The target population size, which is 3389

Based on the sample size determination formula the sample size of the study is made to be 323 household heads. According to Bhattacherje (2012) systematic sampling technique involves a random start and then proceeds with the selection of every k^{th} household head from that starting point onwards (k = N/n), where k is the ratio of sampling frame size N and desired sample size n. Hence, this study used this method to select every 9^{th} household head from "kebele" name list in three "kebeles" until the total sample size of the study reached.

Further, key informants were selected for key informant interview from Gozamin District Agriculture office and East Gojjam Zone Department of Agriculture having deep information about the issues as a result of their official responsibility and professional role.

3.3.3. Data Sources and Data Collection Instruments

The study used both primary and secondary sources of data using different data collection instruments that enabled to achieve the objectives of the study. The primary data was collected from sample household heads and key informants in the study area of Gozamin District. The study used structured questionnaires and key informant interview guidelines as a data collection instrument.

Structured interview questionnaire was prepared and translated to Amharic which is the local language in the study area. These techniques were used to collect cross sectional data from primary sources which are administered by the interviewers in the district who take research course under close supervision of the researcher. The interviewers were well oriented by the researcher and familiarized on the interview process, purpose of the study and how to approach the respondents ethically to generate the right and consistent data.

Key Informant Interview was held with district and zonal agriculture development experts, coordinators and head of the office. This enabled the researcher to get qualitative data to explain the adoption of climate smart agriculture practice. Secondary data was also the other source to collect data from published and unpublished materials (like; sectoral reports, previous researches and regulations) in relation to this study were reviewed well.

3.3.4. Methods of Data Analysis

The collected data was analyzed by using qualitative and quantitative methods. The qualitative analysis was used to present results from the key informant interview and some results from questionnaires asking about reasons and justifications. It was presented in the form of narrations and statements to support the findings of the study. On the other hand, the statistical analysis was taking a form of descriptive and inferential statistics. The descriptive statistics was presented as frequency, percentage, tables, mean and standard deviation to describe the socio-economic characteristics of respondents.

The inferential statistics were used to identify the determinants of adoption of climate smart agriculture. Binary logistic regression was employed to estimate the level of determination of demographic and socio-economic variables on the dependent variable. Then the collected data was entered, cleaned and analyzed using STATA data analysis tool.

3.3.5. Model Specification

The dependent variable in this study is adoption of climate smart agriculture which was measured as a binary outcome. Adoption of climate smart agriculture practice is a dichotomous variable, best measured in terms of adopter and non-adopter by the households. According to Thangata et al. (2007) and Lehmann et al., (1998) climate-smart agriculture includes proven practical techniques like mulching, intercropping, conservation agriculture, soil and water conservation, crop rotation, integrated crop livestock management, agroforestry, improved grazing, and improved water management. Therefore, in this study a respondent who adopt one of these technologies was considered as adopter of climate smart agriculture. Thus, in order to identify determinants of the adoption of climate smart agriculture practices, binary logistic regression model was used. This model is a statistical technique for predicting the probability of an event, given a set of predictor variables.

The effect of predictor variables is usually explained in terms of odds ratio and hence the name logistic regression, also called the log-odds function. This model applies maximum likelihood estimation after transforming the dependent in to a logit variable. Binary logistic regression is one part of logistic regression which is predictive model that can be used when the outcome variable is categorical variable with two choices and the independent variables are of any type.

Binary logistic regression has other application of combining the dependent variables to estimate the probability that particular event will occur, that is a subject which was a member of one of the groups defined by the dichotomous dependent variable. Due to the above-mentioned issues, the binary logistic model of adoption of CSA in this study is specified as:

$$P_i = \frac{e^{\beta_o+\beta_1 X_1+\cdots+\beta_k X_k}}{1+e^{\beta_o+\beta_1 X_1+\cdots+\beta_k X_k}} = \frac{e^{X'\beta}}{1+e^{X'\beta}}$$

Where, P_i = is the probability of adoption. Hence, the logit transformation of P_i given as follows:

$$logit(P_i) = log\left(\frac{P_i}{1-P_i}\right) = \beta_o + \beta_1 X_1 + \cdots + \beta_k X_k$$

Where

P_i: *Is the probability of adoption*

β_0: *Is the intercept term*

β_i: *The coefficient of xi*

X_i: *Are the explanatory variables*

A binary logistic regression model used to determine the relationship between a dichotomous dependent variable and a group of predictor variables. More formally, let **y** be the binary outcome variable indicating adopter or non-adopter with one or zero and p be the probability of y to be one,

$$P = prob\ (y = 1).$$

Let x1... x10 be a set of predictor variables. Then the logistic regression of y on x1... x10 estimates parameter values for β0, β1. . . β10 via maximum likelihood method of the following equation.

$$logit(p) = \log\ (p/(1-p)) = B_{0+}\ B_1 * X_1\ + \cdots + B_{10} * X_{10}$$

Given the above stated model of binary logistics, the likelihood of the farmers to adopt CSA is given by the expression$p_i = \frac{1}{1-e^{-z_i}}$ where $z_i = \beta_1\ +\ \beta_2 X_i$while the probability of not adopting climate smart agriculture is given as $1 - p_i = \frac{1}{1 + e^{z_i}}$. Hence, the log of the odds ratio is the natural log of the two probabilities i.e. $(\frac{p_i}{1-p_i})$ (Gujarati, 2004).

The independent variables in this study are identified based on the existing empirical literatures and actual conditions in the study area which are useful to explain the dependent variable.

