HARAMAYA UNIVERSITY
POSTGRADUATE PROGRAM DIRECTORATE

SMALLHOLDER FARMERS' PARTICIPATION IN SUSTAINABLE LAND MANAGEMENT PRACTICES AND ITS IMPACT ON CROP PRODUCTION AND FARM INCOME IN SOUTHERN ETHIOPIA

PHD DISSERTATION

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SEPTEMBER 2024
HARAMAYA UNIVERSITY, HARAMAYA

Smallholder Farmers' Participation in Sustainable Land Management Practices and Its Impact on Crop Production and Farm Income in Southern Ethiopia

Dissertation Submitted to the School of Agricultural Economics and Agribusiness Management, Post Graduate Program Directorate
HARAMAYA UNIVERSITY

In Partial Fulfillment of the Requirements for the Degree of
DOCTOR OF PHILOSOPHY IN AGRICULTURAL ECONOMICS

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September 2024

Haramaya University, Haramaya

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DEDICATION

This dissertation is dedicated to my wife Debir Legesse, my children Beteal Genene and Kaleb Genene and to my mother Mrs. Yeshewatsehay Gebrekidan and my father Mr. Tsegaye Mekonnen.

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STATEMENT OF THE AUTHOR

By my signature below, I declare and affirm that this dissertation is my work. I have followed all ethical and technical principles of scholarship in the preparation, data collection, data analysis and compilation of this dissertation. Any scholarly matter included in the dissertation has been recognized through citation.

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BIOGRAPHICAL SKETCH

Mr. Genene Tsegaye was born in Arssi zone, Robe woreda, Jawi Mariam rural *kebele* in January 1971. He attended elementary education in Jawi Elementary School and junior and senior high school education in Ticho and Robe Didea Schools, Arssi. After taking the Ethiopian School Leaving Certificate Examination in 1988, he joined Alemaya University (now Haramaya University) and graduated with a BSc. degree in Agricultural Economics in 1992. After graduation, he joined the then South Nation Nationality and Peoples' Region (SNNPR) and worked in Kafa-Sheka and Kembata Tembaro Zones Bureau of Agriculture as a junior economist, and planning and programming expert until he joined the South Agricultural Research Institute (SARI) in 2001.

Genene re-joined Haramaya University in 2004 and graduated with a Master of Science (MSc) degree in Agricultural Economics in 2006. After obtaining his MSc Degree, he served as Planning and Programming head of SARI for two years, and then he joined the same organization, Hawassa Agricultural Research Center (HARC) and served as Socioeconomics researcher and project coordinator. In the meantime, he was assigned as a Center Director of HARC in 2014 and led the research center until he joined Haramaya University for a Ph.D program in October 2017.

Currently, he is a senior agricultural economics researcher at HARC. In his research career, he published 13 journal articles in peer-reviewed journals, edited various working papers and workshop proceedings and published one book with his research colleagues. He has mentored three young researchers in AWARD (African Women in Agricultural R&D), GRASP (Gender Responsive Agriculture System Policy) and PICO-Eastern Africa fellowship programs.

Socially, he is married and has one daughter and one son. He is very compassionate and assertive in his community and social life, and he loves the farming community to which his parents and ancestors belong.

ACKNOWLEDGEMENTS

First of all, I would like to thank the Almighty God for helping me in all aspects of my life. My special and greatest thanks and appreciation go to my supervisors, Professor Mengistu Ketema, his Excellency Dr. Endrias Geta, and Dr. Moti Jaleta for their invaluable guidance and support right from the inception up to the final write-up.

I gratefully acknowledge the South Agricultural Research Institute (SARI) and Haramaya University for allowing me to pursue the PhD program. I am very grateful to SARI for financing this research and to HARC for providing vehicle for field data collection, and for arranging other logistics. My special thanks go to the participant farmers and enumerators for their active engagement in the intensive interviews and focus group discussions (FGDs). I am indebted to the woreda level Agriculture Office staffs who provided me with available documents, and who facilitating data collection, and engaging in the key informant interviews (KIIs). My heartfelt thanks also go to Dr. Mengistu Dinato of Hawassa University for his help in language editing.

Finally, yet importantly, I thank my wife Debir Legesse and children Beteal Genene and Kaleb Genene for their patience, love and support during the whole process of this educational career achievement.

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ACRONYMS AND ABBREVIATIONS

ATT	Average Treatment Effect on the Treated
ATU	Average Treatment Effect on the Untreated
CDF	Cumulative Density Function
CIA	Conditional Independence Assumption
CSA	Central Statistical Authority
DAs	Development Agents
DF	Degrees of Freedom
DiD	Difference-in-Difference
ELD	Economics of Land Degradation
ESR	Endogenous Switching Regression
ESS	Ethiopian Statistical Service
ET2T	Exponential Type II Tobit
ETB	Ethiopian Birr
FDRE	Federal Democratic Republic of Ethiopia
FFW	Food-for-Work
FGDs	Focus Group Discussions
FTC	Farmers' Training Center
GDP	Gross Domestic Product
Ha	Hectare
HARC	Hawassa Agricultural Research Center
HHs	Households
IIA	Independence from Irrelevant Alternatives
IID	Independently and Identically Distributed
IMR	Inverse Mills Ratio
KIIs	Key Informant Interviews
KM	Kernel Matching
LPM	Linear Probability Model
LR	Likelihood Ratio
m asl	meter above sea level
MLE	Maximum Likelihood Estimation

ACRONYMS AND ABBREVIATIONS (Continued)

MNL	Multinomial Logit
MNP	Multinomial Probit
MoA	Ministry of Agriculture
MoARD	Ministry of Agriculture and Rural Development
MVP	Multivariate Probit
NBE	National Bank of Ethiopia
NGOs	Non-Government Organizations
NNM	Nearest Neighbor Matching
OLS	Ordinary Least squares
PPS	Probability Proportional to Size
PRA	Participatory Rural Appraisal
PS	Propensity Score
PSM	Propensity Score Matching
PSNP	Productive Safety Net Program
RCM	Radius Caliper Matching
SARI	South Agricultural Research Institute
SLM	Sustainable Land Management
SLMP	Sustainable Land Management Project
SML	Simulated Maximum Likelihood
SNNPR	Southern Nations Nationalities and Peoples' Region
SUR	Seemingly Unrelated Regression
SWC	Soil and Water Conservation
THM	Truncated Hurdle Model
TLUs	Tropical Livestock Units
TNH	Truncated Normal Hurdle
UNEP	United Nations Environment Program
USAID	United States Agency for International Development
VIF	Variance Inflation Factor
WFP	World Food Program
WOCAT	World Overview of Conservation Approaches and Technologies

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Genene Tsegaye, Mengistu Ketema, Endrias Geta and Moti Jaleta. 2023. Determinants of Farmers' Perception on the Role of Sustainable Land Management Practices: Empirical Evidence from Southern Ethiopia. Ethiop. J. Agric. Sci., 33(2): 9-29.

Smallholder Farmers' Participation in Sustainable Land Management Practices and Its Impact on Crop Production and Farm Income in Southern Ethiopia

ABSTRACT

The heavy dependence of farming communities on agriculture exposes land resources to continuous depletion and ruin. Ethiopia has been implementing sustainable land management (SLM) practices over the last four decades to cope with the problem. Exploring the socioeconomic, institutional, biophysical, and policy aspects contributing to the sustainability and effectiveness of land management practices is of paramount importance. This study analyzed farmers' participation decisions and intensity of participation, and examined socioeconomic, institutional, biophysical, and policy factors that influenced their perceptions of SLM practices and preferred choices at a household level. It also evaluated the impacts of participation in SLM on the value of crop production and farm income. Cross-sectional data were collected in 2020/21 from 475 households drawn randomly from 6 woredas and 12 kebeles. Data were analyzed using descriptive statistics and econometrics models namely ordered probit, truncated double hurdle, multivariate probit model, propensity score matching technique, and endogenous switching regression model. The ordered probit model result revealed that education, cultivated land, training, land market, biophysical attributes of plot, and policy factors (land certificate, community bylaws, and incentives) influenced farmers' perception of SLM practices. The truncated double hurdle model result revealed that gender, social network, perception, land size, extension service, farm location, fertility status, slope gradient, and soil erosion showed a significant association in influencing the SLM participation decision. At the same time, non-farm income, value of crop production, and land market have reduced the participation decision. The second hurdle result also showed that farm size, value of crop production, training, distance of road, and community bylaws show a significant effect on farmers' decision to allocate more proportion of farmland (intensity) to implement land management practices. Furthermore, the multivariate probit model result indicated that gender, education, cultivated land size, livestock holding, farm income, crop choice, institutional, and biophysical farm plot attributes affect SLM choices. The analysis further showed that five of the SLM practices combinations, namely fanya juu with soil bund, *bench terrace and indigenous measure, and soil bund with bench terrace and the indigenous practices were applied jointly as complementary practices, while bench terrace with indigenous conservation measures has trade-off effect to be applied as a remedy to reduce soil erosion threat. The predicted marginal probability showed that a soil bund with a bench terrace was found to be the highest combination (i.e. 67.6%) and the lowest with indigenous conservation measures (26.9%).The propensity score matching estimator disclosed that farm plots that received SLM practices for continuous five years experienced 40.8% significant increments in the value of crop produced. Furthermore, the endogenous switching regression method disclosed that farmers who used SLM practices but they had not applied the measures to mitigate land degradation and soil erosion decreased the value of crop production and farm income by 27.2% and 73.9%, respectively. The study strengths that development programs and policy initiatives should depend on implementing physical structures, pay attention to the non-monetary aspects of farmers' perceptions, participation decisions, and SLM choices within the context of their endowed socioeconomic, institutional, biophysical, and policy factors. Based on the impact finding, this paper concluded that it is also very crucial to train and advice farmers to promote and scaling of area-specific SLM practices that maximize social and economic benefits via policy measurement.*

Keywords: Land degradation, soil and water conservation, determinants, probit models, double hurdle model, perception, intensity, interdependent choices, impact

1. INTRODUCTION

1.1. Background of the Study

The livelihood of most people in Ethiopia exclusively depends on agriculture. Agriculture shares 32.4 percent of the country's gross domestic product (GDP) of the country (NBE, 2022). It provides overall employment for 75% of the workforce and contributes 80% of the country's export earnings (USAID, 2020). It also provides raw materials for the domestic agro-industries; supplies food grains to the citizens and supplies labor for the industrial sector. Moreover, nationally 96% of rural households engage in agricultural (both crop and livestock production) activities (ESS and World Bank, 2023). Ethiopia's agriculture is characterized as rain-fed, fragmented, and subsistence farming type resulting in low agricultural productivity (Menale *et al*., 2010; Paul and wa Gĩthĩnji, 2018; Gebissa, 2021).

Though agriculture remains an important sector in the Ethiopian economy, its contribution to the overall socioeconomic development of the country has been constrained by various challenges. Land degradation coupled with weak institutional support, low access and utilization of irrigation water, undeveloped market, farmland fragmentation, and climate change are the prime challenges that constrained the agricultural sector by lowering land productivity and worsening food insecurity (Temesgen and Hassan, 2009; Meshesha *et al*., 2012; Engdawork and Hans-Rudolf, 2017; Amsalu *et al*., 2018; Schmidt and Fanaye, 2019; Gebissa, 2021; Wondimu *et al*., 2021; Critchley *et al*., 2023).

Land degradation has long been a widespread problem affecting the livelihood of farmers who depend on agriculture. Land degradation in the form of soil erosion and nutrient depletion has imposed challenges to sustainable development (Zerihun *et al*., 2017a; Emerton and Snyder, 2018). It has negatively impacted income and worsened food insecurity and poverty status of Ethiopia (Meshesha *et al*., 2012). It has also reduced the provision of goods and services derived from land by lowering crop and livestock productivity and production (Mirzabaev *et al*., 2015). Moreover, land degradation has imposed both on-site and off-site effects on land resources mainly on soil, water, vegetation, animals, and biodiversity. Besides, it has started to put negative pressure on dams, reservoirs, roads, and other infrastructure (Kirui and Mirzabaev, 2014).

Introducing improved land management practices in Ethiopia's mid and highland areas since the late 1970s and early 1980s was a significant step towards mitigating land degradation, reducing soil erosion, and thereby maintaining and conserving land resources (Hurni *et al*., 2010). Similarly, incentive-based and non-paid sustainable land management practices have also been implemented in mid to highland part of southern Ethiopia to maintain and conserve land resources. Moreover, since the inception of agriculture several millennia ago, indigenous types of land management measures have been implemented by farmers and agro pastoralists to protect, maintain and rehabilitate natural resources (Tesfaye, 2003; Mushir and Kedru, 2012). In southern Ethiopia, contour ploughing, cutoff drains, drainage ditches, waterways, soil/stone bunds, tree planting, manure application and crop residue management are common indigenous land management practices that have been implemented by farmers either individually or collectively (Mushir and Kedru, 2012). The Konso traditional SWC practices and the Gedeo agroforestry practices are exemplary land management practices that have been implemented for many hundred years. The Konso people's traditional stone terracing on cultivated land which existed for more than 400 years has been practiced as an indigenous conservation method to drain surplus runoff (Tesfaye, 2003; Hurni *et al*., 2016).

To cope with the population pressure on the demand side and to reverse environmental threats on the supply side, sustainable land management (SLM) practice is instrumental that is implemented at a wider scale. It comprises technologies and approaches Liniger *et al*. (2011) implemented to mitigate land degradation and reduce soil erosion. SLM is a technology since it contains physical measures that control land degradation and/or improve productivity, and is considered an approach because it comprises technical and material support that involves participation of different stakeholders (Critchley *et al*., 2021). Implementing SLM practices increases food production without degrading soil and water resources (Branca *et al*., 2013). Moreover, it has a dual benefit of maintaining the productivity of land resources to the current population (direct use value) and preserving it for future generations (bequest value). Since 2008, the Ethiopian government has implemented SLM practices in collaboration with different partners. Nationally, from 2008/09 to 2012/13, sustainable land management project I (SLMP-I) was implemented in 45 woredas[1], while since 2013/14, the second phase (SLMP-II) was implemented in 135 districts and 937 rural *kebels*[2] to achieve developmental and environmental objectives of reducing land degradation problems, enhancing land productivity, increasing carbon stock and solving tenure insecurity (MoA, 2014).

The losses caused by land degradation and soil erosion underline the need to pay proper attention to SLM practices from all perspectives including enhancing perceptions of smallholder farmers, farmers' participation, choosing and implementing location specific SLM practices, and its anticipated impact. From sociocultural and socio-economic perspectives, farmers have different perception levels, attitudes, and beliefs in using, choosing, and executing SLM practices. An earlier study on SWC in Ethiopian highlands indicates remarkable insights that lack or poor maintenance of implemented measures, low perception and attitude of farmers and the negative impacts of food-for-work (FFW) schemes were the main threats to the sustainability of land management practices (Hurni, 1993).

Understanding the various socioeconomic, institutional, biophysical, and policy factors influencing farmers' perception of soil erosion and their response to choose, invest and use SLM practices is crucial for effective land conservation efforts (Zenebe *et al*., 2012; Worku and Schneider, 2016). Thus in the face of land degradation in general and soil erosion in particular, providing new and updated insights about farmers' perception about SLM role in mitigating environmental threats, smallholder farmers' participation decisions, the choices of different sets of SLM practices and the likely impact on value of crop production and farm income at household, and plot levels could be essential.

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[1] Woreda is the second administrative hierarchy next to kebele and it is equivalent to district
[2] *Kebele is the local name for the lowest administration level in Ethiopia.*

1.2. Statement of the Problem

Land degradation, particularly soil erosion persists and has become a major threat to the ecosystem and a cause for low productivity and food insecurity and vulnerability of the people in Ethiopia (Hailemariam *et al*., 2013; Zerihun *et al*., 2017b; Wondwosen *et al*., 2020; Hörner and Wollni, 2021). In southern Ethiopia, due to the topographic variations, high population density and different socioeconomic setups, land degradation has become severe environmental threat. On the other hand, once different land management practices, particularly SWC measures are constructed, the effort of maintaining, monitoring and reconstructing such measures is getting less and less.

In Ethiopia, over 85% of the land is degraded and the estimate of land degradation hotspots over the last three decades covered more than 23% terrestrial areas (Kirui and Mirzabaev, 2015; Samuel *et al*., 2016). Soil erosion affects half of the agricultural land and results in an annual soil loss of 1.5-2.0 billion tons, equivalent to 35-42 tons ha $^{-1}$ per year and a value of 1-2 billion US$ (Dessalegn *et al*. 2015). About 941 million tones or 18 tones ha^{-1} soil has been eroded every year from Ethiopian croplands (ELD Initiative, 2015). The failure of land management practices to protect runoff has also imposed social and economic consequences by reducing crop yield. The reduction in crop yield results in low supply of food grains and fiber which ultimately leads to food insecurity and hunger (Dessalegn *et al*. 2015). From the macroeconomic perspective, crop yield loss has impacted in reducing the share of agriculture to the economy (Adisu, 2019). Over the period between 2001-2009, Ethiopia incurred 23% cost (equivalent to US$ 35 billion) of its annual GDP due to land degradation which was the highest loss in the Eastern Africa region (Kirui and Mirzabaev, 2015).

In southern Ethiopia, human interventions, for example, improper farming, clearing of forests, overgrazing, and expansion of farming to marginal lands are major threats to the utilization of land resources. On the other hand, the status quo of farmers to give low priority to implement abour intensive SWC measures, has accelerated land degradation. In these contexts, in southern Ethiopia, there has been few empirical works conducted and reported on how the socioeconomic, institutional, biophysical, and policy attributes have influenced the perception and decision of farmers to choose and use different sets of SLM practices.

Perceptions vary and are influenced by personal interest, locations, cultural values, socioeconomic, and institutional situations of people (Bennett, 2016; Rodríguez-Rodríguez *et al*., 2021). With this perspective, there are insufficient reports on farmers' perceptions of SLM in southern Ethiopia. For example, Engdawork and Hans-Rudolf (2016) focused on the causes of soil erosion, fertility decline, and their adaptation behavior. Similarly, the existing evidences in the western highland and northern Ethiopia focused on farmers' perception of land degradation, causes of soil erosion, fertility decline and severity level (Zenebe *et al*., 2013; Zerihun *et al*., 2017b), and determinants of farmers' perception of land degradation (Gebreyesus, 2019). However, from the socioeconomic setups and diversified environmental perspectives of southern Ethiopia, factors that influenced farmers' perception of the role of SLM practices as a remedy to land degradation and soil erosion threats were not assessed.

Studies conducted in the Central Rift Valley of Ethiopia by Zenebe *et al*. (2012); by Akalu *et al*. (2016) in the northern highlands and in the southern Ethiopia by Engdawork and Hans-Rudolf (2016) focused on farmers' perception of land degradation and how much to invest in land management practices. Farmers' decision to use and choice of land management practices were not assessed which this study gave emphasis to look for. Furthermore, several studies reported about adoption rate of land management practices and their determinants Tesfamicheal *et al*. (2015), Birhan and Assefa (2017 and Zerihun *et al*. (2017a) and level of community participation Fekadu and Engdawork (2020) but less attention was given to the influence of social, biophysical and policy attributes in affecting people's participation. In its scope, how participation decision and intensity are affected by the diversified socioeconomic and biophysical conditions in southern Ethiopia was not reviewed and analyzed.

The available evidence in the literature, e.g. Agere *et al*. (2020) and Alelgn *et al.* (2021) in the northwest and Upper Blue Nile of Ethiopia, Wondimu *et al*. (2021) in Abay basin of Oromia, reported that SWC choices are not mutually exclusive; rather farmers are adopting and implementing more than one practice in a plot simultaneously. Furthermore, these scholars noted that various deterministic factors influence farmers' decision to use SLM practices in their specific localities. However, all possible sets of physical SWC measures as SLM practices were not exhaustively evaluated, and yet there are potential explanatory variables missed in the multivariate probit model coefficient estimation, specifically the biophysical plot attributes. In addition, some of the studies considered different types of SLM practices as one physical SWC measure, e.g. Haftu *et al*. (2019). Nevertheless, Akalu *et al*. (2016) amalgamated different types of bunds as one practice, i.e., bund. Furthermore, some other recent studies conducted in southern Ethiopia, (e.g., Offa woreda) did not show the joint interdependence of the SLM choices, rather they estimated the covariates coefficient using odds ratio that methodologically failed to show interdependent choices, e.g. Mamush and Elias (2023). Very importantly, almost all available empirical evidences were generated from northwest and northern Ethiopia, but the southern Ethiopia whose land use and socioeconomic setups are completely different to adopt the recommendation and generated information were not considred. Thus, this study attempted to consider the prioritized sets of SLM practices and their joint mutually inclusive correlation and regressed the potential explanatory variables expected to influence the choices.

On the other hand, land degradation has become a continuous threat that challenges the livelihood of smallholder farmers by lowering crop productivity, worsening food insecurity and inducing poverty. Empirical research conducted in northern Ethiopia, reported controversial and mixed results regarding impacts of using SLM practices on value of crop production, farm income and the overall livelihood change of farmers. An impact analysis conducted in the Blue Nile River of Ethiopia by Paulos and Belay (2017) reported a positive impact on the value of production. Furthermore, the authors employed continuous treatment effects and reported a positive impact for those users who maintained the structures, and a negative for those users who failed to maintain the structures. A study by Schmidt and Fanaye (2019) using panel survey data in the same area reported a negative impact of SLM on agricultural value of production at a household level, but they emphasized a need for SWC maintenance to receive medium and long-term positive and significant impacts. Thus, beyond the controversial and mixed causal effects and/or impacts of SLM in Ethiopia, in southern Ethiopia in general and the study sites, in particular, the impact of SLM, specifically SWC measures applied on cultivated land cover type, value of crop production, farm income and other possible outcome variables at a household and plot level is largely unknown and not documented. Here as a robust and efficient impact estimation of SLM practices need location-specific analysis to conclude and give evidence based recommendation in scaling the practices for a wider impact and sustainable use. Thus, this research was conducted to fill the aforementioned research gaps, specifically on perception about the role of SLM practices, farmers' participation and its level, their preferred choices, and evaluated its impact on value of crop production and farm income.

1.3. Research Questions

This research attempted to answer the following key research questions:

1. What do the perception situations of farmers look like? Do the underlying factors influence the perception level in using SLM practices at household level?
2. What major driving forces affect the decision of farmers to participate and/or use SLM? To what extent do farmers participate in SLM on their own farmland? Are farmers' participation decisions and the extent of participation affected by the same socioeconomic, institutional, biophysical, and policy factors?
3. What are the prominent SLM practices farmers prefer to implement on their farmland and the major factors determining their choices? Are farmers' choices of SLM practices interdependent or independent?
4. Has using SLM practices improved and/or impacted the value of crop production and farm income at household and plot levels?

1.4. Objectives of the Study

Based on the above key research questions, the general objective of this study was to comprehend farmers' perceptions, their participation in SLM practices, choice, and to quantify the likely impacts on crop production and farm income in southern Ethiopia.

The specific objectives of the study were to:

i. Quantify the perception level and identify the underlying factors that affect farmers' perceptions about the role of sustainable land management practices
ii. Examine smallholder farmers' decision to participate in the sustainable land management practices and the level of their participation on their farmland at household level
iii. Identify the major types of sustainable land management practices applied by smallholder farmers and the factors affecting their choices and
iv. Evaluate the impact of SLM practices on value of crop production and farm income at household and plot level

1.5. Significance of the Study

The significance of this study to the existing literature and policy recommendations is immense. Understanding the perception level of farmers and knowing the underlying factors will assist policymakers, extension service providers, NGOs, and other development practitioners to design and implement well accepted and cost-effective land management practices. Similarly, understanding the decision process of farmers who are willing to participate in land management practices and the driving forces influencing their decision will contribute to the designing and implementation of location-specific land management practices. Coupled with the decision of farmers to participate, the intensity of participation is a learning paradigm that development practitioners should consider in implementing on-farm SWC measures. Thus, proper identification of farmers' preferences will help in implementing more effective land management measures that benefit individual farmers and the farming community as a whole in sustaining the potential of land resources for the future generations.

The impact quantification showing positive output at household and plot level will also assist in scaling the interventions in non-intervened localities. On the other hand, the detailed analysis of perception of farmers, the extent of participation, choices, and impacts of SLM in general and on-farm SWC in particular support development practitioners in designing and implementing location-specific land management practices. Thus this study will give further insights about socioeconomic, institutional, environmental, and biophysical plot characteristics and policy factors that influence farmers' perception, their decision to participate, and choices of SLM practices and it will add to the empirical literature with issues addressed in the study areas. Apart from its significance in bridging the empirical literature gaps, the study tried to identify further researchable issues that will provide input for future empirical studies that need attention in similar contexts.

1.6. Scope and Limitations of the Study

This study depends on a cross-sectional data collected at a given point in time from central zones of the former SNNPR (now Sidama, South Ethiopia and Central Ethiopia regions) where the farming system is known and characterized by intensive agricultural activities of crop and livestock production. The highland and midland agro ecological zones namely Sidama, Wolaita and Silitie, the areas known for vast land degradation, specifically by severe soil erosion were included in the sample. With the exception of the impact analysis, a household was considered a unit of analysis. In addition to the household, farm plot owned by both user and non-users farmers was considered a unit of analysis for the impact analysis. Moreover, the study considered user and non-user farmers in applying SLM practices, particularly on-farm SWC measures at their farmlands. Due to the unavailability of baseline data, the study focused on with-and-without intervention for the impact analysis without employing difference-in-difference (DiD) approach. Moreover, the PSM approach has limitation to capture observable and/or unobservable factors ('hidden bias') that influence the average treatment effects on outcome variables in non-experimental (observational) data. To overcome the limitation, the commonly applied method, the parametric Endogenous Switching Regression (ESR) model was applied to analyse impact of SLM practices on value of crop production and farm income.

This research faced some limitations that may be considered in other courses of action. Due to shortage of finance and time restriction, the study did not use panel data sets. Thus, it failed to demonstrate the variability of SLM measures on farmers' perceptions, participation, choices and their impacts on agricultural production and farm income over time. Moreover, a satellite image and pictorial mapping of the study area were not utilized to support the observational data set. Moreover, the whole highland and midland areas of SNNPR were not framed in the sample, rather three purposively selected zones, 6 sample woredas and 12 kebeles, and a total of 475 farmers were sampled. Having confessed this limitation, the researcher tried to review the available literature, precautionary measures were taken to have a representative sample size for the data collection. Moreover, appropriate models were specified and selected for the data analysis to overcome the limitations and to come up with reliable results.

1.7. Organization of the Dissertation

This dissertation has five main chapters which are organized as follow. The first chapter deals with the background of the study, justifications, objectives, and significance of the study. The second chapter provides a review of literature related to the different topics raised in the study. The third chapter describes the study areas, the research methods employed for data collection followed by the analytical tools applied for the analysis, and the working hypothesis. The fourth chapter presents the results and discussion using narratives, tables, and figures based on the descriptive statistics and the econometric models used to address issues in each objective. The final chapter presents summary, conclusion, and recommendations of the study.

2. LITERATURE REVIEW

In this chapter definition and concepts of SLM, theoretical framework of users' participation decisions, perceptions, choices and SLM impact on value of crop production and farm income are reviewed and synthesized. Following the theoretical review, the methodological, analytical and conceptual frameworks are reviewed and presented. Finally, some relevant empirical studies based on the evidences of the existing literature are reviewed and presented for each sub-topic.

2.1. Definition and Basic Concepts

This section provides operational definitions of basic terms and concepts associated with the study's main and sup-topics.

Land degradation: is defined as ‘‘degradation of land resources, i.e. soils, water, vegetation, and animals leading to land capacity reduction to provide ecosystem goods and services’’ (Critchley *et al*., 2021). Land degradation is viewed as a process that encompasses soil degradation and erosion, and it is called desertification when it occurs in dry lands (ELD Initiative and UNEP, 2015). It includes all processes that diminish the capacity of land resources to perform its essential functions and services in the ecosystems (Hurni *et al*., 2010). In areas where there is no or less physical and biological land management practices, land degradation became severe and led to high moisture stress, drought, less vegetation cover, low soil fertility and declined agricultural productivity. In Ethiopia, in general, and SNNPR, in particular, the interrelated and interwoven socioeconomic and environmental consequences of land degradation have contributed to food security problems. It lowers agricultural productivity as the potential of land fails to respond to the food grain requirement of the people and at the same time it reduces the agricultural export earnings and affects the contribution of agriculture to the GDP.

Soil erosion: is the gradual process of removing soil particles from the top, causing the soil to deteriorate (Hurni *et al*., 2010). In Ethiopia in general, and the study areas in particular, soil erosion is mainly caused by excessive water and wind imposed a negative externality to agricultural production by removing top fertile part of soil ultimately reducing its productivity. Soil erosion is interchangeably named as soil degradation. Soil degradation is a process that lowers the current and/or the potential capability of the soil to produce goods or services (Hurni, 1996).

On-farm SWC measures: it is a farm level SLM intervention, mainly physical soil and water conservation measures and practices adopted and implemented either singly or in combination of the technologies and/ or practices to maintain and conserve the farmland productivity. On-farm SWC measures are primarily implemented to reduce soil erosion and to improve soil moisture of farm plots. With context of this study, it mainly includes soil bund, fanya juu, bench terracing and indigenous SWC measures implemented on private cultivated farmland.

Sustainable land management practices: in a broader sense SLM is defined as a knowledge-based procedure that integrates land, water, biodiversity and environmental management to meet the rising food and fiber demands while sustaining ecosystem and livelihoods (World Bank, 2008). It is the core of maintaining or re-establishing life in the land, comprises both technologies and approaches (Critchley *et al*., 2021). It consists of technical and institutional measures to manage land productivity and other functions of land resources for present and future generations (Hurni *et al*., 2010). In the context of World Overview of Conservation Approaches and Technologies (WOCAT)**,** it is the sustainable use of land resources mainly soils, water, vegetation and animals for the production of goods to meet the changing human needs, while simultaneously ensuring the long-term production potential of these resources and their environmental functions (Liniger *et al*., 2011; Critchley *et al*., 2021). In Ethiopian context, SLM is the use of renewable land resources for agricultural and other purposes to meet community needs, while simultaneously ensuring the long term productive potential use and their maintenance through systematic use of indigenous and introduced measures by participating all stakeholders (Gete *et al*., 2006). From the economic valuation context , it is defined as the use of renewable land resources such as soils, water, plants and animals for the production of goods to meet the changing human needs while at the same time protecting the long-term productive nature of these resources (Requier-Desjardins *et al*., 2011). In this study, the physical SWC measures, i.e., technological component, applied on farm plots of farmers is also taken in to account.

Perception: theoretically, perception is a basic psychological process by which individuals receive and process information and it stems from different sources of knowledge, learning, experience and thoughts (Gifford, 2014). In this study, perception level of smallholder farmers to the role of SLM practices in mitigating land degradation and reducing soil erosion is measured in Likret scale of low, medium and high.

Participation: is the decision making of a farmer as a rational economic agent either to use or not to use SLM practices as a response to the prevailing land degradation and soil erosion problems on farmland over time. From the economics theoretical framework perspective, farmers' decision to participate and use land management practices as response to land degradation is an inter-temporal choice between the cost of action and the cost of inaction (Giger *et al*., 2018). In this study, farmers' participation in SLM practices, particularly SWC measures, depend on biophysical plot attributes, endowed socioeconomic and institutional characteristics.

Choice: is a mental behavioral process of selecting a variety or array from which to choose, and the act of choosing an alternative over another thing or selecting several things out of a list of items (Martin *et al*., 2006). It is farmers' stated preference from a given set of SLM choices that deemed to maximize their utility, in the current case, mitigating or reducing land degradation and soil erosion. SLM choice is farmers' decision of selecting a set of interdependent SWC measures to implement on farmland jointly or simultaneously. In other words, farmers could decide to choose and use a set of SLM practices simultaneously on their farmland as a remedial action against soil erosion risks. In this study, farmers' choice of SLM is the decision of farmers to choose the most efficient, less costly and ecologically suitable and sustainable on-farm SWC measures in reducing soil degradation and thereby enhancing cropland productivity.

Impact: it refers to the economic, social, environmental, institutional positive or negative effects caused by a program or intervention on an outcome of interest at a household, community or country level (Gertler *et al*., 2011). In this study, the researcher intended to estimate economic impact, i.e., value of crop production and farm income at household and plot levels.

Impact evaluation: is the process of designing to quantify the causal effects on the social, economic, institutional, and environmental outcomes of any developmental interventions, programs, projects or policy measures within a specific period of time and place on the welfare of communities, households or individual agents (Leeuw and Vaessen, 2009). In the context of this study, it is the analysis that quantifies the causal effects of using SLM, specifically on-farm SWC measures for at least five consecutive years on the value of crop production and farm income with the counterfactual scenario at household and plot levels.

2.2. Sustainable Land Management Practices in Ethiopia

2.2.1. Historical background of SLM in Ethiopia

The alarmingly growing human population that solely depends on land resources for its livelihood, and livestock that largely depends on the free grazing system are major causes of land degradation (Gete *et al*., 2006). In Ethiopia, the alarmingly high population growth coupled with the traditional land-use type has put a remarkable pressure that resulted in land degradation in general and soil erosion, in particular. Both land and soil degradation process were there for many centuries or both processes are as old as human history but the degradation rate became accelerated due to the increasing demographic pressure on land resources (Hurni, 1993; 1996).

Globally SLM was not given much emphasis as the pace of land degradation has been widely perceived as widespread and environmental threat (Schwilch *et al*., 2011). Land degradation has become the world’s most pressing environmental problems affecting 70% of the glob’s ice free terrestrial ecosystems and approximately 3.2 billion people, particularly the rural poor smallholder farmers are affected (Critchley *et al*., 2021). Over the past two decades, SLM has gained much recognition as a means to combat land degradation focusing on soil, water and vegetation and acts as a tool to climate change mitigation and adaptation strategy (World Bank, 2006). Over the last four decades, the Ethiopian government invested in a variety of SLM programs in order to address the ongoing land degradation, specifically to reduce soil degradation throughout the country (Schmidt *et al*., 2017).

The government of Ethiopia with the support of the international bilateral donor agencies had initiated and launched soil conservation and afforestation in different parts of the country after the outbreak of famine in Ethiopia in 1973 (Hurni, 1993). Institutionally, the Ministry of Agriculture has carried out SWC activities for the past forty years on a large scale, such as contour (level) bunds on cultivated land, afforestation terraces on hillsides and hillside closures on degraded hills (Hurni *et al*. 2016). In Ethiopia, the first FFW supported SWC activities were started in 1971 in Tigray and in 1972 in Wello with the U.S food under PL 480 project to carry out reforestation, construction of low-cost rural roads and small water projects (Hurni 1988; cited in Tesfaye 2003). These activities were replaced by FFW projects funded by the World Food Program (WFP) in 1974. Under FFW, there were massive public soil conservation works on degraded and hillside land on drought-prone areas of the country and consequently, about 15% of Ethiopian degraded highland was covered by SWC (ibid).

During the periods between 1976 and 1988, on highland parts of the country, about 600 km of earth and stone bunds were constructed on cultivated lands; about 980000 ha of cropland were treated with terraces; 280000 ha of hillside terraces were constructed; about 310000 ha of degraded and 100000 ha of hilly land was enclosed; 296000 ha of highly denuded land were re-vegetated; 300000 km hillside terraces for afforestation were built on steep slopes, 300000 ha was re-afforested with planted trees and thousands of tree seedlings were raised in nurseries (Kruger *et al*., 1997). The rehabilitation efforts in constructing soil conservation structures and re-afforestation resulted in ecological benefits like restoring farmlands, increasing soil depth, increasing water holding capacity, improving vegetation cover and pasture land.

In spite of the efforts done to develop sustainable land-use system, during the late 1970s and early 1980s, the rehabilitation program mainly, soil conservation and afforestation efforts were by far less than that of the soil loss rate from cropland (42 ton ha^{-1} per a year) and deforestation rate (Hurni, 1993). The reluctance of farmers to maintain and the efforts of dismantling the rehabilitated measures Engdawork and Hans-rudolf (2016); low perception of farmers and low attitudes to the threat of land degradation Hurni (1993); negative impact of incentivized FFW schemes Million and Belay (2004); removal and/or dismantling conservation structures for various reasons Holden and Bekele (2004); concentration of programs in some highly degraded areas Gete *et al*.(2006); absence and/or little efforts of integrating indigenous SWC with the improved ones Genene and Abiy (2014); low involvement of the community in decision-making process of SLM; unstable institutional frameworks and weak link between research and extension Zenebe *et al*. (2012) are some of the important constraints contributed for inefficient and non-sustained land management practices. Understanding the pro-longed gaps and constraints of the past efforts, policy and many development practitioners have started implementing community-based land management practices in different agro ecological zones of the country that the study sites included in this study have been part and parcel of the developmental interventions.

2.2.2. Current situation of SLM in Ethiopia

In recent years, to sustain the land resources and to lower land degradation threats in the economy and ecosystem, various rehabilitation and intervention programs have been carried out by the government and the farming community in large. Starting in 2011, the government has initiated and launched massive community based participatory watershed management program in SNNPR, Amhara, Oromia, and Tigray regions as part of Climate-Resilient Green Economy strategy to protect and maintain the land resources, to reduce greenhouse gas emission and thereby to achieve green economy (FDRE, 2011). In such massive watershed management program, a community campaign has been organized annually during the offset of the main agricultural activities to construct different SWC structures on private farm and communal lands to protect and maintain the land resources (MoARD, 2005). In the annual campaign program, the farming community has participated from planning to implementation of the labor intensive SWC structures on individual farmlands and communal lands.

To reduce land degradation and improve land productivity, the government of Ethiopia with the support from bilateral and multilateral development partners designed and implemented SLM innovations in 135 selected woredas of six regions as a policy instrument (MoA, 2014). Integrated watershed and landscape management with sub-components of sustainable natural resource management in public, communal lands, homestead and farmland development with livelihood improvements and climate-smart agriculture are the main components of SLM implemented through the provision of capital investment, technical assistance and smallholder farmers training (MoA, 2014). Nationally, the first phase of the project (SLMP-I) was implemented during 2008/09 to 2012/13 in 45 woredas in which 10 woredas were included in SNNPR aimed to reduce land degradation in agricultural landscapes and improve the agricultural productivity of smallholder farmers (MoARD, 2011). A follow-up of SLMP-I, namely SLMP-II was implemented with the same objectives and components in 135 woredas (including 45 from SLMP-I) from 2013 to 2018 period led by the Ministry of Agriculture (MoA) and financed by World Bank, Global Environment Facility and the government of Norway (MoA, 2014). SLMP-II was implemented in six of the nine regions of the country. Out of 135, about 21 densely populated and crop-livestock farming system dominated woredas of the SNNPR were included to tackle land degradation challenges and thereby to improve land productivity (MoA, 2014). In this study, three woredas of the sample areas, namely Arbegona (Sidama), Boloso Bombe (Wolaita) and Hulbareg (Siltie) were included from SLMP-II target intervention sites.

2.3. Theoretical Perspectives

2.3.1. Theories about causes and effects of land degradation

Land degradation and soil erosion on farmland have been regarded a serious environmental and economic problem in many agricultural dependent developing countries (Critchley *et al.*, 2021). In environmental economics there are three theories, namely, theories of social cost, collective goods theory, and property right theory that explain land degradation (Ostrom, 1999). The social cost theory is the relation between private and social costs (Wachter, 1992). The theory of social cost explains land degradation happens because of farmers' failure to bear the full costs, for example, downstream soil erosion, or positive externalities that force landowners to adopt and practice inappropriate production practices (Wachter, 1992). Externalities are harmful or beneficial effects resulting from a set of activities related to production or consumption (Ostrom, 1999). In our case, the negative externalities i.e., the practice of cultivating sloppy land, marginal land, and clearing of vegetation cover for farm expansion without considering its social cost accelerate land degradation and soil erosion. Moreover, upper-stream farmers' actions of farming and other agricultural activities impose harmful effects on those neighboring farmers living downstream of their locality.

The theory of collective goods is related to the social cost theory that in both theories externalities are a constituent part of collective goods (Wade, 1987). The author further argued that a long line of collective action theorists has argued that people placed in a situation in which they could all benefit from cooperation will be unlikely to cooperate in the absence of external enforcer agreements. The argument is that everyone wants to free ride, but there are possibilities of internal enforcement mechanisms, for example, the community's by-laws and rules act as enforcing mechanisms. According to the theory of collective goods, environmental problems such as land degradation and soil erosion emerge when land users exploit scarce land resources, like farmland, grazing lands, forests, or any other renewable resources without conserving and maintaining them (Wachter. 1992). We argued that in the case when no one has an interest or an incentive to conserve land resources, specifically, farmland the government should help local systems by providing a legal framework and technical assistance that enable local collective action to obtain legally enforceable recognition to conserve and maintain their resources.

Similar to the two theories, the property rights theory has its contribution to land degradation problems. It is a "bundle of rights" including access and withdrawal, exclusion, management, and alienation rights (Ostrom, 1999). Property rights theorists argued that the main causes of land degradation are both externalities (similar to the social cost and collective good theories) and absent or poorly defined property rights to environmental goods (Wachter, 1992). The government has to provide clearly defined property rights to smallholder farmers to conserve and maintain their land resources both for the current and future generations. Furthermore, to achieve the goal of conserving and maintaining land resources, specifically, smallholders' farmland, the government has to provide the legal framework and enabling environment that incentivizes land users to improve their short and long-term productivity potential.

On the other hand, land degradation is very severe in countries where there are huge population and land resource scarcity, for example, China (Liu and Luo, 2018). There are controversial theories and arguments concerning population pressure and land degradation links. Two prominent population pressure hypotheses are known with different views, that is, the pessimistic view of Malthusian classical thought of population growth and the optimistic view about technological improvement. A theory developed by Boserup (1965) argued that in growing populations, farmers can preserve and improve land fertility by improving production methods. The author argued that a growing population allows the invention of technological improvement in the situation of land scarcity without affecting its quality. An earlier work by Clay *et al*. (1994) argued that there is no direct significant link between human population and land degradation, rather it should be considered from the context of the intermediate linkage. They argued that, indirectly, population pressure leads to soil erosion and depletion from the perspective of landholding structure (farm size, fragmentation, fragile, and tenure system). In contrast to the pessimistic view i.e., "More people-high erosion," some scholars argued that population pressure is not always a prime cause of land degradation. For example, the Netherlands where population density is high has a very low rate of soil erosion Panagos *et al*. (2014). Population increase led to intensification of production, tree planting, and SWC activities in the Kenyan semi-arid Machakos district Ovuka (2000).

Supporting the pessimistic view of Thomas R. Malthus, in Ethiopia, population growth is a cause of soil erosion and poor soil fertility leading to land clearing onto marginal lands (Grepperud, 1996). Population growth and livestock increase have accelerated soil erosion by removing vegetation cover, expanding farmland and aggravating overgrazing (Meshesha *et* *al*., 2012). It is a cause of land degradation Grepperud (1996) and Pender *et al*. (2004); the growing human population accelerated human-induced soil erosion Pimentel and Burgess (2013) and ultimately that has resulted in poor livelihood. In Ethiopia, in response to high population pressure, the potential of land has deteriorated from time to time due to runoff, continuous cultivation, farming on steep slopes, overgrazing, and deforestation (Hurni *et al*., 2010; Meshesha *et al*., 2012; Genene and Abiy, 2014). In addition, the growing population of Ethiopia coupled with fragmented land use practices put a remarkable negative pressure on land, soil, forest, and water (Akalu *et al*., 2016; Gebissa, 2021). In all the cases, the supporter of Thomas Malthus argued that, in response to population pressure, farmers are forced to cultivate marginal lands, pasture lands, grasslands, and woodlots that expose the land to rapid degradation and high soil erosion. In this study, the researcher argued that population increase should be integrated with proper land management practices and family planning that should be supported by enabling policies and regulations.

2.3.2. Farmers' perception about SLM practices

Theoretically, farmers' perception of SLM practices to protect and maintain their land resources, in our case farmland stems from their cognitive behavior, awareness, and experience (Gifford, 2014). Cognitive behavior theory revealed that humans' awareness, perceptions, and thoughts are closely interconnected and linked (Lyman *et al*., 2023). Hence, in this study, it was assumed that farmers' perception of SLM practices' role and function is linked with their experience, knowledge and awareness of the risk and negative externality associated with land degradation and soil erosion.

From an economic, social, and ecological perspectives, perceptions of land degradation problems vary between farmers and other stakeholders and with time (Hurni, 1997). From an economic perspective, farmers and stakeholders may assess environmental problems regarding the short-run costs and economic viability of the technologies at individual and societal levels. Social perspective may consider poverty issues and social differentiation of affected groups but ignore economic considerations. The ecological perspective may only consider the effects of land degradation on soil, vegetation, wildlife, and ecological processes by disregarding social and economic problems (Hurni, 1997). Given the other conditions, in this study, the perception of farmers to SLM practices role and function was considered from the economic, social, and ecological consequences of land degradation that impose negative impact on the productivity potential of the land resources, particularly to the cropland.

2.3.3. Farmers' participation in SLM practices

Land degradation is one of the world's most pressing problems that exists in many part of the world affect the soils, water, vegetation, animals and bio-diversity (Critchley *et al*., 2021). From the economic perspective, land degradation has imposed severe negative impact on the livelihood of less developing countries whose economy largely depends on natural resources and their investment to combat the problem is low (Nkonya *et al*., 2016). To combat the negative impacts of land degradation, SLM practice is the widely introduced and adopted approach applied on the farm plots at individual farmlands and communal lands at the community level (Samuel *et al*., 2016; Paulos and Belay, 2017). From the very beginning, Hurni (1996) defined sustainable land management as a system of technologies and/or planning that aims to integrate ecological with socioeconomic and political principles in the management of land for agricultural and other purposes to achieve inter and intergeneration equity. It is a multi-level stakeholder approach composed of technology, policy and land use planning developmental components to conserve and maintain land resources in a sustainable way (Hurni, 1997).

The scope of this study was limited to looking at the component of land, specifically farmland linking it with individual farmers' decision to participate and the choices he/she makes. Farmers' decision to protect and maintain their farmland for sustainable use depends on their decision to use SLM practices, particularly on-farm SWC measures. Again, the decision of farmers to participate in SLM is the likely probability of individuals to use SLM practices, specifically SWC measures of any type on farm plots to reduce accelerated soil erosion. Soil erosion is a long-term irreversible consequence on soil productivity (Hurni, 1996) that need farmers' urgent decision to reduce the negative impacts on crop production. Farmers' decisions to construct or remove soil conservation structures, or their decision to use manure and fertilizer affect soil erosion and nutrient depletion, respectively, affect crop productivity in later years (Holden and Bekele, 2004).