Table 3.1: Definition of Variables and their Expected Signs

Variables	Definition of variables	Measurement	Expected sign
Dependent variable			
Adoption of CSATechnology	Farmer's adoption of climate smart agriculture (1, if yes, otherwise 0)	Binary	
Independent Variables			
Age	Age of the respondent in years	Continuous	+
Sex	Sex of the household head	Binary	+
Education level	Year of schooling	Categorical	+
Family size	Number of family members in the household	Continuous	+
Off farm income	Participation in non-farm activities	Dummy	-
Land size	The amount of land size in hectare	Continuous	-
Access to extension	Access to agriculture extension service	Categorical	+
Access to credit	Household heads access to credit from financial institutions	Categorical	+
Climate variability	Farmers perception on climate variability	Ordered	+
Source of income	The main income source of the household	Categorical	-
Farming experience	Farming experience in year	Continuous	-
Access to training	Access to agriculture related trainings	Binary	+
Access to market	Access to market for products	Binary	+
Livestock ownership	Household heads livestock ownership	Binary	-
Land ownership	Household heads land use right certificate	Binary	+
Membership	Agricultural association membership	Binary	+
Distance	Distance from home to farmland	Continuous	-
Radio/Television	Radio/TV ownership of the household	Binary	+

Source: Derived from literature review, 2021

3.4. Reliability and Validity of the Instruments

The reliability of the questionnaires used in the study was assured through critical and successive review of this instrument for data collection by academicians where relevant changes and additions were made where necessary. On the other hand, to assure validity, questionnaires were designed on the basis of previous studies' questionnaires and review of related literatures and objective realities of the study area. Furthermore, to make the instruments even more suited to the rural household in the study area. In addition, a pilot test was conducted by some sample questioners to refine the methodology before administering the final data collection. The structured questionnaires were tested on potential respondents to make the data collecting instrument's objective, relevant, suitable to the problem and reliable.

3.5. Ethical Considerations

The study tried to keep the data collection effort in line with ethically acceptable guideline. First, the researcher got a written consent of the concerned agriculture institution. Added to this, all participants included in the study were duly informed about the purpose of the study and their willingness was secured before filling up the questionnaire and conducting key informant interview. The study also maintained the confidentiality of the identity of each participant.

CHAPTER FOUR: RESULT AND DISCUSSION

4.1. Introduction

This segment presents the thesis result and discussion of the study in line with objectives set in chapter one of this study. The first part of this chapter presents the results on respondents' characteristics, summary statistics of main variables using descriptive statistics and qualitative support. Moreover, the appropriateness test of the model is presented before getting into the parts presenting binary logistic regression model estimation results. The main part of this chapter presents the results from estimation of the econometrics models of adoption of climate smart agriculture, where significant predictors of adoption of climate smart agriculture are identified and discussed coherently with relevant findings of other studies.

4.2. Results of Descriptive Statistics

4.2.1. Demographic and Socio-Economic Characteristics

The study surveyed a total of 323 sample respondents through interview questionnaires which makes the response rate for the study to be 100% without default from the expected sample size. The results presented in this study are based on this number of sample respondents from the study area. Looking first to the age of respondents, Table 4.1.Shows that, the average age was 38.22 years with standard deviation of 9.44 from the mean age of the respondents. The result indicated that most of the respondents of the study were adults given the mean value of age with its average variation. When the age variation is considered, the respondents have a huge difference in their age where the minimum age was 26 years while the maximum respondent is aged 68. The wide gap in age between sampled respondents enables to better understand the adoption of climate smart agriculture practice among households of different age level.

Table 4.1. Respondent's age and family size characteristics

Variable	Obs	Mean	Std. Dev.	Min	Max
Age	323	38.22291	9.442528	26	68
FamSize	323	4.294118	1.157019	3	6

Source: 2021 field survey

The results in Table 4.1 also indicates that, the average family size of respondents was 4.29 members with standard deviation of 1.15 from the mean family size of the respondents. The result indicated that most of the respondents of the study have nuclear family given the mean value of family size with its average variation. When the family size variation is considered, the respondents have a reasonable difference in their family size where the minimum family size was 3 members while the maximum respondent family sizes are 6 members. The reasonable gap in family size between sampled respondents enables to better understand the adoption of climate smart agriculture practice among households.

The estimation result in Table 4.2 on the sex of respondents indicates that the highest proportion in this study is contributed by male respondents which makes (80.19%) of the total sample respondents, whereas female respondents have a lesser contribution, which accounts (19.81%). The resulting data from respondents also gives a clue that the majority of male household heads tend to engage in the outside works of agricultural practice.

Table 4.2. Respondent's sex and education characteristics

Variable	Freq.	Percent	Cum.
Sex			
Female	64	19.81	19.81
Male	259	80.19	100
Total	323	100	
Education			
No formal schooling	153	47.37	47.37
Grade 1-8	78	24.15	71.52
Grade 9-12	58	17.96	89.47
TVET Diploma and above	34	10.53	100
Total	323	100	

Source: 2021 field survey

Further, on educational qualification of respondents of the study, the result in Table 4.2 shows that most of the participants (47.37%) have no formal schooling followed by primary school attendants, which account (24.15%) as a manifestation of how much as the household heads are less involved to adopt the technologies of climate smart agriculture. The key informant interview with the locality government experts also supported this argument that low level of formal education is a hurdle to adopt climate smart agriculture. On the other hand, respondents who have secondary school and college level and above educational status accounts (17.96%) and (10.53%) respectively.

Table 4.3. Distribution of the respondent's source of income

Variable	Freq.	Percent	Cum.
Source of income			
Crop production	181	56.04	56.04
Livestock rearing	2	0.62	56.66
Non-farm income	5	1.55	58.2
Mixed	135	41.8	100
Total	323	100	

Source: 2021 survey

The resulting distribution on the sources of income of the respondents show that, (56.04%) are engaged in crop production for their income, (41.8%) of the respondents are engaged in mixed agricultural activity. Whereas, (0.62%) and (1.55%) of the respondents in the study area are engaged in livestock rearing and non-farm income respectively.

4.2.2. Types of the Adopted Climate Smart Agriculture Practice

The classification of types of climate smart agricultural practices into different types in the study area is based on the literatures reviewed and manuals for climate smart agricultural development practice. The resulting distribution show that, climate smart agriculture practices: crop rotation(25.53%), inter-cropping (20.57%), soil and water conservation (16.31%), organic fertilizer (15.6%), agroforestry (8.51%), mulching (4.96%), improved grazing (4.26%), improved seed (2.13%) were adopted by the respondents in the study area.

Table 4.4. Distribution of types of climate smart agriculture practice adopted by respondents

types of CSA practiced	Freq.	Percent	Cum.
soil and water conservation	23	16.31	16.31
using organic fertilizer	22	15.6	31.91
inter cropping	29	20.57	52.48
Agroforestry	12	8.51	60.99
crop rotation	36	25.53	86.52
Mulching	7	4.96	91.49
improved grazing	6	4.26	95.74
improved seed	3	2.13	97.87
improved water management	2	1.42	99.29
Others	1	0.71	100
Total	141	100	

Source: 2021 field survey

Further, the least majority of respondents, accounts (1.42%) and (0.71%) adopted improved water management and other climate smart agriculture technologies respectively.

4.2.3. Extension Service and Training Characteristics

The descriptive summary statistics result on extension service and training characteristics of the respondents, as presented in table 4.5 show that the farm experience of households, the mean length of farm experience was 20.46 years with standard deviation of 8.00 from the mean length of farm experience of the respondents. The result indicated that most of the respondents have a relatively long period of stay in practicing farming, given the mean value of length of farm experience with its average variation. The minimum year of farm experience is 3 years, whereas the maximum year of farm experience was 35 years in the study area.

Table 4.5. Respondent's farm experience and land size

Variable	Obs	Mean	Std. Dev.	Min	Max
Farm Experi~e	323	20.4644	8.000842	3	35
Distance	323	1.294427	0.666943	0.1	2.6
Land Size	323	0.939412	0.594084	0.2	2

Source: 2021 field survey

Further, the result on distance of respondents from their home to farm land shows that, the mean distance was 1.29 kilometer with standard deviation of 0.66 from the mean distance of the respondents. The result indicated that most of the respondents have a reasonable distance from their farm land given the mean value of its average variation. The minimum distance was 0.1 kilometer while the maximum distance was 2.6 kilometers from their home to farm land. The gap in distance between sampled respondents enables to observe the adoption of climate smart agriculture practices among households.

Further, the result in table 4.6 from summary statics on the extension service show that, (43.03%) of the respondents have access to extension service. Whereas, (56.97%) of the respondents have no access to extension service. The result is supported by the findings of key informant interview, in which inconsistent and/or absence of extension service is creates a gap to accelerate the adoption rate of climate smart agriculture in the study area.

Table 4.6. Distribution of respondent's access to training, extension service, access to market, Access to credit and membership of agricultural association.

Variable	Freq.	Percent	Cum.
Access to training			
No	186	57.59	57.59
Yes	137	42.41	100
Total	323	100	
Extension Service			
No	184	56.97	56.97
Yes	139	43.03	100

Total	323	100	
Access to market			
No	123	38.08	38.08
Yes	200	61.92	100
Total	323	100	
Membership Asso			
No	194	60.06	60.06
Yes	129	39.94	100
Total	323	100	
Access to credit			
No	193	59.75	59.75
Yes	130	40.25	100
Total	323	100	

Source: 2021 field survey

Looking to the variable access to credit in table 4.6 above shows that, 40.25% of the respondents have access to credit service from financial institutions, whereas the vast majority of respondents contributing (59.75%) have no access to credit service. The result indicates that most of the respondents have no sufficient access to finance from financial institutions to engage in non-farm sectors and to adopt and expand climate smart agriculture technologies.

The result of descriptive statistics on the variable access to training indicates that, (42.41%) of the respondents have access to training on agricultural development (including climate smart agriculture) practice. Whereas, the rest 59.59% of the respondents have no access to agricultural trainings. The result indicates that most of the respondents are not trained to create fertile ground for climate smart agriculture in the study area.

The result from descriptive statistics table 4.6 shows that, only 39.94% of the respondents are members of the rural agricultural associations in the study area. While most of the respondents are not member in any of the agriculture associations, which accounts (60.06%) of the total respondents.

According to the result from the descriptive statistics table 4.6 above , most of the respondents have access to market for their agricultural products, which accounts (61.92%) of the respondents. On the other hand (38.08%) of the respondents have no access to nearby market for their agricultural products. The result indicates that most of the respondents are living in the far rural marginalized areas with no market infrastructure.

4.2.4. Asset Ownership Related characteristics

The descriptive result on asset ownership related characteristics of the respondents is presented in table 4.7 as follows. Looking to landholding (79.26%) of the total sampled respondents have certified land use right, where as the rest (20.74%) have no land use right, who use land by rent and share cropping contracted from those who have land use ownership right and from their parents.

Table 4.7. Respondents land holding right, non farm income, livestock ownership and information characteristics

Variable	Freq.	Percent	Cum.
Landholding right	S		
No	67	20.74	20.74
Yes	256	79.26	100
Total	323	100	
Non-farm income			
No	230	71.21	71.21
Yes	93	28.79	100
Total	323	100	
Livestock ownership			
No	73	22.6	22.6
Yes	250	77.4	100
Total	323	100	
Owning radio/television			
No	83	25.7	25.7

Yes	240	74.3	100
Total	323	100	

Source: 2021 field survey

In the above Table 4.5 looking to the land size of respondents, the average land size was 0.93 hectares with standard deviation of 0.59 from the mean land size of the respondents. The result indicated that most of the respondents have less than a hectare of land given the mean value of its average variation. Considering the variation, respondents have a huge difference in their land size where the minimum land size was 0.2 hectare while the maximum respondents have 2 hectares of land. The clear difference in land size between sampled respondents enables to better understand the adoption trends of climate smart agriculture among households.

According to table 4.7above, A smaller number of respondents are participating in non-farm income generating activities contributing about (28.79%) of the total sampled respondents while the majority of the proportion belongs to non-participants in non-farm income generating activities, which are (71.21%).

Moreover, the result in the above table 4.7 show that most of the respondents (77.4%) are the owners of livestock assets. On the other hand, the rest (22.6%) of the respondents have no livestock assets.

Moreover, the summary result from descriptive statistics shows that, majority of the respondents have radio or television, which accounts (74.3%) of the respondents. Whereas, (25.7%) of the respondents have no radio or television. From the result we can understand that most of the respondents have access to information including climate change and climate agriculture through radio or television.