2.3.4. Farmers' choices of SLM practices

To enhance the sustainability of natural resources, specifically the land resources, SLM practices are highly promoted and implemented in developing countries the economy of which largely depend on subsistence agriculture (World Bank, 2008). In enhancing the productive capacity of cropland, farmers have a possibility of choosing SLM option from a given choice set. The commonly adopted and practiced on-farm SWC in most of densely populated areas of the Southern Ethiopia are soil/stone bund, fanya juu, bench terraces, trenches, indigenous SWC of various types (cut-off drains, contour farming, manure) and planting strip grasses, forages and shrub species in between structures as a biological stabilizer (SARI, 2018).

In Ethiopia, farmers' choice of SWC measures solely depends on local situations like agroecology type, slope range or gradient, soil type, its effectiveness in reducing soil erosion, retaining moisture, conserving organic matter, stabilizing the structures and its overall local applicability in terms of labor, material and other inputs requirement (Hurni *et al*., 2016). In addition to the criterion to choose the best SLM alternatives, there are underlying socioeconomic, institutional, environmental and bio-physical plot attributes that affect farmer's preferences (Wagayehu, 2006). The theoretical framework for farmers' choices of SLM starts from the individual farmers' utility maximization. In the choice analysis of this study, it makes use of the random utility model as a basis. Following Greene (2012), in the random utility model, individual farmer choose a specific type of SLM or combination of practices jointly that maximizes the utility from farmland. Based on farmers' experience, their endowed socioeconomic attributes and the constraints they have faced by soil erosion, they stated their preferred choice/s from the different set of SLM practices Wagayehu (2006), particularly on-farm SWC measures introduced and adopted in the study areas that maximize their utility.

2.3.5. Impact evaluation of SLM practices

In development interventions, impact evaluation is principally concerned with the effects of the final results and outcome of interventions on the welfare of communities, households or individual agents (Leeuw and Vaessen, 2009). It is an empirical study that quantifies the causal effects of intervention on outcome of interest (White and Raitzer, 2017). It is based on a quantification of results with an intervention, compared with an empirically estimated counterfactual scenario of what would have happened in the absence of intervention. From its casual-effect context, impact evaluation is distinct from monitoring that tracks a continuous day-to-day performance and from evaluation that concerns with periodic assessments of development interventions or projects at a discrete point in time (Gertler *et al*., 2011).

Based on the survey data, the difference in the monetary value of crop production and farm income between the user (treated) and non-user (resembles the counterfactual) farmers show the impact attributed due to the intervention. In impact evaluation, to know the effect of the intervention on the participating agent, the observed outcome should be compared with the outcome that would have resulted had that agent not participated in the program. In other word, two outcomes cannot be observed for the same individual, rather the factual outcome can be observed.

Impact evaluation is not concerned with implementation process that concerned what, how, and where the developmental intervention proceeds rather it concerned with the final effect and outcome of intervention on the welfare of communities or any economic agents (White and Raitzer, 2017). In some developmental programs and projects, impact evaluation is concerned with impact attributed by the intervention (s) on the ecosystem and environment welfare. Impact analysis of any interventions is done for multifaceted purposes. First, impact evaluation is needed to assess the value of the results derived from a given intervention. Secondly, it is used to assess intended (anticipated) and unintended (unanticipated) effects; identify the short-term (quick impact) versus long-term (overtime change) effects; detect the sustainability of effects and draw key message or positive feedback based on measurable indicators to policymakers and to scale-up interventions that work well (Leeuw and Vaessen, 2009; Gertler *et al.*, 2011).

2.4. Methodological Framework

The methodology provides the theoretical approach that links a research problem (s) with a particular method (s) and determines how the method or tool is utilized (Hesse-Biber, 2010). A brief outline of the methodological framework employed to achieve the objectives and address the research problems is provided for each objective in subsequent sections.

2.4.1. Farmers' perception about the role of SLM practices

The proposed methodological framework for farmers' perceptions about the role of SLM and the underlying factors affecting the attitudes and knowledge constitute the methods or tools of data collection and the procedure used to address the research question. The perceptions or knowledge of farmers about the role of SLM, particularly, on-farm SWC measures in reducing soil erosion, and enhancing land productivity emanates from the perception of farmers who know the severity of the problem and its effect in their livelihood both at household and community levels. After deciding farmers' feelings and perceptions in reference to soil erosion severity and land management practice in mitigating and reversing the environmental threat and improving the land productivity was interviewed using survey instruments.

A combination of an in-depth interview with sample respondents, FGDs, and KII with selected discussants and field observation was carried out to collect the data. During the household interview and discussions, the cognitive behavior of the respondents was serving as an instrument to know the perception of farmers about the phenomena under consideration. The response of farmers to SLM with trivalent outcomes (low, medium and high) as a dependent variable and the socio-economic, institutional factors and biophysical plot attributes as potential explanatory variables were employed to predict the probability of farmers' perceptions. Last but not least, a descriptive statistic and the ordered probit model were employed for the data summary and analysis to estimate the unknown coefficient of parameters (βs and cut points) (Wooldridge, 2010; Greene, 2012).

2.4.2. Farmers' participation in SLM

Grouping of sample farmers into user and non-user of SLM practices was done based on observational data and expert judgment of the area under considerations. To attain the objective of examining the decision of farmers to use and the intensity of participation in SLM, cross-sectional data were collected using qualitative and quantitative data collection methods. A mixed methods research approach that resides between the qualitative and quantitative data collection techniques was used to collect data from respondents to address research questions. The practice of mixed research has leaned towards a more positivist methodological orientation, one that employs qualitative data as second best to the quantitative data to illustrate or assist in getting more robust quantitative results, such as survey research (Hesse-Biber, 2010). Deployment of a mixed research approach enriches the research through the application of qualitative and quantitative methods in complementary ways.

Quantitative research approach tests objectivity theories. It relies on deductive reasoning and general premises to reach specific conclusion, uses quantitative or numeric data, is based on instruments that measure individual performance and attitudes, uses observational data based on clearly predefined categories, is exploratory and theory generating, predictive, and employs survey techniques (Wheeldon, 2010). In contrast, qualitative research approach assumes social reality to be subjective and varied, involves emerging questions and procedures, tests theories using inductive reasoning and specific premises, uses qualitative data, is descriptive, tends to be open to new information, bases on themes that emerge through open-ended interviews and participant observations, or review of documents (Hesse-Biber, 2010; Wheeldon, 2010).

While using mixed methods, data will be collected through a quantitative survey using closed-ended questions and qualitative interviews using open-ended questions at the same time. In both methods, the conceptual and recalling approach of households using open and closed-ended questions was administered to collect the primary data. Based on the individual interviews, two-stage decision process was carried out to answer the basic question of farmers' participation decision and acreage allocation for on-farm SWC measures. After identifying user participants involved in SLM in the first stage, acreage involvement was entertained in the second stage to know the intensity level. The primary data sets used to illustrate farmers' participation and the intensity decision evidence was grouped as one of the four measurement levels as nominal or classificatory scale, ordinal or ranking scale, and interval scale and ratio scale variable measurement level. The analytical tool, after describing the correlation and inferences between the dependent variable and the hypothesized regressors by descriptive statistics, employed the choice model (in this case the binary probit model) and truncated double hurdle model to estimate the likely probability of user decision and the extent of participation simultaneously (Cragg, 1971; Wooldridge, 2010).

2.4.3. Farmers' choice of SLM practices

Farmers' choice among sets of SLM implemented in crop land use type primarily depends on socioeconomic characteristics, biophysical farmland attributes, externally imposed supportive institutional services and constrained environmental factors. Institutionalizing the multi-stakeholder SLM approach and technologies to reduce soil erosion in farmland and to attain sustainable land management, farmers' choices need to be identified and the underlying factors that are supposed to influence it should be articulated.

Structured questionnaire was designed to identify the direct preference of farmers' choices of SLM applied and implemented in their farm plots. The questionnaire was designed to differentiate the various on-farm SWC types that are commonly applied by most smallholder farmers in the study areas. Moreover, structured observation and view to identify the top SWC implemented on the ground was carried out. The quantitative method of research administrating closed-ended questions during the household survey was used and the qualitative methods were also applied to triangulate and complement the quantitative data (Hesse-Biber, 2010; Wheeldon, 2010). Asking the sample respondents directly, that is analogous to economic valuation technique direct method helps the researcher to value the impact of the preferred choice on crop production and the underlying factors influencing the choices. The data set utilized to identify farmers' choices was organized as nominal categorical and ratio numeric type variable level. Finally, the multivariate probit model that basis on individual random utility model was deployed for the analysis (Cappellari and Jenkins, 2003; Greene, 2012) and thereby the result was narrated and presented. The variance-covariance matrix showing the joint correlation of the set of specified SLM choices was displayed to know the complementarity and substitutability effect of the practices applied as a remedy to reduce soil erosion on cultivated lands.

2.4.4. Impact evaluation of SLM practices

The methodological framework to impact analysis depends on the type of data set to be collected and the research question the researcher plan to address. Cross-sectional and longitudinal panel data sets before and after the intervention with baseline data, with and without intervention with and without baseline data are the most data sets employed in most impact analysis literature. In this study, cross-sectional data sets without baseline data were employed for SLM impact on crop production and farm income at household and plot levels. In our case, the quantitative methods approach was employed to collect the data. Quantitative data collection approach uses quantitative or numeric data; it seeks casual or effect relationships; it has a deductive connection to theories and data; it relies on general premise to reach specific conclusions; it is based on survey instruments that measure individual performance and it is explanatory (Wheeldon, 2010).

Impact evaluation for a particular program, project, intervention or policy reform is based on counterfactual analysis that compares what would have happened in the absence of an intervention to actual outcomes occurring with the intervention (White and Raitzer, 2017). In the current study context, impact evaluation seeks to measure the treatment effect, for which the treatment is farmers who are exposed to participate in using SLM on their farm plots, and the effects is the exposure that makes difference in value of crop production and farm income between the treated (users of SLM) and non-treated (non-users of SLM). The assignment of treatment for the user and non-user groups was decided before proceeding to the data collection process.

The quantitative data were collected by sub-grouping the entire population into user and non-user of SLM, specifically on-farm SWC land management practices. In the analysis, the user and non-user was stratified as farmers with (treated) and without (non-treated) of the SLM interventions. In the impact estimation procedure, the matched farm households were compared by the hypothesized average outcome variables (in this case, the value of crop production and farm income). In conclusion, in all the methodological process of impact analysis after designing the questionnaires, sample respondents were framed for in-depth interviews.

2.5. Analytical Framework

Based on the economic theory, literature, a researcher view of the research problems the statistical tool and the econometric analytical models employed for the analysis of farmers' participation decisions, perceptions, choices, and SLM impacts are presented as follows.

2.5.1. Farmers' perception about SLM practices

Farmers perceive the role of SLM practices, particularly on-arm SWC practices differently. Based on farmers' perceptions of soil erosion severity on their farm plot, on the one hand, and perceiving the role of a given SLM option to minimize the risk associated with soil on the other side, they have an opportunity to choose the best land management option. The perception level to SLM role varied based on the socioeconomic and institutional characteristics of farmers and plot related biophysical attributes. The socio-economic, institutional, biophysical and farm related factors account for smallholder farmers to perceive the severity of soil erosion and enable them to act against by implementing SLM practices on their farm plots (Zerihun *et al*., 2017b).

Smallholder farmers are supposed to have the possibility of having different perception to the role of SLM in halting land degradation, particularly soil erosion at their locality. Choosing a mix of SLM practices than sticking in a single practice to minimize the risk of land degradation in general and soil erosion, in particular on their farm plots depends on their perceptions. In a case where farmers have different perceptions in choosing multiple practices to apply on their farm plots the decisions are independent and ordinal. The attitude or perception of farmers was asked to know farmers' opinion about SLM role in Likert-scale. In a Likert scale, the respondents are asked to respond to the statement (s) in terms of several degrees usually five, but at time three or seven may also be used (Kothari, 2004). In this study, a three Likert scale type, i.e., low, medium and high was employed to compute farmers' perception index.

When farmers' perception to SLM role is independent, multiple and ordered, the multinomial probit or logit model would fail to account for the ordinal nature of the dependent variable (Greene, 2012). In such cases when the dependent variable is ordered, multi- response ordinal models are commonly applied. Whenever the perception is independent and ordinal, the ordered choice models are applied to estimate the ordinal outcomes jointly on an individual specific basis (Wooldridge, 2010; Greene, 2012). The Multi-response ordinal models are developed to describe the probability of each of the possible outcomes as a function of personal or alternative specific characteristics. The two standard models widely utilized as a methodological framework for the analysis of ordered multi-response outcome variables are the ordered probit and the ordered logit (Greene, 2012). An ordered probit or logit models used to estimate the relationship between an ordinal dependent and a set of explanatory variables. Both approaches are equivalent, except the ordered probit follows the standard normal CDF while the ordered logit follows the logistic CDF. The error term in ordered probit and logit is assumed to be distributed normally and logistically across observations, respectively. The extensions of univariate probit model, namely the ordered probit model was proposed and deployed for the data analysis.

The MLE procedure was employed to estimate parameter coefficients and the cut points. Moreover, the marginal effect of a change in the hypothesized explanatory variables was computed to quantify farmers' perceptions about SLM practices in reducing soil erosion (Greene, 2012; Greene, 2018). In the model specification and application, the assumption of homoscedasticity, endogeneity, autocorrelation and multicollinearity was tested to have unbiased, consistent and efficient estimate of parameters and cut points. The ordered probit model fitness was tested with LR- $\chi 2$ test, Pseudo R^2 and Wald test.

2.5.2. Farmers' participation decision in SLM practices

In analyzing farmer's decision to use and the next sequential decision of acreage allocation was analyzed using the discrete choice and truncated double hurdle model. There are many discrete choice models in which the dependent variable is an indicator of discrete choices, such as ''yes or no'' decision (Greene, 2012). The dependent variable is dummy, i.e., 1 for the user of SLM and 0 for non-user who did not use/apply SLM practices particularly on-farm SWC measures in any of his plots for the last five years. The probability of success in participating in SLM (y=1) is a linear function on the explanatory variables (x_i), thus ordinary least square (OLS) with a binary dependent variable called the linear probability model (LPM) can be used to estimate the parameters. However, due to some shortcomings of the LPM, estimated probability does not make sense and it is also difficult to interpretive the results.

Some of the important undesirable properties of LPM are: (1) some of the predicted probability values lie out of the range of 0 and 1 violating the basic logic of the probability, (2) the predicted probability is linearly related to a continuous independent variable for all possible values that does not make sense, and (3) the residual (ε) is heteroscedastic that ε depends on β and it is not normally distributed (Greene, 2012). The inadequacy or the shortcomings of LPM suggests that binary choice models can solve the problems and can be applied.

When the outcome variables of interest are discrete, binary response models such as binary logit and probit models are proposed and utilized for the analysis (Wooldridge, 2010). The binary logit and binary probit models are jointly referred as the binary regression model (BRM). Except for the mathematical convenience of the logistic distribution, the question of which distribution to use is still difficult to provide practical reasons (Greene, 2012). The logistic distribution is similar to the normal except the tails are heavier in the former one; the logistic distribution tends to give larger probabilities to y = 0 when x'β is extremely small and small probabilities when x'β is large than the normal distribution (ibid). Even though the discrete choice model provides important insights how the different socioeconomics, institutional and biophysical characteristics influence the probability of farmers' participation in SLM at their farm plots, it fails to provide further insights on the intensity of farmers how much acreage of land being allocated for SLM after the participation decision is made.

The shortcomings of the binary probit model to look for the sequential decision process of farmers' participation in SLM, the double hurdle model was proposed for the analysis. When the decision process is sequential, double hurdle model is utilized for the analysis (Greene, 2012). Here, it is assumed that there are two sequential decision process of farmers' participation in SLM practices. The two sequential decision processes are (1) a binary response of a farmer whether he participates or not in SLM (y > 0 versus y= 0) and (2) how much acreage of farmland is allocated for SLM activities if the farmer enrols once in using SLM. In the double hurdle model approach, two models can be specified separately for both stages (i.e. the decision to use and the level of involvement in SLM) taking the two assumptions, that is, independence of irrelevant alternatives (IIA) and independence assumptions.

IIA assumption**:** The first decision of participation (binary choice of yes or no) and level of participation (acreage of farm land allocated) are independent, i.e. the covariance of unobserved factors (error terms) is zero (Greene 2012; Wei *et al*., 2016). The independence assumption follows from this assumption shows that the disturbances are independent and homoscedastic.

Interdependence assumption: The level of involvement in SLM (in allocating acreage of farm land) depends on the first participation decision, i.e. the error terms have non-zero value that IIA assumption is violated (Wei *et al*., 2016).

When the decision process is sequential, i.e., the initial decision of the choice between y > 0 versus y = 0 should be separated from the second decision of how much y given that y > 0 should not be done with standard Tobit model. The two-tier/ double hurdle model was originally developed by Cragg (1971) is used to analyze the two separate decision processes of user participation and the level of involvement. For this reason, an extension to the univariate Tobit model, i.e. the double hurdle model or two-tiered models is parameterized to formulate the two-step decisions separately (Wooldridge, 2002). The double-hurdle model application to any empirical study divided the decision into two stages, i.e. a first discrete probability of participation model conditioned on participation and a second decision is made on the intensity of participation (in the current case acreage allocation for on-farm SWC). The first step involves a probit estimation while the next step assumes a truncated normal distribution.

The difference between the Heckman model and the double-hurdle model is that in the second stage where the Heckman estimates an OLS equation while the double-hurdle model estimates a censored regression usually a truncated regression (Wooldridge, 2010). Hence, in the second relaxed assumption, the ET2T model or Heckman method or Heckit was adopted and results were compared among the three models. The ET2T model contains the conditional lognormal hurdle model but the unknown correlation between the errors (ρ) is non-zero and cannot be identified if the explanatory variables that appear in acreage amount decision, i.e. $y^* = exp(x\beta + \varepsilon)$ is the same as the participation decision, i.e. $w = 1[x\gamma + u > 0]$. Therefore, in this study both the double-hurdle model and ET2T model were adopted for the analysis and the results were also compared in each model.

The maximum likelihood estimation (MLE) technique was employed to estimate the unknown parameters from the data collected (Wooldridge, 2010). Following Greene (2012), the marginal effect (dy/dx) for a change in the hypothesized explanatory variables on the probability of participation and its intensity in double-hurdle and ET2T models were estimated. In the model specification, the assumptions of homoscedasticity, endogeneity, autocorrelation and multicollinearity were tested to have unbiased, consistent and efficient parameter estimates. The goodness-of-fit (gof) test was also employed to validate the overall model fitness whether the proposed model is correctly specified or not. The Wald test statistic using chi-squared test ($\chi 2$) and Vuong test using t-test were employed for the goodness-of-fit tests for both the double hurdle and ET2T models.

2.5.3. Choices of SLM practices

The choice of major SLM, mainly SWC measures, implemented by farmers on their farmland depends on socio economic, institutional, environmental and technological attributes. The decision on the choice of different SLM investment in reducing soil erosion and enhancing land productivity depends on individual farmer characteristics, institutional and biophysical factors (Akalu *et al*., 2016). Land use/cover type also affects farmers' decision to choose and implement agro ecologically area-specific land management practices (Wondwosen *et al*., 2020). In valuing non-market goods and services, several types of stated preference techniques have been developed. The stated preference valuation techniques of non-market goods are commonly used to combine economic theory and survey research to estimate the economic value that individuals, group of individuals or households can place on various goods (private, communal or public), services or public programs (Wagayehu, 2006).

Methodologically, multiple choice model can be applied where there is a single decision among two or more alternatives without assuming several decisions each between two alternatives (Greene, 2012). The two broad types of choice sets are ordered and unordered choice model, both models are motivated by a random utility model. Among the unordered choice models, the multinomial response models namely multinomial logit (MNL) and multinomial probit (MNP) models failed to consider two or more independent decisions of economic agents (Wooldridge, 2010). The MNL model has disturbances which are independent and identically distributed (IID) that leads to the conditional logit model, while MNP model, in contrast, does not assume IID that has errors which are not necessarily independent and identically distributed by a multivariate normal distribution (Greene, 2012). When the independence from irrelevant alternatives (IIA) assumption is violated, MNL model is incorrectly specified and the estimates are biased and inconsistent.

Smallholder farmers are supposed to have the possibility of choosing a mix of SLM practices rather than sticking in a single practice to minimize the risk of land degradation and soil erosion on their farm plots. In a case where farmers have a possibility of choosing multiple alternative practices to apply on their farm plots, the decisions are interdependent and simultaneous. Whenever the decisions are interdependent and simultaneous, the multivariate probit (MVP) model with a multivariate normal distribution is applied to estimate the correlated binary outcomes jointly on an individual specific basis (Long, 1997). The MVP model is a useful extension of the random effects probit model that provides more detailed of endogeneity in non-random sampling and used to estimate several correlated binary outcomes jointly. Multivariate probit model is different from the bivariate probit model, in that MVP model estimate several correlated binary outcomes jointly on an individual specific basis (Greene, 2012). In this study, there are four SLM options to be applied on individual farm plot, the decision of applying or adopting all options are binary (y=0 or y=1) but still interdependent decisions that would be estimated jointly using MVP model.

The simulated maximum likelihood (SML) estimation procedure using Stata software was employed to estimate parameter coefficients by drawing the samples as many times as possible (Cappellari and Jenkins, 2003). In this study, to get consistence and accurate estimates, 100 random draws were done and obtain the expected estimates after five iterations. Moreover, the marginal success and failure probability for each SLM choices and the joint probabilities for all options were computed to analyze farmers' best choices of SLM in reducing soil erosion at individual farmer level. The model fitness was tested with the Likelihood-ratio (LR- χ^2) among the six equations for heteroscedasticity among the residuals variance, and VIF test for multicollinearity problem among the explanatory variables was also checked. The goodness-of-fit test employed to validate the assumption of normality of the error terms to check whether the specified model is correctly specified or not. In the SML procedure, the MVP probit model overall fitness was tested with Wald- $\chi 2$ test with DF equal to the explanatory variables included in the model to show whether the farm household decision of SLM choices are mutually inclusive or independent.

2.5.4. Impact of SLM on crop production and farm income

In observational studies that employs non-experimental designs, the assignment of treatment to units is non-random as opposed to the experimental designs that employ random assignment of treatments to units under considerations (Rubin, 2006). In observational studies, there are challenges in assigning treatment randomly to units. Some of the commonly reported challenges are selection bias, spill over effects and contamination or contagion (White and Raitzer, 2017). Hence, the impact analysis under this research was proposed to be a quasi-experimental design selecting the two groups differentiated by the exposure to the SLM practices and the selection bias supposed to be created by non-random assignment of treatment was reduced by statistical adjustment to matched sample units and by careful selection of sample area and units.

Propensity score matching (PSM) is the commonly used estimation procedure in most literature (Rosenbaum 2002; Smith and Todd, 2005; White and Raitzer, 2017). Propensity score estimation is done to balance the distribution of relevant observed covariates between the participant and non-participant of agents in a given intervention. For the impact quantification, matching procedure that depends on the balancing score known as PSM procedure was employed to estimate the casual treatment effect. According to Rubin (2006), balancing scores, b(x) is used to group treated and untreated unit for direct comparisons and it is a function of the observed covariates (x) such that the conditional distribution of x given b(x) is the same for treated (y = 1) and control group (y = 0). The propensity score is one of the balancing score analysis of the statistical method developed for estimating treatment effects with non-experimental or observational data (Guo and Fraser, 2015).

Estimating ‘average treatment effect on the treated’ (ATT) employing PSM procedure is the parameter of interest that got most attention in program evaluation literature (Rubin, 2006; Wooldridge, 2010). ATT is the expected mean effect of treatment for a randomly drawn individuals from a given population who actually participate in a given program or interventions (Wooldridge, 2010). Hence, in this case, ATT is considered as the average effect of treatment for those households drawn from the population of the study area who actually received the treatment. In our case, PSM procedure was employed to estimate the probability of farmers participating in SLM at household and plot level given the observed socioeconomic, institutional, environmental factors as well as biophysical plot characteristics.

In implementing PSM, the five implementation steps are (1) choosing the PSM functional model, (2) choosing the best matching algorithm, (3) checking the common support regime or overlap condition, (4) checking the matching quality or balancing, and (5) conducting sensitivity analysis (Rosenbaum 2002; Rubin 2006).

Before going to the estimation of propensity scores, one has to choose the functional form of the appropriate model and the variables (outcome variable (s) and the set of the explanatory variables or covariates). In estimating the conditional probabilities of receiving treatment using a vector of observed covariates, several methods such as probit model, logistic regression model and discriminant analysis are commonly applied (Guo and Fraser, 2015). Among these methods of estimating propensity scores (PS), with the exception of their distribution, probit and logit model has no difference on the estimates. In choosing the variables, covariates should be exhaustively included in the PS model without any exclusion and the matching strategy should follow the conditional independent assumption (CIA) that the outcome variable (s) should be independent of the treatment conditional on propensity score (Rosenbaum, 2002). In this study, the binary probit regression model was applied to identify the determinants of user and non-user of SLM practices. Moreover, it was used to identify which type of farm plot of participant household's is more likely to use SLM measures. The univariate probit model was selected based on individual choices or utility maximizing behavior of individuals provided by the random utility model (Greene, 2012).

Following the model and variable choice, the best matching algorithm should be selected, and a comparison between the outcome of treated and control group members should be made. The common matching techniques applied are nearest-neighbor matching (NNM), caliper or radius matching, Kernel-based matching (KM), and stratification matching (Rubin, 2006; Guo and Fraser, 2015). After matched samples, the treatment effect using SLM practice was estimated by comparing the mean outcome of treated with untreated groups in the matched sample using different matching techniques. The choice of each matching estimator is based on the criterion of balancing test (equal means test with an insignificant mean difference), low pseudo R^2 value, and large matched sample size (Rubin, 2006).

Nearest-neighbor matching (NNM): the nearest individual in terms of its absolute value of PS is chosen from the comparison group as a matching partner to the treated counterfactual individuals (Rubin, 2006). Nearest-neighbor matching with replacement, NNM without replacement and oversampling are the common variants of matching that involve a trade-off between variance and bias in the matching partners (Guo and Fraser, 2015). Matching with replacement occurs when an untreated household can be used more than one while matching without replacement is when untreated household matched only once.

Calipers or radius matching: whenever the NNM faces the risk of bad matches during the treated unit is far away from its neighbor, caliper or radius matching is applied by imposing a tolerance level on the maximum propensity score distance (Guo and Fraser, 2015). By doing so, bad matching is avoided and thereby the matching quality is expected to rise. In this matching technique, individual from the comparison group is chosen as a matching partner for a treated individual that lies within the caliper and is the closest in terms of propensity score. However, the difficulty to know the tolerance level is the drawback of caliper matching (Smith and Todd, 2005). NNM and radius matching estimators use a few observations from comparison group to construct a counterfactual outcome of a treated individual.

Kernel-based matching (KM): unlike the NNM and radius matching that focuses on few observations for comparisons, kernel matching is a recently developed non-parametric matching technique that constructs a match for each program participant individuals using a kernel-weighted average over multiple persons in the comparison group (Smith and Todd, 2005). KM estimator has the advantage of having low selection bias and variance due to the fact that it utilized more information to estimate the matched sample. In applying KM one has to decide the kernel function type and bandwidth parameter (Guo and Fraser, 2015).

Stratification matching: is based on the same stratification or the partition of common support of the propensity score into a set of intervals and/or strata (Smith and Todd, 2005). The impact within each stratum is calculated by taking the mean difference between treated and control observation in a given data set.

Checking the common support regime: next to the choice of matching estimator, in order to get unbiased, consistent and asymptotically normal matching estimator, the treatment effect of interest should satisfy the basic assumptions of ignorability or unconfoundedness (i.e. assignment of treatment is independent of the outcome conditional on covariates) and overlap condition (i.e $0 < p (w=1|x < 1)$ (Wooldridge, 2010).

Balancing test and testing matching quality: the researcher has to check whether the matching procedure is able to balance the distribution of the relevant variables in both groups after choosing the best estimator. In balanced matching, the intuition is the comparison group should be similar to the treatment group in terms of the observables before the intervention or start of the treatment (White and Raitzer, 2017). Implementing matching requires choosing a set of variables, x that plausibly satisfy the conditional mean independence assumption that the outcome variable must be conditionally mean independent of treatment conditional on the propensity score, P(x) (Smith and Todd, 2005). The reduction in the standardized bias (SB) after matching; equality of the means using a two-sample t-test; pseudo R^2 to indicate how well the regressors explain the probability of participation; and F-test to indicate the joint significance of regressors are applied to test the mean difference of each variable between the two groups.

Sensitivity analysis: the estimation of treatment effects is based on the CIA that the propensity score matching is depend on vector of observed covariates. However, if the assumption is relaxed, sensitivity analysis is applied to detect unobservable heterogeneity which affect treatment assignment and the outcome variable simultaneously by creating hidden bias (Rosenbaum, 2002). When the hidden bias is raised due to unobservable covariates, it is impossible to estimate robust matching estimators in non-experimental observational studies and thus the bias problem is addressed with bounding approach proposed by Rosenbaum (2002). Whenever an observational study has a selection or hidden bias, the adverse consequences of applying regression models to such data is to produce biased and inconsistence estimates of treatment effects (Guo and Fraser, 2015). To reduce bias in non-experimental observational studies, in matching or matched sampling, the sample should be drawn from the populations in such a way that the distributions of the confounding variables are similar in some respects in the sample and control the bias due to the x-variables by both matched sampling and statistical adjustment (Rubin, 2006). Moreover, during sample area and respondent selection, the researcher should have updated information about the intervention area, the nature of the intervention, the presence of other interventions (spillover effects) to reduce the risk of bias.

2.6. Review of Empirical Literature

Relevant studies conducted on SLM practices in Ethiopia and other countries in the context of the farmers' perceptions, participation decision, choices and impacts of SLM are reviewed and presented in the following sections.

2.6.1. Farmers' perceptions about SLM practices and its determinants

Perception is one type of information that provides important insights and understanding of the farming community for evidence based conservation practices and land management (Bennett, 2016). A better understanding of household's demographic, economic, institutional and biophysical plot characteristics (plot shape, slope, soil depth, soil fertility status) affect farmers' perception to soil erosion severity and their respond to invest in SLM practices to combat soil erosion problems (Zenebe *et al.*, 2012; Worku and Schneider, 2016). The perception of farmers about the role of SLM in managing and using the land resources depends on farmers' perception to the severity and/or seriousness of the soil erosion on their farm plots (Zerihun *et al.*, 2017b) and on their perceptions about the landscape (Engdawork and Hans-rudolf, 2016). Moreover, it also depends on farmers' perceptions about the land quality, land fragmentation and tenure systems (Akalu *et al.*, 2016) and very importantly on farmers' interactions with development agents (DAs) in designing and implementing the interventions (Zerihun *et al*., 2017a). Perception also varies with agro ecological, socioeconomic condition, institutional factors and biophysical farmland attributes of farm households (Gebreyesus, 2019).

Farmers' perceptions about the role of SLM in reducing degradation process and improving land capability potential are linked to the decision to participate in land management practices. Understanding perception status of local people (farming community) about the land management provides complete picture on which to base the decisions to use or not to apply the interventions against the environmental threats (Bennett, 2016). Farmers' perceptions of land quality in terms of slope class, soil depth, soil type and fertility status, farm size and tenure system influence SLM investments (Akalu *et al*., 2016). In the traditional land management practices context, in southern Ethiopia, the awareness and perceptions of farmers in responding to the land degradation problems particularly to soil erosion, soil fertility decline and overgrazing made farmers to develop and practice traditional and indigenous knowledge based land management practices supported by traditional rule and norms (Engdawork and Hans-Rudolf, 2016). But nowadays, due to population dynamics and the need for high agricultural productivity, the traditional and indigenous land management practices are incorporating the improved SLM practices with other infrastructural development packages by involving and benefiting farmers right from planning to implementation. While perceiving SLM interventions as development endeavors in combating land degradation and improving land productivity, it should be supported with other developmental interventions packages (Schmidt *et al*., 2017).

On the contrary, in some cases, though smallholder farmers are aware of and perceived the role of SLM in managing the land resources positively, they are not willing to implement the conservation measures due to some technical and economic problems, for example, structural/design problems of terraces, difficulties in oxen ploughing, harboring rodents, compete cultivated land and its nature of demanding intensive labor work (Engdawork and Hans-rudolf, 2016). From the sociological point of view, farmers perceived soil erosion as a non-threatening process can be explained by the slow overall pace of soil erosion Hurni *et al*.

(2010) that some farmers are reluctant to implement SLM. Very importantly, farmers' perceptions and knowledge to land degradation in general, and soil erosion, in particular are important to use and implement land management practices on their farmland (Birhan and Assefa, 2017; Gebreyesus, 2019).

2.6.2. Farmers' participation decision in SLM and its determinants

The SLM is essential to sustain and improve livelihoods while protecting the land resources; seeks to increase production, helps to improve resilience to food insecurity, land degradation, vegetation and biodiversity loss and climate change (Liniger *et al*., 2011). The dilemma in Ethiopian SLM practices versus the degradation challenges yet remains key developmental issues and it should be seen from socioeconomic, biophysical and policy perspectives. On the other hand, knowing the decision of smallholder farmers to actively participate and how much farmland is allocated to implement on-farm SWC measures are instrumental to investigate the dilemma. Many studies indicated that the decision to participate in SLM practices and how much to invest are influenced by a number of socioeconomic characteristics of the households, biophysical features of farm plots and institutional service types offered to the given farming community (Zenebe *et al*., 2012; Paulos and Belay, 2017; Ndagijimana *et al*., 2018).

There are household demographic, socioeconomic, institutional and biophysical farm plot related driving forces that influence farmers' decision either to use any of SLM practices or not willing to apply the technologies themselves on their farm plots for consecutive years (Paulos and Belay, 2017; Zerihun *et al*., 2017a). An explorative research done on farmers' investment in land management in central rift valley of Ethiopia by Zenebe *et al*. (2012) identified that households' resource endowments, farming experience and knowledge, access to information, social capital and availability of family labor are crucial influencing factors that determine farmers' decision how much and where to invest in land management practices. A case study on understanding farmers' investment in SLM in Burundi by Ndagijimana *et al*. (2018) reported that farmers' access to credit, farming experience, education enrolment at primary level, time spent on agricultural activities and age have influenced the decision of farmers to invest in SLM positively.

Similar to farmers' decision to participate in using land management practices including wetland restoration, the intensity or extent of enrollment in deciding the acreage amount is also impacted by the socioeconomic, policy and biophysical attributes of the participant households (Wei *et al*., 2016). At a plot level, differences in the biophysical characteristics of plots such as slope, soil depth, fertility status, size and the difference among the farm households with respect to their demographic, social, economic and cultural characteristics lead to the differences in how much and where to invest in SLM (Zenebe *et al*., 2012). A study conducted Gibe Basin, southwest Ethiopia by Fekadu and Engdawork (2019) using an ordered probit model, household size, extension service, training, and perception of soil erosion had a positive and significant influence on participation and intensity decisions of watershed management practices aimed to restore land resources.

Understanding the participation decision in SLM can also be viewed from the adoption behavior of smallholder farmers. By exploiting the WOCAT technology database and by analyzing observed costs and perceived cost/benefit ratios of the existing SLM technologies, though SLM practices incurred high initial investment costs in terms of labour and other inputs, the majority of the technologies are perceived by the land users as being profitable in the long run (Giger *et al*., 2018). A similar study conducted by Worku and Schneider (2016) on preferences for forms of land conservation measures in Ethiopian highlands revealed that the rural land administration and land use policy of the country, specifically land certification reform, acted as a legal instrument to the farm-household's decision to adopt land conservation strategy as well as the intensification of conservation measures on their land resources. Thus, from this, it can be triangulated that the economics of SLM from profit, cost/benefit ratio perspective and policy perspective are important key factors to be perceived for farmers to participate and use SLM practices on their farmland thereby to have a wider impact.

2.6.3. Farmers' choices of SLM practices and their determinants

Farmers' choice of various sets of SLM options, particularly land conservation measures in a given agroecology and local farming system condition is a complex decision. A study made by

Worku and Schneider (2016) in Ethiopian highlands revealed that no single driving factor contributes to the differences in farm households' preferences for various forms of soil conservation measures; rather a mix of factors contribute to such variations. They found that tenure security and farm plot's biophysical characteristics have positive effects while some institutional services, for example, market accessibility has no influence on the farm-households' land conservation measure choices. A study conducted in the north-western Ethiopian highlands by Akalu *et al*. (2016) and east Harerge, Ethiopia by Million *et al*. (2019) reported that the choices of SLM practices by farmers are considered from the context of their substitution and complementarity nature. Whenever SLM practices choices are complementary (positive correlation), it has a synergy effect that farmers could apply the SLM practices jointly or simultaneously in their farmlands to protect and reduce soil erosion and excessive runoff. On the contrary, when SLM choices show substitution effect (negative correlation), it has a trade-off effect that implies using either of the practices could have the probability of reducing the alternative practice. When choices or preferences for interventions are complementary, it needs to be addressed simultaneously (Wagayehu, 2006).

A number of previous studies conducted in different parts of the country using a multivariate probit model (MVP) estimation showed that some of the SLM practices and agricultural intensifications are complementary and yet others are substitutable, for example, Zerihun *et al.* (2017a), Million *et al*. (2019), Agere *et al.* (2020), Alelgn *et al*. (2021), Wondimu *et al.* (2021), Wudineh *et al*. (2023) and Dessalegne *et al*. (2024). In addition, the scholars reported that different socioeconomic, institutional, biophysical farm plot and policy related factors have influenced the investment and use of interrelated SLM practices on farmland as a developmental intervention against soil erosion threats.

A farm household's preference for a decision among different land conservation measures on farm plots was found to be influenced by poverty level, land tenure security, farm size, extension advice, access to market, and farmers' plot characteristics differently (Worku and Schneider, 2016). Profitability and the costs accrued to establish and maintain structures are key factors for farmers' choice to adopt or not to adopt a given SLM technology and/or practice (Giger *et al*., 2018). However, for highly labor intensive and time taking long-term

SLM practices, the investment cost outweighs profitability at the early time of the interventions would not be key factors for farmers' choice decision (Schmidt and Fanaye, 2013). To shift farmers' choice to SLM practices that outweighed the profitability, long term SLM investment and its maintenance should be incentivized (Schmidt *et al*., 2017).

2.6.4. Impact of SLM on value of crop production and farm income

Impact evaluation of SLM is distinct from the economic valuation of SLM, that in the latter case the net production gains of each SLM intervention is compared with its costs of implementation using the internal rate of return (IRR) to assess the economic return of each action (Requier-Desjardins *et al*., 2011). The comparative advantage with vs. without SLM intervention is employed as an approach to value the economic benefit. However, in impact evaluation semi-parametric matching methods, and other parametric methods are commonly employed for the estimation Smith and Todd (2005) and Menale *et al*. (2010) comparing the outcomes occurring due to the treatment and its counterfactual component. The ATT employs with and without interventions and DiD or double-difference method utilizes baseline (before intervention) and end line dataset (after intervention) to compare the change in outcome between treated and non-treated groups over time (Rubin, 2006; White and Raitzer, 2017).

Methodologically, in applied science, social science and in other fields like political sciences, impact evaluations of programs, project, policy reforms or any intervention are evaluated using the semi-parametric estimation techniques of ATT and DiD or double-difference methods based on the datasets. Some of the previous empirical studies on impact evaluation using PSM estimates includes: impacts of SLM on crop production (Paulos and Belay, 2017); impacts of PSNP on households income diversification (Zerihun and Prowse, 2013) and impacts of SLM practices on crop productivity (Menale *et al*., 2010) are few empirical research conducted in Ethiopia that all employ either NNM, KM and radius caliper matching or mix of algorithms to compare the average outcomes with and without the specified interventions using single difference estimate procedure, i.e. ATT. Analytically, a number of researchers applied PSM for impact analysis, for example, Babu *et al*. (2023) conducted an impact of SWC on food security in eastern Ethiopia; Abebe *et al*. (2024) studied impact of contract farming on economic efficiency of malt barley in northwestern Ethiopia. On the other hand, there are few rigorous empirical studies conducted in Ethiopia that used PS estimators to evaluate SLM impacts using DiD methods with baseline and end line data sets, for example, Schmidt and Fanaye (2019). To overcome the limitations of PSM, some scholars have adopted Endogenous Switching Regression (ESR) Model as an efficient and robust estimator to estimate impact of SLM practices, specifically SWC, on household vulnerability to food insecurity e.g. Million *et al*. (2019b); on household welfare in South Africa, e.g. Oduniyi and Tekana (2021).

In Ethiopian highlands, a study conducted on impacts of SLM practices on the value of crop production, and productivity indicated a positive response at household level (Schmidt and Fanaye, 2013; Paulos and Belay, 2017). A farm plot received SLM have responded to a higher yield as compared to those plots with no or little efforts of the intervention (Paulos and Belay, 2017). A household and plot level survey conducted by Menale *et al*. (2010) in Amhara and Tigray regions, Ethiopia compare the impact of SLM practices, namely commercial fertilizer and minimum tillage on crop productivity using a semi-parametric matching methods, reported that fertilizer was more productive than the minimum tillage and farmers traditional practices in high agricultural potential and low in the low-potential areas of the same regions.

In spite of the positive impacts of SLM, there are few empirical studies reported a negative impact of SLM on households' value of production and income. A study made on impacts of SLM in Blue Nile Basin, Ethiopia using panel dataset by Schmidt and Fanaye (2019) reported that there was no significant impact on households' agricultural value of production after four years of participation. Furthermore, a study conducted in rainfall-sufficient highlands of the same basin by Schmidt *et al*. (2017) to measure SLM impacts on agricultural production and income found that relying only on SLM practices of SWC could not showed a significant impact rather it was suggested to integrate with other rural investment packages.

In most areas, farmers are reluctant to maintain and manage the established SLM technologies both at communal and private farmlands which tend to affect the socioeconomic and environmental impacts of SLM (Million and Belay, 2004). Moreover, in anticipating the positive impacts of SLM practices, one has to consider the time horizon of the structure place on the farm plot Paulos and Belay (2017) that it should stay for a longer period of time for a positive impact or change to user farmers. In line with this finding, the impact of sustainable land and watershed management on private farm plots in Ethiopian highlands showed that the SLM structures, namely terraces, bunds or check dams must be in place for at least seven years to have a significant increase in value of crop production Schmidt and Fanaye (2013). This, in turn, suggests the need to long term investment of land management practices. Another empirical study also witnessed that SLM investments must be maintained for at least seven years to have a significant increase in the value of production (Schmidt *et al*., 2017).

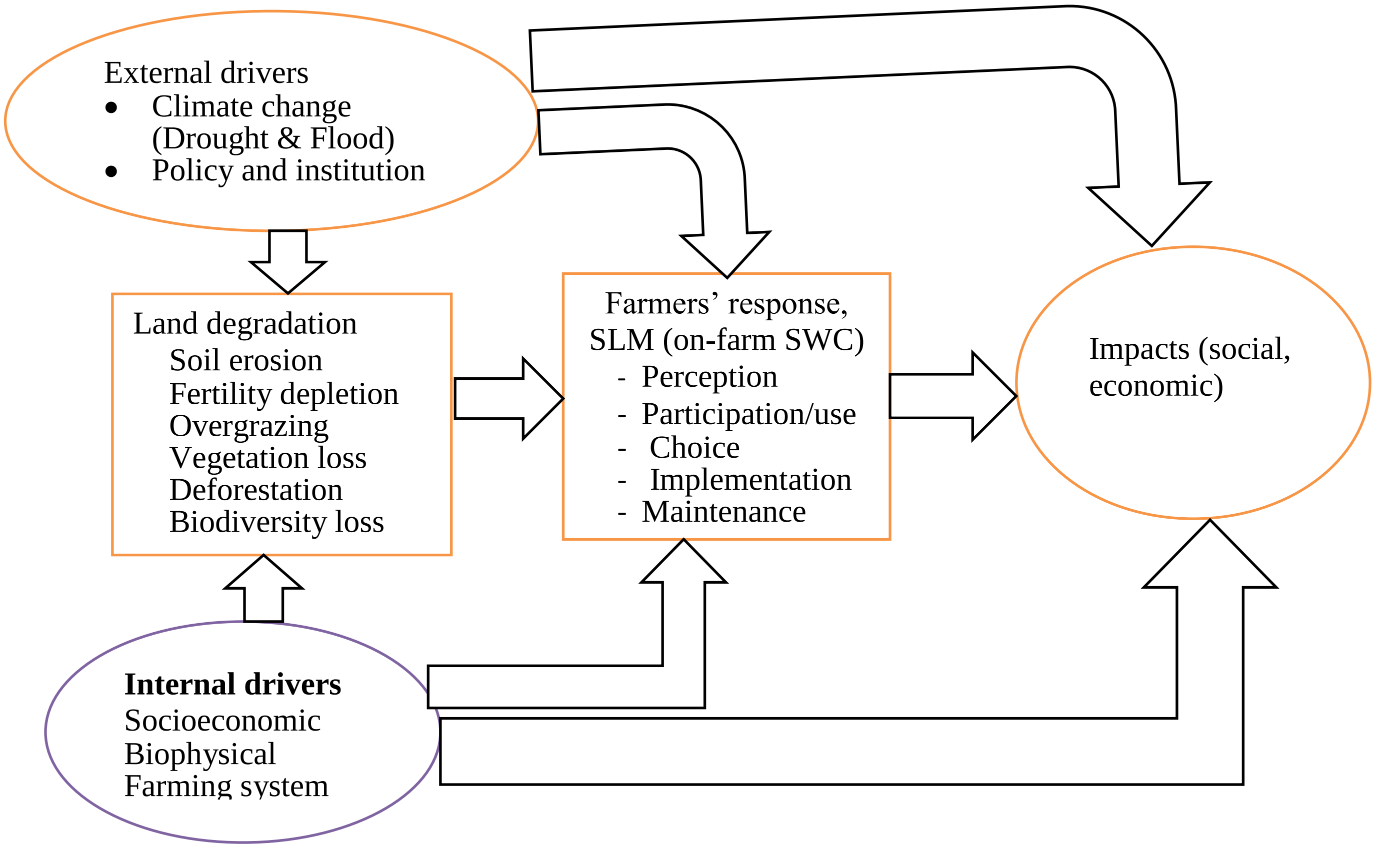
2.7. Conceptual Framework

The conceptual framework for smallholder farmers' participation in SLM practices starts from understanding the existing problem of land degradation. Land degradation is a pressing environmental problem that constraints agriculture through imposing negative impact on land resources by lowering its potential use to the current and future generations. Land degradation is a process that encompasses increased runoff, soil erosion, topsoil loss, reduced vegetation cover, biodiversity and habitat loss (both fauna and flora) and deforestation (Critchley *et al*., 2021).