Based on the result observed from Figure 4.1 that the majority of the respondents (49.85%) and (17.03%) agree and strongly agree on climate variability in the study area respectively. This clearly manifested that most of the respondents agree and perceive that climate variability is there is the study area. On the other hand (21.98%) and (7.12%) of the respondents disagree and strongly disagree on the existence of climate variability respectively. The rest of the respondents (4.02%) of the respondents are in a neutral category.

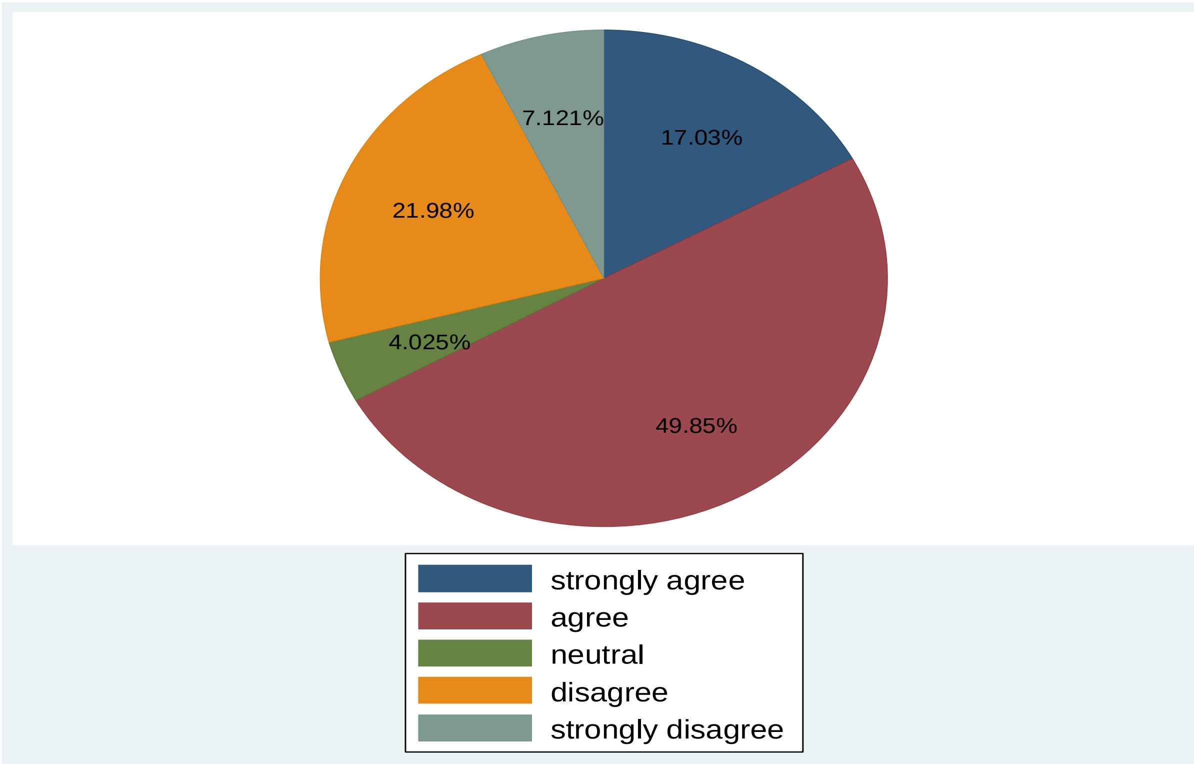


Figure 4.2.4-1 Climate variability perception category of participants computed from STATA

Source: 2021 field survey

Findings from key informants reveal that, farmers have good awareness on climate variability in the study area. They mention deforestation, soil erosion and degradation and extinction of wet-lands are the major problems that affect climate variability in the study area. Sustainable Land Management (SLM), Integrated Soil Fertility Management in Africa (ISFM), Livestock and Fisheries Sector Development Project (LFSDP), Green Innovation Center (GIC), Sasacawo Global (SG) are among the projects that support the area in relation to climate smart agriculture. According to the key informants the annual productivity of their land increases when they adopt climate smart agriculture technologies.

4.3. The Adoption Level of Climate Smart Agriculture

The descriptive statistics result on the respondent's adoption distribution of climate smart agriculture in table 4.8 show that the least majority of respondents adopted climate smart agriculture in the study area.

Table 4.8. Distribution of respondents CSA adoption and distance from their farm land

Variable	Freq.	Percent	Cum.
Adoption of CSA			
No	183	56.66	56.66
Yes	140	43.34	100

Source: 2021 field survey

The descriptive statistics result in Table 4.8 on the respondent's adoption of climate smart agriculture practice indicates that (43.34%) of the respondents adopted climate smart agriculture. On the other hand (56.66%) of the respondents are not adopters of the climate smart agriculture in the study area. The key informant was also supporting this finding of low status of climate smart agriculture adoption.

4.4. Results of the Econometric Model

4.4.1. Goodness Fit of Binary Logistic Regression

The goodness of fit of a model measures how well the model describes the response variable. Assessing goodness of fit involves investigating how close values predicted by the model are to the observed values. The appropriateness of the fitted logistic regression model needs to be examined before it is accepted for use as in the case of all regression models.

The validity of inferences drawn from modern statistical modeling techniques depends on the assumptions of the statistical model being satisfied. In order for the analysis to be valid, our model has to satisfy the assumptions of binary logistic regression, such as: logistic regression requires the dependent variable to be dichotomous. The dependent variable is binary outcome taking 1 for adoption of climate smart agriculture and 0 for those not adopted. Larger samples are needed than for those in linear regression analysis. A minimum of 50 cases per predictor is recommended for logistic regression. Here in this study 323 sample respondents are involved. There should be no high multi co linearity among the predictor variables. We do not have one unique method of detecting it or measuring its strength, but there are some rules of thumb. For instance, variance inflation factor test used to check the existence of the problem.

4.4.2. Result of Binary Logistic Regression Analysis

Binary logistic regression is used to analyze relationships between a dichotomous dependent variable and independent variables. Logistic regression combines the independent variables to estimate the probability that a particular event will occur. In this study, logistic regression was performed to assess the effect of independent variables on the adoption of climate smart agriculture among rural households. The result of the binary logistic regression obtained from the STATA output is given in Table 4.9 which displays the coefficient, standard error, significance level and confidence interval.

Therefore, this study used a binary logistic regression model to estimate the parameters of determinants of the adoption of climate smart agriculture. The estimated model coefficients cannot be interpreted directly but they tell us much about the direction and significance of the predictor variables. Hence, in this study the determinants are identified by using the coefficients, while the magnitude of influence is expressed using the odds ratio.

Table 4.9. Determinants of the adoption of climate smart agriculture in the study area

Logistic regression			Number of obs	=	323
			Wald chi2(19)	=	114.11
			Prob > chi2	=	0.000
Log pseudo likelihood	=	-34.8923	Pseudo R2	=	0.8421

		Robust				
Adoption	Coef.	Std. Err.	Z	P>z	[95% Conf.	Interval]
Age	0.030492	0.039964	0.76	0.445	-0.04783	0.108819
Sex	1.061238	0.560473	1.89	0.058	-0.03727	2.159744
Edu						
Grade 1-8	2.07702	0.977968	2.12	0.034	0.160239	3.993801
Grade 9-12	2.612697	1.011426	2.58	0.010	0.630339	4.595055
Diploma and above	0.318006	0.763008	0.42	0.677	-1.17746	1.813474
FamSize	0.579015	0.456753	1.27	0.205	-0.3162	1.474234

LivestockHolding	-1.72832	0.967466	-1.79	0.074	-3.62452	0.167875
farmExperiance	-0.02782	0.037051	-0.75	0.453	-0.10044	0.044802
LandSize	-2.10685	0.795414	-2.65	0.008	-3.66583	-0.54786
CVariability	0.162095	0.31734	0.51	0.609	-0.45988	0.78407
Extension	5.928385	0.980616	6.05	0.000	4.006413	7.850358
NonAgriIncome	-1.16949	0.790107	-1.48	0.139	-2.71808	0.379089
Credit	1.418885	0.747722	1.9	0.058	-0.04662	2.884392
Training	5.740284	1.106676	5.19	0.000	3.571239	7.909328
Land_holding	-0.5847	0.75494	-0.77	0.439	-2.06435	0.894958
Distance	-0.01978	0.473116	-0.04	0.967	-0.94707	0.907507
AccessMarket	0.938568	1.425282	0.66	0.510	-1.85493	3.732069
MembershipAsso	0.332662	0.800496	0.42	0.678	-1.23628	1.901605
Radio_TV	0.613912	1.358397	0.45	0.651	-2.0485	3.27632
_cons	-8.04326	2.447039	-3.29	0.001	-12.8394	-3.24716

Source: 2021 field survey

Based on the binary logistic regression result, looking first at the variable sex, the estimated binary logistic regression coefficient shows that sex of the respondents significantly affects the adoption of climate smart agriculture in a positive direction. The regression result indicated that being male increases the likelihood of adopting climate smart agriculture among respondents, which is significant at 95% confidence interval. The positive effect may be because of the male exposures to practice agricultural practices.

Further, the estimated logistic regression coefficients shows that education level (grade 1-8 and grade 9-12) significantly affects the adoption of climate smart agriculture in a positive direction. The regression result indicated that joining grade 1-8 and grade 11-12 increases the likelihood of adopting climate smart agriculture among respondents which is significant at 95% confidence interval. The positive effect of education may be attributed to the increased understanding of environmental degradation and climate change problems compared to those of the respondents with no formal schooling.

On the other hand, the estimated logistic regression result coefficient show that land size significantly determines the adoption of climate smart agriculture among farmers in a negative direction. As the land size of the farmers increases the likelihood of adopting climate smart agriculture decreases among respondents which is significant at 95% confidence interval. The negative direction may be because of the farmer's wrong perception on the large size of their holding make them less concerned to climate change issues.

Further, the estimated binary logistic regression result coefficient indicates that access to extension service significantly and positively determines the adoption of climate smart agriculture among farmers. Thus, when the farmers have access to extension service, the likelihood of adopting climate smart agriculture increases among respondents which is significant at 99% confidence interval. The positive effect may be because of the extension service empowers the individual farmers attitude and awareness on climate smart agriculture.

Moreover, the estimated logistic regression coefficient indicates that credit significantly determines the adoption of climate smart agriculture among farmers in a positive direction. When farmers have access to credit from financial institutions, their likelihood of adopting climate smart agriculture increases among respondents which is significant at 95% confidence interval. The positive direction may be because of farmer's financial capacity to practice better and environmentally friendly agricultural technologies.

Finally, the estimated logistic regression result coefficient indicates that access to training significantly affects the adoption of climate smart agriculture in a positive direction. When farmers have access to training, their likelihood of adopting climate smart agriculture increases among respondents which is significant at 99% confidence interval. The positive direction may be because of the farmer's skill and enhanced capacity.

As the binary logistic regression model revealed in Table 4.10 below, sex, educational status, land size, access to extension service, access to credit and training are found to be significant in determining the probability of farmers to adopt climate smart agriculture. We can interpret odds ratio in terms of the change in odds. If the value exceeds one, then the odds of success (being adopter) is increases, if the value is less than one, any increase in the predictor variables leads to a minimize in the odds of adoption of climate smart agriculture. The odds ratio gives the relative amount by which the odds of the outcome increase (if odds ratio >1) or decrease (if odds ratio<1) when the value of predictor is increased by 1 unit. Therefore, odds ratio was computed to be used in order to show the magnitude of determination of independent variables on the dependent variable the adoption of climate smart agriculture practice. Based on this, the binary logistic regression result displayed the proportional odds ratio as presented in Table 4.10: below.