Land degradation is broadly classified as soil erosion, fertility loss, and vegetation loss caused by internal and external driving forces. Awareness of the internal and external causes of land degradation is considered as a cognitive state (Gifford, 2014). The external driving force mainly encompasses climate change (drought and flood), policy, and institutional arrangement. Land degradation results from unsustainable land management practices enhanced by the negative impact of climate change and internal socio-economic drivers (Liniger *et al*., 2011). The internal drivers contributing to land degradation consist of socioeconomic factors including population pressure, and biophysical attributes of farmland such as soil quality, slope gradient of the farm plots and soil erosion severity. Land degradation can be mitigated or reduced through the application of SLM practices. While using SLM practices in general and on-farm SWC measures, in particular, farmers' perceptions of the role of SLM practices, the decision of farmers to use, choose, and implement SLM practices is instrumental as a solution to mitigate or reduce the threat (Zerihun *et al*., 2017a; Agere *et al.* 2020, Alelgn *et al*. 2021). Farmers' perception of the role of SLM practices in mitigating land degradation, their decision to participate and choose appropriate SLM practices is considered as adaptation behavior.

Farmers' response to implement area specific SLM practices, particularly, on farm SWC measures is considered as mitigation actions. The response to land degradation (on-farm SWC measures) resulted in positive anticipated socioeconomic impact over time at household and plot levels (Schmidt and Fanaye, 2013; Paulos and Belay, 2017). The anticipated positive change or impacts of SLM practice include increase in farm income and crop yield of farm households who decide to use recommended choice or combination of practices.

The scope of the problem starts from farmers' understanding of their farmland whether it is affected or not by land degradation within the farming community. In reducing the challenges through implementing different interventions including SLM, specifically on-farm SWC measures has been designed and implemented at various scales both at the farm and communal land. While designing and implementing SLM, interlinked and mutually inclusive decision processes of farmers' participation, choice, and use of SLM and their anticipated change or impact are linked in the conceptual framework indicated in Figure 1.



Note: The solid arrows indicate the direct effect of attributes (measures) indicated in the box. The external and internal drivers are direct causes for land degradation, farmers' response to land degradation is using, perceiving, choosing and implementing/maintaining SLM (in our case on-farm SWC) result in socioeconomic impact (anticipated or unanticipated).

Source: Own sketch, 2023

Figure 1 Conceptual framework of the study

3. RESEARCH METHODOLOGY

In this chapter, the details of methodology used to address the research questions and the objectives is provided. Description of the study areas, the research methods, sample size determination, sampling techniques, and data collection methods are explained and presented. The statistical tools that were used for the summary of the variables; the inferential statistics; the econometrics models specified and employed for the data analysis and the hypothesized variable and definitions are presented sequentially as per the research objectives.

3.1. Description of the Study Areas

The then SNNPR is located in the south and south-western part of Ethiopia. Geographically, it is situated between the coordinates of $4^0 27'$ and $8^0 30'$N and $34^0 21'$ and $39^0 11'$E (Figure 2) with altitude ranging from 376 to 4207 m asl and with mean annual temperature ranging from 15^0c to 30^0c. Including Sidama region, it covers a total area of 110931.9 km^2 which shares ten percent of the country's total area and the total population is projected to be more than 21.9% million in 2023 (CSA, 2013). In the current administrative structural adjustment, the central areas include Sidama Region, South Ethiopia Region (Wolaita and Gedio) and Central Ethiopia Region (Hadiya, Kembata-Tembaro, Halaba, Siltie, and Gurage zones).

They are characterized by high population pressure, 196 persons per square kilometer; low per capita landholding (that is, 0.294 ha in Sidama and 0.51 ha in SNNP Regions) (ESS, 2022C). Agro ecologically, the central zones are categorized into high and midland. They are known for intensive farming which has exposed to high soil erosion and fertility depletion. The zones are known for their intensive effort in implementing SLM practices. The farmland area covered by annual and perennial crops is estimated to be 55.83% of the total regional cropland and production (ESS, 2022b).

In institutionalizing SLM as an integrated approach to combat land degradation and soil erosion, the central zones of southern Ethiopia were targeted. In the first phase of SLMP (2008-2012), five woreda, from Sidama, Gedio, Gurage, Silitie and Kembata-Tembaro zones participated (MoARD, 2011). In its second phase (2013 to 2018), 11 woredas namely Arbegona and Hawassa Zuria (Sidama), Boloso Bombe and Kindo Didaye (Wolaita), Gumer and Geta (Gurage), Gibe and Soro (Hadiya), Hulbareg and Mirab Azernet (Siltie) and Tembaro (Kembata-Tembaro) were included in land management interventions (MoA, 2014). The study was conducted in 3 SLM woredas, namely Arbegona, Boloso Bombe and Hulebareg and in 3 non-project woredas at Malega, Boloso Sore and Dalocha. They are characterized by high population pressure, low average land holding, intensive farming, and severe soil erosion. Moreover, the study areas have diverse socioeconomic setups and physical condition in livelihood, natural resource endowments, weather conditions and farming system. The farming system of the areas is characterized by mixed farming system, where crop production is dominant, which in turn contribute to land degradation and soil erosion.

Arebegona and Malega woredas are located in Sidama Region, Ethiopia. Arbegona is one of the SLMP whereas Malega is non-SLMP woreda. Toshine and Hurre are the two *kebeles* selected for data collection. The traditional agro ecology of the woreda is midland (36%) and highland (64%) type with altitudes ranging from 2000 to 3336 m asl. According to ESS (2023) population projection Arbegona has a total population of 189625 of whom 94701 (49.94%) are male and 94924 (50.06%) are female while Malega has 151146 (76 522 males and 74624 females) (ESS, 2023). The total area of the woreda is 27100 ha, of which 24840 is cultivated, 1650 ha is plantation and 610 ha is natural forest area. Malega has midland (21.7%) and highland (78.3%) agro ecology. Barana and Abake Torshe are sample *kebeles* drawn from this woreda. The total land area of the woreda is estimated to be 32650 ha, of which the highest amount i.e., 18177 ha is cultivated. Both woredas have a mixed farming system where *ense*t[3], barley, wheat, maize, faba bean, field pea, potato and vegetables dominate. Cattle, sheep, goats, poultry, and equine are major livestock species reared in both woredas. Their topography is fragile land where intensive SLM practices, particularly, on farm SWC are commonly applied to abate the environmental threats, i.e., soil erosion caused by frequent farming, overgrazing, removal of vegetation cover and by excessive runoff.

[3] *Enset (*Ensete *ventricosum*) is Ethiopian native and perennial root crop cultivated near homestead and is a stable food sources in south and southwestern parts of Ethiopia.

Boloso Bombe and Boloso Sore woredas are found in Wolaita zone, South Ethiopia Region. The sample *kebeles* selected were Farawacha and Zaba from Boloso Bombe and Chama Himbecho and Gurumo Koyisha from Boloso Sore. According to ESS (2023) population projection, the total population of Boloso Bombe and Boloso Sore was estimated to be 117882 (48.68% men and 51.32% female) and 308598 (48.33% men and 51.67% female), respectively. Agro ecologically, Boloso Bombe is covered by lowland (75%), midland (20%) and highland (5%) whereas Boloso Sore is majorly midland (91%) and the remaining 9% is highland. The total area of Boloso Bombe is about 21859 ha, out of which 13592 ha (62.18%) is cultivated. The major types of crops grown in Boloso Bombe include common bean, maize, *teff*, *enset*, coffee, root crops, fruit (mango, avocado, and banana), and ginger. Maize, wheat, *teff*, haricot bean, *enset*, taro, sweet potato, fruits, coffee, and vegetables are the dominant crops grown in Boloso Sore. Cattle, goat, sheep, poultry, and donkey are the major animals reared by farmers in both woreda. Boloso Sore is known for its high population density and lower land holding, i.e., 993.7 persons per square kilometer ESS (2022a) which aggravates land degradation and soil erosion as the people compete for farmland for their livelihood.

Hulbareg and Dalocha are sample woredas selected from Siltie Zone (Central Ethiopia Region). Wacho Obiso and Warabat Shama from Hulbareg and Dalocha Talikessa and Golacheba from Dalocha were selected as sample *kebeles* for data collection. The total projected population of Hulbareg is about 107084 (47.87% male and 52.13% female) whereas Dalocha has 128854 (49.88% men and 50.12% female) (ESS, 2022a). Agro ecologically, Hulbareg woreda is a midland type (70%) and dry midland (30%) whereas Dalocha is dominated by midland type (ESS, 2023). The total land area of Hulabareg woreda is estimated to be 43140 ha, of which the majority of the land area is cropland utilized for cereals, *enset*, and chat cultivation. Maize, wheat, barley, *teff*, sorghum, and pepper are major crops grown in Dalocha. The major livestock reared in both woredas include cattle, sheep, goat, donkey, and poultry. Declining soil fertility, soil erosion, and land degradation in the form of gully, landslide, flooding, siltation, and deforestation are the major natural resource problems of the woredas. To abate the aforementioned problems, Bureau of Agriculture (the natural resource management wing) and the extension services at kebele, woreda and zonal level have implemented different types of on-farm SWC measures on private farmland, communal land and other land use types.

3.2. Sampling Procedure

The study employed non-randomized purposive sampling to identify zones/regions, each having two or more woredas implementing SLM practices on at least one-quarter of owned farmland for five consecutive years (2013-2018). The SLM intervention and non-intervention woredas are found in the same highly populated zone characterized by land degradation and severe soil erosion. The difference between the two groups is that the SLM woredas are supported by the government project, namely by SLMP in implementing SWC such as resources and frequent training. They are provided with construction equipment, planting materials, seed and cash payment to compensate their labour cost while implementing SWC measures. The non-project intervened ones access this opportunity through the usual extension services and advices without any cash or kind payment.

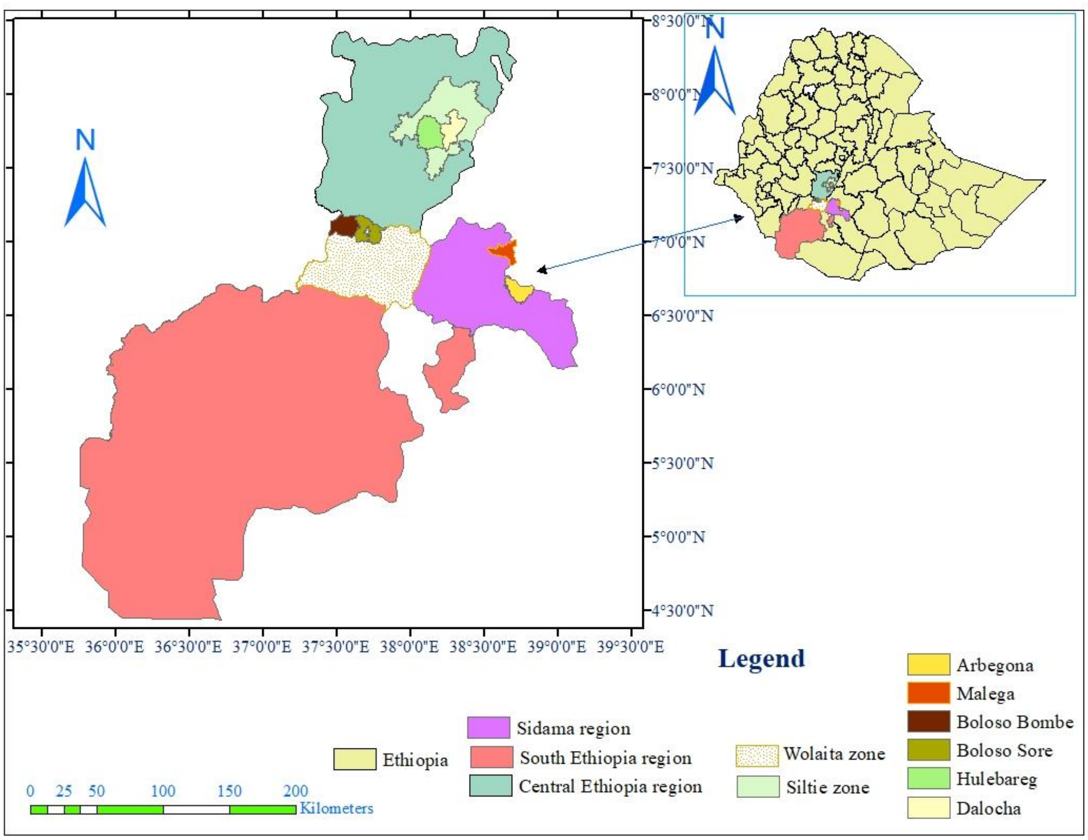


Figure 2 Geographical locations of the study areas

Based on the objectives of the study, sample zones were framed based on population density, number of SLM implementing woredas, and intensity of SLM interventions, mainly on-farm SWC measures. Accordingly, the top five zones that have two woredas included in the SLMP-II, the lowest land holding ratio, and with the highest effort of land management practices are Sidama, Wolaita, Siltie, Hadiya, and Gurage. Among these, three highly densely populated zones with the lowest land holding ratio ESS (2022c) having two or more woreda included in the SLM project MoA (2014), and those with the highest effort of land management practices were selected purposively. Based on the criteria, Sidama region, Wolaita, and Siltie zones (Figure 2) were identified purposively. Once the zones were identified, stratified random sampling technique was employed to identify sample units.

Sampling technique: the stratification was based on land management intervention, mainly on-farm SWC measures implemented for continuous five years (2013 to 2018). After the stratification of woredas (i.e., SLM intervened mainly on-farm SWC measures for at least five years and the non-intervened with no or little effort in implementing SLM practices), a two-stage sampling technique was employed to select the sample units from the intervened woredas. In the first stage, one woreda was included in the SLM project and one from non-SLM, and a total of 6 woredas were drawn randomly. During the survey, Sidama had 30 districts (3 SLM and 27 Non-SLM), Wolaita had 16 (3 SLM and 13 non-SLM) and Siltie zone had 10 (2 SLM and 8 non-SLM) woredas. The six woredas selected were Arbegona and Malega (Sidama region), Boloso Bombe and Boloso Sore (Wolaita zone), and Hulebareg and Dalocha (Siltie zone).

In the second stage, two *kebles* from each woreda and a total of 12 *kebeles* were selected randomly. A total of 165,343 (i.e., 86,120 from SLMP and 79,223 non-SLMP woredas) population size was considered to decide the sample size using Kothari's (2004) sample size determination formula. As a result, a sample size of 432 was taken based on probability proportional to size (PPS) sampling using a simple random sampling technique. Additionally, 10% of the total sample households (i.e., 43 HHs) were included in the survey. Finally, a total of 475 households (365 users and 110 non-users) from six woredas and twelve *kebeles* were randomly selected for the household survey (Table 1).

3.3. Sample Size Determination

For household and plot level primary data collection, representative sample size was obtained. The size of households was decided using an appropriate sample size determination formula for estimating the number of participants and non-participant farmers of SLM practices. On the basis of the nature of the universe (homogeneity or heterogeneity nature of the population), the nature of the study, the level of precision (e), the level of confidence (Z) and other considerations an optimum total sample size for finite population was determined before proceeding to data collection (Kothari, 2004).

Following Kothari (2004) the optimum sample size for this study was determined as:

$$n = \frac{Z^2.p.q.N}{e^2(N-1)+Z^2.p.q} \tag{1}$$

$$= \frac{1.96^2*0.5*0.5*165343}{0.05^2\ (165343-1)+1.96^2*0.5*0.5} = \frac{158795.4}{414.32} = 383$$

where, n is the desired sample size, Z is the value of the standard variate corresponds to a level of confidence with a value of 1.96 showing area under a normal curve, p is the sample proportion or percentage with value of 0.5 to get the desired minimum sample size at 95% confidence interval and ±5% precision level, q is 1-p, N is the size of total population from which sample is drawn, and e is the level of precision or standard of accuracy. Accordingly, from the total household heads of 6 woerdas a sample of 432 households were selected based on PPS as shown in Table 1 below. Moreover, 10% of the total sample households (i.e. 43 households) were additionally included in the household survey. For the plot level analysis, a minimum of 1 plot or plot equivalent to 25% of the farmland owned by the sample household heads was considered in the plot data collection. About 1257 (942 of users and 315 non-users') plots were considered for SLM impact analysis at a plot level. The sample *kebeles* and sample households were selected using simple random sampling technique based on PPS sampling from each woerda.

Table 1 Distribution of the sample woredas and households

Sample zone	No. of woredas			Sample SLM woreda			Non SLM woreda		
	SLM	Non-SLM Intervened	Non-SLM Non-intervened	Name	Total HHs	Sample HHs	Name	Total HHs	Sample HHs
Sidama	3	16	11	Arbegona	36920	96	Malega	29771	78
Wolaita	3	9	4	Boloso Bombe	27100	71	Boloso Sore	27852	73
Siltie	2	5	3	Hulbarg	22100	58	Dalocha	21600	56
Total	8	30	18	3	86120	225	3	79223	207

Source: Zone Agricultural Offices (unpublished), 2021.

3.4. Data Types, Sources and Methods of Collection

Data type: to achieve the objectives of this study, secondary and primary data were collected from sample households and other sources. Cross-sectional data from sample households and owned plots were collected. Primary data were collected from participants and non-participants of land management practice, farm plots, and households representing the social stratum at village level, knowledgeable farmers, and expertise in natural resource management.

Methods of data collection: while collecting the primary data, combinations of formal household survey and participatory rural appraisal (PRA) known as the informal methods of data collection were employed. In the formal methods of data collection, a structured questionnaire was designed and executed to collect primary data from sample households. Based on the objectives of the study, a household survey data collection instrument was designed and executed to collect primary data from sample households. Discussions were held with subject matter experts working in areas of natural resource management to have clear insights and understanding of what should be included in the data collection instrument. Moreover, a structured observation and transect walk were also made to have a clear picture of the research question and objectives of the intended project. Household data collection instrument was designed based on the discussions; transect walk, research objectives and questions of the study.

Before administering the household survey, the data collection instrument was pre-tested and validated by interviewing randomly selected farmers in the study areas. Once the instrument was tested and validated, data from sample households and own plots were collected using a household survey from October to December 2020. The data comprised a mix of demographic, socioeconomic, institutional, and bio-physical characteristics and attributes hypothesized to affect farmers' participation decisions, perception, choices, and impacts of land management practices at household and plot level. To substantiate and complement information collected though formal survey, qualitative data were collected using focus group discussions (FGDs), interview with knowledgeable farmers and experts, and direct observation of SWC measures implemented on farm fields. Moreover, secondary data from published and unpublished sources i.e. progress and annual reports, documents, operational manuals, and guidelines were collected and organized using data templates, formats, and tables to present and narrate the information obtained.

3.5. Methods of Data Analyses

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The study employed descriptive and econometric methods to analyze the data. The descriptive statistics method of data analysis was employed to quantify and summarize the data set. Based on the literature, economic a priori criteria, and the research objectives and questions of the study, different econometric models were specified and used for the analysis. The major analytical steps applied to each research objective are presented sequentially as follows.

3.5.1. Descriptive statistics

In using descriptive statistics, both the qualitative and quantitative data were organized, summarized, and presented in an informative way in tabular or graphical form. In this method, frequency distribution, graphic representation, a measure of central tendency (mode, mean), and measures of dispersion (range, standard deviation) were employed to summarize and present the data. The participants and non-participants of SLM were compared using different attributes by descriptive statistics. Moreover, inferential statistics were employed for making inferences about the whole population based on sample observation. They were also used to test the significance level of the hypothesized regressors with the dependent variables included in the econometric models for each objective. Prior to the econometric models, they were employed to test, validate, and predict the hypothesis to make inferences about the population. The parametric tests like the t-test for continuous variables were applied for statistical inferences. The non-parametric chi-square (χ^2) test was applied to measure the association between two nominal or categorical variables.

3.5.2. Econometric models

Based on the literature, economic a prior criterion, and the research questions or hypothesis of the study, different econometric models were specified, tested and used for the empirical data analysis. Once the models specified, the parameters were estimated, tested, validated and finally the results were interpreted and synthesized from an economic point of view using the estimated output of the data sets. Apart from the descriptive statistics result, the econometric models specified and employed for each objective of the study are presented and discussed in the subsequent sections.

3.5.2.1. Analysis of farmers' perception about SLM

Different econometric models were specified and tested to analyze farmers' perception of SLM, specifically on-farm SWC measures. Based on the economics literature, and the research questions of the study, an ordered probit model was specified, tested and used for data analysis. When farmers' perception of SLM role is independent and ordinal, the multinomial probit or logit model fails to account for the analysis; rather the ordered choice models are applied to estimate the ordinal outcomes jointly on an individual specific basis (Wooldridge, 2010; Greene, 2012). The main assumptions drawn in such cases are (1) the dependent variable is measured on an ordinal scale (2) one or more of the independent variables are continuous, categorical or ordinal (3) no multi-collinearity (4) proportional odds i.e., that each independent variable has an identical effect at each cumulative split of the ordinal dependent variable and (5) the βs are the same for each choice.

The two standard models widely utilized as a methodological framework for the analysis of ordered multi-response outcome variables are the ordered probit and the ordered logit (Greene, 2012). Both approaches are equivalent, except the ordered probit follows the standard normal cumulative density function (CDF) while the ordered logit follows the logistic CDF. The error term in ordered probit and logit is assumed to be distributed normally and logistically across observations, respectively. Moreover, the errors ε_i are independently distributed in the ordered probit model. Thus to achieve the objective and to answer the research question of this study, the extensions of the univariate probit model, namely the ordered probit model was proposed and utilized for the data analysis. The maximum log-likelihood (ML) estimation procedure was employed to estimate parameter coefficients and the cut points.

Following Greene (2012), the ordered probit model built around a latent regression in the same manner as binomial probit model is given by the structural model as:

$$y_i^* = x_i\beta + \varepsilon_i \quad , \ \varepsilon_i|x_i \ \sim N\,(0,1) \tag{2}$$

where, y* is the latent or un observed variable ranging from -∞ to ∞, x represents the set of explanatory variables and does not contain a constant, β is the parameter estimates, ε is a random error follows a cumulative distribution function (CDF) and i is the observations.

The measurement model for binary outcomes divides y_i* in to j ordinal categories, following a standard ordered probability model the probability of observing outcome i is given as:

$$\Pr(outcome_j \ = i) = Pr(\mu_{m-1} \ < \ y_i{}^* \leq \mu_m)$$
$$\Pr(outcome_j \ = i) = Pr(\mu_{m-1} \ < \ x_i\beta + \varepsilon_i \leq \mu_m) \tag{3}$$

where the parameters of estimate, i.e., β is a vector of coefficients to be jointly estimated with cut points, μ_1, μ_2… $\mu_{m-1,\, m}$ is possible outcomes and ε is a stochastic term.

Let μ_1, μ_2 and μ_3 be unknown parameters (cut points or thresholds) estimated with β, when y_i taking the values 1, 2 and 3 with three categories, the link between the observed ordinal outcome y_i and the unobserved y_i* is related with equation as:

$$y_i = \begin{cases} 1\ if -\infty \leq y^* \leq \mu_1 \\ 2\ if\ \mu_1 \leq y^* \leq \mu_2 \\ 3\ if\ \mu_2 \leq y^* \leq \mu_3 \end{cases} \tag{4}$$

Following Wooldridge (2010) and Greene (2018) , given the standard normal assumption that the error term, ε is normally distributed across the observations as binomial probit model, it normalize the mean and variance to zero and one then the conditional distribution of y_i given x_i, the probability of each response for farmers' perception of SLM is computed as:

$$Pr\ (y = 0|x) = Pr(y^* \leq \mu_1|x) = Pr(x\beta + \varepsilon \leq \mu_1) = \Phi(\mu_1 - x\beta) = 1 - \Phi(x\beta) \tag{5}$$

$$\begin{aligned} Pr(y = 1|x) &= Pr(\mu_1 <\ y^* \leq \mu_2) = P(\mu_1 < x\beta + \varepsilon \leq \mu_2) = \Phi(\mu_2 - x\beta) - \Phi(\mu_1 - x\beta) \\ &= \Phi(\mu - x\beta) - \Phi(-x\beta) \end{aligned}$$

$$\begin{aligned} Pr\ (y = 2|x) &= Pr(\mu_2 <\ y^* \leq \mu_3) = P(\mu_2 < x\beta + \varepsilon \leq \mu_3) = \Phi(\mu_3 - x\beta) - \Phi(\mu_2 - x\beta) \\ &= 1 - \Phi(\mu - x\beta) \end{aligned}$$

where, Φ (.) denotes the ordered normal cumulative distribution function.

The partial effects of the regressors $\mathbf{x_i}$ on the probabilities are not equal to the coefficients. Similar to the univariate probit model, in the ordered probit model the marginal effect can be computed to know the partial effects of a small change in explanatory variables x_i, on the predicted probabilities of the ordered response variables (Greene, 2012; Greene, 2018).

Proceeding equation 5, the marginal effects of the regressors for the three probabilities are derived as:

$$\begin{aligned} \frac{\partial\ Prob\ (y=0|x)}{\partial x} &= -\Phi(x\beta)\beta \\ \frac{\partial\ Prob\ (y=1|x)}{\partial x} &= [\Phi(-x\beta) - \Phi(\mu - x\beta)]\beta \\ \frac{\partial\ Prob\ (y=2|x)}{\partial x} &= \Phi(\mu - x\beta)\beta \end{aligned} \tag{6}$$

The parameters of estimate, i.e., μ and β in ordered probit model was estimated using the MLE procedure using Stata.[4]

Following Wooldridge (2010), the log-likelihood function was specified as:

$$L_i(\mu,\beta) = 1(y_i = 0)Log[\Phi(\mu_1 - x_i\beta)] + 1(y_i = 1)Log[\Phi(\mu_2 - x_i\beta) - \Phi(\mu_1 - x_i\beta)] + 1(y_i = 2)Log[\Phi(\mu_3 - x_i\beta) - \Phi(\mu_2 - x_i\beta)] \quad (7)$$

3.5.2.2. Analysis of farmers' participation decisions

The econometrics models were specified to analyse farmers' participation decision and the sequential-decision making of acreage allocation. The discrete choice models provide important insights into how different socioeconomic, institutional, and biophysical characteristics influence the likely probability of farmers' participation in SLM. Still it fail to provide further insights on the intensity of farmers' enrolment and how much acreage of land is allocated for SLM once the participation decision (crossed the first tier) is made. Cragg (1971) suggested the double-hurdle model to overcome the limitation of the standard Tobit model that truncates the distribution at zero. The double hurdle model nests the Tobit model and is widely applied to two sequential-decisions making processes, i.e., the first hurdle (selection model) and the second hurdle (outcome model).

The main assumptions in Cragg truncated hurdle model are: (1) the lower limit binding the dependent variable is 0 (2) it has two-part or hurdle models without specific distribution which are independent conditional on explanatory variables, x (3) the outcome variable assumed to have a truncated normal distribution and (4) the decision process is sequential. In the double hurdle model approach, taking IIA and independence assumptions, two models are specified separately for both stages. The two sequential decision processes are (1) a binary response of a farmers whether or not to participate in SLM (y > 0 versus y= 0), and (2) how much acreage

[4] Stata 17.0 basic edition (BE) statistical package with license serial number: 301709001668 was utilized for data analysis

of farmland is allocated for SLM activities if the farmer enrolls once in using SLM. The limitations of Cragg truncated hurdle model (THM) are the coefficient estimates are not directly interpretable rather margins are used and it is commonly applied for large sample size (Cragg, 1971). The limitation of the standard Tobit model to consider the first stage decision, i.e., the probability of y being zero or positive; the failure of binary probit model to look for the sequential decision process of farmers' participation and the Vuong test statistic in favor of THM than other competing models forced the author to apply the Cragg truncated hurdle model for the data analysis. Therefore, the Cragg truncated hurdle model for both participation decision and intensity of participation was specified and applied simultaneously in the iteration process.

The multiple functions of the binary participation decision, w, and the choice of non-negative acreage decision for SLM, y^* is proposed as the interaction of both as

$$y = w.y^* = 1[z\gamma + u > 0]exp(x\beta + \varepsilon) \quad (8)$$

where y^* is a non-negative continuous random and w is a binary variable

Independence of the two decisions assumption: the first decision of participation (binary choice of yes or no) and level of participation (acreage of farmland allocated) are independent; that is, the covariance of unobserved factors (error terms) is zero (Greene 2012; Wei *et al.*, 2016). The assumption of independence shows that the disturbances are independent and homoscedastic.

Following Wooldridge (2010), the lognormal hurdle model for the first independent assumption was specified and used for the analysis as follows:

$$y_i = {y_i}^* \ if \ w_i = z_i'\gamma + u_i = 1,\ {y_i}^* = \ {x_i}'\beta + \varepsilon_i > 0 \quad (9)$$

$$y_i = 0 \ \ if \ w_i = z_i'\gamma + u_i = 1, \ \ {y_i}^* = \ {x_i}'\beta + \varepsilon_i \leq \ 0, \text{ i} = 1, 2, 3,\dots \text{n}$$

where z_i and x_i are the vectors of explanatory variables that influence participation and the amount of farmland allocation decision respectively, γ and β is a vector of unknown parameters; u_i and ε_I are independently, distributed error terms with distribution N (0,1).

The first-stage decision variable w, that is, a farmer to participate in SLM, is estimated using the univariate probit model as follows:

$$w_i^* = z_i\gamma + u_i \qquad u|z_i \sim Normal(0, \sigma^2) \tag{10}$$

From Equation 10, the decision variable w is assumed to follow a probit model is proposed as:

$$Prob(w = 1|z) = E\,(w|z) = \int_{-\infty}^{z'\gamma} \Phi(t)\,dt = \Phi(z\gamma) \tag{11}$$

Both the lognormal and truncated normal hurdle models can be used to model the decision process, in which all zero observations are truncated (Wooldridge, 2010). From equations, 8 and 9, y is specified as:

$$y = 1[z_i\gamma + u]\;exp\;(x_i\beta + \varepsilon) > 0 \tag{12}$$

$$y = \begin{Bmatrix} y^* > 0\;if\;w = 1 \\ 0 \quad otherwise \end{Bmatrix} \tag{13}$$

Following Wooldridge (2002, 2010), the truncated normal hurdle (TNH) model to specify the density of y given was specified as:

$$f(y|x) = [1 - \Phi(x\Upsilon)]^{1[y=0]}\{\Phi(x\Upsilon)[\Phi(x\beta/\sigma)]^{-1}\,\phi[(y - x\beta)/\sigma]/\sigma\}^{1[y>0]} \tag{14}$$

To formulate the lognormal hurdle model (LHM), y was specified as:

$$log(y)|(x, y > 0) \sim Normal(x\beta, \sigma^2) \tag{15}$$

Relaxing the independence assumption that the amount of acreage allocation depends on the first participation decision in SLM leads to the interdependence assumption; the error terms have a non-zero value such that the independence assumption is violated (Wei *et al*., 2016). Unlike the lognormal hurdle model, unobservable factors can affect both the participation (w) and enrolment (y) decisions of SLM, that is, cov (u, ε) ≠ 0. Following Wooldridge (2002, 2010), in the second relaxed assumption, the ET2T model or Heckman method was adopted, and the results were compared among the three models (Table 18 and Annex Table 8).

The maximum likelihood estimation (MLE) technique was employed to estimate unknown parameters from the dataset. Moreover, it was attempted to estimate the marginal effect of a change in the hypothesized explanatory variables on the probability of participation and its intensity in the double-hurdle and ET2T models. In the model specification, the assumptions of homoscedasticity, endogeneity, autocorrelation, and multicollinearity were tested to obtain unbiased, consistent, and efficient parameter estimates. The Wald test statistic using chi2 and Vuong tests using a t-test were used to determine the overall goodness-of-fit for both the double-hurdle and ET2T models.

3.5.2.3. Analysis of farmers’ choice of SLM

Farmers’ choices for SLM among the top four prioritized SWC measures was elicited using a stated individual preference method and a random utility model to analyze the determinants influencing farmers’ preferences of SLM practices. When farmers’ decision is interdependent and simultaneous, the multivariate probit (MVP) regression model is applied. Thus, in this study, the multivariate probit was specified and employed to estimate the interdependent SLM choices of farm households. The MVP model estimates three and more than three equations using simulated maximum likelihood (SML) procedure that is different from the binary probit and biprobit models which estimates one and two equations, respectively, using maximum likelihood estimation method (Cappellari and Jenkins, 2003). While using SML in this study, the number of draw was 100 than the default 5.

While using MVP model in this study, there are four interdependent outcome variables that decision maker in each option have two alternatives either to accept the option or otherwise (i.e., y=1 vs. y=0).

The model is similar to a seemingly unrelated regression (SUR) model, except that the dependent variables are binary indicators in MVP and the explanatory variables needs not include the same set of explanatory variables in both cases (Cappellari and Jenkins, 2003). Following Cappellari and Jenkins (2003) and Greene (2012), the seemingly unrelated regression model is specified as:

$$y_{mi}^{*} = x_{mi}'\beta_m + \varepsilon_{mi},$$

$$y_{mi} = \begin{cases} 1\ if\ y_{mi}^{*} > 0 \\ 0\ otherwise \end{cases},\ \text{m = 1, . . ., m and i = 1, . . ., n} \tag{16}$$

$$(\varepsilon_{m1}, \ldots, \varepsilon_{iM}) \sim N[0, R].$$

Where y_{mi} represents whether a farm household chooses one of the SLM practices or not to apply in his/her farmland, x_{mi} is a vector of explanatory variables affecting the choices, β_m is a vector of parameter coefficient to be estimated, and ε_{mi} (m =1, 2, 3, 4) is unobserved random error terms, jointly follow a multivariate normal distribution with zero conditional mean and non-constant variance-covariance matrix R. R has values of 1 on leading diagonal and correlations rhoji = rhoij as off-diagonal elements.

There are four types of SLM practices implemented by sample farmer in his farm plot. The four SLM practices prioritized and used by sample farmers in the study areas were level soil bund with trench, level fanya juu, bench terrace, and indigenous SWC measures (contour ploughing, cutoff drain, bund, biological stabilizer and any other practices). While preferring and implementing the four SLM practices, farmers might consider the paired choices as complementarity (positively correlated) and substitutability (negatively correlated).

To overcome the expected simultaneity problem while applying MVP regression model, a seemingly unrelated multivariate probit simulation model is utilized (Cappellari and Jenkins, 2003)). Suppose there are four mix of SLM practices used by farmer i, the SUR model separate equations are specified as:

$$\left.\begin{aligned} y_{1i}^{*} &= x_{1i}'\beta_1 + \varepsilon_{1i} \\ y_{2i}^{*} &= x_{2i}'\beta_2 + \varepsilon_{2i} \\ y_{3i}^{*} &= x_{3i}'\beta_3 + \varepsilon_{3i} \\ y_{4i}^{*} &= x_{4i}'\beta_4 + \varepsilon_{4i} \end{aligned}\right\} \tag{17}$$

Where y_{1i}, y_{2i}, y_{3i} and y_{4i} are the four choices (equations) with binary outcomes each observed variable take 1 if the underlying continuous latent variable takes a positive value (success) and 0 otherwise (failure). Whereas, x_{1i}, x_{2i}, x_{3i} and x_{4i} represents vector of explanatory variables,

$\beta_{1\ldots}$ β_4 represents vector of simulated maximum likelihood parameters estimate and $\varepsilon_{1\ldots}$ ε_4 are correlated random error terms of the choices. The mean, variance and covariance of error terms given the explanatory variables can be summarized in matrix form as:

$$R = \begin{pmatrix} \varepsilon_{1i} \\ \varepsilon_{2i} \\ \varepsilon_{3i} \\ \varepsilon_{4i} \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} \begin{pmatrix} 1 & \rho_{12} & \rho_{13} & \rho_{14} \\ \rho_{12} & 1 & \rho_{23} & \rho_{42} \\ \rho_{13} & \rho_{23} & 1 & \rho_{34} \\ \rho_{14} & \rho_{42} & \rho_{34} & 1 \end{pmatrix} \right] \tag{18}$$

Hence $E\left[\varepsilon_m | x_{1,} \ldots, \; x_m \right] = 0, \; Var\left[\varepsilon_m | x_1, \ldots, x_m\right] = 1, Cov\left[\varepsilon_j, \varepsilon_m | x_1, \ldots, x_m \right] = \rho_{jm}$

where ρs'(rho) are pairwise correlations of the error terms between any two SLM practices endogenous variables, the off-diagonal figures of the matrix represent unobserved correlation between latent SLM equations, the diagonal matrix normalized to one.

Following Greene (2012), the joint probabilities of the observed events that forms the basis for the log-likelihood function is expressed as:

$$Pr\ (y_{1i}, \ldots, y_{mi} | x_{1i}, \ldots, x_{mi}) = \ L_i = \Phi(\mathrm{B}_1 x'_{1i}, \ldots, \beta_m x'_{mi}, \rho) \tag{19}$$

where Φ denotes the bivariate standard normal distribution

The probabilities that enter the likelihood function simulation can also be specified as:

$$\begin{aligned} &\Pr(y_{1i} = 1, y_{2i} = 1, y_{3i} = 1, y_{4i} = 1) \\ &= \ \Phi\left(\beta'_1 x_1,\ \beta'_2 x_2,\ \beta'_3 x_3,\ \beta'_4 x_4, \rho\right) \\ &= Pr\left(\varepsilon_{1i} \leq \beta'_1 x_1,\ \ \varepsilon_{2i} \leq \beta'_2 x_{2,}\ \ \varepsilon_{3i} \leq \beta'_3 x_{3i,}\ \ \varepsilon_{4i} \leq \ \beta'_4 x_4\right) \end{aligned} \tag{20}$$

3.5.2.4. Impact evaluation of SLM on crop production and farm income

Propensity score matching (PSM) was proposed to estimate the probability of farmers using SLM at household and plot level given the observed socioeconomic, institutional, environmental and biophysical plot characteristics, and policy attributes. The treatment is participating in SLM practices, specifically using one of the SWC measures to halt and/or minimize land degradation problem and to reduce soil erosion, in particular.

The binary probit regression model is the selected choice model to identify the determinants of users and non-users of SLM practices at household and plot level. Suppose users of SLM measures, Y_k and Y_m represents the farmer utility of two choices denoted by U_k and U_m where U_k represents the utility maximized in using SLM and U_m for non-user. The observed utility indicator equals 1 if $U_k > U_m$, and 0 if $U_k \leq U_m$.

Following Greene (2012), the linear utility model formulation is specified as:

$$U_k = \beta_k X_i + \varepsilon_k \ \ and \ \ U_m = \beta_m X_i + \varepsilon_i \tag{21}$$

where

U_k and U_m are perceived utility of choosing k and m treatments, respectively

X_i is the vector of explanatory variables that used to describe the perceived utility

ε_k and $\varepsilon_k$are the independently and identically distributed (IID) disturbance terms

Letting Y=1 for a farmer to choose k, the probability that farmer i will use alternative k is:

$$Pr\ [Y_i = 1|X] = Prob\ [U_{ki} > U_{mi}], \text{k} \neq \text{m, i} = 1, \ldots, \text{N}$$

$$= pr\ [\beta_k X_i + \varepsilon_k - \ \beta_m X_i + \varepsilon_m > \ 0|X]$$

$$= pr\ [\beta_k X_i - \ \beta_m X_i + \varepsilon_k - \varepsilon_m > \ 0|X] \tag{22}$$

$$= pr\ [X_i(\beta_k - \ \beta_m) + (\varepsilon_k - \varepsilon_m) > \ 0|X]$$

$$= Pr[\beta^* X_I + \varepsilon^*]\text{ , where } \beta^* \text{ is } \beta_k - \beta_m \text{and } \varepsilon^* \text{ is } \varepsilon_k - \varepsilon_m$$

Following the formulation of linear utility function, the estimation of conditional probability of receiving treatment when there are binary treatment conditions (y_i =1 vs. y_i = 0) using a probit regression model is specified as:

The underlying unobserved/ the latent variable of the model is $y_i = \begin{cases} 1\ if\ y_i^* > 0 \\ 0\ if\ y_i^* \leq 0 \end{cases}$ (23)

Then the probit model is proposed as:

$$y_i^* = x_i' \beta + \varepsilon_i \tag{24}$$

Where, y_i^* is unobservable farmer's decision of willing to use SLM, $x_i^{'}$ is vector of explanatory variables affecting farmers' decision to implement and ε_i is the error term that distributed normally with mean 0 and constant variance (i.e. $\varepsilon_i \sim N(0, \sigma^2)$).

Proceeding equation (24), the binary treatment condition is denoted as y_i (y_i = 1if the household is using SLM and y_i=0, otherwise), x_i representing vector of conditioning explanatory variables, βs represents vector of parameters, then the estimation of conditional probability of receiving treatment when there are two treatment conditions using probit model is specified as:

$$Prob\ (y_i = 1|x) = \Phi(x'\beta) = \int_{-\infty}^{x'\beta} \phi(z)dz \tag{25}$$

where the density $\phi(z) = (2\pi)^{-\frac{1}{2}}\, exp - \frac{1}{2}\left(\frac{x-\mu}{\sigma^2}\right)^2$

According to Rubin (2006), given the conditional independent assumption (CIA) of treatment assignment condition on x_i and the common support assumption of the probability, the PSM estimator for ATT is specified as:

$$\begin{aligned} \tau ATT \quad &= E\{y_{1i}|b(x_i), w = 1\} - E\{y_{0i}|b(x_i), w = 1\} \\ &= E\{y_{1i} - y_{0i}\ |b(x_i), w = 1\} \end{aligned} \tag{26}$$

where

τATT is the average effect of treatment on the treated
y_{1i} denotes the outcome with treatment (user of SLM)
y_{0i} denotes the outcome with no treatment (non-user)
x_i denotes vector of observed pretreatment covariates for the i^{th} unit
w indicates treatment indicator and $b(x_i)$ is a balancing score

In PSM estimation procedure, following the model choice, the best matching algorithm was selected based on the criteria and comparison between outcome of treated and control group members was done at household and plot level. Once a balanced sample is achieved, fairly low pseudo R2, high matched sample size, large number of insignificant covariates based on two-sample insignificant t-value and low percentage mean bias were applied to choose the best matching method to evaluate the impact of SLM practices on the value of crop production and farm income at household and plot level. The commonly known matching estimators, namely nearest neighbor matching (NNM) method, radius caliper matching (RC) with different caliper, kernel matching (KM) with different bandwidth and stratification matching methods were compared against the criteria.

1. Letting P_t and P_c are propensity scores (PS) for treated and control units; J_1 and J_0 are the set of treated (user of SLM) and control units (non-user), respectively. Assuming that a neighborhood $C(P_t)$ contains a control, c (i.e., $c \in J_0$) as a match for treated participant, t (i.e., $t \in J_1$), then following Smith and Todd (2005) the absolute difference of the traditional, pair wise matching, called single nearest-neighbor matching without replacement sets is given as:

$$C(P_t) = \min_{j} ||P_t - P_c||, \quad c \in J_0 \tag{27}$$

where $C(P_t)$ is the set of control units matched to the treated unit, t with estimated propensity score of P_t, that $P_C \in C(P_t)$.

2. For the analysis of this study, the radius or caliper matched with different caliper size was tested and utilized for the impact evaluation. The radius or caliper matching is defined as:

$$C(P_t) = \{p_c |\, \|P_t - P_c\| < r\},\; c \in J_0 \tag{28}$$

where r is a tolerance level or a caliper

3. Following Smith and Todd (2005), the kernel matching estimator ($\bar{\beta}KM$) is given by:

$$\bar{\beta}KM = \frac{1}{n_1} \sum_{t \in J_1} \left\{ Y_{1t} - \frac{\sum_{c \in J0} Y_{0c}\, G\left(\frac{P_c - P_t}{bw}\right)}{\sum_{K \in J_0} G\left(\frac{P_k - P_t}{bw}\right)} \right\} \tag{29}$$

where G (.) is a kernel function and bw is a bandwidth parameter.

Under a standard condition of bandwidth and kernel, $\frac{\sum_{c \in J0} Y_{0c}\, G\left(\frac{P_c - P_t}{bw}\right)}{\sum_{K \in J_0} G\left(\frac{P_k - P_t}{bw}\right)}$ is a consistent estimator of the counterfactual outcome, i.e., Y_{0C}, $E\{y_0 | b(x),\ J = 1\}$

Following Guo and Fraser (2015), the standardized bias to check imbalances on covariates (x) before (SB_x) and after matching (SB_{xM}) is computed as:

$$SBx = 100 * \frac{(\bar{X}_1 - \bar{X}_0)}{(0.5*(V_1(X) - V_0(X))^{1/2}}, \qquad SB_{XM} = 100 * \frac{(\bar{X}_1 - \bar{X}_0)}{(0.5*(V_{1m}(X) - V_{0m}(X))^{1/2}} \tag{30}$$

where $\bar{X}_1$and $\bar{X}_0$ are the mean and $V_1(x)$ and V_0 (x) are variance for treated and control unit.

The estimation of treatment effects with the best-chosen matching estimator is based on the assumption of the CIA. If the assumption of CIA is relaxed or if the assignment into treatment effect and the outcome variable is affected by unobservable factors simultaneously, 'a hidden bias' might be created. In such cases, impact evaluation using PSM will not be robust and efficient. Thus, sensitivity analysis is applied to detect unobservable heterogeneity that affects the treatment effect and outcome variable. Following Rosenbaum (2002) who proposed a bounding approach of sensitivity analysis in estimating the probability of participation in SLM due to the unobservable covariates is given as:

$$Log\left(\frac{P_{[j]}}{1-P_{[j]}}\right) = K\left(x_{[j]}\right) + \gamma U_{[j]} = f[x\beta + U\gamma] = e^{x\beta+U\gamma},\ 0 \le U[j] \le 1 \quad (31)$$

where p(j) is the treatment receive by unit j, K(.) is unknown function, and the parameter γ is the effect of U_j (unobservable factors) on the participation decision and x [j] and U[j] are observed and unobserved covariates, respectively.

Rosenbaum bound sensitivity test was conducted to detect the possible hidden bias caused by unobservable factors. It examined how strong the influence of γ (gamma) on the participation decision that reduces the impact of participation on potential outcomes. Let assume there is a matched pair of household j and k, and assume F is the logistic distribution, then the odds that households receive treatment is given by $\frac{P\ (x_j)}{\left(1-P(x_j)\right)}$ and $\frac{P(x_k)}{(1-P(x_k))}$, and the odds ratio is:

$$\frac{\frac{P(X_j)}{1-P(X_j)}}{\frac{P\ (X_k)}{1-P(X_k)}} = \frac{P\ (X_j)\left(1-P(X_k)\right)}{P\ (X_K)\left(1-P(X_j)\right)} = \frac{\exp\left(\beta X_{k+\gamma U_k}\right)}{\exp(\beta X_j{+}\gamma U_j)} = \exp\left[\gamma\left(U_j - U_k\right)\right] \quad (32)$$

The bounds on the odds ratio of the participation probability of both group is specified as:

$$\frac{1}{\gamma} \le \frac{P[X_j]\left(1-P_{[X_k]}\right)}{P\ [X_k](1-P[X_j])} \ \le\ \gamma\text{, for all j, k with } X_{[j]} = X_{[k]}\,. \quad (33)$$

If γ is 1, then $p_{[j]} = P_{[k]}$ when the covariates x(j)= x(k), implies that both matched households have the same likely probability of participating only if γ = 1, so the study assumed to be free of hidden bias. However, if γ is > 1 or more units it seems to have the same x would differ in their odds of receiving the treatment by a factor of γ and thus the bias affecting the probability of participation on potential outcome (s) is said to be sensitive to the unidentified hidden bias.

Furthermore, the robustness of the average treatment effects obtained through the non-parametric PSM approach was checked using the parametric Endogenous Switching Regression model. In PSM method, the real observation of expected value of the outcome of SLM users, that is, the average treatment effects on the treated (ATT) and the expected value of the outcome of SLM non-users, i.e., average treatment effect of the untreated (ATU) in real and counterfactual scenarios is computed. Following Khonje *et al*. (2015) and Million *et al*. (2019b), the expected value of the outcomes of SLM users (region 1) and non-users of SLM practices (region 2) in reality and counterfactual scenarios are given as follows.

Users using SLM practices (observed in the sample, real)

$$\mathrm{E}[y_{i1}|W = 1; x] = x_{i1}\beta_1 + \sigma_{\varepsilon 1}\lambda_{i1} \tag{34}$$

Non-users not using SLM practices (observed in the sample, real)

$$\mathrm{E}[y_{i2}|W = 0; x] = x_{i2}\beta_2 + \sigma_{\varepsilon 2}\lambda_{i2} \tag{35}$$

Users had they decided not to use SLM practices (counterfactual)

$$E[y_{i2}|W = 1; x] = x_{i1}\beta_2 + \sigma_{\varepsilon 2}\lambda_{i1} \tag{36}$$

Non-users had they decided to use SLM practices (counterfactual scenario)

$$E[y_{i1}|W = 0; x] = x_{i2}\beta_1 + \sigma_{\varepsilon 1}\lambda_{i2} \tag{37}$$

The average treatment effect on treated (ATTs) is computed as the difference between equation 34 and 36 as:

$$\begin{aligned}\mathrm{ATT} &= E[y_{i1}|W = 1; x] - E[y_{i2}|W = 1] \\ &= x_{i1}(\beta_1 - \beta_2) + \lambda_{i1}(\sigma_{\varepsilon 1} - \sigma_{\varepsilon 2})\end{aligned} \tag{38}$$

Likewise, the average treatment effect on the untreated (ATUs) is computed as the difference between equation 37 and 35 as:

$$\begin{aligned}ATU &= [y_{i1}|W = 0; x] - [y_{i2}|W = 0; x] \\ &= x_{i2}(\beta_1 - \beta_2) + \lambda_{i2}(\sigma_{\varepsilon 1} - \sigma_{\varepsilon 2})\end{aligned} \tag{39}$$

Where x_{i1} and x_{i2} are vector of exogenous covariates expected to affect use of SLM, β_1 and β_2 are vectors of parameters, $\sigma_{\varepsilon 1}$ and $\sigma_{\varepsilon 2}$ are random disturbance terms λ is the selection term that captures unobservable variables effects

3.6. Description of Variables and Working Hypothesis

Based on economic theory, literature, the nature of objectives of the study, and the researcher's view, a number of dependent and explanatory variables were identified, and hypothesized to make relevant inferences using statistical tools.

3.6.1. Description of variables and working hypothesis of farmers' perception

Based on a priori economic theory, available literature, the study's objective, and the authors' view, dependent and potential explanatory variables were identified and hypothesized to make relevant inferences, test, and estimate the parameters (Table 3). The dependent variable is a trivalent response of farmers' perception of SLM role (l= low, 2 = medium, and 3 = high perception) computed as index in a three Likert scale as an ordinal variable. Moreover, during the FGDs, discussants were asked to state their perception level about the role of SLM in reducing land degradation and improving production as low, medium and high level. Likert-type data falls into an ordinal measurement scale of which frequency distribution shows variability and the chi-square (χ^2) measure the association (Boone and Boone, 2012).

Level fanya juu, level soil bund, bench terrace, and indigenous SWCs are the commonly applied on-farm SWC measures in the study areas. Other SWC measures, for example, stone bund, check dam, trench and conservation tillage were implemented by few sample farmers in small proportion (less than 2%), but considered as outliers and excluded in the analysis. How farmers perceive the role of SLM practices to combat land degradation and reduce soil erosion was asked during the survey. Even though the survey result indicated that level soil bunds, fanya jju, bench terraces and indigenous SWCs are the commonly applied SLM practices, initially farmers were asked to reflect on their perception about the role of SLM, specifically, SWC measures applied on cultivated land as one general statement. During the household survey, the choices were not considered as different independent responses to categorize farmers' perception levels, rather as SWC measures applied on cultivated land.

The hypothesized explanatory variables are household socioeconomic, institutional, biophysical and policy attributes. The socioeconomic characteristics included farming experience, gender, active labor force, education, livestock holdings, farm revenue, off-farm income, and cultivated land size. The institutional variables included training, extension service, and land rental market. The biophysical plot attributes included topsoil erosion occurrence, perceived slope type, soil fertility status, soil erosion severity (minor, moderate, and severe) and land quality (minor, moderate and high) and location of the parcel (lower and upper stream). The policy variables included land certificate, community bylaws, access to incentives, and tenure arrangement. Moreover, the study locations, that is, Sidama, Wolaita and Siltie were considered as dummy variables (Table 2).

Table 2 Description of variables and working hypothesis of perception of SLM practices

Variable name	Measurement	Description	Ho sign
Dependent variable			
Perception level	Ordinal categorical	Farmers' perception level (1= low, 2 = moderate and 3 = high)	
Independent			
Farming experience	Number of years	Farming experience of household heads in years (continuous)	+
Gender	1= male, 0 = female	Sex of household head (dummy)	±
Active labor force	Count	No. of active family members (15-64 years) living with household	+
Education level	Years of formal education	Attained formal education level by household heads (continuous)	+
Livestock holding	Tropical livestock units (TLUs)	Total livestock holding of the household in TLU (continuous)	+
Farm revenue	Ethiopian Birr (ETB)	Value of crop at harvest and income from livestock sale at price	+
Non-farm income	Ethiopian Birr (ETB	Annual income obtained from non-farm and off-farm activities	-
Cultivated land size	Hectare (ha)	Cultivated land size of household in ha (continuous)	±
Training	Dummy (1 = yes, 0 = no)	Training on land management taken by household heads	+
Extension service	1= yes, 0 otherwise	Extension service accessibility by households on SLM (dummy)	+
Land rental market	Dummy (1=yes, 0 = no)	Farmers' involvement in land renal market (rent/share)	-
Plot distance	Kilometers (km)	Average plot distance from household's resident in km	-
Slope status of plot	Gentle, moderate, steep	Farmers' perception of slope gradient status of plots	±
Soil fertility status	Poor, moderate, fertile (yes/no)	Farmers' perception of soil fertility status	±
Soil erosion	Dummy (1 = yes, 0 = no)	Farmers 'perception of topsoil erosion presence	+
Soil erosion severity	Minor, moderate, severe (yes/no)	Farmers' perception of soil erosion severity status	±
Soil quality status	Poor, moderate, good (yes/no)	Farmers' perception of soil quality status	±
Farm plot location	1 = upper, 0 = lower stream	Location of the farmland in the study areas/watershed (dummy)	±
Land certificate	Dummy (1 yes, 0 = no)	Farmers whether they received land certificate or not	+
Community bylaws	Dummy (1= yes, 0= no)	The presence of enforced community bylaws or norms	+
Incentive	Dummy (1=yes, 0= no)	The availability of economic incentive to implement SLM	+
Tenure arrangement	1=owned, 0=family	The landownership status of household heads (dummy)	+
Sidama	Dummy (1=yes, 0 = no)	Location of the specified study area	+
Wolaita	Dummy (1= yes, 0 = no)	Location of the specified study area	+
Siltie	Dummy (1= yes, 0 = no)	Location of the specified study area	+

Note: Hypothesis is made for discrete change from 0 to 1 for dummy variables

3.6.2. Variables description and hypothesis of participation decisions and choices

Based on a priori economic theory, literature, the nature of the objective of the study, and the authors' view, dependent and explanatory variables were identified and hypothesized to make inferences using inferential statistics (Table 3 and 4). Inferential statistics tests the significance level of the hypothesized regressors with the dependent variables included in the econometric model. Prior to the econometric model, inferential statistics test, validate and predict the hypothesis to make inferences about the population. The Parametric tests like the t-test and F test for continuous variables were applied for the statistical inferences. The non-parametric chi-square test was deployed to measure the association that exists between categorical variables.

In this study, factors affecting farmers' decision to participate and choices of SLM, specifically on-farm SWC measures were identified. While employing the double hurdle model for the decision of farmers, the dependent variable is dummy or binary that took 1 for participants and 0 otherwise. The participants are farmers who use and apply integrated SWC measures at least in one of their farm plots or on 25% of owned farmland for five consecutive years. On the contrary, non-participant farmers are those who have not continuously applied SLM practices specifically SWC measures since 2013 in any of their plots. The total amount of farmland utilized for on-farm SWC measures was taken as a dependent variable for the second hurdle (truncated regression). Since the decision to participate and to allocate a portion of the farmland is sequential, the amount of farmland used was selected after the choice decision is made.

Similarly, identification of the choices of major SLM, specifically on-farm soil and water conservation measures adopted and used by farmers was carried out using the survey instruments, mainly observations in transect walk and KII. The most applied four top prioritized choices of SLM practices were taken and evaluated by taking the likely probability of the correlated and interdependent choices jointly. The top prioritized choices of SLM practices namely, level *fanya juu*[5], level soil bund with trench[6], bench terrace[7] and indigenous traditional SWC practices were taken as on-farm SWC measures in the study areas. Level fanya juu, level soil bund, and bench terrace are improved SWC measures that are applied to prevent excessive runoff, reduce soil erosion, retain moisture, and discharge excessive water safely from farmlands (Hurni *et al*., 2016). The indigenous traditional SWC practices include counter ploughing, cutoff drain, manure application, crop residue management, planting stabilizers, and other conventional measures implemented intentionally on owned farmlands to retain moisture, drain excessive water, reduce runoff velocity, prevent soil erosion and enhance soil fertility. Other conventional measures of indigenous SWC measures also includes conservation agriculture, check dam and stone faced soil bund implemented in small proportion in farmlands. In the estimation process, four mutually inclusive SLM choices were specified and taken as dependent variables. The decision maker in each option has binary alternatives, either to accept the option or otherwise (i.e., y = 1 vs. y = 0).

The explanatory variables expected to affect the decision to participate and probability of farmers' preferred choices of the specified SLM practices were the household socioeconomic, farming system, institutional, plot related biophysical attributes and environmental factors. The individual and household characteristics included individual farmers' perception of soil erosion, gender, marital status, farming experience, household size, active labour force and dependency ratio. The socioeconomic variables included education level, social network, size of cultivated farmland, total owned land, livestock holding, annual farm income, non-farm income, and value of annual crop produced. The institutional variables included training, extension visits, land market, road distance and market distance from the homestead. The biophysical attributes included the agroecological location of the farmland, soil fertility status

[5] Level fanya juu (‘throw uphill’ in Swahili language) is an embankment along the contour made of soil and/or stone, with a basin at its lower side tied ridges every 10 meters to prevent runoff flowing sideways and the soil is moved upslope during construction. Soil eroded between two fanya juus is deposited behind the lower one.

[6] Level soil bund is an embankment along the contour made of soil with water retention basin at upper side usually tied ridges placed every 10 meters to prevent runoff from flooding sideways and to concentrate overflow at one point along the bund (Hurni *et al*., 2016, p72).

[7] Bench terrace is a conservation structure when slope is converted into a series of steps, with a horizontal cultivated area on the step and steep rises between two steps. It usually developed from bunds and fanya juus in the course of several years (5 to 15 years), they are level along the contour, graded to drain excess runoff sideways to the next waterway (Hurni *et al*., 2016, p60).

of the plots (index), slope status of farm plots, and soil erosion presence. Incentive and community bylaws were considered as policy driving forces hypothesized to influence smallholder farmers' participation and intensity decisions of land management practices. The ‘‘hypothesis” were tested for the expected effect on the dependent variables of farmers' participation decision to use SLM and its intensity, and the joint interaction of both decisions was tested using the statistical inferences. Likewise, the factors that influence farmers' choice of SLM measures were hypothesized to affect the choices positively or negatively and their coefficients of parameters were estimated using SML of the MVP model. The null hypothesis regarding the coefficients of the independent variables (β's) determining the respective outcomes was hypothesized to be different from zero. The explanatory variables that were hypothesized and their effects on the farmers decision to participate, their intensity and choices of SLM practices are presented in Tables 3 and 4 sequentially.

The household socioeconomic characteristics that were hypothesized to influence farmers' decision to participate and choice of SLM practices are farmers' perception of soil erosion, gender, marital status, active labour force, dependency ratio, farming experience, social network, education level, cultivated land size, number of farm plots, livestock holdings, and farm and non-farm income of household head. Gender is a biological sex of household head being male or female. A gender being male household was hypothesized to affect the decision to participate in SLM and choices of fanya juu, soil bund and bench terrace positively while it expected to influence indigenous SWC measures negatively. This hypothesis is in agreement with the hypothesis of Zerihun *et al*. (2017b), Agere *et al*. (2020), Alelgn *et al*. (2021), Oduniyi and Tekana (2021) and Bichaye *et al*. (2022). Marital status is a human capital indicator whether a household head is being married, not married (single), divorced or widowed. It is a socio demographic variable hypothesized to influence the specified SLM choices differently. Married household head was hypothesized to influence the choices positively, while a single, divorced or widowed household head was hypothesized to have a negative correlation.

Perception of SLM role in halting land degradation, particularly, soil erosion was hypothesized to influence farmers' participation decisions and intensity. It was computed as a a composite index measured in Likert-scale of low, medium, and high type imposed positive effect on farmers' participation and enrolment decisions. More specifically, as the perception of households to SLM's role in mitigating land degradation increases to a higher level, their decision to participate in SLM practices, specifically, on-farm SWC measures increases. This hypothesis is supported by Worku and Schneider (2016) and Zerihun *et al*. (2017b) who stated that as farmers' perception towards the role and benefits of SLM in managing land resources increases to a higher level, the likely probability of farmers' decision to participate and invest in SLM increases.

Active labour force was hypothesized to influence the choice of SLM practices positively. A household having a family member aged 15 to 64 years was expected to influence the choices of fanya juu, soil bund and bench terrace positively, while it was expected to affect the indigenous SWC measures negatively. Agere *et al*. (2020) reported that household size with high labour force influenced the decision to choose and use soil bund positively. However, higher dependency ratio, i.e., the ratio of dependent inactive to active labour force, was associated negatively with farmers' decision and choices. Higher dependency ratio was expected to influence the participation decisions and SLM choices negatively. This hypothesis is consistent with that of Million *et al*. (2019) in which a household with high dependency ratio influenced the choice of conservation structure, specifically, soil and stone bund negatively.

Farming experience is a number of years a household head has stayed in or devoted to farming or agricultural activities including natural resource management. From the SLM perspective, it is the accumulated knowledge and positive experience of farmers in implementing a set of choices to protect and maintain farmland. In this study, it was anticipated to influence the decision to participate and choice of SLM practices positively and significantly. The hypothesis is supported by a study made in Tanzania by Nyanga *et al*. (2016) and is opposed by studies conducted by Desalew and Aklilu (2017), Haftu *et al*. (2019), Agere *et al*. (2020) and Alelgn *et al*. (2021) in Ethiopia.

Social network is a proxy variable to social capital, defined as communicating and sharing ideas and experiences of SLM practices with peers and neighborhood farmers. It was expected to influence farmers' participation decisions in SLM practices and the intensity of enrolment positively. This hypothesis is supported by Tesfamicheal *et al*. (2015) and Akalu *et al*. (2016) who stated that social capital increases farmers' cooperative behavior in exchanging information and sharing experiences that is deemed to increase smallholder farmers' participation decisions in SLM practices.

Educational level is a continuous variable defined as years of formal schooling a household head attained. Education has a crucial role that enables farmers to have full awareness on the benefit and implication of SLM measures. Here, it was hypothesized to affect farmers' decision to participate and choices of the four specified SLM practices positively and significantly. This is supported by Genanew and Alemu (2012), Million *et al*. (2019), Alelgn *et al*. (2021), Bereket *et al*. (2021), Oduniyi and Tekana (2021) and Wondimu *et al*. (2021) who all agreed that literate farmers are more likely to adopt, use and maintain various SLM practices than the illiterate counterparts. Yet, scholarly works by Pender and Berhanu (2008) and Zerihun *et al*. (2017b) negated the positive association of education and choices of SLM practices arguing that educated farmers are less willing to invest and use labour intensive SLM practices, particularly SWC measures.

Cultivated farmland and number of plots were hypothesized to influence the likely probability of farmers' participating decisions and choosing fanya juu, soil bund, bench terrace and indigenous SWC measures positively and statistically significantly. This hypothesis is consistent with that of Akalu *et al*. (2016), Haftu *et al*. (2019), Agere *et al*. (2020), Alelgn *et al*. (2021), Bereket *et al*. (2021), Wondimu *et al*. (2021), Bichaye *et al*. (2022), and Mamush and Elias (2023) who all argued that farm households who own large farmland are more likely to choose and invest in SLM practices, particularly on on-farm soil conservation practices. Conversely, there are ample evidences in the literature that hypothesize a negative influence of farmland size on the choices of SLM practices, for example, Nyanga *et al.* (2016), Zerihun *et al*. (2017a) and Million *et al.*(2019).

Farm and non-farm incomes are liquid assets hypothesized to affect the decision to participate and choices SLM practices positively and negatively, respectively. Farm income is obtained from the sale of agricultural products (both crop and livestock, live and byproducts), while non-farm income is generated from off-farm and non-agricultural activities like hiring labour, fire wood and grass selling, pity trade, etc. Both are financial capital that help to access and buy farm tools, cuttings, hire labour and incentivize farmers to construct and maintain SLM practices, but the latter share time and labour for non-agricultural activities. Thus, in this study it was hypothesized that farm income influences the participation and choices positively, but non-farm income is expected to influence them negatively. The hypothesis is consistent with that of Million *et al.* (2019) and Alelgn *et al*. (2021) that farm income was hypothesized to affect the choices positively. On the contrary, *Zerihun et al.* (2017b), Emerton and Snyder (2018), Habtamu *et al*. (2023) and Mamush and Elias (2023) hypothesized that off-farm income affected SLM choices negatively.

Livestock holding is a number of live animals measured in TLUs owned by a household head. Beyond its food contribution, livestock is a source of cash income that increases farmers' financial capital to invest in SLM and it is also a source of manure that enhances soil fertility. It is a continuous variable hypothesized to affect farmers' participation decisions of SLM and the choices of fanya juu, soil bund and bench terrace differently and the choice of indigenous SWC measures positively and significantly. This hypothesis is consistent with that of Zenebe *et al*. (2012) and Menale *et al.* (2015) who hypothesized that livestock holding influenced the decision to invest and choices of SLM practices positively. Conversely, a study by Akalu *et al*. (2016) and Alem-meta and Singh (2018) negated the hypothesis saying that livestock has negative associations with decision to participate and choices of SLM.

Annual crop preference, perennial crops choice and fertilizer use are household farming system characteristics expected to influence the choice of SLM practices positively. The mixed farming system typology of the study areas guides farmers to decide their choices of SLM practices. Farmers who frequently practice annual and perennial crop farming actively engaged in applying SLM measures on their farmland. Likewise, fertilizer use that is intended to enhance soil fertility and crop productivity was hypothesized to influence the choices of fanya juu, soil bund and bench terrace positively, while it was expected to influence negatively the choice of indigenous SWC measures. Farmers who apply chemical fertilizer primarily engaged in choosing SLM practices and/or measures to maintain and protect their farmland from being eroded and depleted. This is supported by Paulos and Belay (2017) and Haftu *et al*. (2019) who hypothesized that chemical fertilizer affected the adoption and use of SLM practices positively and significantly.

Similarly, the institutional characteristics hypothesized to affect the participation decisions and choices included extension visits, training, market distance, community bylaws and land market. Extension services and trainings offered to farmers in areas of natural resource management were hypothesized to affect farmers' participation decision and choices of SLM practices positively. Similarly, community bylaws that are formulated by the community and implemented by individual farmers were hypothesized to influence farmers' participation and choice of SLM practices positively. This hypothesis is supported by Zenebe *et al*. (2012), Oduniyi and Tekana (2021) and Setsoafia *et al.* (2022). A study by Birhan and Assefa (2017), Fekadu and Engdawork (2019) and Alelgn *et al*. (2021) supported the positive and significant correlation of training with participation and SLM choices.

Market and road distance are proxy variables to market access associated with transaction costs while transporting and selling farm produce. It is the distance of a household residence from the nearest all-weather road and market in km. It was hypothesized to affect participation decision and choice of SLM negatively. The nearest distance from market increases the probability of choosing the aforementioned SLM practices because it lowers the transaction cost related to transporting inputs, materials and selling of farm products. This hypothesis is consistent with the hypothesis of Wondimu *et al*. (2021), but contradicts with that of Genanew and Alemu (2012) and Menale *et al*. (2015). They hypothesized that if market distance increases, it lowers the cost of hiring labour and opportunity cost of labour-intensive land conservation practices.

Land market is the engagement of smallholder farmers in land rental related market. Land rental market was expected to influence farmers' participation decisions negatively. In other words, farmers who engaged in land rental and share out market are less willing to participate and use SLM practices to manage and conserve their land resources, specifically, farmland. This hypothesis was supported by Genanew and Alemu (2012) who stated that farmers who are involved in land rental market are expected to have a lower probability of participating and implementing SLM practices to reduce runoff and fertility decline on their farmland as compared to their counterfactual.

The biophysical and environmental traits that influenced farmers' decision to participate and choice of SLM comprise plot distance, soil erosion severity level, farmland with degraded infertile and fertile soil, steep and moderate slope proportion, agro ecological location, and rainfall intensity. Plot distance is the average distance between household residences and farm plots indicating farmlands' proximity or spatial location. It is equivalent to the walking distance in hours/minutes. It was hypothesized to affect the choices of SLM practices negatively. This hypothesis was consistent with Desalew and Aklilu (2017), and Mamush and Elias (2023).

The existence of soil erosion and its severity level are biophysical plot related variables expected to influence the decision to participate and choices of SLM practices differently. Farmers who perceive the existence of soil erosion were expected to have a higher probability of participating and using SLM practices, specifically on-farm SWC measures as a remedial developmental action against the threat. This hypothesis was in line with Paulos and Belay (2017) and Wondimu *et al*. (2021) who stated that farmers who perceive the threat of soil erosion are more likely to participate and use land conservation measures, specifically SWC measures on their farmland. High, moderate, and low types of soil erosion severity levels have mixed effects on the decision of households to choose and use SLM practices. A household whose farmland is constrained with severe soil erosion is expected to have a higher probability of selecting the specified SLM choices to abate the threats than farmers with low to moderate type of soil erosion severity. This hypothesis is consistent with studies conducted by Engdawork and Hans-Rudolf (2016), Alelgn *et al*. (2021), and Wondimu *et al*. (2021).

Degraded infertile soil proportion of farmland is the percentage share of infertile soil from the total farmland size owned by a household. Degraded infertile soil proportion of farmland influenced households' choice of the specified SLM practices either positively or negatively. This hypothesis was in line with Zenebe *et al*. (2012) who hypothesized that farm households who own fertile land make a better decision to choose and use appropriate SLM practices to maximize agricultural production than their counterparts.

Steep and moderately sloped land proportion is the slope gradient estimated as the percentage share from the total farmland. Steeply sloped farmland was expected to influence farmers' participation decision and to choose fanya juu, soil bund, and bench terrace positively, but it affected indigenous SWC negatively. At the same time, moderately sloped land was hypothesized to influence households' choice SLM practices differently and the indigenous measures positively. This hypothesis was supported by Zenebe *et al*. (2012), Tesfamicheal *et al*. (2015), Desalew and Aklilu (2017), Haftu *et al*. (2019), and Wondimu *et al*. (2021), all of whom hypothesized that farmers who owned steeply sloped plots are more likely to choose and use SLM practices than farmers who operate in gentle to moderately sloppy farmlands.

Agro ecological location and perceived rainfall intensity are environmental attributes expected to influence the choice of the specified SLM practices differently. Farm location is an environmental factor hypothesized to affect farmers' SLM participation and enrolment decisions differently. The agro ecological location of the study areas being highland was hypothesized to influence the choices of fanya juu, soil bund, bench terrace, and indigenous SWC measures positively and significantly. Perceived rainfall intensity that was perceived as low, moderate, and high amounts was hypothesized to influence SLM choices differently. A study area with high rainfall intensity was hypothesized to influence the specified SLM choices more positively than areas receiving low to moderate rainfall. This hypothesis is supported by Zerihun *et al*.(2017b) who hypothesized that rainfall intensity positively influenced the choice and utilization of SLM practices.

Table 3 Variables description and hypothesis of farmers' SLM participation decisions

Variables	Description	Measurement	Hypothesized effect
Dependent			
SLM participation	HHs implementing on-farm SWC measures on at least a quarter of owned farmland for five continuous years	Users =1, Non-users = 0	
SLM land size	Land covered by SLM (for on-farm SWC)	Hectare	
Independent			
Gender	Sex of the household head: male headed household influence participation and enrolment decisions positively and vice versa	Dummy: Male = 1, female =0	+/-
Farming experience	The farming experience of HH head, as it increases it affects positively	Years	+
Household size	The number of individuals living together with a household head	Persons	+/-
Dependency ratio	The ratio of dependent inactive to active labour force, higher dependency ratio associated negatively with farmers' decision	Percent	-
Education level	The formal education attained, high education level affects positively	Years	+
Social network	It is communicating and sharing ideas and experience with peers, it influences farmers' participation decision and intensity positively	Dummy: Yes =1, otherwise =0	+
Perception index	Perception level of farmers to SLM in halting land degradation, measured in Likert-scale of low, medium and high type imposed +ve/-ve effect	Percent	+/-
Farm size	Is cultivated farm size of HHs, has +ve effect on enrolment decision	Hectare	+
Total owned land	Total land size owned by HHs, imposed +ve influence on participation	Hectare	+
Livestock holding	The number of livestock owned by a HHs, affects positively	TLU	+
Farm income	Annual farm income obtained from sale of agricultural products	ETB	+
Non-farm income	Farmers engaged in non-farm activities, affects the decision negatively	ETB	-
Value of crop	Total amount of crop produced in its market value in a year, has +ve effect	ETB	+
Training	Farmers accessing training would likely increase participation in SLM	Yes =1, No = 0	+/-
Extension contact	Higher extension contact with farmers influence participation decision	No. of days	+
Land market	Involvement in land rental market imposed negative effect	Yes =1, No = 0	-
Main road distance	Is a proxy for market access expected to affect both decisions differently	km	+/-
Community bylaw	Enforced community bylaws has positive effect on participation decision	Yes =1, No = 0	+
Incentive	Incentive in cash or kind imposed +ve effect to implement on-farm SWC	Yes =1, No = 0	+
Farm location	It is environmental attributes of farmers' farm plots can either be in the upper or lower stream affected participation decision differently	Upper = 1 Lower = 0	+/-
Soil fertility index	Is calculated on the basis of the Likert scale (infertile to fertile); expected to affect the probability of farmers' decision to participate differently	Percentage	+/-
Slope status of plots	The slope gradient of farmland of HHS, farmland with steeped slope hypothesized to affect participation decision positively	Percentage	+
Soil erosion	Farmers aware of soil erosion on farmland would participate in SLM	Yes =1, No = 0	+/-

Table 4 Description of explanatory variables and working hypothesis of SLM choices

Variable name	Description	Hypothesized effect (Ho sign)			
		Fanya juu	Soil bund	Bench Terrace	Indigenous SWC
Gender (dummy)	Biological sex of household head (1. Male, 0. Female)	+	+	+	-
Marital status	The state of household head being married, single, or divorced	–	–	–	–
Active labour force	The number of active labour force (15-64 yrs. old) of a HH	+	+	+	–
Farming experience (yrs.)	Number of years a household head stayed in farming	+	+	+	+
Education level (years)	Formal educational attainment of the household head in years	+	+	+	+
Cultivated land size (ha)	A non-liquid asset owned by a household head in ha	+	+	+	+
Number farm plots	Total number of farm plots owned by a household head	+	+	+	+
Livestock holding	Livestock size owned by the household in TLU	±	±	±	+
Farm income	The income obtained from sale of agricultural products in ETB	+	+	+	+
Non-farm income	Income obtained from off- farm and non-farm activities in ETB	–	–	–	–
Annual crop preference	the choice of annual crop in the mixed farming system typology	+	+	+	+
Perennial crop preference	The choice of perennial crop in mixed farming system typology	+	+	+	+
Fertilizer use (dummy)	The accessibility and utilization of fertilizer align with SWC	+	+	+	+
Extension contact	The average number of contacts with farmers by DAs	+	+	+	+
Training (dummy)	NRM related training accessibility of household heads	+	+	+	+
Market distance (km)	The distance of household head residence from market in km	–	–	–	–
Community bylaws	The presence of enforced and functional community bylaws	+	+	+	+
Plot distance (km)	The average walking distance of plots from household residence	–	–	–	–
Soil erosion severity level	High, moderate and low soil erosion severity level of farmland	±	±	±	±
Degraded infertile soil proportion	Percentage share of degraded infertile soil from the total owned farmland	±	±	±	+
Steep slope proportion	Steep slope % share of farm plot out of the total farmland	+	+	+	–
Moderate slope proportion	Medium slope % share of farm plot out of the total farmland	±	+	±	+
Agro ecological location	The study areas whether they are located in midland or highland	±	±	±	±
Rainfall intensity	Perceived rainfall intensity of the areas (low, moderate and high)	±	±	±	±

Note: H0 = +, - and ± indicates the expected effect of the explanatory variable is positive, negative or both, respectively.

3.6.3. Description of variables and working hypothesis of impact evaluation

Based on the literature review and researchers' observation, several covariates were hypothesized to affect the use of SLM practices and supposed to predict the propensity score (PS) on the value of crop production and farm income identified at household and plot level. The treatment and outcome variables that were used as dependent variables were also identified based on the study's objectives

Treatment variable: the treatment variable in propensity score matching (PSM) is participation in SLM at household and plot level, and it was considered a dependent variable. The participation is a dummy variable that assumes one for those sample households who use SLM practices, specifically on-farm SWC measures, and take zero for non-users at household and plot level. At a plot level, user farmers who owned plots that are managed with on-farm SWC measures take value 1, whereas those without on-farm SWC measures take 0. In this study, user farmers are defined as those who implement SLM practices specifically introduced on-farm soil and water conservation measures at least in a quarter (25%) of their owned farm plots for a minimum of five consecutive years since 2013. In contrast, non-users are those who have not and/or rarely applied on-farm SWC measures in any of their owned plots since 2013. Moreover, farmers who implement SLM, specifically on-farm SWC measures in less than 25% of their farm plots for less than five years were considered as non-users. Hence for the impact analysis in the participation decision, the users are considered treated and non-users are taken as non-treated (control) sample groups. The introduced on-farm SWC measures were primarily chosen and applied by participant farmers considered as SLM practices were soil bund, fanya juu, bench terrace, and indigenous SWC measures.

Outcome variables: one of the main outcome variables is the value of total crop production (in ETB) both at the household and plot level. Moreover, farm income is also considered an outcome variable for the impact quantification of SLM at household and plot levels. The value of total crop production is the annual monetary value of all crops produced from the owned plot in 2019/20.Value of crop production was computed by taking the market price and the total quantity of harvest in the same year. Farm income in ETB is the total revenue obtained from the sale of any of the agricultural products including sale of live livestock and its products in the same production year (2019/20).

Explanatory variables: the household socioeconomic characteristics, institutional factors, plot-level biophysical and environmental attributes are hypothesized variables influencing the outcome variables at household level. The explanatory variables hypothesized to affect SLM practices and predict the propensity scores are named as covariates. The socio-economic variables that are considered as covariates were gender composition (dummy), household size, farming experience, educational level, number of active family members, livestock holding, cultivated land size, and off-farm activity (dummy). The hypothesized institutional factors that were considered include chemical fertilizer use (dummy), improved seed use (dummy), extension advice (dummy), incentive availability (dummy), distance to market from homestead and distance to all weather roads from the homestead. The biophysical plot level characteristics included distance of parcel from home, location of farm plots in the watershed (dummy), severity of soil erosion on the plot (ordered), choices of crop (dummy), slope index (computed as composite index taking the proportion of steep, moderate and flat slope) and proportion of infertile soil. Finally, land certificate issuance as policy attribute and environmental factors such as agro ecology and perceived rainfall intensity (categorical) were considered to affect SLM and to predict PS (Table 5).

Similarly, at a plot level, household socioeconomic characteristics such as household size, education level, farming experience and plot size were expected to affect SLM practices and to predict the PS for matched pairs of plots. Extension service, road distance, market distance and fertilizer usage are the hypothesized institutional factors to affect participation of SLM practices and its impact on value of crop production and farm income. Plot distance from household residence, proportion of steep slope farm plots, share of moderate slope, topsoil erosion occurrence, infertile soil proportion of farm plots, shallow depth plot proportion, soil quality, farm plot location in the watershed, and perceived rainfall intensity (categorical) were the main biophysical covariates that affected SLM practices, participation and its annotated impact on value of crop production and farm income (Table 6).

Table 5 Description of variables and working hypothesis of SLM impact (household level)

Variable name	Measurement	Description	Ho sign
Treatment variable			
SLM participation	User =1 non-users=0	Farmers using on-farm SWC for five consecutive years on owned farmland	
Outcome variables			
Value of crop produced	ETB	Market value of total crop produced at harvest time (quantity * price)	
Farm income	ETB	Sale of crop and livestock live and byproducts at market (farm revenue)	
Covariates		Farming experience of household heads in years (continuous	
Gender	Male =1, female = 0	Sex of household head (dummy)	+
Household size	Count in person	The no.of family members living within household head for > 6 months	±
Active labor force	Count in person	Number of active family members (15 to 64 years) living with households	+
Education level	Years	Education level of household heads measured by years of schooling	+
Farming experience	Years	Farming experience of HH heads engaged in his/her own farm business	+
Livestock holding	TLUs	Total livestock holding of the household head in TLU (continuous)	+
Cultivated land size	ha	Total owned farmland allocated for crop production measured in ha	+
Off-farm activity	Yes =1, 0 = otherwise	It is a proxy variable to off-farm income obtained by HH head (dummy)	-
Fertilizer use	Yes =1, 0= otherwise	It refers to the experience of farmers in using fertilizer on their farm plots	+
Improved seed	Yes =1, 0= otherwise	Refers to the experience of farmers in using improved seed of crops	+
Extension service	Yes=1, 0 = otherwise	It the extension service accessibility by farm households on SLM (dummy)	+
Distance to roads	Kilometers (km)	Is walking hours measured in kilometer from homestead to main road	±
Distance to market	Kilometers (km)	It is a distance from homestead, and a proxy variable for market access	±
Incentive	Yes=1, 0 = otherwise	It is the accessibility/availability of economic rewards either in cash or kind	+
Choice of crop	Yes=1, 0 = otherwise	Farmers' decision to choose annual/perennial crops	±
Plot distance	Kilometers (km)	Average farm plots distance from household's resident in km (continuous)	±
Farm plot location	Upper =1, lower =0	Households' farmland location in the given watershed of the study areas	+
Soil erosion severity	Low, moderate, high	Farmers' perception about the severity level of soil erosion on farmland	+
Slope index	%	The composite index computed by summing up households' farm plots flat, moderate and steep slope proportion (continuous)	±
Infertile soil propn	%	It is the proportion of degraded infertile soil part of owned farmland of HHs	+
Land certificate	1 yes, 0 = no	Farmers whether they received land certificate or not for owned land	+
Agro ecology	Highland, midland	It is the agro ecological location of the sample households (categorical)	±
Rainfall intensity	Low, medium, high	Perceived rainfall intensity received by farmland (categorical)	±

Table 6 Description of variables and working hypothesis of SLM impact (plot level)

Variable name	Measurement	Description	Ho sign
Treatment variable			
SLM participation	User =1 non-users=0	Farmers using on-farm SWC for five consecutive years on farm plots	
Outcome variables			
Value of crop produced	ETB	Market value of total crop produced at harvest time (quantity * price)	
Farm income	ETB	Sale of crop and livestock live and byproducts at market (farm revenue)	
Covariates			
Household size	Count in person	The number of family members living within HH head for > 6 months	±
Education level	Years	Education level achieved by household measured by years of schooling	+
Farming experience	Years	Farming experience of HH heads engaged in his/her own business	+
Farm plot size	ha	Refer to size of all owned farm plots by a household measured in ha	+
Extension service	Yes=1, 0 = otherwise	Refer to extension service accessibility by farm households on SLM	+
Fertilizer usage	Yes =1, 0= otherwise	It refers to farmers experience of using fertilizer on their farm plots	+
Distance to main road	Kilometers (km)	The average walking distance to all pots from homestead to main road	±
Distance to market	Kilometers (km)	It is a distance from home, and a proxy variable for market access	±
Plot distance	Kilometers (km)	Average farm plots distance from household's resident in km	±
Farm plot location	Upper =1, lower =0	Owned plots location in the given watershed of the study areas	+
Topsoil erosion	Yes=1, 0 =otherwise	The occurrence of topsoil erosion as a threat on a given farm plot	+
Steep slope proportion	%	Refer to the steep slope proportion of a farm plot out of owned farmland	+
Moderate slope proportion	%	Is moderate slope proportion of a farm plot out of a whole farmland	+
Infertile soil proportion	%	It is the proportion of infertile soil part of a farm plots in a percent	+
Shallow depth plot%	%	It is the proportion of shallow depth part of a farm plots in a percent	+
Soil quality	Poor, medium, high	Quality of plot in terms of fertility, colour, workability and texture	+
Rainfall intensity	Low, medium, high	Perceived rainfall intensity received by farm plot (categorical)	+

Note: Hypothesis is made for discrete change from 0 to 1 for dummy and 1 to 3 for categorical variables

4. RESULTS AND DISCUSSION

This chapter presents the results and discussion, the core components of the study, using descriptive statistics and econometric models. Prior to the econometric model estimation and prediction, simple descriptive statistics are employed to summarize and present the data. The demographic, socioeconomic, institutional and biophysical characteristics of the sample households are discussed and presented using the descriptive statistics. The commonly used classical inferential statistics such as mean comparison t test; Z and chi square (χ^2) tests are used to make inferences of the whole population on the basis of the selected sample units. Next to the summary of descriptive statistics, different econometric models are specified and used for the analysis. The ordered probit model, the cragged double hurdle model (CDH), Heckman selection method (ET2T), the multivariate probit (MVP) model, PSM and the ESR were specified and applied for the parameter coefficient estimation. The descriptive statistics results, the econometric model analysis and estimation outputs with respect to each research objective are presented and discussed in the following sections sequentially.

4.1. Descriptive Analysis

In using descriptive statistics, qualitative and quantitative data were organized, summarized, and presented in a tabular form. Frequency distribution, a measure of central tendency and dispersion and graphic representation were employed to summarize and present the data. Moreover, prior to the specification of econometric models for the estimation, the inferential statistics were applied to make inferences of the population.

4.1.1. Description of households' perception level

Farmers' perception about the role of SLM in reducing the land degradation process and improving land capability potential are linked to the decision to participate in land management practices. Farmers' perceptions of SLM differ from low to high depending on socioeconomic, institutional, and biophysical attributes of farm households. In this study, a three-point Likert-type scale (low, medium, high) was employed to solicit sample households' perception response of SLM's role. Initially, farmers were asked how they perceive the role of SLM practices to combat land degradation and reduce soil erosion during the survey. Their responses were computed as a composite index and finally categorized as low, medium and high. Moreover, FGDs were held within the selected 24 villages of the study areas with separate groups of respondents (youths, women, model farmers, recognized elders and others) to investigate the perception level of farmers about the role of SLM practices, specifically SWC measures implemented on their farmlands. The discussants were asked to quantify their perception level as low, medium and high qualitatively during the FGDs. The FGDs result showed that about 15.6%, 23.4% and 60.9% of the discussants have low, medium and high perception level of SLM practice's role in their perspective locations (Table 7).

Table 7 Farmers' Perception level of SLM practices

Perception about the role of SLM practices	FGDs		Perception level (Score in %)		
	No.	Discussants no.	Low	Medium	High
Farmers perceive the role of SLM to reduce land degradation and rehabilitate land resources (soil)	24	240	8.33	16.67	75.00
SLM improves production	24	240	12.50	22.92	64.58
SLM reduces risk of disasters	24	240	16.67	29.17	54.17
SLM has no negative impact (for ox ploughing, not competes cultivated land, do not harbor rodents and insects)	24	240	25.00	25.00	50.00
Average score	24	240	15.63	23.44	60.94

Source: FGDs result, 2022

Household perception level is a Likert-type data that falls into an ordinal measurement scale. The descriptive statistics mainly frequency distribution to show variability and the chi-square (χ^2) to measure the association were applied. As depicted in Table 8, the descriptive result indicates that approximately 61% of farm households perceived the role of SLM as high, 23.6% perceived it as medium and 15.4% as low. Furthermore, the Chi^2 measure of association pointed out that households' perception on the role of SLM in Wolaita showed a significant symmetric difference across the three categories of identified perception levels (Table 8).

Table 8 Perception level of farm households about the role of SLM (n=475)

Location	Farmers perception level about the SLM role			Total	χ^2-value
	Low	Medium	High		
Sidama	27 (5.68)	43 (9.05)	116 (24.42)	186 (39.16)	0.258
Wolaita	29 (6.11)	43 (9.05)	86 (18.11)	158 (33.26)	4.402 *
Siltie	17 (3.58)	26 (5.48)	88 (18.52)	131 (27.58)	2.852
Total	73 (15.37)	112 (23.58)	290 (61.05)	475 (100)	

Note: * Significant at 10% probability level

4.1.2. Households and farm characteristics

The demographic, socioeconomic, institutional characteristics of households and biophysical attributes of farm plots are discussed in the following paragraphs. Demographic characteristics of sample farmers contribute either positively or negatively for perceiving, participating in, and choosing SLM practices in their owned farmland. Among these, farming experience, household size, active labour force, labour dependency and gender of a household head are some of the proxy variables hypothesized to determine farmers' perception, participation, choices of SLM and its impacts, specifically on-farm SWC measures. Moreover, marital status is household demographic characteristic that was hypothesized to influence farmers' choice of SLM practices. As depicted in Table 9, the mean farming experience was 24.37 (±9.52) ranging from 6 to 50 years. The average family size was 7.59 (±2.47) persons which lies above the rural average household size of SNNPR and the national average, i.e. 4.9 persons (CSA, 2008). The mean active labour force of the sample farm households was found to be 3.73 (± 1.90) ranging from 1 to 12 persons. The mean labour dependency ratio was about 1.36 (±1.14) which consists of more than 36% inactive family labour force supposed to affect the labour supply of households negatively to implement SLM practices. Concerning the gender composition of the sample respondents, 94.7 % of sample households are male-headed, while the remaining 5.3% are female-headed. Regarding the marital status of households, about 93.5%, 4.2% and 2.3% were married, single and widowed, respectively.

The socioeconomic characteristics of households are important decision variables in the process of farm households' perception, participation in SLM and choosing the measures to apply on their farm plots. The socioeconomic characteristics of farm households comprises the social and economic endowment variables. Education level, perception, livestock holding, farm income, farm revenue, non-farm income, value of crops produce, cultivated land, total owned land and plot size and are key socioeconomic characteristics hypothesized to affect farmers' perception level, participation decision, choice and impacts SLM practices differently.

Education is a very important deterministic social factor in farm households' to understand the role of SLM practices, to participate in and the application of on-farm SWC on own farmland. An educated farmer is able to use improved agricultural technologies and land management practices, and as a result manage land resources properly. From the household survey made at the study areas, the mean education level of sample households was found to be 4.20 (±3.78) grades composed of illiterate households (28.8%) and the majority of the sample respondents are educated (71.2%) attaining grade 1 to a maximum of attaining first degree (15) (Table 9). Likewise, farmers' perception about the role of SLM, specifically on-farm SWC, differed among farm households. As shown in Table 9, the mean perception index of farmers was found to be 0.80 (±0.24) with minimum of 0.33 (low perception) and a maximum of 1.00 (high perception).

The economic variables, such as livestock holding, farm income, non-farm income, crops produced, owned land, cultivated farmland, farm revenue and number of farm plots are capital assets affect farmers' perception about the role of SLM, participation and choice decisions, and to use SLM practices. Livestock as part of a mixed farming system is a paramount importance to a household economy. Cattle, sheep, goats, and chickens are reared by farmers for income sources, draft power, and food sources purposes. The mean livestock holding was found to be 4.37 (±2.81) TLUs ranging from 0.32 to 23.86 TLUs. On the other hand, the farm income obtained from the sale of agricultural produce, for example, crops and livestock are essential deterministic factors in participating, choosing, and applying area-specific SLM practices. The mean farm income and the value of crops produced in 2018/19 were found to be 22,670.00 (±18,610.00) and 26,660.00 (±21,860.00) ETB, respectively. The descriptive result indicated that the mean farm revenue from sale of crop produced and livestock was ETB 35,210 per annum. Non-farm income obtained from engagement in non-agricultural activities was hypothesized to influence farmers' perception, participation decision, choices, and SLM impacts negatively. About 44% of households participated in non-farm activities with a mean value of 8,100.00 (±5,750.00) ETB ranging from 1,000.00 to 33,500.00 ETB per annum.

Similarly, total land holding, cultivated farmland and number of farm plots are assets that affected farmers' willingness to participate in SLM and allocate their farmland to most preferred SWC measures to mitigate soil erosion. The mean landholding and cultivated farmland of the sample household heads were 1.29 (±0.74) and 1.10 (±0.59) ha, respectively. The mean cultivated land holding is higher than the regional and the national average private land size of about 0.39 and 0.78 ha per household, respectively (ESS, 2022c). The number of farm plots was found to be about 3 plots ranging from 1 to 5 per a household. Likewise, the average plot size of sample households in the study areas was found to be 0.45 (±0.29) ha.