Table 4.10. Determinates of adoption of CSA using odds Ratio

Logistic regression			Number of obs	=	323
			Wald chi2(19)	=	114.11
			Prob > chi2	=	0
Log pseudolikelihood	=	-34.8923	Pseudo R2	=	0.8421

		Robust				
Adoption	Odds Ratio	Std. Err.	Z	P>z	[95% Conf.	Interval]
Age	1.030962	0.041201	0.76	0.445	0.953291	1.114961
Sex	2.889946	1.619736	1.89	0.058	0.963417	8.66892
Edu						
Grade 1-8	7.980647	7.804814	2.12	0.034	1.173791	54.26072
Grade 9-12	13.63578	13.79157	2.58	0.010	1.878247	98.99356
Diploma and above	1.374384	1.048666	0.42	0.677	0.30806	6.131713
FamSize	1.784281	0.814975	1.27	0.205	0.728911	4.367691
LivestockHolding	0.177582	0.171804	-1.79	0.074	0.026662	1.182788
farmExperiance	0.972566	0.036035	-0.75	0.453	0.904443	1.045821
LandSize	0.121621	0.096739	-2.65	0.008	0.025583	0.578183
CVariability	1.175971	0.373183	0.51	0.609	0.631359	2.190368
Extension	375.5476	368.2681	6.05	0.000	54.94939	2566.653
NonAgriIncome	0.310524	0.245348	-1.48	0.139	0.066002	1.460952
Credit	4.13251	3.089967	1.90	0.058	0.954448	17.89269
Training	311.1527	344.3451	5.19	0.000	35.56064	2722.561
Landholding	0.557275	0.420709	-0.77	0.439	0.1269	2.447233
Distance	0.98041	0.463848	-0.04	0.967	0.387874	2.478136

AccessMarket	2.556317	3.643472	0.66	0.510	0.156463	41.76541
MembershipAsso	1.394676	1.116432	0.42	0.678	0.290463	6.696635
Radio_TV	1.847645	2.509834	0.45	0.651	0.128929	26.47816
_cons	0.000321	0.000786	-3.29	0.001	2.65E-06	0.038885

Source: 2021 field survey

The predicted result of the binary logistic regression indicted that holding other factors constant, being male increases the odds of adoption of climate smart agriculture, compared to the based category being female. Thus, being male increases the odds of adopting climate smart agriculture by 2.88 times. This may be because of the male dominancy in the rural areas in practicing the agricultural activities and socio-economic exposures to practice climate smart agricultural practices. The result is in line with the findings of Francis M. et al., (2017); Tran N. et al., (2019); Belay et al., (2017) and Ndambiri H. et al., (2019), they found that sex of the respondent was the significant determinant for the adoption of climate smart agriculture.

Further, the predicted result from binary logistic regression indicted that holding other factors constant, going from no formal schooling to primary school (1-8) increases the odds of adopting climate smart agriculture practice by 7.98 times, compared to those who have no formal schooling. In addition, when educational status of the respondents going from no formal schooling to secondary school (9-12), it increases the odds of adopting climate smart agriculture practice by 13.63 times, compared to those who have no formal schooling. This may be because of the power of formal education in increasing the awareness of farmers in understanding changes in their physical environment. The result is in line with the findings of Francis M et al, (2017);AbegundeV. et al, (2019); Belay et al, (2017) and Wamalwa W., (2017) found that level of education as a significant factor on the adoption of climate smart agricultural practice among household heads.

The result revealed that assuming all other factors remains constant, a unit increase in land size of the respondents decreases the adoption of climate smart agriculture practice by 0.12 times. This may be because of the farmer's view that of their land as large enough and poor awareness on climate change. This result is in line with the result of study conducted by Francis M et al, (2017); Abegunde V. et al, (2019); Belay et al, (2017) and Ndambiri H. et al (2019), argue that size of farm land as a major determinant for the adoption of climate smart agricultural practices.

Moreover, the logistic regression results displayed in Table 4.10 show that, assuming all other factors remains constant, getting access to extension service increases the probability of adopting climate smart agriculture practice by 375 times. The possible explanation for this might be access to extension service gives an insight to climate smart agriculture and extension service provision of knowledge and practice. The result is in line with the findings of Abegunde V. et al, (2019) and Belay et al (2017) they argue that access to extension service has a significant positive effect on the adoption of climate smart agriculture practice.

The other regression result revealed that assuming all other variables remains constant; the access to credit increases the odds of adopting climate smart agriculture by 4.13 times compared to those who have no access to credit from financial institutions. This might be because of the farmer's financial capacity to exercise climate smart agriculture technologies. This result is in line with the findings of Francis M. et al, (2017) and Zakari S. et al (2019) who found that access to credit has a significant and positive effect on the adoption of climate smart agriculture.

Finally, the binary logistic regression result show that, assuming all other variables remains constant, the access to training increases the odds of adopting climate smart agriculture by 311 times compared to those who have no access to training on the agricultural sector. This might be because of the farmer's understanding and knowledge on climate change and environmental degradation. Evidence from key informant interview also indicated that there is a problem of getting right training on climate smart agriculture. This result is in line with the findings of Zakari S. et al, (2019) and Maharjan S. et al (2018) argue that farmers who have access to training on agricultural development have significant and positive effect on the adoption of climate smart agriculture practice.

CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

From the binary logistic regression, different factors were identified on the adoption of climate smart agriculture practice in the study area Gozamin District. To give conclusions about the determinants of the adoption of climate smart agricultural practice, the researcher combined both descriptive and inferential analysis results together. The researcher focused on the mean values of continuous variables and percentages of the categorical response variables besides with key informant result to identify the determinants determining the adoption of climate smart agricultural practice.

In the descriptive part of the study the result showed that the least majority of respondents adopted climate smart agriculture practice, whereas most of the respondents are found to be non adopters. From the resulting distribution this study can conclude that, among the climate smart agriculture practices: the respondents adopted crop rotation, inter-cropping, soil and water conservation, organic fertilizer, agro-forestry, mulching, improved grazing, improved seed are in the study area. Thus, based on the study findings crop rotation, inter-cropping, soil and water conservation and organic fertilizer are the most adopted CSA practices in the study area.