Infrastructural and institutional accessibility to the farming community have a twin benefit that, on the one hand, they enable beneficiary farmers easily access the services, and on the other hand, they ease the exchange of information and delivery of the farm produces with low transaction costs. Among the infrastructural and institutional services, extension service, training, land market, incentive, community bylaws, road and market distance found to be vital for the farming community to perceive, participate, choose and use SLM practices to mitigate land degradation and reduce soil erosion in their farmland. Moreover, input use, that is, improved seed and inorganic fertilizer use are institutional attributes deemed to affect the impact of SLM practices on value of crop production and farm income.

The household survey revealed that sample respondents have access to FTC at an average of 2.25 km from the homestead that 93.7% of sample households have access to extension service and on average; a household has an opportunity of 2.29 (±1.13) days visit by extension agents within a month (Tables 9 and 10). Moreover, the majority of sample households, i.e., nearly 77% of farm households did get 2.57 days of training on function and applicability of SLM annually. Access to market and main road are other institutional services that facilitate the selling and buying process of agricultural produces at a lower transaction cost, which influences farmers' perception, participation decision, choices and impact of SLM practices.

The average distance of market from home was computed to be 7.09 (±4.14) km, that ranged from 1 to 19 km, the farthest was observed in Boloso Bombe woreda (Zaba *kebele*). Similarly, the statistical result revealed that the average main road distance from homestead was found to be 2.79 (±3.63) km.

Though the Ethiopian Federal Democratic Republic Constitution prohibits land market, nearly 53% of the sample households participated in land rental marketing. Incentive in the form of cash, kind or both is one of the deterministic variables influencing farmers' perception, and participation decision in private on-farm SWC or public work through different 'adaptive social protection' schemes, for example FFW schemes or PSNP. As indicated in Table 10, about 81% of the sample households revealed that receiving economic incentives influenced their perception level and participation decision to implement land management practices, specifically, on-farm SWC measures on their farm plots. Moreover, land certificate is a policy variable hypothesized to influence farmers' perception of the role of SLM practices and its impact on value of crop production and farm income. The statistical result revealed that a higher percentage of sample households, i.e., 91.8% received land certificate books. Furthermore, a well-functioned community bylaw influences the perception level of farm households to implement land management practices. About 47% of the sample respondents replied that community bylaw has influenced the perception level of households. Tenure arrangements are policy issues expected to influence farm household perception level. About 86% of the sample households have own farmland (titled) expected to increase their perception level of SLM.

The farming system characteristics affecting the choice and impact of SLM practices include crop choice (annual crop and perennial crop choice), fertilizer usage, and improved seed use. In a mixed farming system, annual crop choice, perennial crop preference, fertilizer, and improved seed use experience of farmers are the underlying determinants of SLM choices and their use. About 96%, 86%, and 92% of the sample households perceived fertilizer usage, improved seed and crop choice, respectively, to affect the choices of SLM practices on their farmlands and are supposed to impose influence on impacts of SLM on crop production and farm income.

Farm plot location, plot distance, soil fertility status, slope status, soil erosion and its severity level, agro ecology, and perceived rainfall intensity are biophysical plot-related and environmental attributes that were hypothesized to influence farmers' perception level, participation decision, choices and impacts of SLM practices differently. The average distance of farm plots from homestead was found to be 0.49 (±0.45) km that varied from 0.02 to 3.05 km, and it implied that as the farm distance gets far from the homestead the perception level and participation decision expected to be less. In the Likert scale measurement, soil fertility index was found to be 0.59 (±0.24) ranging from 0.17 to 1.00 that revealed nearly three-quarters (¾th) of the respondents' farm plots soil fertility is found to be moderately fertile.

Moreover, nearly half of the respondents' farm plots slope were categorized as moderate whilst 38% and 12% of them reported that their farm has flat and steep slope, respectively. The proxy variables for land quality and soil erosion, for example, degraded infertile farmland, fertile farm plots, steeply and moderate sloppy farm plots proportion were computed to be 0.40 (±0.25), 0.43 (±0.11), 0.40 (±0.25), and 0.56 (±0.25), respectively. The descriptive statistics analysis revealed that the average slope index of households' farmland was found to be 0.56 (±0.24) ranging from 0.17 to 1.0. Moreover, the household survey result indicated that majority of farmers responded that their farmland was moderately sloppy (46%), moderate fertile soil (73.5%), and consist of moderate soil quality (72%). Moreover, during the FGDs, majority of farmers responded that their farmland has moderate fertile soil, shallow depth and moderate slope, which implies the need for systematic and effective land management practices to maintain and conserve its productivity.

Soil erosion severity of farmland was also hypothesized to affect the perception level, choice and impact of SLM practices. As presented in Table 10, about 45%, 46% and 9% of the households' farmlands have low, moderate and severe levels of soil erosion, respectively. In area where soil erosion severity is moderate to high, farmers are forced to construct and implement appropriate on-farm SWC measures to maintain and conserve the potential of the farmland (Akalu *et al*., 2016). Farmers' perceived rainfall intensity was also one of the environmental deterministic factors that influenced the choice and impact of SLM practices on value of crop production and farm income. As observed from the survey data, 45.5%, 35.4%

and 19.1% of sample respondents perceived rainfall intensity of the study areas as receiving low, moderate and high rainfall amount, respectively.

The study areas were located in the midland (*weyna dega*) (68.9%) and highland (*dega*) (31.1%) agro ecology. Out of the study woredas, the sample from Arbegona (21.68%), part of Malega (8.42%) and one sample *kebele* of Boloso Bome (1.05%) are categorized under the highland, while the remaining are located in midland agro ecological belt. On the other hand, a higher number of the sample households, i.e., about 64% are located at the lower stream while the remaining 36% are located in the upper stream of the watershed of the respective woredas. Furthermore, the perception level across the study zones was found to be different implying that the intensity and scope of land management practices are location specific.

Table 9 Summary of descriptive statistics of continuous variables

Explanatory variables	Mean	Std. Dev	Min	Max
Farming experience	24.37	9.52	6	50
Household size	7.59	2.47	2	20
Active labour force	3.73	1.90	1	12
Dependency ratio	1.36	1.14	0	10
Education level	4.20	3.78	1	15
Perception index	0.80	0.24	0.33	1
Cultivated farmland	1.10	0.59	0.31	5
Land size	1.29	0.74	0.34	7.5
Plot size	0.45	0.29	0.05	1.5
Livestock holding	4.37	2.81	0.32	23.86
Farm income (000’s)	22.67	18.61	1.6	236.4
Non-farm income (000’s)	8.10	5.75	1.0	33.5
Value of crop (000’s)	26.66	21.86	1.77	330.83
Farm revenue (in 1000 ETB)	35.21	26.34	3.27	370.83
Extension contact	2.29	1.13	0	6
Road distance	2.79	3.63	0.03	16
Market distance	7.09	4.14	1	19
Number of farm plots	2.56	0.66	1	5
Average plot distance	0.49	0.45	0.02	3.05
Soil fertility index	0.59	0.24	0.17	1
Degraded infertile soil proportion	0.40	0.25	0.04	1
Fertile farmland proportion	0.43	0.11	0.025	0.51
Slope index	0.56	0.24	0.17	1
Steep slope farmland proportion	0.40	0.25	0.04	1
Moderate slope farmland proportion	0.56	0.25	0.06	1

Source: Own computation from the survey data, 2022

Table 10 Summary of descriptive statistics of discrete variables

Variables		Percentage (%)	Cumulative %
Gender	Male	94.7	94.7
	Female	5.3	100.0
Marital status	Married	93.5	93.5
	Single	4.2	97.7
	Widow	2.3	100.0
Social network	Yes	73.5	73.5
	No	26.5	100.0
Off-farm income	Yes	43.6	43.6
	No	56.4	100.0
Extension service	Yes	93.7	93.7
	No	6.3	100.0
Training	Yes	76.8	76.8
	No	23.2	100.0
Fertilizer use	Yes	95.6	95.6
	No	4.4	100.0
Crop choice	Yes	92.0	92.0
	No	8.0	100.0
Improved seed use	Yes	86.3	86.3
	No	13.7	100.0
Land rental market	Yes	52.8	52.8
	No	47.2	100
Tenure arrangement	Owned	85.68	85.68
	Family	14.32	100.0
Community bylaws	Yes	46.5	46.5
	No	53.5	100.0
Incentive	Yes	80.6	80.6
	No	19.4	100.0
Land certificate	Yes	91.8	91.8
	No	8.2	100.0
Soil erosion	Yes	81.5	81.5
	No	18.5	100.0
Slope status	Gentle	38.32	38.32
	Moderate	49.68	88.0
	Steeply	12.0	100.0
Soil erosion severity	Low	45.0	45.0
	Moderate	45.9	90.9
	Severe	9.1	100.0
soil fertility	Low	13.47	13.47
	Moderate	73.47	86.94
	High	13.06	100.0
Soil quality	Poor	8.84	8.84
	Moderate	71.58	80.4
	Good	19.6	100.0
Perceived rainfall intensity	Low	45.5	45.5
	Medium	35.4	80.9
	High	19.1	100
Study location	Sidama	39.16	39.16
	Wolaita	33.26	72.42
	Siltie	27.58	100.0

Source: Own computation from the survey data, 2022

4.1.3. Test statistics of determinants of participation and impacts

The grouping of sample farmers into participant (user) and non-participant (non-user) of SLM is based on observational data and expert judgment of the area under consideration. Comparison is made between users and non-users of SLM practices, specifically on-farm SWC, regarding socioeconomic, institutional, biophysical, and policy attributes. The discrete variables that affected participation decisions in using SLM practices were training, community bylaws, land market, farm plot location, social network, slope status and soil erosion occurrence. Moreover, fertilizer uses, improved seed, crop choice and land market influenced the impact of SLM practices. In all cases, with the exception of gender, off farm income, incentive and land certificate, the chi-square value showed that there is a symmetric relationship between the aforementioned explanatory variables and SLM participation, and they affect statistically significantly as compared to the base variables (Table 11).

The statistical results revealed that farm households with access to training, the presence of effective community bylaws, perceptions of SLM functions, and social network like experiences of model farmers showed a significant difference between users and non-users of SLM practices. The comparison between users and non-users of SLM practices in terms of extension services and input use publicized statistically significant and positive differences in SLM impacts on crop value and farm income. The result revealed that a higher percentage of SLM users received extension advice (i.e., 94%), applied inorganic fertilizer (i.e., 96%), and utilized improved seed (i.e., 86%) on their farmlands. This is supposed to have a positive impact on crop production and farm income compared to the non-users (Table 11). The institutional attribute, namely, development agents, in offering extension advice and making frequent contact with farm households to implement and maintain on-farm SWC, affects the participation decision significantly at 1% probability level.

The bio-physical attributes of farm plots that were considered in this study, that is, the physical location of the farm in the given watershed, soil erosion occurrence, and the slope of the farm plots being steep or moderate, affect farmers' SLM participation level statistically significantly at the 1% probability level. Likewise, severity of soil erosion and perceived rainfall intensity being low, moderate and high affected the impact of SLM practices on value of crop production and farm income significantly at less than 1% probability level.

On the other hand. household size, perception of farmers regarding SLM role, livestock holding, land size, farm income, value of crop produced, extension contact and soil fertility status (index) of farm plots significantly affected participation decisions. The mean difference of household size of farm households in the study areas was 0.49 persons. Similarly, livestock holding and cultivated land size showed significant and positive differences between users and non-users of SLM practices. The mean difference of livestock holding and cultivated farmland size were found to be 1.45 TLU and 0.32 ha, respectively. Likewise, the average plot size between the user and non-user farm households show significant differences. The mean difference of plot size between users and non-users was found to be 0.45 ha.

The biophysical plot-related attributes that were found to affect the impact of SLM on value of crop production and farm income are plot distance, degraded infertile soil proportion, soil erosion severity and slope status (flat, moderate, steep). The statistical result revealed that the plot distance was found to be significant between the two groups at $p < 0.01$. Moreover, the comparison between user and non-user farmers revealed that households that own farmland with a higher proportion of degraded infertile soil, steeply sloped farmland, and severely degraded land practiced different land management practices when compared to that of farmers who have fertile, flat to moderate slope and low soil erosion severity level. The descriptive statistics analysis revealed that the mean value difference of slope index and degraded infertile soil proportion of user and non-user households were found to be 0.13 and 0.07 and statistically significant at $p < 0.01$ and $P < 0.05$, respectively (Table 12).

Perceived rainfall intensity and agro ecological location found to be statistically significant in influencing the impact of SLM on crop production and farm income between users and non-users of SLM practices. About 45%, 35% and 19% of sample households perceived rainfall intensity as low, medium and high, respectively, which is statistically significant in influencing the impact of SLM practices. The agro-ecological location was also found to affect the participation decision and impact of SLM on crop production and farm income significantly at household level. The statistical result described that about 69% and 31% of the respondents are located at midland and highland agro ecological locations. During the FGDs, respondents reported that in locations where households are residents of highland agro ecological areas, the environments are endowed with medium to high rainfall intensity that exposes their farmland to high soil erosion, runoff, and fertility decline that in turn forces farmers to implement SLM practices. Farm plot location of households also showed symmetrical differences between users and non-users of SLM practices (Table 11).

Table 11 Test of symmetric relations of variables

variable	Response	Participant /user (n=365)		Non-participant /Non-user(n =110)		Combined (n=475)	χ^2-value
		No.	%	No.	%	%	
Gender	Male	347	73.05	103	21.68	94.74	0.348
Social network	Yes	334	70.32	15	3.16	73.47	262.98***
Off-farm income	Yes	159	33.47	48	10.11	43.58	0.0002
Extension service	Yes	353	74.32	92	19.37	93.68	24.426***
Training	Yes	302	63.58	63	13.26	76.84	30.807***
Fertilizer use	yes	358	75.37	96	20.21	95.58	23.373***
Improved seed	Yes	321	67.58	89	18.74	86.32	3.543**
Crop choice	Yes	255	53.68	1	0.21	53.89	161.74***
Community bylaw	Yes	187	39.37	34	7.16	46.53	14.033***
Incentive	Yes	296	62.3	87	18.3	80.63	0.218
Land market	Yes	185	38.95	66	13.89	52.84	2.943*
Land certificate	Yes	338	71.16	98	20.63	91.79	1.383
Farm location	Lower	258	54.32	47	9.89	64.21	28.75***
	Upper	107	22.53	63	13.26	35.79	
Soil erosion	Yes	328	69.05	59	12.42	81.47	73.49***
Soil erosion severity	Low	138	29.05	76	16.0	45.05	
	Moderate	189	39.79	29	6.11	45.89	33.471***
	High	38	8.0	5	1.05	9.05	
Slope status	Flat	119	25.05	63	13.26	38.32	
	Moderate	192	40.42	44	9.26	49.68	26.385***
	Steep	54	11.37	3	0.63	12.00	
Agro ecology	Midland	238	50.10	94	19.79	69.89	16.471***
	Highland	127	26.74	16	3.37	30.11	
Perceived rainfall intensity	Low	149	31.37	67	14.11	45.47	15.362***
	Moderate	136	28.63	32	6.74	35.37	
	High	80	16.84	11	2.32	19.16	

Notes: *** and * indicates significant at 1% and 10 probability level.

Table 12 Mean equality test of continuous variables

Variables	User (365)	Non-user (110)	Mean difference	t-value
Household size	7.71 (2.53)	7.21 (2.21)	0.49 (0.27)	1.861**
Farming experience	24.52 (9.53)	23.91 (9.50)	0.61 (1.04)	0.585
Active labour force	3.79 (1.91)	3.53 (1.88)	0.26 (0.21)	1.264
Labour dependency ratio	1.34 (1.08)	1.41 (1.32)	-0.07 (0.12)	-0.57
Education level	4.21 (3.76)	4.19 (3.85)	0.02 (0.41)	0.042
Perception index	0.89 (0.16)	0.50 (0.22)	0.39 (0.02)	20.591***
Livestock holding	4.70 (2.99)	3.25(1.68)	1.45 (0.29)	4.854***
Land size	1.38 (0.75)	1.01(0.63)	0.37 (0.08)	4.702***
Cultivated farmland	1.17 (0.60)	0.86 (0.49)	0.32 (0.06)	5.041***
Plot size	0.49 (0.29)	0.33 (0.23)	0.45 (0.29)	8.649***
Farm income (000’s)	24.29 (19.93)	17.27 (11.93)	7.02 (2.00)	3.507***
Crop value (000’s)	28.56 (23.66)	20.37 (12.49)	8.18 (2.35)	3.483***
Non-farm income (000’s)	7.63 (4.89)	9.72 (7.89)	- 2.08 (0.89)	-2.139**
Extension contact	2.39 (1.08)	1.95 (1.22)	0.44 (0.12)	3.656***
Road distance	2.80 (3.49)	2.79 (4.10)	0.01 (0.39)	0.027
Market distance	7.16 (3.95)	6.87 (4.73)	0.29 (0.45)	0.649
Farm plot distance	0.54 (0.47)	0.30 (0.29)	0.24 (0.05)	5.111***
Soil fertility index	0.61(0.24)	0.53(0.22)	0.08 (0.03)	3.148***
Slope index	0.58 (0.24)	0.46 (0.20)	0.13 (0.03)	5.011***
Degraded infertile soil proportion	0.18 (0.26)	0.12 (0.24)	0.07 (0.03)	2.397 **

Notes: ***, ** and * are significant at 1%, 5% and 10% probability level respectively
The parentheses indicate the standard deviation for the mean and standard error for the mean difference.

4.1.4. Test statistics of determinants SLM choices

Farmers’ choices of SLM practices are determined by the combined effects of socioeconomic, institutional, and biophysical plot attributes of farm households. Socioeconomic factors such as cultivated farmland size, number of owned farm plots, livestock holding, and farm income affected farmers’ choice of fanya juu and level soil bund at a 1% probability level. The association shows that farm households with high land holding size and larger number of plots choose and invest in fanya juu and soil bund structures to reduce the velocity of overland runoff and soil erosion. Farm households with high farm income and livestock holding get the opportunity of hiring labour to construct and maintain the structures to function properly.

Likewise, extension services offered by development agents in supervising and advising farmers to implement fanya juu and soil bund as per the recommended design and slope orientation of plot affected farmers' preference of the aforementioned practices at 5% and 1% probability level, respectively. Distance of plot from home affected farmers' fanya juu and soil bund choices at 1% probability level. The possible reason for such significant associations is that farmers who own fertile land around their homestead are naturally accustomed to maintain its productivity level to maximize the benefit. Moreover, degraded infertile soil proportion of farm plots affected the households' choice of soil bund at $p < 0.01$, implying that farmers are optimistic to maintain and conserve infertile plots of their farm plots.

Akin to fanya juu and soil bund, farmers' choices of bench terrace and indigenous SWC practices are affected by the combined associations of various factors at household level. The socioeconomic deterministic factors, for example, education ($p<0.05$), cultivated farmland size ($p<0.01$), number of farm plots ($p<0.01$), livestock holding ($p<0.01$), farm income ($p<0.01$) and non-farm income ($p<0.1$), showed statistically significant associations with farmers' choice of bench terrace and indigenous SWC measures. Similarly, extension service and plot distance from home showed significant associations with households' choice of bench terrace at 1% and 5% significance level, respectively. Apart from the aforementioned socioeconomic factors, distance of market from home, plot distance, and degraded infertile soil proportion of farmland affected farmers' choice of indigenous SWC measures at 5%, 1%, and 5% probability level, respectively (Table 13).

Table 13 Summary of mean equality test of variables affecting SLM choices

Variables	Fanya juu			Soil bund			Bench terrace			Indigenous SWC		
	Yes	No	t-value	Yes	No	t-value	Yes	No	t-value	Yes	No	t-value
Active labour force	3.82	3.55	1.46	3.83	3.61	1.26	3.84	3.61	1.34	3.76	3.64	0.62
Education level	5.73	5.96	-0.63	5.85	5.75	0.28	6.20	5.32	2.54**	5.74	5.96	-0.56
Farming experience	24.32	24.48	-0.18	24.25	24.51	-0.29	24.29	24.47	-0.20	24.39	24.32	0.07
Market distance	6.98	7.30	-0.81	7.13	7.04	0.25	7.20	6.98	0.59	6.82	7.85	-2.40**
Cultivated farmland	1.21	0.91	5.45***	1.28	0.90	7.47***	1.20	1,00	3.60***	1.17	0.93	3.3.89***
Number of farm plots	2.70	2.31	6.44***	2.76	2.35	7.04***	2.74	2.39	5,94***	2.64	2.35	4.32***
Livestock holding	4.79	3.57	4.59***	4.96	3.70	4.96***	4.97	3.74	4.88***	4.67	3.50	4.06***
Farm income (000's)	24.67	18.93	3.24***	26.96	17.86	5.48***	25.61	19.61	3.56***	24.06	18.72	2.77***
Non-farm income (000's)	7.66	8.91	-1.58	7.95	8.29	-0.45	7.42	8.81	-1.84*	7.59	9.75	-2.46**
Extension contact	2.36	2.14	2.01**	2.42	2.13	2.80***	2.49	2.08	4.02***	2.32	2.18	1.25
Plot distance	0.56	0.35	4.95***	0.59	0.38	5.07***	0.53	0.44	2.24**	0.55	0.32	5.02***
Infertile farmland%	0.38	0.43	-1.295	0.36	0.46	-2.83***	0.37	0.43	-1.61	0.37	0.48	-2.45**
Steep sloppy land proportion	0.40	0.38	0.39	0.39	0.40	-0.13	0.41	0.37	0.64	0.38	0.45	-1.26
Moderate sloppy land proportion	0.55	0.57	-0.65	0.52	0.61	-3.59***	0.55	0.57	-0.95	0.56	0.57	-0.36

Notes: ***, ** and * are significant at 1%, 5% and 10% probability level, respectively

Source: Own computation from the survey data, 2022

4.2. Econometric Model Results

4.2.1. Farmers' perception about the role of SLM practices

Based on the literature, economic a prior criterion and the research question of the study, different econometric models were specified and taken into account. After the models were specified, the parameters were estimated, tested, validated and, finally, the results were interpreted from an economic point of view using the analyzed data. An ordered probit model was used to estimate relationships between an ordinal dependent variable, perception levels and a set of hypothesized independent variables. A three Likert scale type, i.e., low, medium and high was employed to compute the farmers perception that was taken as dependent variable in the specified model. The econometric model was specified and applied for the analysis. The parameter was estimated, and the post estimation and interpretation are presented as follows.

The likelihood of framers to perceive the role of land management practices as lowest, medium, and highest perception levels was 15.2%, 23.6%, and 61.1%, respectively (Table 14). The mean predicted probability of farmers to perceive the role land management practice is the highest (i.e., 61.1%) implying that farmers in the study areas are willing to participate and implement SLM practices to combat land degradation in the long run and soil erosion in the short run expecting use and non-use value of the land resources (Figure 3).

Table 14 Predicted probability of perception level of SLM (N=475)

Predicted probability level	Mean	Std.dev	Min.	Max.
Lowest perception	0.152	0.166	0.001	0.299
Moderate perception	0.236	0.103	0.008	0.367
Highest perception	0.611	0.243	0.037	0.991

Source: Own computation from the household survey data, 2022

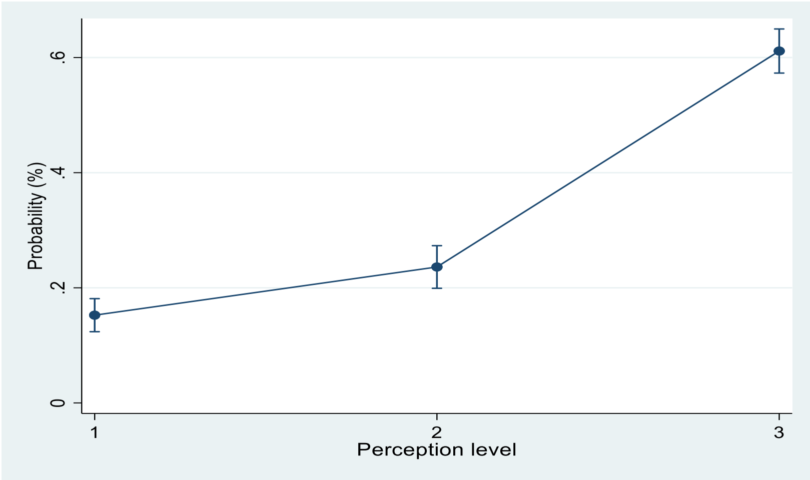


Figure 3 Predicted margins of perception level (95% CIs)

4.2.1.1. Model specification test

In model specification and application, the assumption of homoscedasticity, endogeneity, autocorrelation, and multicollinearity should be tested to have unbiased, consistent, and efficient estimate of parameters and cut points. Before rushing into the estimation, different tests were performed. First, the exact perfect linear correlations between the independent variables were tested using VIF and it was found out that there is no linear relationship or multicollinearity problem between the regressors (Appendix Table 1). Second, the Kernel density estimation for the dependent variable was assessed and showed normality and moderately smooth as the density approaches the normal curve (Figure 4).

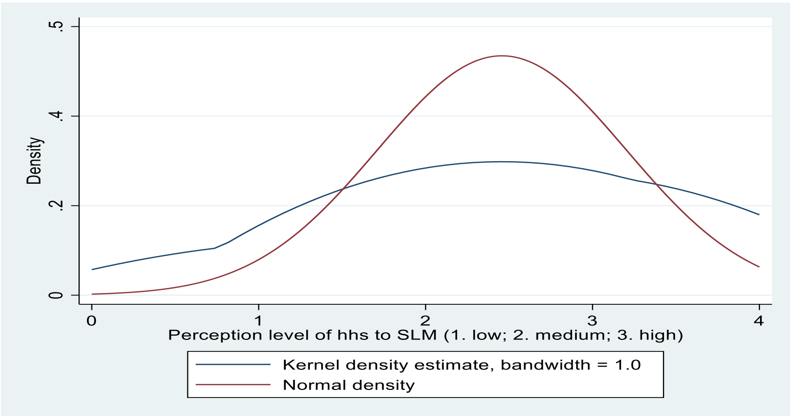


Figure 4 Kernel density estimate of perception level of SLM

Third, Hausman specification test was carried out to detect an endogeneity problem of regressors and the error term. As a result, the test showed that the asymptotic distribution under the null hypothesis supporting no correlation between the errors and regressors is accepted or the estimator is an efficient and consistent estimator of the true population parameters (Appendix Table 2). Fourth, the Wald chi-squared statistics test is significant at less than 1% probability level, which indicates the null hypothesis that states the joint test of all slope coefficients equal to zero is rejected (Wald chi2 (28) = 137.53, p = 0.000), showed that the ordered probit model fits the data very well (Table 16). Fifth, the model fitness was also tested with the Likelihood-ratio (LR- χ2) test. The LR test statistic (i.e., LR chi2 (12) = 13.19; Prob > chi2 = 0.355) was found to be insignificant (Table 15). Moreover, the LR test, Akaike and Bayesian information criterion (AIC and BIC) were used for the comparison of restricted and unrestricted ordered probit models (Greene and Hensher, 2010). The observed insignificant LR test, and smaller AIC and BIC revealed that the inclusion of all hypothesized independent variables in the ordered probit model resulted in a better goodness of fit (Table 15) than the constrained model (Appendix Table 3). Therefore, the post-estimation test concluded that the ordered probit model is consistent and efficient to estimate the parameters with no heteroscedasticity.

Table 15 Likelihood ratio test

Model	N	ll (null)	ll (model)	Df	AIC	BIC
OprobitRst	475	-441.63	-370.97	18	777.895	852.89
oprobitUnrst	475	-441.63	-364.38	30	788.76	913.66

Note: AIC denotes Akaike's information criterion and BIC for Bayesian information criterion
Assumption: The restricted model is nested within unrestricted ordered probit model
LR Chi (12) = 13.19; Prob > chi2 = 0.355 (35.5%)
Source: Own computation from the household survey data, 2022

4.2.1.2. Determinants of farmers' perception of SLM practices

The ordered probit model explains the variation in the perception level of farmers to the role SLM as a function of the hypothesized socioeconomic, institutional, biophysical plot-related characteristics and policy attributes. The parameters of estimate, i.e.,β, μ and ε are carried out using the ML estimation procedure using the statistical package called StataBE 17. Moreover, following the ordered probit estimation, the marginal effects were computed to investigate a change in the perception level of the farm households due to a unit change of each explanatory variable expected to affect the perception of households about the role of SLM (Table 16).

The ordered probit model estimation result demonstrates that the hypothesized household socioeconomic characteristics, institutional factors, plot-related biophysical, and policy attributes influence farmers' perception of SLM measures, either positively or negatively. The socio-economic characteristics, institutional and biophysical farm related factors account for the smallholder farmers' perception of the severity of soil erosion and enable them to act against by implementing different types of SLM practices and technologies on their farm plots *(*Zerihun *et al*., 2017b). The ML estimation output of the ordered probit model revealed that education level, cultivated land size, training, plot distance, slope (moderate and steep), moderate soil fertility, topsoil erosion, moderate soil erosion severity, land certificate, community bylaws, and incentive were found to influence household perception of the role of SLM positively and significantly. In contrast, land market, soil quality (low and moderate) and the location Wolaita affect farmers' perception statistically negatively (Table 16).

Education plays a crucial role in shaping individuals' perception levels. Farmers who have received a higher level of education are more likely to have a positive perception of SLM. Marginal effect analysis confirms this association indicating that a one-year increase in formal education level raises the probability of having a high perception level by 1.3% but reduces the probability of having low and medium perception by 0.6% and 0.7%, respectively (Table 16). The possible explanation is that formal education gives better chance to farmers to perceive and understand the role of SLM practices and exposes them to wider social networks. Education also increases individual perceptions, thoughts, and insights of natural resource conservation and management (Rodríguez-Rodríguez *et al*., 2021). Hence, farmers with more years of education perceive more economic and environmental impacts and develop richer social capital (Bereket *et al*., 2021). This finding agrees with the findings of Alelgn *et al*. (2021) who reported that education has a positive effect on farmers' decisions and perception to implement SLM technologies in upper Blue Nile of Ethiopia. By contrast, where the formal education curriculum is not well suited to deliver programs in mitigating land degradation, it will have a negative association in that educated farmers are less likely to perceive SLM (Zerihun *et al*., 2017b). In conclusion, this study underlines that proper attention should be given to raise educational status of farmers that ultimately raises their perception about how, why, and where to implement land management practices.

Cultivated land size was found to affect the perception level positively and significantly. The result revealed that an increase in cultivated land size by one hectare raises the probability of having a high perception level by 10.8% and the likely probability of farmers having low and moderate perception levels decreases by 4.9% and 5.9%, respectively. A plausible justification would be that as cultivated farmland increases, farmers get interested in allocating part of it to implement on-farm SWC measures to maximize the use value of SLM interventions. A similar study testified that farmers with large farm holdings perceive more benefits of land management practices (Bereket *et al*., 2021).

Training is an institutional factor that enables farmers to perceive, acquire knowledge and skills to apply SLM practices, particularly on-farm SWC measures on their farm plots. The marginal effect analysis verified that farmers who had training opportunities are likely to have a 10.7% higher perception level of SLM than the base with no training opportunity. This finding is consistent with that of Birhan and Assefa (2017) and Alelgn *et al*. (2021) who reported that training increases farmers' awareness in implementing SLM practices. Thus, akin to other empirical studies, this study verified that training that targets smallholder farmers to increase their awareness and perception of SLM practices at household level is a key institutional factor that should be taken into consideration from planning to implementation.

Plot distance is a bio-physical farm plot factor that affects the perception of farm households differently. Contrary to the prior expectation, the model output demonstrated that plot distance affects the perception level differently. The marginal effect analysis pointed out that as the farm plot distance gets closer to farmers' residents, the perception tends to be low and medium by 5.1% and 6.1%, respectively, while as it gets farther, the perception index becomes higher (i.e., 11.2%). The possible justification for this typical association is that farm plots located at the nearest distance are utilized for homestead garden activities that demand less land management practices, but as the farm gets far from farmers' residents, labor-intensive work is required to maintain and sustain the farmland productivity. Furthermore, the transect walks at the study areas confirmed that plots around the homestead are utilized to grow e*nset*, vegetables, and fruit, that need less land management practices, for example, SWC measures. In line with this, a study made on farmers' perception of SLM practices in Ghana by Sungbaahee and Kpieta (2020) reported that smallholder farmers had good perception (positive index) for animal manure, compost, and minimum tillage at the nearest distance to homestead and it completely changed as the land use type altered to other forms and on distant farm areas. The nobility of this finding is that plot distance from homestead vs. perception types varies among land management practices that guide development practitioners to identify the land use type before designing and implementing land management practice.

Land market is the selling, mortgaging, renting, and transferring of land rights on a cash, lease, or contractual basis. However, in Ethiopia, except for the usufruct rights of access, control, and some alienation rights of rent out/in and bequeath, the other tenure systems are constitutionally prohibited. Land market imposed a negative effect that farmers who engaged in land market were found to have a reduced probability of having a high perception level by 8.5% ($p<0.1$). The justification could be that farmers who have engaged in land rent in/out are less willing to implement on-farm SWC measures. They rather prefer to switch to non-farm activities that can generate short-term benefits. On the other hand, landowners who rent out their farmland lack the decision-making power to perceive and implement SLM practices. This is supported by Genanew and Alemu (2012) who reported that plots that are either mortgaged or rented receive lower intensity of land conservation than farmlands cultivated by the land owner. This implies the need to refine the existing policy related to land rental market and how to engage landholders in land-related management practices investment to maintain and conserve the land potential.

The variation in slope status of farm plots affects the perception level of farm households either positively or negatively. Farmers who owned moderate and steep slope farmland were found to have a probability of having high perception level of SLM than those with farmlands of flat or gentle slope (i.e., 12.2% and 19.1%, respectively). The possible explanation is that farmlands located in steep or moderately slope areas are exposed to severe soil erosion, fertility depletion, and high runoff caused by heavy rainfall, and poor water and moisture infiltration capacity of the soil. Moreover, from an economic point of view, as the farmland slope became steep, the soil fertility status became less and less, resulting in low agricultural production. This result is in line with Akalu *et al*. (2016), Zerihun *et al*. (2017b), and Wondwosen *et al*. (2020) who found that farmers who own steeply sloped farmlands are more likely to perceive SLM as a remedy to soil erosion. For example, households whose farms are situated at steep uphill slopes preferred ditch digging to maintain and conserve their farmland (Worku and Schneider, 2016). The implication is that responsive strategy and agricultural policy should be designed and implemented to increase farmers' perception to invest in land management practices on steep and moderately slope farmland.

Soil erosion is a biophysical attribute that influenced farmers' perception of the role of SLM. About 78% of the sample farm households perceived the existence of topsoil erosion on their farmland, which warns them to look for and implement SLM practices, particularly on-farm SWC measures (Table 16). The marginal analysis verified that a farmer whose farmland is susceptible to topsoil erosion is likely to have a higher perception of the role SLM by 28.5% at $p < 0.01$ than a farmer whose farmland has less environmental threat. The possible reasons are that farmers whose farmlands are exposed to moderate to severe erosion are aware of the negative effects imposed on land productivity, while those whose farmlands are not exposed to topsoil erosion have low to medium perception levels. Similar findings reported that farmers who noticed and perceived the existence of severe soil erosion on their farmlands are cautious in investing in SLM practices (Zenebe *et al*., 2013; Engdawork and Hans-Rudolf, 2016; Birhan and Assefa, 2017; Dessalegne *et al*. 2024). The implication is that farmers should be alarmed and well aware of soil erosion problems and its severity to raise their perception.

Soil erosion severity is a proxy variable for soil fertility status, soil quality, and slope gradient of farmland. Soil erosion severity became high in shallow soil, steeply sloped and infertile farmlands. Conversely, it became low in deep soil, gentle to flat slope and fertile farmlands (Hurni *et al.*, 2010). Moreover, in the study areas farmers have their own indigenous way of understanding soil erosion severity to quantify as minor, moderate, and severe type. As depicted in Table 16, the marginal analysis verified that farmers whose farmland is susceptible to moderate and high erosion severity are likely to have high perception of the role of SLM by 13.1% ($p < 0.01$) and 8.5%, respectively than farmers with farmlands of less environmental threat. Conversely, as the severity level decreases to minor level, the likely probability of farmers perceiving SLM practices shifts to low and medium levels by 5.9% and 7.2%, respectively. In other words, farmers owning farmland susceptible to severe soil erosion damage have a high perception, while those with low to moderate class have a low to medium perception of land management practices. The possible reasons for such associations are, on the one hand, farmers whose farmland is exposed to severe erosion are aware of the negative effects imposed on land productivity, and consequently they are eager to implement land management practices on their farmland. On the other hand, farmers whose farmland is exposed to low to moderate soil erosion, have low perception level of land management practices, that ultimately, they are not willing to implement land management practices. Scholarly works support this finding, for example, Engdawork and Hans-Rudolf (2016). However, other scholars negate this result. Explorative research conducted in the Central Rift Valley of Ethiopia by Zenebe *et al*. (2013) found out that farmers who perceive high soil erosion severity in their farmland are less interested in implementing land management practices to combat soil erosion and fertility depletion.

Soil quality is a bio-physical attribute hypothesized to affect the perception of farmers of land management practices. It encompasses fertility, soil texture, color type, soil depth, and soil workability. Analogous to the a priori expectation, the model estimation revealed that soil quality affects the perception level of farmers positively and significantly. The result verified that farmers who owned farmland with low and moderate soil quality, decreased the probability of having high perception by 33.1% ($p < 0.01$) and 23.6% ($p < 0.01$), respectively, as compared to farmers with high quality farmland. Moreover, farmers who owned farmland with moderate soil fertility were found to have high perception level (i.e., 13.2%) as compare to farmers with degraded infertile land. The possible justifications are first, farmers who own farmland with high fertility, moderate to deep soil depth, and black and grey soil color situated at steep slope land are cautious and highly aware to maintain the quality and fertility level. Consequently, they are psychologically ready to implement different land management practices to maintain soil quality. Secondly, a farmer whose land is characterized by coarse texture, thin soil depth, and being hard to plow are reluctant to invest and rehabilitate the degraded farmland because it needs intensive labor and is highly costly. Scholarly works support the finding, for example, farmers apply compost on deep and medium soil depth to maintain fertility Akalu *et al*. (2016), they prefer conservation structures on steeply sloped land Worku and Schneider (2016) and farmers' long experiences raise their perception of land management practices to mitigate land degradation Engdawork and Hans-Rudolf (2016).

Community bylaw is a local institutional characteristic expected to affect the perception level of farmers to SLM practices differently. Community bylaws were found to increase probability of having high perception by 12.2% ($p< 0.01$) and in its absence, it reduced to low and moderate by 5.6% and 6.7% ($P<0.05$), respectively. The justification is that community bylaws enable farm households to be aware of and internalize the benefit of land management practices in conserving and protecting the farmland from erosion. It governs and facilitates communities through developing a sense of ownership in managing and conserving the land resources to offer maximum economic benefits both to the current and future generations (Cardenas *et al*., 2011). Limited involvement of local communities and stakeholders in formulating (East Africa); weak responsibility of organizations to enforce bylaws (East Africa); ignoring indigenous laws and customs in collective management of natural resources (Ethiopia), overlooking the aspect of site-specific natural resource problems (East Africa); and top-down community-based initiative (Tanzania and Uganda) led to low perception of land management practice in curbing natural resource abuse (Mowo *et al*., 2016).

Incentives and land certificate are policy tools that stimulate developmental works, for example, land management practices. Farmers who access incentives were found to have a high perception level (i.e., 16.8%, $p<0.05$), while with its absence; it reduced to low and moderate by 8.8% and 8% at 5% and 1% probability level, respectively. Moreover, during the FGDs, farmers verified that incentives in the form of FFW or farm implements encourage the implementation and maintenance of land management practices, particularly on-farm SWC measures. This observation is supported by a study conducted in the Bolivian Andes by Hartman and Cleveland (2018). They reported that incentives stimulate long-term investment in land management practices such as terrace construction, watershed rehabilitation, and wetland restoration. Furthermore, a study by Kindie *et al*. (2014) reported that terraces and other physical structures with long payback periods need economic incentives and other opportunities to be adopted and perceived by smallholder farmers. Likewise, land certificate was found to increase farmers' perception to a higher level by 19.7% ($p < 0.05$). Conversely, farmers with no land certificate were found to have low and moderate perception level, i.e., 11.1% ($p<0.1$) and 8.6% ($p<0.01$), respectively. The policy implication is that constructing SWC measures should be seen with caution that the long-lasting dependency syndrome attribute of incentives should be looked at from the perspective of its long-term contribution.

With regard to the study location, farmers at Wolaita were found to decrease their perception as it converges to a higher level by 15.9%. Conversely, it shows positive associations as the probability switches to low and medium levels. The possible justification could be that average landholding ratio of Woliata is relatively small (i.e., 0.28 ha) as compared to Sidama Region (0.29 ha), SNNPR (0.51 ha), and Ethiopia (0.92 ha) ESS (2022c) that farmers seem pessimistic to apply exotic land management practices. Furthermore, the FGDs verified that in Wolaita (Boloso Bombe and Boloso Sore) farmers preferred indigenous land management practices, for example, farmyard manure, compost application and intercropping expecting short-term benefits than exotic SWC measures with long payback periods.

The likelihood of farmers having low perception levels about the role of SLM practices in Wolaita, Sidama, and Siltie were found to be 15.3%, 13.0%, and 9.7%, respectively. Likewise, the likely probability of farmers having a moderate level of perception of SLM is estimated at 31.9%, 30.2%, and 26.8% in Wolaita, Sidama, and Siltie zones, respectively. Finally, the highest probability of farmers' perception of SLM practices in Siltie, Sidama, and Wolaita zones were found to be 63.6%, 56.8%, and 52.7%, respectively. The marginal analysis result revealed that the probability of farmers having low perception level is the highest in Wolaita (15.3%), while the highest was observed in Siltie (63.6%) zone (Appendix Table 4).

Table 16 Estimation and marginal effects of the ordered probit (Unrestricted model)

Variables	Coefficients (Robust SE)	Marginal effect for different perception levels		
		Low =1	Medium =2	High =3
Farming experience	-0.0003(0.007)	0.0001 (0.001)	0.0001 (0.001)	-0.0001 (0.003)
Gender	0.140 (0.252)	-0.026 (0.050)	-0.028 (0.048)	0.054 (0.098)
Active labour force	0.034 (0.039)	-0.006 (0.007)	-0.007 (0.008)	0.013 (0.015)
Education level	0.034 (0.019)*	-0.006(0.003)*	-0.007 (0.004)*	0.013 (0.007)*
Livestock holding	0.0001 (0.034)	-0.0001 (0.006)	-0.0001(0.007)	0.0001 (0.013)
Farm revenue (ln)	0.090 (0.118)	-0.015 (0.020)	-0.018 (0.024)	0.034 (0.044)
Nonfarm income (ln)	-0.011 (0.015)	0.002 (0.003)	0.002 (0.003)	-0.004 (0.006)
Cultivated land size	0.288 (0.154)*	-0.049 (0.027)*	-0.059 (0.032)*	0.108 (0.058)*
Training	0.278 (0.148)*	-0.052 (0.031)*	-0.054 (0.028)*	0.107 (0.058)*
Extension service	0.018 (0.242)	-0.003 (0.042)	-0.004 (0.049)	0.007 (0.091)
Land market	-0.227 (0.128)*	0.039 (0.022)*	0.046 (0.026)*	-0.085 (0.047)*
Plot distance	0.299 (0.170)*	-0.051 (0.029)*	-0.061 (0.036)*	0.112 (0.064)*
Slope moderate	0.327 (.136)**	-0.056 (0.024)**	-0.066 (0.028)**	0.122(0.050)**
Slope status steep	0.565 (0.225)**	-0.073 (.023)***	-0.118 (0.046)**	0.191 (0.066)***
Topsoil erosion	0.737(0.149)***	-0.162 (.041)***	-0.123 (.023)***	0.285(0.056)***
Erosion moderate	0.352 (0.131)***	-0.059 (0.023)**	-0.072 (.027)***	0.131 (0.048)***
Erosion high	0.235 (0.228)	-0.035 (0.030)	-0.049 (0.049)	0.085 (0.079)
Soil fertility low	0.336 (0.262)	-0.049 (0.032)	-0.071 (0.056)	0.119 (0.087)
Fertility moderate	0.345 (0.172)**	-0.066 (.036)*	-0.067 (0.032)**	0.132 (0.067)**
Soil quality low	-0.856(0.288)***	0.217 (.097)**	0.114 (0.019)***	-0.331(0.105)***
Soil quality moderate	-0.679 (0.165)***	0.097 (0.022)***	0.139 (0.035)***	-0.236 (0.052)***
Farm plot location	0.191 (0.126)	-0.031 (0.024)	-0.035 (0.026)	0.066 (0.049)
Community bylaws	0.329(0.126)***	-0.056 (0.022)**	-0.067 (.026)**	0.122(0.046)***
Incentive	0.433 (0.180)**	-0.088 (0.042)**	-0.08 (0.031)***	0.168 (0.070)**
Land certificate	0.505 (0.249)**	-0.111 (0.067)*	-0.086 (.033)***	0.197 (0.098)**
Tenure arrangement	-0.339 (0.226)	0.049 (0.028)*	0.071 (0.048)	-0.121 (0.075)
Sidama	-0.289 (0.214)	0.052 (0.040)	0.058 (0.042)	-0.109 (0.081)
Wolaita	-0.418(0.215)*	0.078 (0.044)*	0.081 (0.040)**	-0.159(0.082)*
Cut 1/μ_1	1.765 (1.065)*			
Cut 2/μ_2	2.718(1.072)***			
Log likelihood	-364.38			
Wald chi2 (28)	137.53***			
No. of observation	475			
Predicted probability		10.01	26.60	63.39

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05 and * p<0.1
Source: Own computation from the household survey data, 2022

4.2.2. Farmers' participation decision to SLM practices

4.2.2.1. Model specification tests

Based on the literature, the economic a priori criterion, and the research questions of farmers' participation decision to SLM, specifically on-farm SWC measures, different econometric models were specified, and pre and post-estimation tests were carried out. The exact perfect linear correlations between the independent variables were checked using variance inflation factors (VIF) and tolerance value, i.e. 1/VIF, and it was found out that the tolerance value of independent variables are close to one and VIF is less than 10 indicating no exact or linear relationships between regressors. The distribution of land covered by on-farm SWC among the sample farmers is shown in a histogram. As shown in Figure 5, the curve was somewhat smooth because the density estimate was close to the normal curve. A series of model specification tests were carried out to validate and select the best-specified models that fit SLM participation and farmers' farmland covered by on-farm SWC sequentially.

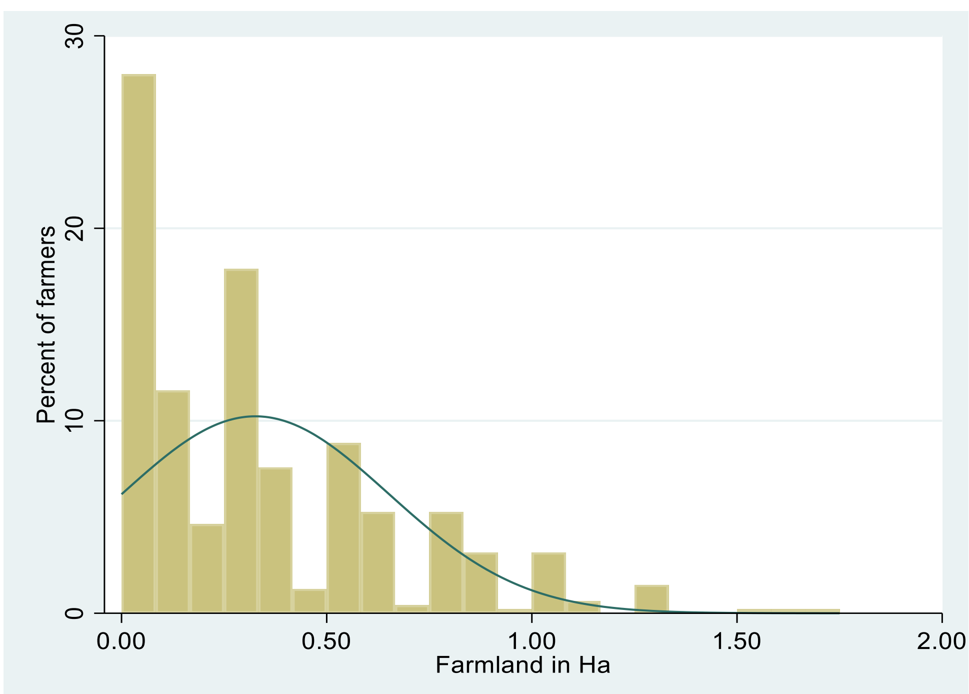


Figure 5 Histogram distribution of farmland covered by on-farm SWC

The truncated hurdle model nests the usual Tobit model but the lognormal distribution model nests neither the Tobit nor the truncated normal model. Thus, the likelihood ratio statistic could not be applied to choose the fittest model (Greene, 2012). In this case, the non-nested test suggested by Vuong (1989) was applied to choose the better model, i.e., the truncated hurdle model from its counterfactual lognormal hurdle specification.

In the Vuong non-nested classical model selection approach, first, the truncated hurdle model was tested against its counterpart, that is, the lognormal hurdle. Second, it was tested against the Heckman two-stage specification to select the fittest estimator for parameter estimation. Using the Vuong non-nested test procedure, under the null hypothesis, it was stated that the two counterparts' models fit equally to the predicted probabilities of the two estimators to the given data sets. Based on the predicted y, a Wald test that follows the chi-square distribution with degrees of freedom (DF) equal to the included explanatory variables in the model was found to be significant at 1% probability level, indicating that the model fits the data very well (Tables 17 &18). Using the Vuong non-nested test procedure, under the null hypothesis, it was stated that the two counterparts' models fit equally to the predicted probabilities of the two estimators to the given data sets. Based on the predicted probabilities of the two models, the Vuong test validated that the null hypothesis was rejected in favor of the truncated hurdle model ($t = 5.37$) at the 1% probability level (Appendix Table 5).

Heckman's two-step sample selection method was also employed, and the model estimation output suggested no sample selection bias because the inverse mills ratio (IMR) was statistically insignificant (Appendix Table 6). Thus, the Heckman method is not an appropriate model for estimating participation and enrolment decisions, testified by the absence of sample selectivity bias. Furthermore, the Heckman method of maximum likelihood estimation showed that the null hypothesis, which states the interdependence of the participation decision and farmland covered by SLM practices, is rejected. More specifically, the null hypothesis that the covariance of the error terms of the independent equations is zero (rho=0) is accepted by the Wald chi-square test, that is, χ^2 (1) = 1.97 at P= 0.160 (Appendix Table 7).

The results of the post-estimation procedures indicate that the lognormal hurdle model and Heckman's two-step method are inefficient for estimating the parameters (Appendix Table 7). Thus, it is validated that the truncated hurdle model is the best fit among the three in estimating the deterministic variables affecting the participation decision and the intensity of involvement of sample farmers in land management practices. Moreover, the goodness of fit of the selected truncated hurdle model was checked with the Pseudo R2 and likelihood ratio test (LR) shown by a Wald test that follows the chi-square distribution was found to be significant at 1% probability level, indicating that the model fits the data very well (Tables 17 and 18).

The results of the truncated hurdle model coefficient estimation, the associated robust standard error, and its marginal effect given the hypothesized explanatory variables are presented in Tables 17 and 18. Moreover, the lognormal hurdle and Heckman's two-step methods of coefficient estimation were regressed for comparison against the truncated hurdle model and the model output affirmed that the THM found to be the best estimator (Appendix Table 7). The coefficients in the participation equations (first hurdle) revealed how each explanatory variable affected farmers' decision to participate in on-farm SWC, and the value equations (second hurdle) indicated the intensity that sample farmers' farmland covered by on-farm SWC measures. Furthermore, the marginal effect was computed to investigate the change in the dependent variable due to a unit change in each explanatory variable expected to affect both decisions.

4.2.2.2. Determinants of SLM participation decision

The results demonstrated that the hypothesized socio-economic, institutional and biophysical attributes mattered to the participation decisions of households in SLM, specifically on-farm SWC measures. The maximum likelihood estimation output of the first hurdle model (the binary probit estimation) revealed that gender, social capital, perception index, land size, extension contact, soil fertility index, slope status of farm plots, and the existence of soil erosion influenced the participation decision of the sample farmers significantly and positively. Conversely, non-farm income (log), the value of crops produced (log), and the dummy land market and farm location of participation of sample households affected farmers' participation decisions negatively and significantly (Table 17).

From a gender perspective, male-headed households were hypothesized to positively influence farmers' on-farm SWC participation decisions. The estimation results revealed that male-headed individuals are more likely to participate in SLM practices, specifically in farm SWC measures than their counterfactuals. Possible reasons for the lower participation of female households are having less access to farmland, SWC technologies, other resources, and the highly labor-intensive nature of on-farm SWC measures. As shown in Table 17, the likely participation of male-headed households in SLM is approximately 8.3% of their counterfactuals because they have more access to land resources and more strength and social networks in applying on-farm SWC measures. The current finding is supported by the studies of Oduniyi and Tekana, (2021) and Bichaye *et al*. (2022) that a male headed household participates more in land management interventions than a female headed because of their physical strength and better access to resources and services.

Social networks expose farmers to share ideas and exchange information from their neighborhood farmers and peers who are experienced in implementing SLM; specifically on-farm SWC measures contribute positively to adopting the same practices on their farmland. It is a proxy for social capital that enhances the exchange of information, sharing of best experience, information exchange, and accessing available SLM technologies to SLM that help in conserving and managing farmland resources in a sustainable manner. As demonstrated in Table 17, social networks positively and significantly influenced the participation decisions of the sample farmers in SLM. Keeping all other variables constant, the sample households with a social network had a 16.1% ($p < 0.01$) higher chance of participating than those with no social network with their neighboring farmers. This result is supported by Bereket *et al*. (2021) who reported that social capital influences farmers' participation and perception in watershed development, which mainly includes on-farm SWC measures in southern Ethiopia. Another empirical studies that focused on the role of social capital in the adoption of improved land management practices in Ethiopia found out a positive and significant determinant effect on the probability of adopting SWC measures

(Tesfamicheal *et al*., 2015; Akalu *et al*., 2016). Furthermore, a study by Zenebe *et al*. (2012) found out that social capital increases cooperativeness behavior among farmers and facilitates information flow that support land management practices. The implication is that, apart from the usual extension delivery service, social networks should be promoted in exchanging information and sharing experiences in using land management practices to mitigate land degradation and reduce soil erosion.

The perception level of farmers regarding the role of SLM is one of the explanatory variables hypothesized to influence farmers' participation decision. The perception level of farmers regarding SLM in halting land degradation, particularly, soil erosion, is measured on a Likert scale of low, medium, and high types. As shown in Table 17, the computed marginal effect of the perception index showed a positive and statistically significant deterministic effect on farmers' decisions to participate in SLM practices at the household level. This indicates that as the perception of households increase to a higher level, their decision to participate in SLM practices (in this case on-farm SWC measures) increases by 29.2% ($p< 0.01$), *Ceteris Paribus*. A possible reason for this is that farmers are more optimistic about implementing on-farm SWC on their farmlands expecting direct environmental and economic benefits of reduced land degradation and enhanced farmland productivity. This finding is supported by previous studies, for example, Worku and Schneider (2016) and Zerihun *et al*. (2017b) that farmers decide to participate and invest in SLM depending on their perceived benefit of SLM in managing land resources. Thus, this study verified that awareness and perception of farmers should be raised either by training or by exposure visits that enable them to participate and apply SLM practices.

Land size is an important asset that influences the participation decisions of farmers in SLM, specifically on-farm SWC measures. Farmers who owned large size of land are willing to participate in applying SWC practices either in their farmland or in any land use type to reduce soil erosion. Farmers who own large size of land can optimistically allocate their land to implement on-farm SWC practices, assuming the economic use-value of the resource on hand. As demonstrated by the first hurdle model output in Table 17, keeping all other variables constant, for a unit of increase in owned land, the likely decision of farmers to participate and implement land management practices, specifically on-farm SWC practices, increased by 3.4%, at $p < 10\%$. These results are consistent with the findings of Alem-meta and Singh (2018) and Wondimu *et al*. (2021) who reported that farmers with relatively large land size have a higher probability of participating in watershed management and adopting SWC practices. However, contrary to this research, land size is negatively and significantly correlated with participation decisions; farmers with large landholdings are less likely to participate in land management practices and thus they are usually non-adopters of SWC measures (Akalu *et al.*, 2016; Haftu *et al*., 2019). Generally, this finding affirms that participating and implementing SLM practices in general and on-farm SWC measures, in particular, is highly associated with asset capital, in particular to owned land.

Non-farm income generated from off-farm and non-agricultural activity was hypothesized to influence participation decisions negatively. As per a priori expectations, the maximum likelihood estimation result of the first hurdle model confirmed that non-farm income affects farmers' decisions negatively and significantly (Table 17). The marginal analysis revealed that as the non-farm income increases by one ETB, the probability of farmers engaging in SLM decreases by 0.4% ($p < 0.05$), *Ceteris Paribus*. The reasons for this are that, on the one hand, farmers with low land resources, livestock assets and less farm income are forced to look for alternative income sources that make them less interested in participating in land management practices. On the other hand, some farmers are pessimistic about land management practices because they are labor-intensive, competitive with farmland, and costly in their nature (of on-farm SWC). This finding is consistent with Emerton and Snyder (2018), who reported that farmers may be less interested in considering SLM as a priority than other income-generating activities that can yield a higher return or offer essential life support services. Furthermore, partly synonymous with non-farm income, off-farm income activities influenced the adoption of land management practices significantly negatively, specifically, soil bund in the Handosha watershed, Omo-Gibe River basin of Ethiopia (Habtamu *et al*., 2023).

The Value of crop produced is expected to positively influence farmers' decisions to participate in SLM practices. However, the model output demonstrated that the value of crop produced affected farmers' participation decisions negatively and significantly. The marginal analysis revealed that one ETB increase in value of the crop produced, the likelihood of farmers participating in SLM decreased by 5.4% at the 5% probability level. The possible justification for the negative contribution is that SLM takes place over a long investment period, usually more than seven years, and consequently fails to offer short-term economic benefits or returns to farmers. This result is supported by the finding of Schmidt *et al*. (2017) that SLM investment requires a long period of at least seven years to show a significant increase in the value of crop produced. Another study conducted in Africa (Tanzania and Malawi) supported this finding that the decision and uptake of SLM during the initial period is low because the benefits, including crop production, are insignificant during earlier periods (Emerton and Snyder, 2018). The implication therefore is that institutions and development practitioners should demonstrate and convince the long-term benefit of land management practices to smallholder farmers in conserving and protecting the land resources without being bound only to the short-term payback of the practices.

Extension service, credit accessibility, rural market availability, and other institutional services are of paramount importance in improving the livelihood of farming communities. Among others, frequent contact with extension workers at farmers' training centers (FTCs) or technology demonstration sites enhances awareness and knowledge about the economic and environmental benefits of land management practices. For these reasons, as per the a priori expectation, extension contact of farmers by the DAs influenced the participation decision of farmers in land management practices positively and significantly. As demonstrated in the model output, one day^{-1} month contact with DAs increased the probability of participation decisions by 2.5% ($p < 0.01$), *Ceteris Paribus.* The positive correlation between extension contact and participation decisions is supported by Zenebe *et al*. (2012) who stated that the closer the farmers are to DAs, the higher the farmers invest in land management practices. This finding is confirmed by studies made by Oduniyi and Tekana (2021) (South Africa) and (Setsoafia *et al*., 2022) (Ghana), who found out that farmers who have access to extension services are more likely to adopt sustainable agricultural practices, including SWC. Contrary to this finding, a study by Alem-meta and Singh (2018) in northern Ethiopia reported that the frequency of extension contact is negatively associated with participation decisions due to the inadequate number of agricultural extension workers and weak working facilities. Hence, this study verified that extension delivery system targeting smallholder farmers to increase their awareness of SLM practices' benefits is a key institutional factor that should be considered during interventions.

Land market is one of the deterministic institutional factors hypothesized to influence farmers' participation decisions in land management practices. Conceptually, land market involves the selling, mortgaging, renting, and transferring of land rights on a cash or contractual basis. However, in Ethiopia, except for the usufruct rights of access, control, and some alienation rights of renting out and bequeath, other tenure systems, including land marketing, are hardly possible and constitutionally prohibited. The first hurdle likelihood estimation output demonstrated a negative and statistically significant association between land market and farmers' participation decisions in SLM practices. The marginal analysis verified that farm households' probability of participating in land management practices decreased by 4.5% ($p < 0.01$) as they engaged in land rental marketing. Moreover, the information obtained during the FGDs verified that farmers who rent farmland on a contractual basis are less willing to implement on-farm SWC measures; rather, they are highly engaged in non-farm activities including land marketing that can generate short-term benefits. This is supported by Genanew and Alemu (2012) who reported that farmers who either mortgaged or rented out their farmland have a lower intensity in implementing land management practices as compared to landowners who are not engaged in land rental marketing. This implies the need to restrict farm households from engaging in the land rental market which should be further addressed by strategies and agriculture policies of the country.

Farm location is a dummy environmental attribute of the sample households that affected farmers' participation decisions of land management practices differently. Farm location of the farm plots can either be in the upper or lower stream of the given watershed and could affect participation decisions either positively or negatively. The first hurdle model estimation demonstrated that households that owned farm plots located in the lower stream of the watershed were less likely to participate in land management practices than those located in the upper stream. The marginal analysis explained that as the farm location of household shifts to lower stream of a given watershed, the probability of participating in land management practices decreased by 7.1% ($p < 0.01$) as compared to households living in the upper stream. The possible justification for this is that farm plots located in the upper stream are highly exposed to severe soil erosion owing to the topography and sloping nature of the plots (Birhan and Assefa, 2017). The implication of this is that farmers located at upper stream of a watershed should be proactive and well aware of the hazard of soil erosion problems in investing in land management practices.

Soil fertility is a biophysical condition expected to influence the participation decision of farm households in land management practices. The composite index was calculated based on the Likert scale[8] of the average soil fertility status of farm plots of sample households. The marginal analysis showed that as the average soil fertility status of plots developed from low (infertile) to a higher level (fertile), the probability of farmers' decision to participate in land management practices increased by 9.1% ($p < 0.05$), *Ceteris Paribus*. Possible reasons for this are first, farmers who perceive the soil fertility status of their farm plots can improve it by implementing land management practices, for example, on-farm SWC measurers. Second, individual farmers perceive it positively because soil erosion reduces the fertility status of farm plots; consequently, they can manage owned farmland to maintain the fertility level to maximize the return. This finding is supported by a study conducted in the central rift valley of Ethiopia that farmers who own fertile plots make better decisions to invest in land management practices to maximize crop production than those with infertile soils (Zenebe et al., 2012). Thus, it can be concluded that farmers who positively perceived maintaining their farmland fertility status, at least to a moderate level, are more willing to participate in land management practices.

[8] *In Likert-scale the respondents are asked to categorize their farm plots' average fertility status in three-point Likert alternatives as low (infertile soil type), moderate (somewhat good), and high (high fertile soil type).*

Slope status is a biophysical attributes of farm plots and was hypothesized to influence the participation decision of households in land management practices. According WOCAT[9] slope gradient classification, flat to gentle (0–5%), moderate (6–30%), and steep (31–60%) are considered to estimate the likely association with participation decision. The first hurdle model estimation output revealed that as the slope gradient of households' farm plots is inclined to a steep type, the probability of farmers' participation turns out to be a positive decision at 3.3% at $p < 0.05$. This result is consistent with the studies of Zenebe *et al*. (2012), Haftu *et al.* (2019) and Wondimu *et al*. (2021) who reported that farmers who owned steeply sloped plots are more likely to adopt and implement SLM practices than those with gentle-to-moderate farmland. Another study conducted by Tesfamicheal *et al*. (2015) in Ethiopia indicated that the slope of plots positively and significantly affect farmers' adoption decisions regarding land management practices. Similar results were also illustrated by Akalu *et al*. (2016) who found out that farmers who operate on gentle-slope land are less likely to participate and implement SWC measures. The implication is that land management practices, mainly on-farm SWC measures, should be implemented strictly on sloppy lands to protect runoff velocity and soil erosion to ultimately reduce topsoil loss and fertility decline.

Similarly, soil erosion influences farmers' participation decisions in land management practices. Soil erosion naturally indicates the presence of topsoil loss, flooding, landslides, and any form of erosion caused by water or wind. As demonstrated by the model estimation, farmers who have farmlands exposed to soil erosion are more likely to participate and implement land management practices. The marginal analysis verified that farmers who owned farmland exposed to soil erosion increased the probability of participating in land management practices by 6% ($p<0.01$). In such circumstances, farmers are forced to implement on-farm SWC measures to mitigate the risk associated with losses caused by soil erosion, runoff, or fertility decline. The negative externalities of fertile soil loss from cultivated land, agricultural production reduction, and disturbance of the ecosystem due to soil degradation are some of the main reasons for the positive association between soil erosion and

[9] WOCAT slope gradient classification: flat (0-2%), gentle (3-5%), moderate (6 -15%), rolling (11-15%), hilly (16-30), steep (31-60), and very steep (>60%).

farmers' participation decisions. This finding is consistent with studies conducted by Akalu *et al*. (2016), Paulos and Belay (2017) and Wondimu *et al*. (2021) who found out that farmers who perceive soil erosion hazards on their farmland are more likely to participate in and adopt land conservation technologies, specifically SWC measures. The implication is that given the consequences of land degradation in general and soil erosion, in particular, farmers' decision-making on SLM practices should be shaped by and considered in policy formulation, planning and implementation.

Table 17 Cragg Truncated Hurdle model estimates of SLM participation

(a) Selection equation

Variables	Coefficient estimates	Robust Std. error	dy/dx	Robust Std. error
Farming experience	-0.006	0.015	0.0001	0.001
Gender ^	1.083**	0.483	0.083	0.036
Household size	0.019	0.061	0.001	0.005
Dependency ratio	0.040	0.099	0.003	0.008
Education level	-0.031	0.042	-0.002	0.003
Social network^	2.105***	0.279	0.161	0.014
Perception index	3.831***	0.67	0.292	0.042
Land size	0.449 *	0.250	0.034	0.019
Livestock holding	0.064	0.063	0.005	0.005
Farm income (ln)	0.283	0.274	0.022	0.021
Non-farm income (ln)	-0.057**	0.029	-0.004	0.002
Crop value (ln)	-0.711**	0.358	-0.054	0.026
Training^	0.355	0.264	0.027	0.020
Extension contact	0.323***	0.120	0.025	0.009
Land market^	-0.586***	0.221	-0.045	0.017
Road distance	0.021	0.031	0.002	0.002
Community bylaws^	-0.109	0.281	-0.008	0.021
Incentive^	0.319	0.307	0.024	0.023
Farm location^	-0.932***	0.254	0.071	0.017
Soil fertility index	1.198**	0.513	0.091	0.036
Slope status of plots	0.434**	0.188	0.033	0.014
Soil erosion^	0.785***	0.255	0.060	0.021
Constant	-2.590	2.643		
Number of Observation		475		
Wald chi2 (22)		174.90***		
Pseudo R^2		0.741		

Notes: ***, ** and * are significant at 1%, 5% and 10% probability level
(^) dy/dx is for discrete change of dummy variable from 0 to 1
Source: Own computation from the household survey data, 2022

4.2.2.3. Determinants of farmers' participation decision intensity

It was predicted that the socioeconomic, institutional, and biophysical attributes of sample households that affect the participation decision may or may not affect the extent of involvement in SLM practices. The maximum likelihood estimation of the Cragg truncated hurdle model (the second hurdle) estimation output indicated the intensity of households' farmland covered by on-farm SWC measures. Thus, among the 22 hypothesized explanatory variables, farm size, value of crops produced, training, and community bylaws were found to have positive and significant association with SLM participation. Contrary to prior expectations, farming experience, education, extension contact, and road distance were found to have negative and significant influence on the intensity decision. Table 18 presents the likelihood estimation output of the Cragg truncated hurdle model and its marginal effects. The interpretation and justification referring to the model output and past studies are discussed in the following paragraphs.

Farming experience was hypothesized to affect the intensity of participation positively. Contradictory to the hypothesis, the Cragg THM estimation result indicated that a farm household with long farming experience has a lower probability of allocating part of owned land to implement SWC measures than farmers with low farming experience. The possible arguments for such association are: (1) land management practices, specifically, SWC measures are labor-intensive demanding high labor force; hence, households with long farming experience are mostly aged and that hinders the implementation of on-farm SWC measures. (2) As farmers get aged, they are reluctant to engage in farming, including land management practices, and (3) aged and long experienced farmers have large family members (populated) which enforces them to fragment farmland to their members and consequently makes them reluctant to allot portion of it to implement land management practices. The second-hurdle model marginal analysis revealed that as the farming experience increased by a year, the intensity or level of involvement of allocating farmland for SWC measures reduced by 0.2 ha at $P<0.05$. This result is consistent with past studies who stated that labor-intensive nature of SWC hinders its adoption and sustainable use (Haftu *et al*., 2019) and older farmers are less likely to adopt SLM technologies (Alelgn *et al*., 2021). The implication is that aged farmers with long farming experience could have low land holding as they share their farmland to family members. Hence, policymakers and development practitioners should pay attention to the technological development in response to population growth.

Education is a social driver for farmers' decision in allocating owned farmland to implement SLM. Education was hypothesized to positively and significantly affect the intensity of farmers' enrolment. Contrary to the hypothesis, education affected the level of farmers' involvement in allocating their land for on-farm SWC measures negatively and significantly. Marginal effect analysis confirmed this association that an increase in education by one year in formal learning reduced the probability of allocating owned farmland for on-farm SWC measures by 1.5% ($p< 0.01$), *Ceteris Paribus.* This finding is supported by Pender and Berhanu (2008) and Zerihun *et al*. (2017b) who reported that educated households are less likely to implement labor-intensive land management practices; rather, they prefer to engage in other income-earning activities. Furthermore, discussants in the KII verified the negative association between farmers' education level and the intensity is that educated farmers have low interest to engage in labor-intensive SLM practices because they spend much of their time in non-agricultural income-generating activities. Contrary to this study, many empirical studies have shown that educated households have better knowledge to make a well-informed decisions to implement agricultural technologies including on-farm SWC measures (Alelgn *et al.*, 2021; Oduniyi and Tekana, 2021). Though this finding overlooks the importance of education in the decision-making to allocate farmland to implement SLM practices, proper attention should be given in raising educational status and awareness of farmers to reverse the status quo and beliefs that could have significant implications for environmental conservation and socioeconomic development.

Cultivated farm size was expected to positively and significantly affect farmers' intensity decisions. The truncated hurdle model estimation confirmed that the size of cultivated farmland affected the decision positively and significantly. The result of the marginal effect showed that a unit increase in cultivated land increased the likelihood of farmers' decisions to allocate farmland by 13.6% ($p < 0.01$), but the reality in the study areas witness that the per capita landholding do not allow smallholder farmers to use more farmland for on-farm SWC measures. A plausible justification for this argument is that as owned farmland increases, farmers are interested in allocating part of it to implement on-farm SWC measures to maximize the use value of SLM. A similar study testified that farmers with relatively large farm holdings perceive more economic and social benefits from land management practices (Bereket *et al*., 2021). Contrary to this finding, a study by Nyanga *et al*. (2016) in Tanzania found that farm size showed a negative association with SLM investments; farmers who owned less plot size invested more than those with large holdings. Hence the author argued that in the face of land degradation and soil erosion, farmers should be motivated to allocate farmland to on-farm SWC aimed at enhancing agricultural production.

Value of the crop produced was hypothesized to affect the intensity decision of farmers in allocating part of their farmland to SWC measures positively and significantly. As expected, the truncated hurdle model estimation affirmed that the value of the crop produced affected the intensity decision positively and significantly. As demonstrated by the model output, as the value of crop production increases by one ETB, the probability of farmers allocating farmland to SLM practices, particularly the SWC measure, increased by 13.7% ($p < 0.01$), *Ceteris Paribus*. The possible reasons for the positive and significant association are: (1) the farm income increment due to enrolment incentivized farmers to allocate part of their farmland to on-farm SWC measures, and (2) the benefit in terms of increased crop production made participants more willing to invest in land management practices. Comparable empirical studies support this finding; for example, implementing land management practices, specifically SWC measures, increases value of crop production by restoring land and soil, while simultaneously achieving land degradation neutrality (Haftu *et al*., 2019; Critchley *et al*., 2023). The implication is that implementing land management practices is associated with high value of crop production to which development agents and practitioners should pay proper attention in terms of monitoring and coaching farm households to allocate farmland for on-farm SWC measures.

Training is an institutional variable that was expected to influence intensity decisions positively. The marginal effect analysis demonstrated that as farmers got access to training, the extent of allocating farmland to SLM practices increased by 6.5% ($p < 0.05$). Training on the role of SLM practices in reducing soil erosion and fertility loss increases farmers' awareness and perception of allocating farmland to SWC measures. This result agrees with the study by Fekadu and Engdawork (2019) and Alelgn *et al*. (2021) who reported that training creates awareness among farmers to implement different types of land management practices. The implication of this finding is that training is a key institutional factor that should be operational targeting smallholder farmers to increase their awareness and perception of SLM.

Likewise, extension contact is an institutional variable hypothesized to affect farmers' decisions to enroll in SLM practices positively. Unexpectedly, extension contact had an inverse association with the intensity of SLM; the likelihood of farmers allocating farmland to on-farm SWC measures decreased by 1.1% ($p < 0.05$) as the number of visits increased by one day month^{-1}, *Ceteris Paribus*. The possible justification is that the extension delivery system of the country in general and the study areas, in particular, has skewed to crop production which mostly undermines natural resource management. This research finding is consistent with Pender and Berhanu (2008) who reported negative association with land management practices, but is in contradiction with that of Fekadu and Engdawork (2019); Oduniyi and Tekana (2021) and Setsoafia *et al*. (2022) who found out that extension contact has a significant positive association with farmers' engagement in land management practices. The author argued that the country's skewed extension delivery system should equally consider and support the natural resource management component to stimulate effective land management practices.

Road is an infrastructural attribute and was expected to affect the allocation of farmland to land management practices differently. It is the distance from the homestead to the all-weather road, and is used as a proxy for market access associated with transaction costs while transporting and selling farm produce. Market access offers incentives for farmers to improve or conserve their farmland. Farmers' homesteads located at the nearest distance from market have an opportunity to sell at a lower transaction cost, and gain a higher price for their produce. Economically, those who gain a higher crop sale benefit at a lower cost are more likely to allocate a higher farmland to SLM practices. Surprisingly, the model output showed a significant positive association with farmers' land management decisions; a farmer whose homestead is located at a distant location from the main road has a higher probability of allocating farmland to land management practices. The marginal effect also verified that as a main road increased by 1 km from a home, the probability of allocating farmland to SWC increased by a small proportion, i.e., 1% at $p < 0.01$. The probable justification for this may be in most cases SWC measures at the study areas are implemented at distant point from the homestead; hence it imposes less implication to allocate farmland to on-farm SWC measures. A study by Teklewold and Koĥlin (2011) in Ethiopia opposes and supports this finding. Both negative and positive associations were reported between distance of the road and the probability of adopting soil bunds and stone terraces, respectively. The implication is that researchers should further work on road implications for the implementation of SLM practices both at the nearest and farthest distances from the homestead.

Community bylaws is a sociocultural proxy variable that was predicted to positively and significantly affect the intensity decision. The second hurdle model result testified that community bylaws affect farmers' decisions to allocate farmland to construct on-farm SWC measures positively and significantly. A marginal effect analysis also verified that farm households that are bounded by community bylaws increase the likelihood of allocating farmland to SLM practices by 4.1% ($p < 0.05$). A possible justification for this positive association is that community bylaws can influence farmers to allocate relatively more farmland to implement different types of on-farm SWC measures that ultimately reduce soil erosion. It also governs and facilitates farming communities to develop a sense of ownership to maintain and conserve land resources to offer economic and environmental benefits (Cardenas *et al*., 2011). In the highlands of Ethiopia, akin to community bylaws, social norms, and commitments are instrumental in maintaining and conserving land resources. A study conducted in the Gamo highland of Ethiopia by Engdawork and Hans-Rudolf (2017) reported that the unique social organization and commitment embedded in the farming community are non-monetary drivers that have contributed to the long-term success of indigenous land management practices, specifically in constructing and maintaining terraces. Thus, the policy implications are that community-based initiatives are essential institutional tools that should be strongly considered and placed while implementing SLM practices on farm plots.

Table 18 Cragg Truncated hurdle model estimates of SLM participation intensity

(b) Intensity equation (SLM land size)

Variables	Coefficient estimates		Marginal effect	
	Coefficient (βi)	Robust Std. err	dy/dx	Delta-method Std. err.
Farming experience	-0.004**	0.002	-0.002	0.001
Gender	0.025	0.082	0.041	0.044
Household size	0.0001	0.009	0.001	0.005
Dependency ratio	0.001	0.019	0.001	0.010
Education level	-0.027***	0.006	-0.015	0.003
Social network	-0.038	0.077	0.036	0.038
Perception index	-0.026	0.106	0.087	0.055
Cultivated farm size	0.262 ***	0.049	0.136	0.027
Livestock holding	-0.008	0.007	-0.003	0.004
Farm income (ln)	-0.015	0.042	-0.001	0.023
Non-farmincome (ln)	0.001	0.004	-0.001	0.002
Crop value (ln)	0.30***	0.058	0.137	0.028
Training	0.108**	0.050	0.065	0.027
Extension contact	-0.038**	0.017	-0.011	0.011
Land market	-0.052	0.036	-0.042	0.019
Road distance	0.018 ***	0.005	0.010	0.020
Community bylaws	0.085**	0.037	0.041	0.020
Incentive	-0.008	0.040	0.004	0.022
Farm location	0.011	0.040	-0.019	0.021
Soil fertility index	-0.104	0.075	-0.022	0.040
Slope status of plots	-0.022	0.026	0.0003	0.014
Soil erosion	0.082	0.063	0.063	0.033
Constant	-2.598***	0.49		
/sigma ($\hat{\boldsymbol{\sigma}}$)	0.257***	0.014		
Observation	475			
Log-likelihood	29.741			
Wald chi2 (22)	291.39 (P=0.00)			
Pseudo R^2	0.633			
Vuong test	t= 5.37*** (p-value =0.000)			

Notes: ***, ** and * are significant at 1%, 5% and 10% probability level.
Source: Own computation from the household survey data, 2022

4.2.3. Farmers' choices of SLM practices and their determinants

Based on FGDs, the list of prioritized SLM practices, specifically, on-farm SWC comprised of level soil bund with trench, level fanya juu, bench terrace, indigenous SWC measures, stone faced soil bund, check dam, trench bund, and conservation agriculture (Appendix Table 8). The qualitative data result indicated that indigenous SWC measures, level fanya juu, soil bund, and bench terrace ranked from 1 to 4 were the majorly applied measures in the study areas. As the same time, the four SWC measures that ranked from 1 to 4 were taken as outcome variables in the multivariate choice model analysis. The four on-farm SWC measures namely level fanya juu, level soil bund, bench terrace and indigenous SWC practices were taken as correlated outcome variables in the multivariate choice model.

The frequency distribution, of the dependent variables across the study zones is presented in Table 19. As presented in Table 19, about 65%, 53%, 51%, and 74% of the farm households in the study areas use fanya juu, level soil bund, bench terrace and a combination of indigenous on-farm SWC measures, respectively. The statistically significant chi2 distribution showed a symmetric distribution of on-farm SWC measures across the study areas, indicating that farmers are alarmed against land degradation problems to maintain and conserve their farmland resources.

Table 19 Distribution of the outcome variables across the study zones

Zones	Level fanya juu		Level soil bund		Bench terrace		Indigenous SWC	
	Yes	No	Yes	No	Yes	No	Yes	No
Sidama	123	63	83	103	111	75	140	46
Wolaita	93	65	80	78	92	66	96	62
Siltie	93	38	88	43	39	92	115	16
Total	309	166	251	224	242	233	351	124
(%)	(0.65)	(0.35)	(0.53)	(0.47)	(0.51)	(0.49)	(0.74)	(0.26)
Chi2 (pr.)	4.79 (0.09)*		16.15 (0.00)***		32.53 (0.00)***		27.42 (0.00)***	

Source: Own computation from the household survey data, 2022

The probability of farmers' decisions to choose more than one SLM practice is supposed to have a multifaceted benefit in minimizing soil erosion and fertility depletion. Farm households used a combination of at least two on-farm SWC measures on their farmlands. As shown in

Table 20, about 59%, 48%, and 45% of sample households used a combination of fanya juu with Indigenous, soil bund, and bench terrace at their farmlands, respectively. Similarly, 47%, 44% and 40% of farm households applied a combination of soil bund with indigenous, bench terrace with indigenous and with soil bund, respectively. The highest and lowest combination of on-farm SWC measures was found in Indigenous with fanaya juu and with bench terrace, respectively. The practices' combination and associated correlations are displayed in the MVP model analysis result and variance covariates matrix.

Table 20 Distribution of combination of SLM practices utilized by households

Combination of SLM practices	Combination		None-combined		Rank
	Number	%	Number	%	
Fanya juu and soil bund	228	0.48	247	0.52	2
Fanya juu and bench terrace	212	0.45	263	0.55	4
Fanya juu and indigenous SWC	278	0.59	197	0.41	1
Soil bund and bench terrace	192	0.40	283	0.60	6
Soil bund and indigenous SWC	223	0.47	252	0.53	3
Bench terrace and indigenous SWC	210	0.44	265	0.56	5

Source: Own computation from the survey data, 2022.

4.2.3.1. Econometric model specification test

Different models were specified to evaluate the interdependent choices of SLM practices at household level. When farmers' decision is interdependent and simultaneous, the MVP model that follows the simulated maximum likelihood (SML) estimation procedure is applied. The MVP regression model is a natural extension of the probit model with more than two outcome variables and with correlated disturbances analogous to seemingly unrelated regression (SUR) model (Greene, 2012). In other words, the MVP model is a generalization of the probit model used to estimate several correlated binary outcomes jointly. Estimating such interdependent choices using a binary logit/probit, bivariate probit/logit, multinomial logit/probit, and tobit models will exclude useful information of the interdependence and simultaneous choices decision of households, that ultimately leads to a biased and inefficient estimates (Greene, 2012). While considering other choice models to estimate the interdependent equations simultaneously, it will: (1) exclude the potential correlations among unobserved disturbances and (2) it ignores the inter-relationship (complementary or substitute effect) between the different SLM practices that can be implemented by farmers.

While using MVP model, relevant pre and post estimation tests were performed. Before running the regression, it was attempted to test multicollinearity using VIF among the explanatory variables and showed that there was no exact perfect liner relationship between the regressors. Under a standard condition, the SML estimator is consistent as the number of observations and random draws number become high. To get consistence and accurate estimates we used 100 random draws (than the default 5) and got the expected numerical estimates after five iterations. Thus, other things remain equal, as there is more random draws, the SML estimator became asymptotic that includes all maximum likelihood (ML) estimators. As usual, the model fitness was also tested with the Likelihood-ratio (LR- $\chi 2$) among the six equations ($rho_{ji}s/rho_{ij}s$) and it rejected the null hypothesis of independent assumption. The LR test statistic (i.e., LR chi2 (6) = 124.95; Prob > chi2 = 0.0000) was found to be significant indicating the interdependence of the four specified SLM choices. The null hypothesis that stated there is no correlation between the error terms of six equations shown by rho likelihood ratio test i.e., rho21 = rho31 = rho41= rho32 = rho42= rho43 =0.000, was rejected (at p<0.01). Therefore, in this study the alternative hypothesis of mutual interdependence among the four specified SLM practices was adopted.

The overall fitness of the model was also tested with the Wald chi-square test with 95 DF equal to the included explanatory variables and found to be statistically significant at less than 1% probability level indicating that the MVP model fits the data very well. In other words, the null hypothesis that stated all coefficients in each equation is equal to zero was rejected (Wald chi2 (95) = 587.17, P<0.01; chi2 (6) = 124.95, P<0.01 and $\rho ij=\rho ji$ = 0.000) validated the specified model statistically. Thus, it is concluded that the joint estimation by MVP model is asymptotically efficient than estimating the mutually inclusive SLM practices by other binary models. Therefore, the post-estimation tests indicated that the multivariate probit model is consistent and efficient to estimate the parameters of interest as well as fits the data reasonably well than the competing models, i.e., univariate probit or bivariate probit models.

Tables 21 and 22 present the results of the MVP model SML estimates of the parameter coefficients and their statistical significance, the associated robust standard error and the variance-covariance matrix estimates of the cross-equations random errors. The slope coefficients under each SLM choices reveal how each explanatory variable affects farmers' choices of SLM practices at household level. The variance-covariance matrix showed the joint interdependence of each choice applied by farm households to mitigate land degradation in general and to reduce soil erosion, in particular. The variance-covariance matrix of the cross-equations random error terms has a value of one on the leading diagonal and non-unity values of rhoji/rhoij in the off-diagonal,

4.2.3.2. Determinants of farmers' choices of SLM practices

The hypothesized socio-economic, institutional, biophysical, and policy-related attributes matter to the farmers' choices of SLM practices at household level. The simulated maximum likelihood estimator of the MVP model showed that there are different sets of explanatory variables affecting the choice of fanya juu, level soil bund, bench terrace and indigenous SWC measures. Furthermore, the variance-covariance matrix element of the residual errors of the six equations showed that except one combination, that is, indigenous SWC with bench terrace (rho43), most of the SLM practices showed a complementarity effect. The last equation showed the substitutability effect of the two SLM practices that bench terrace and indigenous SWC measures can be applied independently at a farmland.

Gender responsiveness is reflected in all agricultural development interventions including natural resource management. As shown in MVP model simulation estimate, other things held constant, male headed households are more likely to choose and use soil bund by 82.9% ($p<0.01$) than their female counterparts. On the other hand, male headed households found to be less likely to choose and use indigenous SWC measures by 82.1% ($p<0.01$) than female headed. The possible arguments for such highly positive and negative associations with soil bund and indigenous SWC measures are: (1) mostly male headed households have better asset ownership (for example, income, farm implements, farmland, etc.) (2) they are physically strong and have adequate active work force to undertake labour intensive SWC measures (3) male headed households have better access to social network to construct and use SLM practices with their peers, and (4) women mostly engage in non-agricultural activities that switches off their time from labour intensive work. On the other hand, female headed households are more likely to choose and use indigenous SWC measures due to the fact that it demands less labour, time and other resources than the introduced measures. This finding is supported by previous studies, for example, Zerihun *et al*. (2017a), Alelgn *et al*. (2021), Oduniyi and Tekana (2021) conducted in south Africa and Bichaye *et al*. (2022), in Ethiopia have reported that man-headed households have better potential to implement SLM practices than woman-headed ones. Another study by Dessalegne *et al*. (2024) reported that male household heads are more likely to adopt and use soil bund, fanya juu, whereas female counterparts are more likely to adopt and use indigenous practices, i.e., manure.

Marital status is another demographic variable expected to influence choices of SLM practices differently. Single, married and widowed households are expected to have different correlations with SLM choices. As expected, the model result showed that widowhood affected households' choices of different SLM practices, for example, level soil bund, bench terrace and indigenous SWC measures negatively and significantly compared to the choices of married households. As shown in model result, widowed households have less probability of choosing and using soil bund, bench terrace and indigenous SWC measures at about 50% ($p<0.1$), 69% ($p<0.05$) and 74% ($p<0.01$), respectively. The possible justifications for the negative association raised during the FGDs were that widowed households mostly rent/share out their land, are constrained with active labour force, are psychologically weak to actively engage in agricultural activities, and in most cases, they are resource poor, dependent on relatives or government support for their livelihood. Thus, they have weak decision power to use different land management practices to maintain and conserve their land resources.

Education level of households found to affect the choices of SLM practices differently. Conceptually, farm households who attained a higher level of education have a better understanding of the benefit of SLM practices and they are more likely to choose and use SLM practices to conserve their land resources than the illiterate counterparts. The MVP model result showed that it affected the choice of bench terrace positively and significantly but declined farmers' choices of fanya juu and indigenous SWC measures significantly. The interpretation, an increase in one year formal education of households increased the probability of farmers' decision to choose and use bench terrace by 5.4% ($p<0.01$), but it declined that of fanya juu and indigenous SWC measures by 3.6 % ($p<0.1$) and 5.3% ($p<0.05$), respectively (Table 22). This finding is consistent with studies made by Million *et al*. (2019a), Alelgn *et al*. (2021) and Wondimu *et al*. (2021) who found out that education status of households has a positive and significant influence on farmers' decision to adopt and use SLM technologies to control soil erosion in Ethiopia. The inverse relationship observed with some of soil and water conservation practices are supported by Pender and Berhanu (2008) in Ethiopia and Ndagijimana *et al*. (2018) in Burundi that most educated farmers have less interest to invest in land management practices. The implication of this is that government and other relevant organizations should capacitate and support farmers to raise their awareness and positive insights towards the benefits of different land management practices.

Farming experience was hypothesized to influence choice decision of SLM practices positively. Contradictory to the hypothesis, the MVP model estimation result showed that there is a negative correlation with choice of SLM practices, that it affected negatively and significantly the choice of fanya juu. The estimation result revealed that a one year increase in farming experience of the households reduced the likely probability to choose and use fanya juu practices on farmland by 2.2% ($P<0.05$), *Ceteris Paribus*. The possible reasons for the negative association might be: (1) the labour-intensive nature of SWC measures make experienced farmers (in most cases aged) reluctant to choose and (2) farmers with long farm experience are mostly aged (correlation = 90.1%), dependent on family labour and are often constrained with working force, and hence discouraged to choose and use SLM practices. This result is supported by previous studies conducted in Ethiopia that farmers with the long farming experience are less likely to use and/or adopt SLM practices on their farmland (Agere *et al*., 2020; Alelgn *et al*., 2021). Furthermore, supporting this result, a study conducted in western Ethiopian highlands by Akalu *et al*. (2016), in north-western highlands of Ethiopia by Desalew and Aklilu (2017)) and Tigrai, Ethiopia by Haftu *et al.* (2019) reported that the labour intensive and time taking nature of the SWC practices make older farmers less willing and reluctant to use SWC measures as a remedy to soil erosion problems.

Cultivated farmland is an economic variable expected to influence the choice of SLM practices positively and significantly. The simulated maximum likelihood estimation result of the MVP model showed that as the cultivated land size increased by one ha, the likely probability of choosing fanya juu, soil bund, and indigenous SWC measures increased by 69.4% ($p<0.01$), 61.0% ($p<0.01$), and 45.1% ($p<0.1\%$), respectively. Even though the model result is statistically valid to report a higher percentage probability increase, the secondary data observed and the information obtained from the KII verified that the small land-holding ratio in the study areas restricted farmers from increasing their probability of choosing SLM practices. This finding is supported by different studies, for example, as land size increases by 1 ha, the likelihood of using stone bunds and grass strips increased in northwest Ethiopia Agere *et al*. (2020); an increase in parcel size increased the probability of farmers to invest and adopt different SLM practices, for example, bunds of different type, manure/compost and fertilizer Akalu *et al*. (2016); size of farm plots affects the preference and choice of conservation structures Haftu *et al*. (2019); large farm size increases the adoption of soil and stone bunds Alelgn *et al*. (2021), and it also increases the adoption of soil bund, fanya juu and stone bund in Offa district, southern Ethiopia (Mamush and Elias, 2023). On the contrary, a study conducted in Ethiopia by Million *et al.* (2019a) and by Nyanga *et al*. (2016) in Tanzania reported that farmers with large cultivated farmland have less probability of adopting and using SLM practices, because it is labour intensive, time-consuming, and occupies a large plot area to construct physical structure. This implies that there should be some farming arrangement to old farmers who own large farmland to construct and use SWC structures.

Household farm income and non-farm income are liquid assets that were hypothesized to affect farmers' choices of SLM practices. Conceptually the use of SLM practices increases with increase of the income obtained from sale of agricultural products. Income enables farmers to easily access SLM technologies, planting material to stabilize structures, to hire labour and buy farm tools to construct and maintain SWC structures on their farmland efficiently. As per the initial expectation, the model result showed that farm income positively correlated with fanya juu, indicating that a one Birr increase in household farm income increased the probability of choosing and using fanya juu by 23.3% at less than 10%

probability level. On other hand, it reduced the likely probability of choosing indigenous SWC measures by 35.5% ($p<0.01$). This implies that wealthier farmers are less willing to use indigenous conservation measures, rather, they want to maximize their agricultural production by using the introduced ones. This finding is in agreement with Million *et al.* (2019a) and Alelgn *et al*. (2021) who reported that farm households with a higher income have more likely probability of adopting a set of SWC measures.