The study can conclude that, male's participation in adopting climate smart agriculture practice is too dominant compared to females. The observed dominance of male adopters is partly associated with the long-time superiority of men in the rural economic activities including agricultural and resource management. The average age of the respondents is 38 years, which is dominated by adult household heads. Most of the participants have no formal schooling. From the result the study can conclude that less than half of the respondents have access to agriculture extension and training services on climate smart agriculture. Evidence from key informant interview also indicated that there is a problem of getting right training and extension especially related climate smart agriculture.

From the binary logistic regressions, the study can conclude that sex, educational (grade 1-8 and grade 11-12), extension service, credit and training have a significant and positive effect on the adoption of climate smart agriculture. Thus, the increase in these variables results in increases the likelihood of adopting climate smart agriculture in the study area.

On the other hand, land size has a significant and negative effect on the dependent variable adoption of climate smart agriculture. The increase in this independent variable undervalued the likelihood of adoption of climate smart agriculture among farmer households. Considering the results of odds ratio, the increase in this independent variable, the likelihood of farmer households to adopt climate smart agriculture decreases.

5.2. Recommendations

Based on the conclusion reached above this study suggests the following recommendations as per the findings of the cross-sectional study. Thus, the following recommendations are suggested for district level government actors and stakeholders to improve the adoption status of climate smart agriculture practice.

Joint effort is needed among the agriculture sector institutions and concerned stakeholders as well as non-governmental organizations with full involvement of the practitioner farmers to improve and enhance the adoption status of climate smart agriculture practices.

Increasing the gender mainstreaming activities is needed to bring participate more women into the adoption of climate smart agriculture. Education should be enhanced that increases the level of knowledge of farmer households to raise their likelihood of adoption of climate smart agriculture practice. Further, the study recommends that the variable access to extension service is crucial for the adoption of climate smart. Therefore, the district should continue supporting farmers in demand driven extension service to enhance climate smart agriculture and promote sustainable agriculture in the country.

Since access to credit was found as a significant factor to adopt climate smart agriculture, finance institutions need to have system to lend for climate smart agriculture technologies. This should be supported by government policies and guidelines.

As the finding revealed that the variable access to training is crucial for the adoption of climate smart agriculture. Therefore, the agricultural sector in general and the district in particular should continue and strengthen trainings on climate smart agriculture practices in order to contributing to green development strategy of the country. On the other hand, widespread awareness creation should be created to break the view of farmers with a relatively large land size and not sensitive to adopt climate smart agriculture. Likewise, elevating the level of awareness on environmental degradation and climate change is needed.

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ANNEXES

Addis Ababa University

College of Development Studies

Center for Environment and Sustainable Development

Dear/Sir/Madam,

This is a structured interview questionnaire prepared to undertake a study entitled “Determinants of Adoption of Climate Smart Agriculture Practice in Gozamin District, East Gojjam Zone, Amhara Region, North West Ethiopia”.

Dear respondent, I am BelaynehYersie, a post graduate student in a Center for Environment and Sustainable Development, College of Development Studies, Addis Ababa University. Currently, I am planning to undertake a research in order to complete the requirements for Master of Arts (MA) degree in Development Studies (Environment and Sustainable Development) given by College of Development Studies, Addis Ababa University.

The research is conducted purely for academic purpose and all the information given are treated as confidential and will not be used for other purposes. I also assure you that no personal identity will be disclosed to third parties. I am so grateful to you by giving reliable and appropriate data and information.

Thank you for your time and cooperation

Code -------------------------

Date of interview -----------------

I. Structured Interview Questionnaire

1. Demographic and Socio-Economic Characteristics

S.No	Items	Options
1.1.	Age of the household head in years?	----------------------------
1.2.	Sex of the household head?	0. Male 1. Female
1.3.	What is your level of educational?	1. No formal school 2. Grade 1-8 3. Grade 9-12 4. TVET Diploma and above
1.4.	How many individuals in your family?	----------------------------
1.5.	What is your source of income for your means of living?	1.Crop production 2.Livestock rearing 3.Off farm income 4. Mixed

2. Extension Service and farm related characteristics

S. No	Items	Options
2.1.	Do you adopt climate smart agriculture (CSA) technologies on your land?	0. No 1. Yes
2.2	If your answer for question number 2.1. Is yes, please select which type of CSA you adopt? More than one selection is possible.	1. Soil and water conservation 2. integrated watershed management 3. use of organic manure 4. conservation agriculture 5. intercropping 6. improved water management 7. Agroforestry 8. crop rotation 9. Mulching

		10. Improved grazing 11. Integrated crop livestock management 12. improved seed
2.3.	How many years you practice farming in this kebele?	----------------------
2.4	Do you have your own land?	0. No 1. Yes
2.5.	What is your total land size in hectare?	---------------------
2.6	Do you have access to extension service?	0. No 1. Yes
2.7	Do you participate in off-farm activities?	0. No 1. Yes
2.8	Are a member of farmers association in your area?	0. No 1. Yes
2.9	Do you have your own livestock?	0. No 1. Yes

3. Knowledge and training related variables

S. No.	**Items**	**Options**
3.1.	Do you have access to credit from financial institutions?	0. Yes 1. No
3.2	Do you have access to agricultural trainings?	0. No 1. Yes
3.3	Do you agree that, there is a climate variability in your area?	1. Strongly agree 2. Agree 3. Neutral 4. Disagree 5. Strongly disagree

3.4	Do you have access to market for your agricultural products?	0. No 1. Yes
3.5.	Do you have radio/television in your home?	0. No 1. Yes
3.6.	What is the distance between your home and farm land in km?	--

Thank you in advance for your time!

II. Key Informant Interview Guidelines

1. How do you explain the farmer's awareness on climate variability?
2. What are the major problems that affect climate variability in your area?
3. Is there any support from NGOs on adoption of climate smart agriculture?
4. Do you think that climate smart agriculture will protect your environment?
5. What merits do you get from CSA technology in your land?

Thank you for your time!

```
. sum Age FamSize farmExperiance LandSize distance
```

Variable	Obs	Mean	Std. Dev.	Min	Max
Age	323	38.22291	9.442528	26	68
FamSize	323	4.294118	1.157019	3	6
farmExperi~e	323	20.4644	8.000842	3	35
LandSize	323	.9394118	.5940836	.2	2
distance	323	1.306192	.6624995	.2	2.6

sex of the respondent	Freq.	Percent	Cum.
female	64	19.81	19.81
male	259	80.19	100.00
Total	323	100.00	

```
. tab Edu
```

educational status of farmers	Freq.	Percent	Cum.
No formal schooling	153	47.37	47.37
Grade 1-8	78	24.15	71.52
Grade 9-12	58	17.96	89.47
TVET Diploma and above	34	10.53	100.00
Total	323	100.00	

```
. tab LivestockHolding
```

Livestock ownership	Freq.	Percent	Cum.
No	73	22.60	22.60
Yes	250	77.40	100.00
Total	323	100.00	

Do you adopt SWC practices	Freq.	Percent	Cum.
No	183	56.66	56.66
Yes	140	43.34	100.00
Total	323	100.00	

. tab Type_CSA

types of CSA practiced	Freq.	Percent	Cum.
0	182	56.35	56.35
soil and water conserva	23	7.12	63.47
using organic fertilizer	22	6.81	70.28
inter cropping	29	8.98	79.26
agro forestry	12	3.72	82.97
crop rotation	36	11.15	94.12
mulching	7	2.17	96.28
improved grazing	6	1.86	98.14
improved seed	3	0.93	99.07
improved water management	2	0.62	99.69
others	1	0.31	100.00
Total	323	100.00	

Do you have access to extension service?	Freq.	Percent	Cum.
No	184	56.97	56.97
Yes	139	43.03	100.00
Total	323	100.00	

. tab credit

do you have access to credit	Freq.	Percent	Cum.
No	192	59.44	59.44
Yes	131	40.56	100.00
Total	323	100.00	

. tab training

have you ever got agricultura l related trainings?	Freq.	Percent	Cum.
No	186	57.59	57.59
Yes	137	42.41	100.00
Total	323	100.00	

```
Logistic regression                             Number of obs     =        323
                                                Wald chi2(19)     =     114.11
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -34.892266               Pseudo R2         =     0.8421
```

Adoption	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
Age	.0304921	.0399635	0.76	0.445	-.0478349	.1088191
sex	1.061238	.5604727	1.89	0.058	-.0372685	2.159744
Edu						
Grade 1-8	2.07702	.9779675	2.12	0.034	.1602385	3.993801
Grade 9-12	2.612697	1.011426	2.58	0.010	.630339	4.595055
TVET Diploma and above	.318006	.763008	0.42	0.677	-1.177462	1.813474
FamSize	.5790154	.4567528	1.27	0.205	-.3162037	1.474234
LivestockHolding	-1.728323	.9674656	-1.79	0.074	-3.624521	.1678746
farmExperiance	-.0278171	.0370513	-0.75	0.453	-.1004363	.0448021
LandSize	-2.106847	.7954136	-2.65	0.008	-3.665829	-.5478648
CVariability	.1620945	.3173401	0.51	0.609	-.4598807	.7840698
Extension	5.928385	.9806163	6.05	0.000	4.006413	7.850358
NonAgriIncome	-1.169493	.7901073	-1.48	0.139	-2.718075	.3790885
credit	1.418885	.7477216	1.90	0.058	-.0466226	2.884392
training	5.740284	1.106676	5.19	0.000	3.571239	7.909328
Land_holding	-.5846973	.7549401	-0.77	0.439	-2.064353	.8949581
distance	-.019784	.4731162	-0.04	0.967	-.9470747	.9075068
AccessMarket	.9385675	1.425282	0.66	0.510	-1.854934	3.732069
MembershipAsso	.3326622	.8004958	0.42	0.678	-1.236281	1.901605
Radio_TV	.6139116	1.358397	0.45	0.651	-2.048497	3.27632
_cons	-8.043264	2.447039	-3.29	0.001	-12.83937	-3.247157

Logistic regression		Number of obs	=	323
		Wald chi2(19)	=	114.11
		Prob > chi2	=	0.0000
Log pseudolikelihood = -34.892266		Pseudo R2	=	0.8421

Adoption	Odds Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
Age	1.030962	.0412008	0.76	0.445	.9532912	1.114961
sex	2.889946	1.619736	1.89	0.058	.9634174	8.66892
Edu						
Grade 1-8	7.980647	7.804814	2.12	0.034	1.173791	54.26072
Grade 9-12	13.63578	13.79157	2.58	0.010	1.878247	98.99356
TVET Diploma and above	1.374384	1.048666	0.42	0.677	.3080595	6.131713
FamSize	1.784281	.8149753	1.27	0.205	.7289109	4.367691
LivestockHolding	.1775819	.1718044	-1.79	0.074	.0266619	1.182788
farmExperiance	.9725662	.0360348	-0.75	0.453	.9044427	1.045821
LandSize	.1216209	.0967389	-2.65	0.008	.025583	.578183
CVariability	1.175971	.3731829	0.51	0.609	.6313589	2.190368
Extension	375.5476	368.2681	6.05	0.000	54.94939	2566.653
NonAgriIncome	.3105242	.2453475	-1.48	0.139	.0660017	1.460952
credit	4.13251	3.089967	1.90	0.058	.9544475	17.89269
training	311.1527	344.3451	5.19	0.000	35.56064	2722.561
Land_holding	.5572745	.4207089	-0.77	0.439	.1269004	2.447233
distance	.9804104	.4638481	-0.04	0.967	.387874	2.478136
AccessMarket	2.556317	3.643472	0.66	0.510	.1564633	41.76541
MembershipAsso	1.394676	1.116432	0.42	0.678	.2904625	6.696635
Radio_TV	1.847645	2.509834	0.45	0.651	.1289285	26.47816
_cons	.0003213	.0007861	-3.29	0.001	2.65e-06	.0388846