Non-farm income reduced the likely probability of choosing fanya juu, soil bund and bench terrace as a SWC measure (but it was statistically insignificant). Even though the association was statistically insignificant, it was found to influence the choices negatively, but it affects indigenous SWC measures positively. This finding is consistent with a study conducted by Mamush and Elias (2023) who reported that engagement in non-farm activity affected the choices of soil bund and fanya juu negatively in Offa district, south Ethiopia. Furthermore Akalu *et al*. (2016) and Alelgn *et al*. (2021) reported that off-farm activity aimed at generating non-farm income constrained farmers with shortage of time and labour and influenced their choices of SLM practices, particularly bunds (soil and stone) negatively in north western Ethiopian highlands. Furthermore, Habtamu *et al*. (2023) reported that due to the immediate causal effect of off-farm activity on the short-term labour market opportunity, non-farm income has affected negatively the adoption of soil bund in Omo Gibe River Basin, Ethiopia.

Livestock holding is a non-liquid asset found to influence the choice and use of indigenous SWC measures positively and statistically. The possible justification is that households who own larger livestock holdings could have the opportunity to use manure to enhance the fertility level of farmland. A number of past studies conducted in Ethiopia, particularly in the northern part of the country and in other African countries support this finding. To mention a few, livestock had a positive and significant influence on adoption of one of the indigenous SWC practices, that is, manure use, in Kenya, Malawi and Tanzania Menale *et al*. (2015) and farmers with larger livestock holdings are more likely to invest in manure and less likely to use introduced SWC measures in Ethiopia Akalu *et al*. (2016) and Million *et al*. (2019a).

The mixed farming system typology of the study areas is mainly dominated by annual and perennial crop cultivation. Crop preference either to practice annual or perennial cropping in the study areas was expected to influence the choices of the specified SLM practices positively and significantly. In this regard, the model result showed that farmers' annual crop preference were found to be more likely to choice fanya juu, soil bund, bench terrace and indigenous SWC measures by 110.2%, 131.2%, 150.5% and by 87.2% at less than 1% probability level, respectively, than their counterparts. Similarly, farmers' who prefer planting perennial crops found to be more likely to choose fanya juu, bench terrace and indigenous SWC measures by 101.2%, 47.9% and 107.5% at less than 1% probability level, respectively. The possible justifications for the highly significant and positive correlation with specified SLM practices are; farmers have rich experience in selecting and cultivating crops by considering the fertility level, slope gradient, and soil quality of their farmland, which are proxy bio-physical indicators to decide what type and combination of SLM practices to implement on their farm plots. In all the cases, farmers preferred and planted perennial crops such as multipurpose trees, fruit trees, forage and grasses as a biological stabilizer to sustain and maintain the quality of SWC measures. This finding implies that while implementing agro-ecological specific and landscape oriented specific SLM practices, the types of crops grown and cultivation practice in the area should be equally considered to sustain the physical structures.

Training and extension contact to farmers are key institutional factors that were hypothesized to affect farmers' choices of fanya juu, soil bund, bench terrace and indigenous SWC positively and significantly. Farmers' access to training increased the probability of choosing fanya juu and indigenous SWC measures at less than 1% probability level. The likelihood of farmers to choose bench terrace increased by 13.4% ($p<0.1$) as the extension agents contact increased by one day a month^{-1}. Training and extension advices enhanced farmers' skill, awareness and competence level how to plan, choose, and implement environmentally friendly and economically feasible SLM practices. This finding is consistent with studies conducted by Birhan and Assefa (2017) and Alelgn *et al*. (2021) who reported that access to SLM related training and extension advice increased farmers' skill and awareness to adopt and use SLM technologies.

Furthermore, a study conducted in Ethiopia by Million *et al*. (2019a) reported that farmers who have close contacts with extension agents have a higher probability of decision in using soil bund, stone bund and bench terrace conservation measures. Conversely, these results are inconsistent with existing evidence reported in northern Ethiopia. For example, training and extension advisory service offered to farmers solely on one land management practices influenced its use negatively Woldegebrial *et al*. (2018); extension agents' frequent contact to farmers is negatively associated with use of SLM practices Alem-meta and Singh (2018); it also affects the preference of physical SWC structures negatively Haftu *et al*. (2019) and extension contact influenced farmers' decision to soil bund negatively Agere *et al*. (2020). This finding implies that a skill and knowledge acquired through practical training and advisory services by extension agents at FTC centers and farmers' field on different choices of SLM practices should be seen from different perspectives to sustain and maximize the benefit of on-farm SWC structures.

In line with the initial expectation, use of fertilizer had a positive influence on the choice of bench terrace. The model result revealed that access and use of chemical fertilizer increased the likely choice of bench terrace positively at less than 1% significance level. The possible justifications for the positive and significant associations of fertilizer use are: the use of fertility enhancing technologies like chemical fertilizer enhances soil fertility thereby boosts agricultural production and productivity. Farmers who use SLM practices utilize farm inputs like fertilizer as complementary technology to maximize the yield benefit. This finding is supported by Paulos and Belay (2017) and Haftu *et al*. (2019) who reported that utilization of farm input, mainly chemical fertilizer is positively associated with the use of SLM practices.

Community bylaws was also found to have a positive and significant influence on farmers' likely decision to choose level soil bund at $p<0.01$. Functional and enforceable community bylaws formulated and implemented by the society are likely to encourage farmers to implement appropriate SLM practices to conserve their resources. On the other hand, it is also used as a legal sanction tool to penalize farmers who loosely maintain and conserve the land resources. Community bylaws also governs communities through developing a sense of ownership to manage private and communal property Cardenas *et al*. (2011) that contributes to collective management and sustainable use of natural resources, including farmland.

Plot distance is expected to affect the choices of specified SLM practices negatively. It indicates the proximity or spatial location of farm plots from farmers' residence. In contrast to the prior expectation, it correlated positively and significantly with fanya juu, level soil bund and indigenous SWC measures, but it showed insignificant association with bench terrace. The MVP model result revealed that as farm plots distance from homestead increased by one km, the likelihood of farmers' choices of fanya juu, soil bund and indigenous SWC measures increased significantly by a higher percentage, that is, 56.9%, 49.1% and 92.6%, respectively, at less than 1% probability level. The possible justifications for such unexpected and highly significant association were reason out by discussants of the FGDs and KIIs at a village and woreda level. Firstly, *enset* and coffee (Sidama and Wolaita) and cereal crops (Siltie) based farming system forced farmers to grow *enset*, coffee and fruit trees around their homestead. These crops by their very physiological nature serve as biological SWC measures that substitute the aforementioned choices. Secondly, the rural land policy of the country 'land should be protected and conserved by holders' enforce holders to conserve and maintain owned farmland. Thirdly, the fragile nature of farmland demands physical SWC measures to protect soil erosion, high runoff and fertility decline. In line with this finding, a farm plot located at distance area should be first conserved and protected to secure their use right over the farm plots at near distance (Genanew and Alemu, 2012). In addition, a study conducted in Upper Blue Nile, North Gojjam by Alelgn *et al*.(2021) reported a mixed result that on the one hand, farm distance has a positive and significant effect on the choice of soil bund, and on the other hand, it imposed negative effect on manure and compost utilization. Furthermore, Menale *et al*., (2015) reported that plot distance influenced the use SWC and manure positively in Malawi and Kenya, respectively, while it affected manure use in Ethiopia and Tanzania negatively. Evidences in the literature have also indicated that plot distance has a negative and significant effect on the choice of SLM practices, for example, Akalu *et al*. (2016), Desalew and Aklilu (2017) and Mamush and Elias (2023).

Soil erosion severity is a biophysical plot attribute expected to affect the choices of the specified SLM practices positively and significantly. As the prior expectation, it influenced the choices of the introduced SLM practices, that is, level fanya juu, level soil bund and bench terracing positively and significantly. The interpretation in this regard, with the exception of indigenous SWC measures, as the soil erosion severity became high, the likely probability of farm households to choose and implement fanya juu, soil bund and bench terrace increased by 23.4% ($p<0.1$), 35.9.0% ($p<0.01$) and 40.7% ($p<0.01$), respectively. The justification is straightforward that farmland that is susceptible and exposed to severe soil erosion and high runoff needs an immediate remedial action to mitigate and reduce the environmental threats so as to sustain and maintain the productive potential of the resource. Moreover, households who possessed farmland with steeply sloped and shallow soil depth were highly exposed to severe soil erosion (Akalu *et al*., 2016; Zerihun *et al*., 2017b). This result is consistent with available evidence in the literature: the existence of severe soil erosion has influenced the adoption and use of soil bunds in North Gojjam, Upper Blue Nile Alelgn *et al*. (2021) and Abay Basin Wondimu *et al*. (2021).

Slope influenced the choice of SLM practices differently. In Ethiopia, while choosing and applying different sets of SLM technologies in rainfed croplands, particularly SWC measures, checking the slope gradient of the farmland is one of the pre-request criteria and major developmental intervention starting point (Hurni *et al*., 2016). The MVP model result revealed that there was a significant and positive association of steeper and moderately oriented farmland slopes with farmers' choice of bench terrace and fanya juu. As expected, though it is insignificant, it was found out negative association between steeper slope land and the choice of indigenous SWC measures. The possible reason is that it is impossible to stop or reduce the velocity of overland water flow and soil erosion in steeper farmland using indigenous SWC measures, rather other sets of introduced SWC structures should be chosen and applied to reduce the threat. This result is harmonious with several previous studies conducted in Ethiopia, particularly in the northern highland parts of the country. All of them agreed that the choice of SLM practices, specifically, SWC measures differ as per the slope gradient of farmland. Farm plots situated on steep slopes have a higher probability of being treated with conservation structures Genanew and Alemu (2012); farmers who own and operate in steeply sloppy farmlands are more likely to invest in bunds of different types Akalu *et al*. (2016); farmers invest more in SWC structures in farm plots located at steeper slope Desalew and Aklilu (2017); slope steepness influences positively and significantly farmers' use of bench terrace and stone bund Million *et al*.(2019a); and gentle, moderate and steeper slope is likely to be treated with manure, soil bund and stone bund, respectively Alelgn *et al*. (2021). The implication is that before implementing SLM practices, the slope should be properly measured, and estimated to achieve the objective of reducing soil erosion.

Agro ecological location of the study areas was associated negatively and significantly with the likely probability of choosing fanya juu, soil bund, and indigenous SWC measures. The possible justification for this tricky output is that about 2/3rd of the study woredas, except Arbegona (21.7%), Malega (8.4%), and Bolso bombe (1.1%) are located in the midland belt, where the implementation of SLM practices is dominant. Because of this reason, midland agro ecological location influenced the choice of specified SLM practices. A higher proportion (i.e., 68.84%) of the sample households fell under this agro ecological belt. There are some working guidelines and evidence in the literature that indicate the need to explore agro ecological location in choosing and implementing SLM practices to account for the data heterogeneity and area suitability of the specified measures, for example, Hurni *et al*. (2016, p 17) and Haftu *et al*.(2019). This implies that at a first step, it is important to identify and know the agro ecological location of the areas before choosing and carrying out SLM practices in general and SWC measures, in particular, for their sustainable use and benefit.

Farmers' perceived rainfall intensity is environmental factor that was found to influence the SLM choices positively and significantly. It affected the probability of farm households' choice of level fanya juu and soil bund positively by 26.3% ($p<0.01$) and 18.9% ($p<0.05$), respectively. The reason for the positive association of rainfall intensity with choices of fanya juu and soil bund is that excessive rainfall is a cause for high velocity of runoff and soil erosion, thus farmers were obliged to construct fanya juu and soil bund on their farmland to retain and protect their rainfed croplands against the environmental threats. A similar finding was reported by Zerihun *et al*. (2017b) that when the amount and intensity of rainfall distribution is heavier during the rainy season, particularly in June and July, farmers perceived the level of soil severity very well and therefore chose and utilized appropriate SLM practices.

The pair-wise correlation coefficients of the SLM choices showed the complementarity and substitutability of the specified choices. The correlation matrix showed the four sets of SLM practices that were assumed to be applied in six combinations. The off-diagonal positive and statistically significant correlation rhoij (ρij) values indicate the complementarity of the two SLM practices. At the same time, the negative rho's, in the current case, rho43 (ρIDBT**)**, showed the substitutability of the choices, but it is statistically insignificant. Fanya juu was positively and significantly correlated with soil bund, bench terrace, and indigenous SWC measures at less than 0.01 probability level that a farm household might choose and apply a combination of any two sets of the complementary SWC measures to conserve and maintain owned farmland for the sustainable use. Similarly, soil bund was correlated with bench terrace and indigenous SWC measures positively and significantly at p<1%. The correlation coefficient of soil bund with bench terrace choice is the highest (i.e., 67.6%), but the lowest with indigenous SWC measures (i.e., 26.9%). Conversely, bench terrace correlated negatively with indigenous SWC indicating the two measures are substitutable (Table 21).

Table 21 Correlation coefficients of SLM choices equations random error terms

	ρFJ	ρSB	ρBT	ρID
ρFJ	1			
ρSB	0.670 (0.064)***	1		
ρBT	0.366 (0.083)***	0.676 (0.059)***	1	
ρID	0.272 (0.097)***	0.269 (0.093)***	-0.163 (0.116)	1

rho likelihood ratio test of ρSBFJ[10] = ρBTFJ[11] = ρIDFJ[12] = ρBTSB[13] = ρIDSB[14] = ρIDBT[15] = 0: 0; chi2(6) = 127.07; P > chi2 = 0.00
*** Statistically significant at 1%
Note: The parenthesis denotes robust standard errors; FJ = fanya juu; SB = soil bund; BT = Bench terrace and ID = indigenous SWC measures
Source: Own computation from the survey data, 2022

[10] The off-diagonal variance-covariance value of soil bund and fanya juu error terms
[11] The off-diagonal variance covariance of bench terrace and fanya juu error terms
[12] The off-diagonal variance covariance of indigenous SWC and fanya juu error terms
[13] The off-diagonal variance covariance value of bench terrace and soil bund error terms
[14] The off-diagonal variance covariance value of indigenous SWC and soil bund error terms
[15] The off-diagonal variance covariance of indigenous SWC and bench terrace error terms

Table 22 Multivariate probit model estimates of SLM choices

Variables	Fanya juu		Soil bund		Bench terrace		Indigenous SWC	
	Coefficient	Ro.Se	Coefficient	Ro.Se	Coefficient	Ro.Se	Coefficient	Ro.Se
Gender	0.524	0.375	0.829	0.289***	0.120	0.291	-0.821	0.298***
Marital status	-0.303	0.280	-0.508	0.300*	-0.693	0.298**	-0.737	0.271***
Active labour force	0.019	0.045	-0.012	0.040	-0.038	0.042	0.007	0.042
Education level	-0.036	0.022*	-0.022	0.020	0.054	0.019***	-0.053	0.019***
Farming experience	-0.022	0.009**	-0.013	0.008	-0.004	0.009	-0.011	0.008
Cultivated land size	0.694	0.212***	0.610	0.214***	0.298	0.209	0.451	0.210**
Number of farm plots	0.083	0.155	0.145	0.149	0.136	0.161	-0.139	0.170
Livestock holding	-0.007	0.050	-0.010	0.031	0.004	0.034	0.076	0.046*
Farm income (log)	0.233	0.133*	0.069	0.123	-0.027	0.144	-0.355	0.140***
Non-farm income (log)	-0.027	0.017	-0.007	0.015	-0.016	0.016	0.004	0.018
Annual crop preference	1.102	0.202***	1.312	0.222***	1.505	0.220***	0.872	0.208***
Perennial crop preference	1.012	0.197***	0.165	0.201	0.479	0.192***	1.075	0.235***
Fertilizer use	0.702	0.460	0.677	0.436	0.629	0.337*		
Training	0.512	0.171***	0.035	0.168	0.116	0.178	0.534	0.167***
Extension contact	-0.040	0.072	0.072	0.068	0.134	0.076*	-0.045	0.067
Market distance	-0.017	0.019	0.0001	0.018	-0.014	0.018	-0.026	0.018
Plot distance	0.569	0.177***	0.491	0.176***	0.274	0.178	0.926	0.225***
Soil erosion severity level	0.234	0.129*	0.359	0.108***	0.407	0.120***	0.152	0.126
Degraded infertile soil%	-0.056	0.320	-0.092	0.277	0.198	0.284	-0.165	0.311
Steep sloppy land propn.	0.599	0.420	0.150	0.372	0.962	0.365***	-0.623	0.371*
Moderate sloppy land%	0.490	0.254*	-0.340	0.230	0.215	0.252	0.321	0.264
Community bylaws	-0.026	0.145	0.415	0.137***	0.087	0.145	-0.043	0.157
Agroecology location	-0.454	0.217**	-0.569	0.180***	0.004	0.188	-0.466	0.228**
Rainfall intensity	0.263	0.106***	0.189	0.093**	0.112	0.091	-0.023	0.107
Constant	-0.251	1.537	-3.215	1.410**	-2.579	1.583*	5.331	1.506***
Predicted probability (%)	64.11		51.94		51.41		73.37	
No. of observation	475							
Number of draws	100							
Wald chi2 (95)	582.99							
Prob > chi2	0.000							
Loglikelihood	-702.61							

Note: ***, ** and * indicates statistically significant at 1%, 5% and 10% probability level, respectively, Ro.Se is robust sta.err.

The predicted marginal probabilities of success and the predicted joint success or failure of the choices based on mvprobit model SML estimates are presented in Table 23. The probability of choosing fanya juu, soil bund, bench terrace, and indigenous SWC measures are found to be 64.1%, 51.9%, 51.4%, and 73.4%, respectively. The predicted marginal success probability showed that the likely use of indigenous SWC practices on farmland to reduce soil erosion and high runoff is higher than the introduced SLM measures, i.e., fanya juu, level soil bund, and bench terrace at the study areas. Furthermore, the predicted joint probability of using the four SLM practices as a remedy to reduce soil erosion is found to be 34.7%, while the likelihood of farm households failing to use SLM practices jointly is estimated to be 15.9%. The joint probabilities of success or failure to choose the four SLM practices suggested that farm households in the study areas are more optimistic in applying the SLM practices jointly rather than sticking on one practice.

Table 23 Marginal probit predicted success and joint probability of SLM choices

Predicted probability	Variable	Observation	Mean	Std. Dev.	Min.	Max.
Marginal predicted probability of success	Fanya juu	475	0.641	0.336	0.004	1.000
	Soil bund	475	0.519	0.308	0.001	1.000
	Bench terrace	475	0.514	0.347	0.001	0.999
	Indigenous SWC	475	0.734	0.280	0.011	1.000
Predicted joint probability of success or failure	Joint success	475	0.347	0.295	5.76e-06	0.996
	Joint failure	475	0.159	0.251	1.00e-09	0.911

Source: Own computation from the survey data, 2022

4.2.4. Impact of SLM on Crop Production and Farm Income

In this study, impact evaluation at a household and plot level was designed to quantify the causal effects of land management practices, specifically on-farm SWC measures, on crop production and household farm income. The socioeconomic, institutional, biophysical plot attributes, and policy factors affecting the impact of SLM practices on the specified economic outcome variables, and the casual effects resulting from the econometric analysis are presented sequentially in the following sections.

The mean difference between value of crop production and farm income of land management practices of users and non-users, specifically on-farm SWC measures showed a significant difference. The two groups' mean value of crop produced and farm income was 26,660 and 22,670 ETB, respectively at household level. Similarly, the mean value of crop produced and farm income of users and non-users of SLM practices were found to be 10,370 and 14,850 ETB, respectively, at plot level (Table 24). The possible justification for the significant positive difference in crop production and farm income between the treated and control groups is that households who practiced on-farm SWC on their farm plots experienced a substantial improvement in agricultural productivity throughout the implementation period.

Table 24 Statistical comparison of outcome variables between users and non-user of SLM

Level of analysis	Outcome variables	User	Non-user	Combined Mean	t-value
Household level	Value of crop produced (000's ETB)	28.55(23.66)	20.37(12.49)	26.66(21.86)	3.483***
	Farm income (000's ETB)	24.29(19.93)	17.27(11.93)	22.67(18.61)	3.507***
Plot level	Value of crop produced (000's ETB)	11.38(11.74)	7.36 (6.96)	10.37(10.88)	5.742***
	Farm income (000's ETB)	16.14(13.66)	10.97 (9.88)	14.85(13.01)	6.207***

Note: *** indicate significance level at less than 1% probability level
Source: Own computation, 2022

4.2.4.1. Determinants of SLM practices

The binary probit model matches users and non-users of SLM practices and provides information about the underlying factors influencing the likely probability of farmers using SLM practices at household and plot levels. The household and plot level determinants of using SLM practices, particularly on-farm SWC measures are shown by the probit model result in Table 25. Among the hypothesized twenty-three socioeconomic, institutional, biophysical, and policy factors, six key factors such as cultivated farmland, crop choice, chemical fertilizer use, farmland location, soil erosion severity, and perceived rainfall intensity were found to affect land management practices at a household level. Likewise, farming experience, livestock holding, plot size, crop choice, extension service and fertilizer use were some of the socioeconomic and institutional factors influencing land management practices at plot level. Moreover, plot distance and soil erosion severity are biophysical attributes of farm plots that were found to affect land management practices significantly.

The result from the probit model marginal effect analysis revealed that as the cultivated land increases by one hectare, the probability of using SLM practices on their farmland increases by 4.8% ($P<0.1$) at a household level. The possible justification is that farmers with large farm holdings are more likely to allocate a higher proportion to land management practices expecting more benefit. The likelihood of using SLM practices at a household level increases by 43.4% and 20.2% ($p<0.01$) as farmers can choose crop types and apply fertilizer, respectively. Likewise, the probability of using SLM practices increases by 4.7% ($p<0.05$) and 11% ($p<0.01$) as the soil erosion severity becomes severe on the farmlands at the upper stream of a given watershed of the study areas at household and plot level, respectively. Furthermore, the probability of using SLM practices was found to increase by 3.5% ($p<0.05$) as the rainfall intensity become high at a household level. This finding is supported by studies made in Ethiopia by Paulos and Belay (2017) and Wudineh *et al.* (2023) who reported that users of SLM practices are more willing to allocate farmland, apply fertilizer and other agricultural intensification practices.

Farming experience was found negative and statistically significant in influencing SLM practices at plot level. The marginal effect analysis explained that as the farming experience of farmers increase by one year, the probability of using SLM practices reduced by 0.3% ($p < 0.01$). At the same time, livestock holding and plot size were found positive and statistically significant in explaining the variations between user and non-user of SLM practices at plot level. The marginal effect analysis confirmed that, as a livestock holding and plot size increases by one unit, the probability of using SLM practices increases by 1.9% ($p<0.01$) and 20.7% ($p<0.01$), respectively. This finding is confirmed by Wondwosen *et al*. (2020) who reported that plot size is important socioeconomic factor that imposed a significant impact on farmers' land management practices. Similarly, as the plot distance from the homestead increased by one km on average, the likely probability of using SLM practices decreased by 2.2% ($p<0.05$) at plot level (Table 25).

Access to institutional services, mainly extension service and technology services encourages farmers to invest in SLM practices on their farm plots expecting short-term and long-term economic and environmental benefits. The marginal analysis after the probit model at plot level showed that farmers who access extension advice from DAs in areas of natural resource management and use of fertilizer increased the probability of using SLM practices by 17.4% ($p<0.01$) and 5.3% ($p<0.1$), respectively. The possible argument for positive associations is that training in natural resource management areas creates enabling environment for the implementation of SLM practices and use of appropriate agricultural technologies. A study in South Africa by Oduniyi and Tekana (2021) and Ethiopia by Paulos and Belay (2017) confirmed this finding in that access to extension services and use of fertilizer influenced sustainable land management practices use and adoption positively. Moreover, the predicted marginal effect of using SLM practices at household and plot level were found to be 95.41% and 91.12%, respectively (Table 25).

Table 25 Probit result on determinants of SLM practices

Variables	Household level		Plot level	
	Estimated coefficients	dy/dx	Estimated coefficients	dy/dx
Gender	0.409 (0.385)	0.053	0.335 (0.216)	0.065
Household size	-0.024 (0.053)	-0.002	0.033 (0.029)	0.005
Educational level	-0.032 (0.025)	-0.003	-0.022 (0.015)	-0.004
Farming experience	-0.006 (0.013)	-0.001	-0.017(0.006)***	-0.003
Active family size	-0.004 (0.068)	-.0004	0.031 (0.035)	0.005
Livestock holding	0.034 (0.060)	0.003	0.12 (0.034)***	0.019
Cultivated land/plot size	0.503 (0.256)*	0.048	1.286 (0.246)***	0.207
Off-farm income	-0.222 (0.190)	-0.022	-0.156 (0.110)	-0.025
Crop choice	2.827(0.371)***	0.434	2.211 (0.14)***	0.442
Extension service	0.533 (0.335)	0.075	0.738 (0.172)***	0.174
Fertilizer use	1.041(0.297)***	0.202	0.295 (0.156)*	0.053
Improved seed use	0.250 (0.320)	0.028	-0.23 (0.144)	-0.036
Incentive	-0.166 (0.232)	-0.011	0.049 (0.145)	0.008
Main road distance	-0.013 (0.032)	-0.001	-0.012 (0.020)	-0.002
Market distance	0.037 ((0.027)	0.004	0.001 (0.016)	0.0002
Plot distance	0.492 (0.406)	0.047	-0.137(0.058)**	-0.022
Farm plot location	0.598 (0.195)***	-0.068	-0.145 (0.112)	-0.024
Erosion severity	0.490 (0.173)**	0.047	0.686 (0.10)***	0.110
Slope index	0.244 (0.512)	0.023	0.371 (0.405)	0.060
Degraded infertile soil proportion	0.257 (0.418)	0.025	0.561 (0.437)	0.090
Land certificate	-0.145 (0.382)	-0.013	-0.241 (0.211)	-0.034
Agro ecology	-0.134 (0.330)	-0.013	-0.183 (0.148)	-0.030
Perceived rainfall intensity	0.359 (0.148)**	0.035	0.536 (0.085)	0.086
Constant	-4.119(1.004)***		-3.737(0.497)***	
No. of observations	475		1257	
Wald chi2 (23)	191.08		376.96	
Prob > chi2	0.000		0.000	
Pseudo R2	55.8%		49.83%	
Log likelihood	-113.61		-355.07	
Predicted marginal effect		95.41%		91.12%

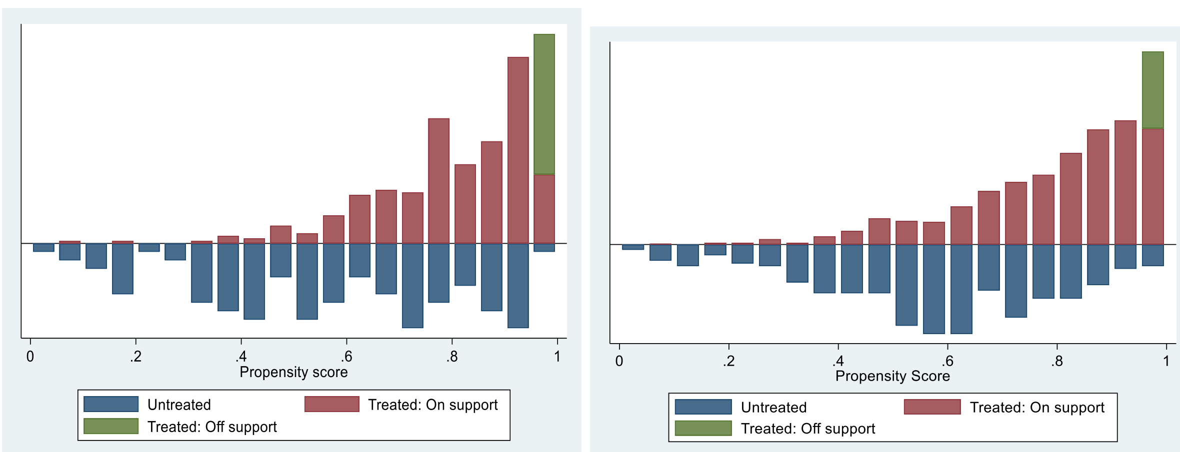
Note: *** p<0.01, ** p<0.05, * p<0.1,
Robust standard errors in parentheses
Source: Own computation, 2022

4.2.4.2. Impact of SLM on value of crop production and farm income

In the context of this study, impact evaluation is the analysis that quantifies the causal effects of using SLM, specifically on-farm SWC measures for at least five consecutive years on the value of crop production and farm income. Before quantifying the impact, propensity scores (PS) are estimated both for the treated and control households using propensity score matching procedure. Sample households were grouped into treated and non-treated based on sustainable land management practices, specifically on-farm SWC measures that were implemented on their farm plots continuously for five years. The PSM was employed to quantify the impacts of SLM practices on the value of crop production and farm income. The estimate was based on the probability of farmers using SLM at household and plot level given the observed socioeconomic, institutional, environmental, biophysical plot characteristics and policy factors. Matching procedure that depends on the balancing score is employed to estimate the casual treatment effect. Before estimating the propensity scores for treated and non-treated farm households, the common support region was checked at household and plot level. In order to get unbiased, consistent and asymptotically normal matching estimator, the treatment effect of interest satisfied the basic assumptions of ignorability or unconfoundedness and overlap condition (i.e. $0 < p\ (w=1|x) < 1$) (Wooldridge, 2010).

At household level, the common support region of the estimated propensity score for matched observations lies between 0.0761 and 0.9999 with mean value of 0.770 (0.204). In other words, the overlap of distribution of the propensity scores across the treatment and control observations are satisfied. The number of on support observations was found to be 420 (88.42%), while the remaining 55 (11.58%) was found to be off support (Figure 6(a)). The mean estimated propensity score for treated households varied between 0.0761 and 0.9999 with mean value of 0.826 (0.153). Similarly, the estimated propensity score for non-treated households varied between 0.0169 and 0.9744 with mean value of 0.572 (0.248) (see Appendix Table 9).

As a robustness check to the household level analysis, a plot level data was also employed to estimate the impact of SLM practices on value of crop production and farm income. At plot level, the common support region of the estimated PS for matched observations laid between 0.0943 and 0.9999 with mean value of 0.752 (0.203). In other words, the overlap of distribution of the propensity scores across the treatment and control observations are satisfied or the mean PS for treated and control groups in each block was the same. The number of on support observations was found to be 1172 (93.24%), while the remaining 85 (6.76%) was found to be off support plots (Figure 6 (b)). The mean estimated propensity score for treated plots varied between 0.0943 and 0.9999 with mean value of 0.826 (0.0.153). Similarly, the estimated propensity score for non-treated plots varied between 0.0169 and 0.9744 with mean value of 0.572 (0.248) (Appendix Table 9). Once a balanced sample is achieved, the average treatment effect of using SLM practices was estimated using preferred matching method both at household and plot levels.



(a)Household level (b) Plot level

Figure 6 Common support region of propensity scores

Furthermore, the propensity score distribution was observed using a histogram distribution of treated and non-treated observations within the common support region at household and plot level (Figure 7). The PS for non-users was not skewed either to left or right; rather it laid in the middle of the common support region. The distribution of the users skewed to right with in the given common support region, i.e., between 0.0761 and 0.9999 at household level and 0.0943 and 0.9999 at plot level. The minimum PS lying outside the common support region of the control observations were trimmed out to make an efficient treatment effect estimation using PSM at both levels.

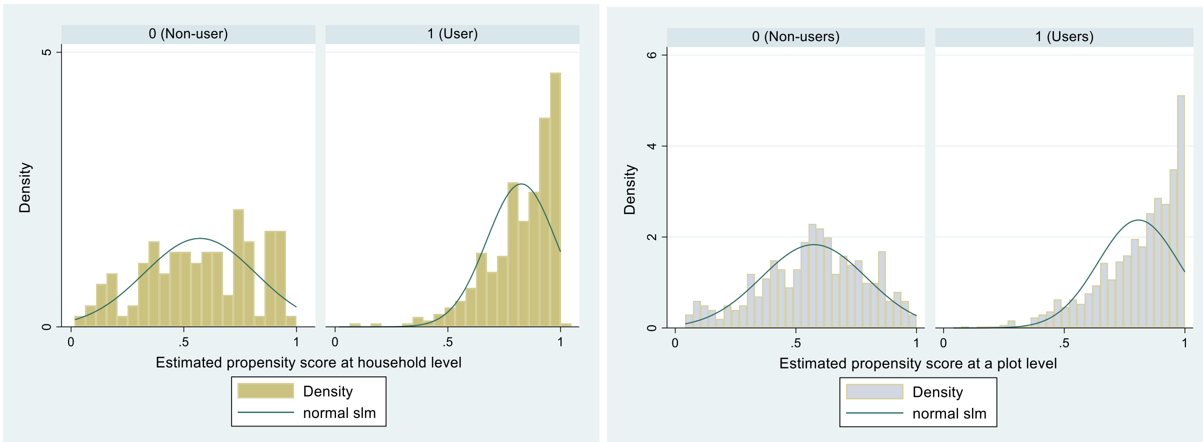


Figure 7 Histogram distribution of propensity scores

To quantify the impact of SLM on the value of crop production and farm income, the average treatment effect on the treated (ATT) households was estimated. Estimating the ATT employing PSM procedure is the parameter of interest that got the most attention in program evaluation literature (Rubin, 2006; Wooldridge, 2010). ATT is the expected mean effect of treatment for randomly drawn individuals from a given population who participated in a given program or intervention (Wooldridge, 2010). While estimating ATT, the pre-request finds close counterfactual control (non-treated) observations for the treated households and plots. The common support option (common) drops treatment observations of the propensity score of which is out of the control observations' range (minimum and maximum). In this study, two observations at household level and six at plot level were found to be below and above the common support region (did not match) and hence were dropped. After the samples were matched, that is, after the balancing score is satisfied, the treatment effect in using SLM practices was estimated by comparing the mean outcome of the treated with that of the untreated groups using different matching techniques.

The choice of each matching estimator is based on the criterion of balancing test, low Pseudo R^2 value, and large matched sample size (Rubin, 2006). The matching techniques that were applied and tested are nearest-neighbor matching (NNM), radius matching, Kernel-based matching (KM), and stratification matching. The matching algorithms are compared against the criteria for selecting the preferable PSM estimator. The matching estimators compared the mean effect of SLM on the value of crop produced and farm income of the treated with the control households. As shown in Table 26, the highest number of matched samples is 473 observed in the kernel (with all bandwidth), stratification, and radius caliper at bandwidth 0.1. All covariates are insignificant in caliper radius (all bandwidth), implying that the estimator balances all covariates after matching. The smaller standardized mean bias is 3.4 in radius caliper with bandwidth 0.05. Similarly, fairly the lowest Pseudo R^2, i.e., 0.9% was observed for the radius caliper, while the highest, i.e., 6.7% was observed for the kernel matching estimator method with 0.05 bandwidth (Table 26). The Pseudo R^2 indicates the joint significance of how well the covariates explained the likely probability of farmers' SLM participation.

Based on the criteria of a large matched sample size, large number of insignificant covariates after matching, lower standardized mean bias, and low PseudoR^2, the radius caliper matching estimator at bandwidth 0.05 was found out as the best fittest method to estimate the impact of SLM practices on the value of crop production and farm income at household level (Table 26). The radius caliper matching estimator yielded large number of matched sample sizes (i.e., 471), lower Pseudo R^2 (i.e., 0.009), all covariates are insignificant (i.e., 17 variables) and a lower standardized mean bias (i.e., 3.4) which shows that all covariates are balanced after matching. Therefore, a radius caliper matching estimator with a bandwidth of 0.05 was used to estimate the ATT. Furthermore, the LR test with chi2 distribution was found to be insignificant (i.e., LR chi2 = 7.61, p > 0.98) after matching. In radius matching, all the control units with estimated propensity scores falling within a radius (r) from propensity score (pi) are matched to the treated unit (i) (Becker and Ichino, 2002).

Table 26 Comparison of different matching algorithms (household level)

PSM Estimator/ Algorithm	Band width	Outcome variable	Criteria				
			Matched sample size	No. of insignificant variables	Mean bias	Pseduo R^2	LR chi2
Nearest neighbor	1.0	Value of crop (ln)	434	7	10.9	0.058	49.45***
		Farm income (ln)	434	7	5.4		
	2.0	Value of crop (ln)	434	13	7.5	0.029	24.59
		Farm income (ln)	434	13	7.5		
	3.0	Value of crop (ln)	434	15	5.7	0.017	14.42
		Farm income (ln)	434	15	5.7		
Radius caliper	0.01	Value of crop (ln)	356	17	5.3	0.015	10.15
		Farm income (ln)	356	17	5.3		
	0.05	Value of crop (ln)	471	17	3.4	0.009	7.61
		Farm income (ln)	471	17	3.4		
	0.1	Value of crop (ln)	473	17	4.1	0.012	10.52
		Farm income (ln)	473	17	4.1		
Kernel matching	0.01	Value of crop (ln)	473	12	9.1	0.028	21.08
		Farm income (ln)	473	12	9.1		
	0.05	Value of crop (ln)	473	9	11.8	0.067	67.81***
		Farm income (ln)	473	9	11.8		
	0.1	Value of crop (ln)	473	12	8.3	0.059	60.07***
		Farm income (ln)	473	12	8.3		
Stratification matching		Value of crop (ln)	473	12	8.9	0.060	60.29***
		Farm income (ln)	473	12	8.9		

Note: *** at 1% significance level

Source: Own computation from the household survey data, 2022

In a similar procedure, once a balanced sample is achieved, the four known matching estimators were compared against the criteria to choose the best estimator to quantify the impact of SLM practices on the value of crop production and farm income at plot level. Based on the criteria, the radius caliper matching estimator with bandwidth 0.05 was found to be the best fittest method to estimate the impact of sustainable land management practices at plot level (Table 27). Radius caliper matching estimator with bandwidth 0.05 yielded a large number of matched sample sizes (i.e., 1251), lower Pseudo R^2 (i.e., 1%), only two significant covariate (i.e., 15 insignificant variables) and a lower standardized mean bias (i.e., 3.8), which shows that, except two, all covariates are balanced after matching. Therefore, similar to household-level impact analysis, a radius caliper matching estimator with a bandwidth of 0.05 was used to estimate the ATT at plot level. Furthermore, the LR test with chi2 distribution showing the joint insignificant level was found to be statistically insignificant (i.e., LR chi2 = 23.54, p < 0.14) after matching

Table 27 Comparison of different matching algorithms (plot level)

PSM Estimator/ Algorithm	Band width	Outcome variable	Criteria				
			Matched sample size	No. of insignificant variables	Mean bias	Pseduo R^2	LR chi2
Nearest neighbor	1.0	Value of crop (ln)	1133	12	5.7	0.022	52.55***
		Farm income (ln)	1133	12	5.7		
	2.0	Value of crop (ln)	1133	13	4.2	0.014	34.37**
		Farm income (ln)	1133	13	4.2		
	3.0	Value of crop (ln)	1133	13	3.7	0.012	28.57*
		Farm income (ln)	1133	13	3.7		
Radius caliper	0.01	Value of crop (ln)	1193	14	4.0	0.013	30.08**
		Farm income (ln)	1193	14	4.0		
	0.05	Value of crop (ln)	1251	15	3.8	0.010	23.54
		Farm income (ln)	1251	15	3.8		
	0.1	Value of crop (ln)	1251	14	4.7	0.016	39.95***
		Farm income (ln)	1251	14	4.7		
Kernel matching	0.01	Value of crop (ln)	1251	11	5.8	0.023	56.30***
		Farm income (ln)	1251	11	5.8		
	0.05	Value of crop (ln)	1251	11	6.8	0.037	96.21***
		Farm income (ln)	1251	11	6.8		
	0.1	Value of crop (ln)	1251	11	6.5	0.039	101.8***
		Farm income (ln)	1251	11	6.5		
Stratification matching		Value of crop (ln)	1251	12	15.1	0.418	993.9***
		Farm income (ln)	1251	12	15.1		

Note: *** at 1% significance level
Source: Own computation from the household survey data, 2022

As a PSM procedure, a balancing test and testing matching quality were done after the best matching estimator is chosen to check whether the matching procedure can balance the distribution of the relevant variables in treated and control groups. In the balancing test, the comparison or control target group should have, on average, the same characteristics as the treatment group at the baseline (White and Raitzer, 2017). Tables 28 and 29 provide the descriptive statistics of the outcome variables and a list of covariates that compare the extent of balancing between the two samples before and after matching used in SLM impact evaluation. In the balanced matching, the intuition is that the comparison group should be similar to the treatment group in terms of the observables before the intervention or the start of the treatment. The displayed standardized percentage bias and its reduction; a two-sample t-test for equality of means between the groups after matching; Pseudo R^2 to indicate how well the regressors explain the probability of participation; and the likelihood ratio test (LR chi2) to indicate the joint insignificance of all covariates after matching verified the covariates balance between the treatment and comparison group for the estimation of SLM impacts at household (Table 28) and plot level (Table 29).

As a rule of thumb, for good balancing and matching quality while using PSM for impact analysis: (1) A two-sample t-test after matching should indicate insignificant for all covariates. (2) The standardized mean bias after matching for covariates should be less than 5%. (3) The standardized percentage bias before matching should also be above the critical value, i.e., 20% as suggested by Rosenbaum and Rubin (1985). (4) The variance ratio of treated V(T) over non-treated V(C) has to show a good matching quality.

For the household level impact analysis, the t-tests for equality of means after matching indicated insignificant for all covariates demonstrating a good balancing test and matching quality. After matching, thirteen covariates had less than 5% standardized %mean as suggested by Rosenbaum and Rubin (1985) showing a good overall matching quality, while the remaining four variables namely household size, slope index, degraded infertile soil proportion and agro ecology had 6.6, 8.1, 6.1 and 8.1 standardize mean bias, respectively. All covariates after matching had a standardized difference in %ranging from 0.2 to 8.1 in absolute value showing good balancing. The standardized %mean before matching was found to be above the critical value, i.e., 20%, ranging from 0.5 to 59.7 except for off-farm income, that is, 0.2. Hence, the standardized percentage bias and its percentage reduction that was seen after matching indicated a good balancing test and matching quality. Likewise, the variance ratio of treated V (T) over non-treated V(C) showed good matching quality for eight and moderate for one continuous covariate. Thus, almost all the criteria applied to check the covariate balancing indicated that the matching effectively built a good control group for the data at household level (Table 28).

Table 28 Propensity scores and covariate balancing tests (household level)

Variable	Unmatch Matched	Mean Treated	Mean Control	Bias (%)	Reduction |bias| %	t-test	V(T)/ V(C)
Propensity score	U	0.826	0.572	123.5		13.03***	0.38*
	M	0.797	0.792	2.4	98.1	0.41	1.03
Gender	U	0.951	0.936	6.2		0.59	.
(male = 1)	M	0.961	0.970	-3.7	40.2	-58	.
Household size	U	7.707	7.209	21		1.86*	1.32*
(persons)	M	7.565	7.720	-6.6	68.7	-0.8	0.98
Educational level	U	4.208	4.191	0.5		0.04	0.95
(years)	M	4.181	4.222	-1.1	-140.3	-0.14	1.09
Active family size	U	3.789	3.527	13.8		1.26	1.03
(persons)	M	3.732	3.762	-1.6	88.5	-0.19	0.82
Livestock holding	U	4.701	3.251	59.7		4.85***	3.16*
(TLU)	M	4.098	3.992	4.4	92.7	0.69	1.24
Cultivated land size	U	1.177	0.862	57.5		5.04***	1.46*
(ha)	M	1.078	1.092	-2.6	95.5	-0.32	0.62*
Off-farm income	U	0.436	0.436	-0.2		-0.01	.
(yes = 1)	M	0.413	0.399	2.7	-1708.8	0.34	
Fertilizer use	U	0.981	0.873	42.2		4.95***	.
(yes = 1)	M	0.977	0.988	-4.0	90.5	-0.98	.
Improved seed	U	0.879	0.809	19.4		1.89*	.
(yes = 1)	M	0.868	0.875	-2.0	89.6	-0.27	.
Extension service	U	0.967	0.836	44.9		5.06***	
	M	0.961	0.956	1.7	96.2	0.31	
Incentive	U	0.811	0.791	5		0.47	.
(yes= 1)	M	0.787	0.784	0.8	84.5	0.09	.
Land certificate	U	0.926	0.891	12.2		1.18	.
(yes=1)	M	0.916	0.915	0.2	98.0	0.03	.
Farm location	U	0.293	0.573	-58.6		-5.52***	.
(upper =1, lower= 0)	M	0.329	0.316	2.8	95.2	0.36	.
Slope index	U	0.585	0.459	57.2		5.01***	1.46*
(%)	M	0.535	0.518	8.1	85.8	1.05	0.94
Degraded infertile soil	U	0.181	0.115	26.5		2.4**	1.12
proportion (%)	M	0.166	0.151	6.1	77.0	0.72	0.91
Agro ecology	U	1.348	1.146	48.2		4.12***	1.81*
(midland=1, highland =2)	M	1.268	1.234	8.1	83.2	0.97	1.09
Perceived rainfall	U	1.811	1.491	44.2		3.93***	1.31*
intensity (low, medium, high)	M	1.707	1.694	1.7	96.1	0.21	0.96

Notes: * If variance ratio outside [0.81; 1.23] for unmatched (U) and [0.80; 1.24] for matched (M)

*** $p < 0.01$, ** $p < 0.05$ and * $p < 0.1$

Source: Own computation from the household survey data, 2022

The impact of SLM practices on the value of crop production and farm income was also evaluated at plot level. Except two covariates, the t-test after matching was found to be balanced. The standardized %bias and its difference, except for four covariates, all covariates had less than 5% (ranging from 0.01 to 5 in absolute value). The standardized %mean before matching is above the critical value, i.e., 20%, ranging from 2.8 to 67.4. Thus, almost all criteria applied indicated that the matching effectively built a good control group (Table 29).

Table 29 Propensity scores and covariate balancing tests (plot level)

Variable	Unmatch Matched	Mean Treated	Mean Control	Bias (%)	Reduction |bias| %	t-test	V(T)/ V(C)
Propensity score	U	0.808	0.574	120.0		19.72***	0.60*
	M	0.789	0.785	2.2	98.2	0.53	1.02
Gender	U	0.947	0.921	10.6		1.71	
	M	0.946	0.946	-0.01	100	-0.00	
Educational level	U	4.242	4.064	4.7		0.73	0.96
(years)	M	4.181	4.021	4.2	10.4	0.90	1.13
Active labour	U	3.783	3.495	15.4		2.35	1.03
(persons)	M	3.678	3.557	6.4	58	1.29	0.76*
Farming experience	U	24.504	23.927	6.1		0.93	1.00
(years)	M	24.329	24.877	-5.8	5.1	-1.24	1.18*
Livestock holding	U	5.027	3.347	63		8.54	3.64*
(TLU)	M	4.406	4.384	0.9	98.6	0.22	1.28*
Plot size	U	0.487	0.330	59.5		8.65***	1.61*
(ha)	M	0.458	0.450	2.9	95.1	0.58	0.98
Off- farm income	U	0.448	0.425	4.6		0.70	
(1 = yes)	M	0.440	0.495	-11.1	-142.9	-2.28**	
Extension service	U	0.970	0.829	48.4		9.10***	.
(1=yes)	M	0.967	0.969	-0.4	99.1	-0.15	.
Improved seed use	U	0.647	0.571	15.4		2.39	
(1 = yes)	M	0.641	0.640	0.1	99.1	0.03	
Fertilizer use	U	0.831	0.705	30.3		4.89***	.
(1=yes)	M	0.825	0.846	-5.0	83.5	-1.16	.
Plot distance	U	0.502	0.523	-2.8		-0.45	0.69*
(km)	M	0.506	0.503	0.4	84.8	0.10	1.39*
Slope index	U	0.320	0.298	15.7		2.29**	1.51*
(%)	M	0.322	0.318	3.0	80.5	0.59	1.12
Soil erosion severity	U	1.740	1.343	67.4		10.03***	1.30*
	M	1.688	1.658	5.0	92.4	0.99	0.91
Agro ecology	U	1.358	1.194	37.3		5.48***	1.47*
	M	1.326	1.332	-1.4	96.3	-0.27	0.99
Farm location	U	0.314	0.390	-16		-2.49**	.
(1=upper, 0=lower)	M	0.326	0.302	5.0	69	1.05	.
Incentive	U	0.814	0.778	9		1.41	
(1= yes)	M	0.806	0.795	2.8	68.6	0.59	
Land certificate	U	0.934	0.898	12.9		2.09**	
(1=yes)	M	0.928	0.898	10.7	17.1	2.18**	

Note: * If variance ratio outside [0.88; 1.14] for U and [0.87; 1.14] for M

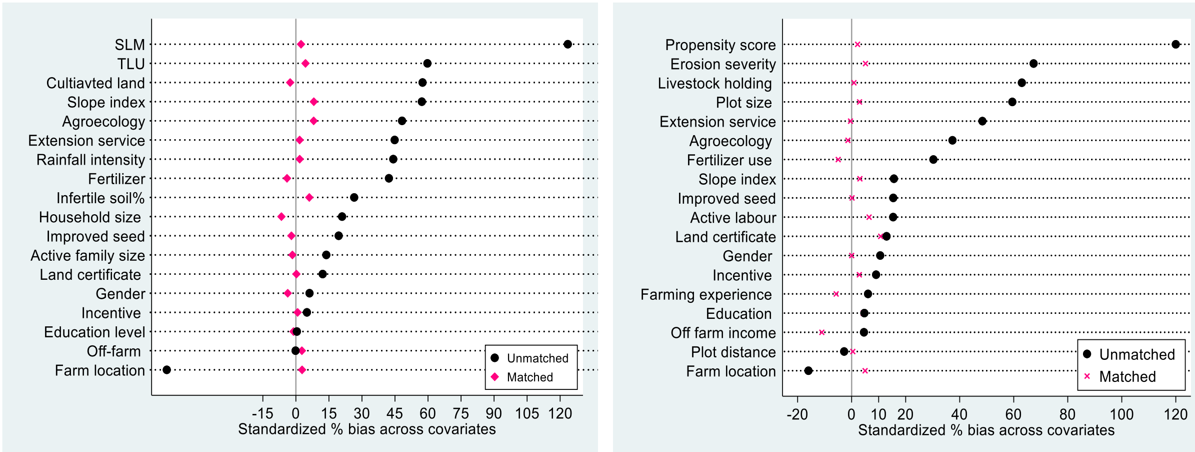
With regard to the matching estimator, the radius caliper matching estimator with bandwidth 0.05 was selected because of the presence of low Pseudo R^2, statistically insignificant likelihood-ratio test (LR-chi2) for matched samples, and lower standardized mean bias after matching. As presented in Table 30, the Pseudo R^2 was reduced from 0.236 to 0.009; the likelihood ratio test (LR-chi2) of the joint insignificance of all regressors became insignificant ($p > 0.98$); the standardized mean and median bias decreased from 35.6 to 3.4 and from 34.4 to 2.7 after matching, respectively at household level. Likewise, the Pseudo R2 reduced from 0.216 to 0.010 was found to be low indicating no systematic differences in the distribution of the covariates of the two groups at plot level. The likelihoods ratio test for the matched sample became insignificant and the standardized mean bias reduced from 24.6 to 3.8 after matching. Thus, the matching quality test of the PS estimation process using a radius caliper estimator with a bandwidth of 0.05 was successful in balancing the distribution of covariates between the user and non-user of on-farm SWC measures at household and plot levels (Table 30).

Table 30 Summary of covariates test before and after matching (radius caliper 0.05)

Unit of analysis	Sample	Pseudo R^2	LR chi2	P > chi2	Mean bias	Med bias	B	R	%Var
Household level	Unmatched	0.236	121.21	0.000***	35.6	34.4	126.3[a]	0.57	70
	Matched	0.009	7.61	0.984	3.4	2.7	22.2	1.34	10
Plot level	Unmatched	0.216	305.09	0.000***	24.6	15.4	119.7[a]	1.39	67
	Matched	0.010	23.54	0.132	3.8	3.0	23.5	1.31	44

Note: [a] if B > 25%, R outside [0.5; 2]; *** at 1% significance level
Source: Own computation from the household survey data, 2022

Furthermore, a graphical summary of covariate imbalance using a dot graph displayed the distribution of the standardized percentage bias across the covariates showing the matching quality (Figure 8). Generally, the tests assessed against the standard and the dot graph verified the distribution of the covariates balance after matching to estimate the impact of SLM on the value of crop production and farm income at household and plot level. The standardized %bias across covariates condensed to normal around the mean after matching. In all the cases, after matching, the two groups had similar covariate distribution. They are sufficiently balanced to estimate the impact of SLM on the value of crop production and farm income at household and plot levels.



(a) Household level (b) Plot level

Figure 8 Covariates imbalances before and after matching at household and plot level

4.2.4.3. SLM impact estimation results using PSM procedure

It was hypothesized that land management practices in general and on-farm SWC measures, in particular, have impacts on crop production and farm income both at household and plot levels in the study areas. While hypothesizing the impact of SLM on crop production and farm income at household and plot level, it was assumed that the users have to implement on-farm SWC measures at least in one of their farm plots and/or on 25% of their owned farmland for five consecutive years from 2013 to 2018. Those farmers who implement it in less than 1/4th of their farmland and failed to implement any on-farm SWC measures for five consecutive years are considered as control households. After choosing the matching method and testing the covariates balance, the estimation of SLM impacts on value of crop production and farm income at household and plot level is quantified and displayed in Table 31.

Impact of SLM on the value of crop production: as presented in Table 31, the impacts of SLM on the value of crop production have shown a positive effect, but insignificant. The value of crop production for farmers who implemented SLM at least on 1/4th of owned farmland was on average higher by 9.3%, 9.5%, and 4.9%%, using radius caliper, nearest neighbor and kernel matching methods, respectively as compared to the counterfactual farmers at household level. Similarly, the impact of SLM on value of production and farm income at plot level is presented in Table 31. The value of crop production by farmers who practiced SLM on their farm plots for continuous five years is higher than that of non-users by 40.8%, 46.5%, 35.2% and 36.0% estimated by radius caliper, nearest neighbor, kernel, and stratification matching methods, respectively. The possible reason for a positive difference in the value of crops produced is that a farmland that is conserved and maintained with on-farm SWC measures has a direct impact on soil fertility and productivity potential enhancement which ultimately contributed to the increment of crop productivity and production. This finding is supported by Paulos and Belay (2017) who reported that farmers who practiced SLM practices for continuous six years received a higher value of production (about 24%) over non-users in Blue Nile River of Ethiopia at household level. Another SLM impact evaluation based on panel survey data was conducted within diverse agro-ecological zones of Amhara and Oromiya regions of Ethiopia by Schmidt and Fanaye (2019) contradicted with this finding in that they reported that there is no impact on household level value of total production after four year of intervention. There was rather only overall change in agricultural productivity trend.

Impacts of SLM on farm income: akin to the impact of SLM on the value of crops produced, it showed insignificant positive effect on farm income at household and plot levels. The average farm income obtained from the sale of crops produced and animals for farmers who implemented SLM at least on 1/4th of owned farmland for five continuous years was on average higher by 6% and 4% using radius caliper and nearest neighbor matching methods, respectively and decreased by 3.8% using Kernel method over that of non-user. Similarly, farmers who practiced SLM practices, specifically on-farm SWC measures on their farm plots got a higher farm income as compared to their counterfactual at plot level. A higher average farm income increment, that is, 25.4%, 17.5%, 22.4% and 25.3% was found using radius caliper, nearest neighbor, Kernel and stratification matching methods, respectively, by farmers who applied SLM practices, specifically on-farm SWC measures on their farm plots. The possible justification for positive farm income differences between the two groups is that farmers who implemented different land management practices, particularly on-farm SWC measures could have got the opportunity to maintain and conserve their farmland. Consequently, they produced, supplied, and sold surplus agricultural products in the market. This finding is supported by Paulos and Belay (2017) who reported that SLM practices have brought impact on farm income at plot level. Furthermore, a study made by Oduniyi and Tekana (2021) in South Africa supported this finding in that using an efficient endogenous switching regression model farmers who adopted SLM practices received a higher household welfare (net farm income) than their counterfactual.

Table 31 Impacts of SLM on value of crop production and farm income

Level of analysis	Matching method	Number of matched observations		ATT	SE	t-value
		Treatment	Control			
Household level	Value of crop produced (log)					
	Nearest neighbor (2)	365	69	0.095	0.097	0.98
	Radius caliper (0.05)	365	106	0.093	0.089	1.04
	Kernel (0.01)	365	108	0.049	0.111	0.44
	Stratification	365	108	-0.084	0.112	-0.75
	Farm income (log)					
	Nearest neighbor (2)	365	69	0.040	0.129	0.31
	Radius (0.05)	365	106	0.060	0.111	0.54
	Kernel (0.01)	365	108	-0.038	0.143	-0.27
	Stratification	365	108	-0.037	0.106	-0.35
Plot level	Value of crop produced (log)					
	Nearest neighbor (2)	942	191	0.465	0.286	1.62*
	Radius caliper (0.05)	942	309	0.408	0.270	1.51*
	Kernel (0.05)	942	191	0.352	0.308	1.14
	Stratification	942	309	0.360	0.224	1.607*
	Farm income (log)					
	Nearest neighbor (2)	942	191	0.175	0.217	0.81
	Radius (0.05)	942	309	0.254	0.200	1.27
	Kernel (0.05)	942	191	0.224	0.229	0.98
	Stratification	942	309	0.253	0.150	1.69*

Note: * significance at 10% probability level.

Source: Source: Own computation from the household survey data, 2022

The impact analysis using the four matching estimators showed nearly similar results. However, among the four estimators, radius caliper estimator was chosen as a best against the criteria employed to select the fittest matching methods. Table 32 shows the impact of SLM practices on value of crop production and farm income after matching using the radius matching method. The estimation of ATT and the associated t-stat revealed that the mean difference between the treated and non-treated groups has a positive increment on the value of crop production. The ATT result showed that farmers who implemented on-farm SWC measures on their owned farmland for five consecutive years gained 9.3% a higher average crop yield over the non-users of SLM practices. Similarly, households who implemented land management practices in general and on-farm SWC practices, in particular gained significant higher crop yield, i.e., 40.8% ($p < 0.1$) compared to the non-users of SLM practices at plot level. This result is in line with the findings of Paulos and Belay (2017) stated that households who implemented land management practices for at least six successive years gained 24.1% and 28.6% higher value of crop production over non-users at a household and plot level, respectively. Furthermore, this result is supported by a study conducted in eastern Ethiopia by Million *et al*. (2019b) who stated that farmers who adopted SWC practices gained a higher and significant net crop value over the non-adopters.

The ATT using radius caliper matching method showed a positive increment on farm income at household level. Even though, the t-statistic showed statistically insignificant result between the mean difference of treated and non-treated households after matching, SLM user households gained 6.0% higher farm income compared to the non-users at household level. Similar to the significant increment of crop production, those who implemented on-farm SWC measures at least on $1/4^{th}$ of owned farmland for five successive years earned 25.4% higher farm income over the non-users who failed to implement SLM. This result conformed to the findings of Oduniyi and Tekana (2021) who reported that SLM imposed positive and significant impact on farm income of maize growing farmers who adopted different land management practices in South Africa. A positive increase in farm income both at household and plot level implies the crucial importance of SLM practices in combating land degradation and reducing soil erosion. Ultimately, it reminds policy makers and development practitioners to incentivize and capacitate smallholder farmers to implement land management practices efficiently and effectively.

Table 32 Impacts of SLM on crop production and farm income (PSM result*)*

Level of analysis	Outcome variable	Mean		Difference	T-stat
		Treated	Control		
Household level	Value of crop production (Log)	10.031	9.939	0.093(0.089)	1.04
	Farm income (Log)	9.763	9.704	0.060 (0.111)	0.54
Plot level	Value of crop production (Log)	8.656	8.248	0.408 (0.270)	1.51*
	Farm income (Log)	9.152	8.898	0.254 (0.200)	1.27

Note: * significance at 10% probability level
The parentheses indicate the standard error.
Source: Own computation from the household survey data, 2022

A Sensitivity analysis test is used to evaluate whether the causal treatment effect from the PSM estimate is susceptible to the influence of unobserved heterogeneity (unidentified hidden bias). The propensity score analysis assumed that all expected covariates are included in the treatment assignment, and thus the bias due to unobservable covariates is ignorable. If there are unobservable covariates suspected to affect the treatment assignment and outcome variable simultaneously, the matching estimators are not robust against the 'hidden bias.' Thus, sensitivity analysis should be conducted to examine how strong the influence of gamma (γ) on SLM participation needs to be, that reduces the impact of SLM participation on value of crop produced and farm income. It assesses the bias of causal effect estimates when the uncofoundness assumption is assumed to fail in some ways. If γ is 1, then $p_{[j]} = P_{[k]}$ when the covariates $x(j)= x(k)$, so the estimate of treatment effect is assumed to be free of hidden bias Rosenbaum (2002) and the participation probability is solely determined by x_i. However, if γ is > 1, the treatment effect is altered that the impact of SLM on the value of crop production and farm income may be due to some unobserved or un measurable covariates or to the unidentified 'hidden bias', rather than a real effect.

Rosenbaum bound sensitivity test for possible 'hidden bias' that comes from unobservable factors for the household and plot level impact analysis of SLM practices on value of crop production and farm income is presented in Table 33. The Rosenbaum bound sensitivity test for hidden bias confirmed that allowing log odds of different assignment (gamma) up to $e^{\gamma} =$ 7 in unobserved covariates, the impact of SLM on value of crop produced and farm income remain unaltered. The outcome variable at t-statistic, p-calculated values (p < 0001), and the upper and lower bound confidence interval are significant at all critical levels of e^{γ}. In other words, the null hypothesis stating the outcome variables, that is, value of crop produced and farm income is affected by 'hidden bias' is rejected showing the estimated impact using PSM procedure of ATT was insensitive to an unobserved selection bias. Thus, the sensitivity analysis verified that the outcomes, i.e., value of crop production and farm income after matching due to the treatment effect are not affected by the hidden bias indicating all important variables expected to influence the use of SLM practices at household and plot level are well addressed.

Table 33 Rosenbaum bound sensitivity analysis test for impact of SLM

Analysis level	Gamma (e^{γ})	Log value of crop				Log farm income			
		Significance levels		Confidence interval		Significance levels		Confidence interval	
		Sig+	Sig-	CI+	CI-	Sig+	Sig-	CI+	CI-
Household level	$e^{\gamma} = 1$	0	0	9.94	10.05	0	0	9.72	9.86
	$e^{\gamma} = 2$	0	0	9.76	10.23	0	0	9.49	10.08
	$e^{\gamma} = 3$	0	0	9.65	10.34	0	0	9.35	10.20
	$e^{\gamma} = 4$	0	0	9.58	10.42	0	0	9.25	10.29
	$e^{\gamma} = 5$	0	0	9.52	10.48	0	0	9.17	10.35
	$e^{\gamma} = 6$	6.3×10^{-15}	0	9.47	10.52	6.3×10^{-15}	0	9.11	10.40
	$e^{\gamma} = 7$	4.7×10^{-13}	0	9.43	10.56	4.7×10^{-13}	0	9.06	10.44
Matched pairs	475								
Plot level	$e^{\gamma} = 1$	0	0	8.81	8.93	0	0	9.23	9.34
	$e^{\gamma} = 2$	0	0	8.42	9.24	0	0	8.89	9.63
	$e^{\gamma} = 3$	0	0	8.17	9.40	0	0	8.67	9.77
	$e^{\gamma} = 4$	0	0	7.95	9.51	0	0	8.49	9.87
	$e^{\gamma} = 5$	0	0	7.74	9.58	0	0	8.35	9.94
	$e^{\gamma} = 6$	0	0	7.49	9.64	0	0	8.23	9.99
	$e^{\gamma} = 7$	0	0	7.05	9.68	0	0	8.12	10.04
Matched pairs	1257								

Note: gamma (e^{γ}) is log odds of different assignment due to unobserved factors; sig+ and sig- refer to upper and lower bound significance level, respectively and CI+ and CI- refer to upper and lower bound confidence interval at alpha 95%, respectively.

Source: Own computation from the household survey data, 2022.

4.2.4.4. SLM impact estimation results using endogenous switching regression

The sensitivity analysis verified that the degree of influence of unobserved selection and hidden bias on the estimated outcomes, i.e., value of crop production and farm income after matching due to the treatment effect are not affected. However, the literature has indicated that direct sensitivity analysis for PSM estimated treatment effects do not indicate the severity of hidden bias problem (Menale *et al*., 2017; Million *et al*. (2019b). Thus, the robustness of PSM result of this study was check by employing ESR model using the same set of data. The ESR model allows the treatment variables to interact with observable variables and unobservable heterogeneity (Menale *et al*., 2017).

The ESR model estimation output inverse mills ratio was found to be insignificant indicating the estimated treatment effect is not affected by unobservable factors (Annex Tables 10 and 11). The first stage ESR binary probit estimation results are presented in Appendix Tables 10 and 11. The Wald chi-squared statistics test is significant at $p < 0.01$, showed the probit model fits the data reasonably well (Wald chi2 (23) = 191.08, P = 0.000). The probit model result showed that the hypothesized household socioeconomic and institutional factors as well as bio-physical plot attributes and environmental factors influenced SLM uses significantly. Cultivated farmland size affected the use of SLM practices, specifically, on-farm SWC measures positively and significantly at less than 10% probability level. This result is consistent with the findings of Paulos and Belay (2017); Million *et al*. (2019b); Alelgn *et al*. (2021) and (Mamush and Elias, 2023) who all reported that the probability of using SLM practices, specifically, SWC measures increases with increase of cultivated farmland size. The possible justification for such a positive association is that farmers who own large farmland size allocate a higher fraction to on-farm SWC measures than those who own smaller one. Crop choice was associated with the use of SLM practices positively and significantly, implying that farmers' choice or preference in cultivating perennial and annual crops has affected the probability of using SLM practices.

Fertilizer use is an institutional factor that was positively and significantly associated with the use of SLM practices, which is in line with the findings of Million *et al*. (2019b) who reported that the use of fertilizer was positively associated with the adoption of SWC measures. Farm plot location and soil erosion severity are biophysical plot attributes found to be positively and significantly associated with the use of SLM practices. The possible justification is that farmers whose farmland is located at the upper stream and susceptible to severe soil erosion are cautious in using SLM practices, to minimize the environmental threats imposed on their farmland. This finding is consistent with the findings of Alelgn *et al*. (2021) and Wondimu *et al*. (2021) who reported that severe soil erosion increases the use and adoption of SLM practices, for example, the use of soil bund. Perceived rainfall intensity is an environmental factor found to be associated positively and statistically significantly with the use of SLM practices. The possible explanation for the positive association is that smallholder farmers who perceive excessive rainfall enforce them to use SLM practices, specifically on-farm SWC measures to reduce soil erosion caused by high runoff.

The predicted ESR based estimation of ATT and ATU for the outcome variables, i.e., value of crop production and farm income is presented in Table 34 under actual and counterfactual conditions. The ATT and the t-test showed that the mean value of crop production and farm income between SLM users and non-users was significant and statistically different from zero. The interpretation, if farmers used SLM practices, but hypothetically would have not used SLM practices as a remedy to land degradation, then their value of crop produced decreased by 27.2% ($p < 0.01$). The average treatment effect on the untreated (ATU) also showed that, non-users would have gained more 13.5% ($p < 0.01$) value of crop produced had they use SLM practices on their farmland. Likewise, if farmers use SLM practices, but theoretically would have not used it, then their farm income would have decreased by 73.9% ($p < 0.01$). The ESR-based ATU estimates for non-users also showed that the probability of farm income would have increased by 20.4% points ($p < 0.01$) if they had use on-farm SWC measures as developmental remedy action to mitigate land degradation and reduce soil erosion.

The ESR and PSM estimation indicated that the use of SLM practices, specifically, on-farm SWC measures has positive impacts on the value of crop production and farm income. The null of no hidden bias or unobserved selection bias on the estimated treatment effects was accepted in the ESR model result. Even though the increase in value of crop production and farm income using the non-parametric PSM procedure is insignificant, the parametric ESR estimation supported the PSM estimation that the difference in value of crop production and farm income between users and non-users of SLM practices. In conclusion, the ESR estimation result showed that use of SLM practices, specifically, on-farm SWC measures increases value of crop produced and farm income significantly. Furthermore, the ESR estimated coefficients of the determinants of value of crop produced and farm income and the associated robust standard errors, and t-value of the outcome variables is presented in Appendix Tables 10 and 11, respectively.

Table 34 Impacts of SLM on crop production and farm income (ESR model estimation)

Outcome variables	Average treatment effect	Decision stage		Treatment effect	t-Value
		To use SLM practices	Not to use SLM practices		
Value of Crop produced	ATT	10.341	10.069	0.272 (0.041)***	6.631
	ATU	9.881	9.746	0.135 (0.059)**	2.262
Farm income	ATT	9.854	9.114	0.739 (0.063)***	11.788
	ATU	9.698	9.494	0.204 (0.063)***	3.233

Note: *** and ** significant at the 1% and 5% probability level, respectively
ATT average treatment effect on the treated
ATU average treatment effect on untreated
Source: Own computation from field survey, 2022.

5. SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1. Summary

In Ethiopia, land degradation has long been a widespread problem affecting farmers' livelihoods. The SLM practices have been implemented to mitigate land degradation and soil erosion. However, the problem persists and has become a major threat to the environment as well as to the livelihood of people. Key socioeconomic, institutional, biophysical, and policy attributes contribute positively or negatively to farmers' perception, participation decision, and choices of land management practices, specifically on-farm SWC measures. With these contexts, there are limited empirical works on how these factors influence participation and choice decisions, perception of SLM practices, and its anticipated economic impact in southern Ethiopia. Thus, this research aimed to study farmers' perception, participation decisions and intensity, choices, and examine the socioeconomic, institutional, biophysical, and policy factors that influenced farmers' perceptions, participation decisions, choice of SLM practices, and its impact on the value of crop production and farm income.

The study used cross-sectional household survey data collected randomly from 475 households in 6 woredas and 12 kebeles drawn from Sidama, Wolaita, and Siltie zones through a stratified sampling technique. FGDs and KIIs were also used to collect qualitative data that complement and substantiate the quantitative survey data. Methodologically, descriptive analysis and econometric models were employed for the analysis to answer the research questions. The econometric models utilized in the analysis include the ordered probit model for farmers' perception, truncated hurdle model for participation decisions and intensity, the multivariate probit model for choice decisions, PSM and ESR for impact assessment of SLM on value of crop production and farm income.

The ordered probit model that estimates relationships between an ordinal dependent variable perception levels and the hypothesized independent variables revealed that education, cultivated land size, training, plot distance, land market, slope (moderate and steep), topsoil erosion, severity of soil erosion, soil quality (low to moderate), fertility level, community bylaws, incentives, land certificate and the agro-ecological location are key factors affecting farmers' perception of SLM role at household level. Meanwhile, the truncated double hurdle first tire, i.e., the probit part showed that gender, social network, perception index, land size, extension contact, soil fertility index, slope status, and soil erosion affected the participation decision of land management practice positively, while non-farm income, value of crop produced, land market, and farm location influenced it negatively at the household level. The Cragg truncated hurdle model (the second hurdle) demonstrated that farmland size, value of crop produced, training, road distance, and community bylaws influenced the intensity decision positively and significantly. On the other hand, farming experience, education level, and extension services influenced the intensity negatively and significantly.

The MVP model using the SML estimator revealed that a number of socioeconomic, institutional biophysical plot-related and environmental factors influenced farmers' choice of fanya juu, level soil bund, bench terrace, and indigenous SWC measures differently. The pairwise variance-covariance matrix of the error terms of five equations of SLM choices, i.e., fanya juu with soil bund, bench terrace, and indigenous SWC; soil bund with bench terrace and with indigenous conservation measures are positively and significantly correlated implying the complementarity effect of the choices. However, bench terrace with indigenous soil conservation measures showed trade-off effect (substitution) with one another applied independently on farmland as a remedy to the soil erosion problem.

Lastly, the result of PSM using the caliper radius matching estimator showed that farmers who utilized SLM practices, specifically on-farm SWC measures for continuous five years at owned farmland gained 9.3% and 6.0% higher value of crop production and farm income at household level over the non-users, respectively. Likewise, households' farm plots that were treated with on-farm SWC measures received 40.8% significant increment of value of crop yield. Moreover, before computing the ATTs, all covariates were balanced after matching against the criteria. The robustness of PSM was also checked using ESR model that the increment in the average treatment effect on the value of production and farm income of SLM was not affected by unobserved heterogeneity. The ESR method indicated that farmers who used SLM practices but had they decided not to use on their farmland, their value of crop produced and farm income decreased by 27.2% and 73.9%, respectively.

5.2. Conclusion and Recommendations

Sustainable land management practices, specifically on-farm SWC are important technical and institutional measures to mitigate land degradation and soil erosion to sustain the use of renewable land resources for the present and future generations. Farmers' perception of the role of SLM practices in mitigating land degradation and reducing soil erosion is highly associated with their educational status, non-liquid asset (land), training accessibility, land market, community bylaws, land certificate, economic incentives, biophysical plot attributes, and agro-ecological locations. While designing and using area-specific SLM practices, development programs and policy initiatives should not only depend on implementing physical structures, but also they should equally consider farmers' perceptions of basic psychological processes within the context of their endowed socioeconomic status, biophysical plot attributes, and the external institutional and policy dimensions. This study, underlined that practitioners should give proper attention to raising the perception level and awareness of smallholder farmers through education and training about the benefit and implication of investment in land-related management practices in maintaining and conserving the potential of land resources for sustainable use.

Farmers' participation, as rational economic agents either to use or not use SLM practices in response to soil erosion problems on farmlands are sequential and independent decisions. The truncated hurdle model analysis result indicated that socioeconomic characteristics, institutional factors, biophysical farm plot attributes, and external policy factors influenced the decisions. Thus, the result of this study implies that to reverse the problems that constrained land resources, the important socioeconomic endowments, the external institutional and policy factors, as well as biophysical attributes of farm plots need to be considered while planning, implementing and maintaining the SLM practices at farmlands and other land use types. From farmers' participation perspectives, gender, the social network of which farmers are living in, farmers' perceptions, owned land size, engagement in off-farm activities and land rental market, extension contact of DAs with farmers, the biophysical attributes of farm plots, for example, farmland location, soil fertility and slope status, and the existence soil erosion are important determinants that should be considered in development efforts of abating land degradation and soil erosion.

The multivariate probit model estimation confirmed that most SLM practices chosen and used are complementary to one another. In this regard, implementing two or more on-farm SWC measures is effective in reducing soil erosion. Moreover, the biophysical plot attributes of farmlands, environmental factors, and the socioeconomic setup of farmers have influenced smallholder farmers to be optimistic about choosing and using SLM practices jointly and simultaneously rather than sticking to one sole practice. The result affirmed that the interdependent SLM choice decisions depend on plot distance, soil erosion severity, slope orientation, agro ecological location, rainfall intensity, crop choices, institutional supports, as well as socioeconomic (education, farm income, and cultivated land size) conditions of farm households. Therefore, smallholder farmers should be aware, trained, and supported by development practitioners and institutions about the benefit of the jointly applied interrelated set of SLM choices as farmers' stated preference is deemed to maximize their utility, i.e., mitigating land degradation. From policy perspective, the interdependent choices of SLM practices should be promoted and smallholder farmers should apply so as maintain and conserve their farmland resources.

The impact of SLM practices showed a positive increment in the value of crop production and farm income for farmers who practiced the specified set of interventions for five continuous years over the non-users. Likewise, it indicated a higher positive and significant crop yield increment at plot level. The ESR result further showed that use of SLM practices have significant increment in value of crop production and farm income in southern Ethiopia. Thus, the paper concludes that, given such positive increment of SLM on the value of crop production and farm income, emphasis should be given by development practitioners and policy initiatives to endure the momentum and scaling of SLM practices for sustainable use and benefit of renewable farmland resources through delivery of extension services, farmers' training, and other institutional services.

In conclusion, the result of this study suggested that while designing and implementing SLM practices, specifically on-farm SWC measures, the key socioeconomic, institutional, and biophysical attributes of farm households need to be considered. Thus, as policy and development implications, the agricultural sector in general, and the extension service in areas of natural resource management, in particular, should consider the key socioeconomic and institutional setups farmers operate in and the biophysical attributes farm plots have as they strongly influence farmers' perception, participation to use, choices of appropriate SLM practices. Moreover, developmental partners and government organizations should give more emphasis in scaling of the best-fit soil and water conservation practices jointly or solely. Overall, these findings do have developmental and policy implications for perceiving, participating, choosing, and using SLM practices to cope with land degradation and soil erosion problems at cultivated cropland and other land use types thereby improving agricultural productivity.

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7. APPENDICES

Appendix 1: Appendix Tables

Appendix Table 1 Multicollinearity test of deterministic factors of Farmers' perception

Variable	VIF(x_i)	1/VIF	Remark
Farming experience	1.56	0.639	Less co-collinearity
Gender	1.09	0.921	’’ ’’
Active labour force	1.40	0.716	’’ ’’
Education level	1.36	0.734	’’ ’’
Livestock holding	1.86	0.538	’’ ’’
Farm revenue (ln)	2.08	0.481	Moderate co-collinearity
Non-farm income (ln)	1.14	0.875	Less co-collinearity
Cultivated land size	2.10	0.477	Less co-collinearity
Training	1.35	0.742	Less co-collinearity
Extension service	1.31	0.0.761	Less co-collinearity
Land market	1.15	0.869	’’ ’’
Plot distance	1.30	0.767	’’ ’’
Slope status moderate	1.35	0.742	’’ ’’
Slop status steep	1.46	0.684	’’ ’’
Top soil erosion	1.23	0.814	’’ ’’
Moderate soil erosion	1.34	0.745	’’ ’’
Erosion high	1.35	0.741	’’ ’’
Soil fertility low	2.53	0.396	Moderate co-collinearity
Soil fertility moderate	2.14	0.468	Moderate co-collinearity
Soil quality low	1.98	0.506	Less co-collinearity
Soil quality moderate	1.80	0.556	’’ ’’
Farm plot location	1.13	0.884	’’ ’’
Community bylaws	1.13	0.885	’’ ’’
Incentive	1.38	0.723	’’ ’’
Land certificate	1.96	0.510	’’ ’’
Tenure arrangement	2.03	0.494	Moderate co-collinearity
Sidama	1.92	0.521	Less co-collinearity
Wolaita	2.36	0.779	Moderate co-collinearity
Mean VIF	1.60		

Note: VIF indicate the variance inflation factor and 1/VIF is the tolerance value of independent variables

Source: Own computation from the household survey,

Appendix Table 2 Hausman specification test for ordered probit model

Variables	Coefficients		(b-B)	Sqrt (diag (V_b-_B))
	(b) consistent	(B) efficient	Difference	standard error
Farming experience	-0.001	-0.001	0	0
Gender	0.178	0.178	0	0
Active labour force	0.024	0.024	0	0
Livestock holding	0.003	0.003	0	0
Farm income (ln)	0.089	0.089	0	0
Non-farm income (ln)	-0.010	-0.010	0	0
Education level	0.031	0.031	0	0
Training	0.289	0.289	0	0
Extension service	0.014	0.014	0	0
Plot distance	0.303	0.303	0	0
Land rental market	-0.211	-0.211	0	0
Cultivated land size	0.247	0.247	0	0
Slope status of plots	0.287	0.287	0	0
Soil fertility status	-0.191	-0.191	0	0
Top soil erosion	0.818	0.818	0	0
Soil erosion severity	0.165	0.165	0	0
Soil quality	0.498	0.498	0	0
Farm plot location	0.191	0.191	0	0
Land certificate	0.103	0.103	0	0
Community bylaws	0.333	0.333	0	0
Incentive	0.356	0.356	0	0
Tenure arrangement	-0.188	-0.188	0	0
Sidama	-0.387	-0.387	0	0
Wolaita	-0.517	-0.517	0	0

b = Consistent under Ho and Ha; obtained from oprobit
B = Inconsistent under Ha, efficient under Ho; obtained from oprobit

Test of H0: Difference in coefficients not systematic

chi2 (0) = (b-B)'[(V_b-V_B) ^ (-1)] (b-B) = 0.000

Prob > chi2 = .

(V_b-V_B is not positive definite), Thus model fitted on the data meet the asymptotic assumption of the Hausman test (no endogeneity problem).

Source: Own computation from the household survey, 2022

Appendix Table 3 Parameter estimation and marginal effects (restricted OPM)

Variable	Coefficients (Robust SE)	Prob (prcpn =1) dy/dx (SE)	Prob (prcpn =2) dy/dx (SE)	Prob (prcpn =3) dy/dx (SE)
Education level	0.034 (0.017)**	-0.006(0.003)**	-0.007 (0.004)*	0.013 (0.006)**
Cultivated land size	0.403 (.122)***	-0.071(.022)***	-0.08 (0.026)***	0.151(0.046)***
Training	0.324 (0.132)**	-0.064(0.029)**	-0.061 (0.024)**	0.125 (0.051)**
Plot distance	0.345(0.168)**	-0.061 (0.029)**	-0.069 (0.035)*	0.130 (0.063)**
Land market	-0.214 (0.124)*	0.038 (0.022)*	0.043 (0.025)*	-0.080 (0.046)*
Slope_moderate	0.271 (0.128)**	-0.048 (0.023)**	-0.054(0.026)**	0.102 (0.048)**
Slope_steep	0.582(0.207)***	-0.077(.021)***	-0.119(.041)***	0.196(0.060)***
Fertility_moderate	0.222 (0.137)	-0.042 (0.028)	-0.043 (0.026)*	0.085 (0.053)
Soil erosion	0.787(0.141)***	-0.18 (0.04)***	-0.124 (.021)***	0.304(0.053)***
Erosion severity_mod	0.301 (0.122)**	-0.052(0.022)**	-0.060 (0.025)**	0.112 (0.045)**
Soil quality_low	-0.62 (0.233)***	0.147 (0.071)**	0.096(0.024)***	-0.242 (0.09)***
Soil quality_modertae	-0.556(0.149)***	0.085(0.022)***	0.113(0.031)***	0.197(0.049)***
Land certificate	0.302 (0.192)	-0.062 (0.045)	-0.055 (0.032)*	0.117 (0.076)
Community bylaw	0.325(0.122)***	-0.057(.022)***	-0.064 (.025)***	0.121(0.045)***
Incentive	0.256 (0.154)*	-0.050 (0.032)	-0.049 (0.028)*	0.099 (0.060)*
Wolaita	-0.254 (0.137)*	0.047 (0.027)*	0.049 (0.026)*	-0.096(0.053)*
Cut 1/μ_1	0.831 (0.311)***			
Cut 2/μ_2	1.764(0.322)***			
Log likelihood	-370.97			
Wald chi2 (16)	122.58***			
LR chi2 (12)	13.19 (p= 0.356)			
No. of observation	475	475	475	475
Predicted probability		10.1	26.4	63.5

Notes: *** p<0.01, ** p<0.05 and * p<0.1
Source: Own computation from the data, 2022

Appendix Table 4 Marginal effects of perception level of households across the study areas

Variable	Marginal effect (Sidama case)			Marginal effect (Wolaita case)			Marginal effect (Siltie case)		
	Low = 1	Medium = 2	High =3	Low = 1	Medium = 2	High =3	Low = 1	Medium= 2	High =3
Farming experience	0.0001(.002)	.0001(.001)	-.0001(.003)	.0001 (.002)	0.00(.001)	-.0001(.003)	0.00 (.001)	.0001(.001)	-.0001(.003)
Gender	-0.03(0.06)	-0.02 (0.04)	0.06 (0.10)	-0.04 (0.07)	-0.02 (0.03)	0.06 (0.10)	-0.03 (0.05)	-0.03 (0.05)	0.05 (0.10)
Active labour force	-0.01(0.01)	-0.01(0.01)	0.01 (0.02)	-0.01 (0.01)	-0.01(0.01)	0.01 (0.02)	-0.01(.01)	-0.01(0.01)	0.01 (0.01)
Education level	-0.01(.004)*	-0.01(.004)*	0.01(.007)*	-0.01(0.05)*	-0.01(0.03)*	0.01(0.01)*	-0.01(.003)*	-.01(.004)*	0.01(0.01)*
Livestock holding	0.00 (0.01)	0.00 (0.01)	0.0001(.01)	0.00 (0.01)	0.00 (0.01)	0.0001(0.01)	0.00 (.01)	0.00 (0.01)	0.0001(.01)
Farm revenue (ln)	-0.02(0.03)	-0.02 (0.02)	0.04 (0.05)	-0.02 (0.03)	-0.01(0.02)	0.04 (0.05)	-0.02 (0.02)	-0.02(0.02)	0.03 (0.04)
Nonfarm income (ln)	0.002 (0.003)	0.002(.003)	-0.004(.01)	0.003(.004)	0.002(.002)	-0.005 (0.01)	0.002(.003)	0.002(.003)	0.004(.01)
Land size	-0.06(0.03)*	-0.05(0.03)*	0.11 (.06)*	-0.07(0.04)*	-0.05(0.03)*	0.11 (0.06)*	-0.05(0.03)*	-0.06(.03)*	0.11(0.06)*
Training	-0.06 (0.04)*	-0.05(0.02)*	0.11 (.06)*	-0.07(0.04)*	-0.04(0.02)*	0.11 (0.06)*	-0.05(0.03)*	-0.05(.03)*	0.11(.06)*
Extension service	-0.004 (0.05)	-0.003(0.04)	0.01 (0.10)	-0.004(0.06)	-0.003(0.04)	0.01(0.10)	-0.003(0.04)	-0.004(0.05)	0.01 (0.09)
Land market	0.05 (0.03)*	0.04 (0.02)*	-0.09(.05)*	0.05 (0.03)*	0.04 (0.02)*	-0.09 (0.05)*	0.04(0.02)*	0.05(0.03)*	-0.08(.05)*
Plot distance	-0.06 (0.04)*	-0.05(0.03)	0.12(0.07)*	-0.07(0.04)*	-0.05 (0.03)	0.12(0.07)*	-0.05(0.03)*	-0.06(.04)*	0.11(.06)*
Slope_ moderate	-0.07(0.03)**	-0.06(.02)**	0.13(.05)**	-0.08(.04)**	-0.05(.02)**	0.13 (.05)**	-0.06(.02)**	-.07(.03)**	0.12(.05)**
Slope status_ steep	-0.09(.04)***	-0.11(.05)**	.21(.08)***	-.11(.04)***	-0.11(.05)**	0.21(.08)***	-.07(.02)***	-.12(.05)**	.19(.07)***
Soil fertility_low	-0.06 (0.04)	-0.07 (0.06)	0.13 (0.10)	-0.07 (0.05)	-0.06 (0.05)	0.13 (0.1)	-0.05 (0.03)	-0.07 (0.06)	0.12(0.09)
Soilfertility_modrt	-0.08 (0.04)*	-0.06(.03)**	0.14(.07)**	-0.09(0.05)*	-0.05(.02)**	0.14 (0.07)**	-0.07(0.04)*	-0.07(.03)**	0.13(.07)**
Top soil erosion	-0.19(.05)***	-0.1(0.03)***	.29(.05)***	-.21(.06)***	-0.08(.03)**	0.28(.05)***	-.16(.04)***	-0.12(.02)***	.28(.06)***
Erosion_moderate	-0.07(.03)***	-0.06(.03)**	.14(.05)***	-0.08(.03)**	-0.06(.03)**	0.14 (0.05)**	-0.06(.02)**	-0.07(.03)**	0.13(.05)**
Erosion_high	-0.04 (0.04)	-0.05 (0.05)	0.09 (0.08)	-0.05 (0.04)	-0.04 (0.05)	0.09 (0.09)	-0.04 (0.03)	-0.05 (0.05)	0.08 (0.08)
Soil quality_low	0.25(0.11)**	0.08 (0.04)**	-.33(.1)***	-0.27(.11)**	0.05 (0.04)	-0.32(.09)***	0.22(.1)**	.11(.02)***	-.33(.1)***
Soil quality_modrt	0.12(.03)***	0.13(0.04)***	-.25(.06)***	.14(.04)***	.12(.04)***	-0.26(.06)***	0.1(.02)***	.14(.03)***	-.24(.05)***
Farm plot location	-0.04 (0.03)	-0.03 (0.02)	0.07 (0.05)	-0.04 (0.03)	-0.03 (0.02)	0.07 (0.05)	-0.03 (0.02)	-0.04 (0.03)	0.07 (0.05)
Land certificate	-0.13 (0.08)*	-0.07(.03)**	0.2 (0.1)**	-0.14(0.08)*	-0.05(.03)*	0.20 (0.09)**	-0.11(0.07)*	-0.09(.03)**	0.02(0.1)**
Community bylaw	-0.07(0.03)**	-0.06(.02)**	.13(.05)***	-0.08(.03)**	-0.05(.02)**	0.13 (0.05)**	-0.06(.02)**	-0.07(.03)**	0.12(.05)**
Incentive	-0.11 (0.06)*	-.07(.02)***	0.17(.07)**	-0.12(.06)**	-.06(.02)***	0.17 (0.07)**	-0.09(.04)**	-0.08(.03)**	0.17(.07)**
Tenure arrangement	0.06 (0.03)*	0.07 (0.05)	-0.13(0.08)	0.07 (0.04)*	0.06 (0.05)	-0.13 (0.08)	0.05 (0.04)	0.07 (0.05)	-0.12(0.08)
Sidama	0.05 (0.04)	0.06 (0.04)	0.11 (0.08)	0.07 (0.06)	0.04 (0.03)	-0.11 (0.09)	0.05 (0.04)	0.06 (0.04)	-0.11(.08)
Wolaita	0.10 (0.06)	0.07 (.03)**	-0.16(.09)*	0.08 (.04)*	0.08 (.04)**	-0.16 (0.08)*	0.08 (0.04)*	0.08(.04)**	-0.16(.08)*
Predicted probability	0.130	0.302	0.568	0.153	0.319	0.527	0.097	0.268	0.636

Note: * **, ** and * indicates p < 0.01, p < 0.05 and p < 0.1, respectively, the parentheses indicate the standard error

Appendix Table 5 Vuong test of model specification of truncated and lognormal hurdle models

Source	SS	df	MS		Number of observation = 365
Model	0	0	.		F(0,364) = 0.0, Prob > F =.
Residual	1058.862	364	2.909		R-squared = 0.000
Total	1058.862	364	2.909		Adj R-squared = 0.000
					Root MSE = 1.7056
Dif_1	Coefficient	std.err.	t	P>|t|	[95% conf. interval]
Constant	0.479	0.089	5.37	0.000	-0.304 0.655

Source: Own computation from the household survey, 2022

Appendix Table 6 Heckman estimation output of SLM participation selection model

Variables	SLM participation decision		Enrollment decision	
	Coefficients	SE	Coefficients	SE
Farming experience	-0.006	0.015	-0.007*	0.004
Gender	1.083*	0.573	-0.051	0.146
Household size	0.019	0.069	-0.008	0.014
Dependency ratio	0.040	0.101	0.003	0.030
Education level	-0.031	0.035	-0.041***	0.009
Social network	2.105***	0.288	-0.171	0.156
Perception index	3.831***	0.616	-0.342	0.237
Land size	0.449	0.331	--	
Livestock holding	0.064	0.083	-0.003	0.013
Cultivated farmland	---		0.434***	0.087
Farm income (ln)	0.283	0.269	-0.054	0.072
Non-farm income (ln)	-0.057*	0.031	0.007	0.007
Crop value (ln)	-0.711*	0.382	0.499***	0.097
Training	0.355	0.282	0.197**	0.082
Extension contact	0.323**	0.132	-0.062**	0.029
Land market	-0.586**	0.293	-0.112*	0.064
Road distance	0.021	0.036	0.042***	0.009
Community bylaws	-0.109	0.322	0.241***	0.066
Incentive	0.319	0.311	-0.034	0.069
Farm location	0.932***	0.272	-0.053	0.070
Soil fertility status index	1.198**	0.600	-0.035	0.134
Plot slope status	0.434**	0.220	-0.067	0.048
Soil erosion	0.785***	0.300	0.175*	0.105
Constant	-2.590	2.809	-5.442***	0.849
Mills/Lambda (λ)			-0.256	0.174
Rho ($\hat{\boldsymbol{\rho}}$)			-0.452	
Sigma ($\hat{\boldsymbol{\sigma}}$)			0.566	
Wald chi2 (22)		327.11 (p = 0.000)		

Note: *** p<0.01, ** p<0.05, * p<0.1; SE is standard errors
Source: Own computation from the household survey, 2022

Appendix Table 7 Lognormal hurdles and Heckman model estimates of SLM participation

Model	Lognormal Truncated Hurdle		Exponential Type II Tobit	
	Coefficient	dy/dx	Coefficient	dy/dx
Selection equation				
Dependent variable	SLM participation		SLM participation	
Farming experience	-0.006 (0.015)	0.000 (0.001)	-0.010 (0.016)	-0.001 (0.001)
Gender	1.083 (0.483)**	0.083 (0.036)	1.089 (0.468)**	0.083 (0.034)
Household size	0.019 (0.061)	0.001 (0.005)	0.020 (0.062)	0.002 (0.005)
Dependency ratio	0.040 (0.099)	0.003 (0.008)	0.045 (0.096)	0.003 (0.007)
Education level	-0.031 (0.042)	-0.002 (0.003)	-0.030 (0.043)	-0.002 (0.003)
Social network	2.105(0.279)***	0.161 (0.014)	2.10 (0.289)***	0.159 (0.014)
Perception index	3.831 (0.67)***	0.292 (0.042)	3.901(0.685)***	0.296 (0.042)
Land size	0.449 (0.25)*	0.034 (0.019)	0.475 (0.258)*	0.036 (0.019)
Livestock holding	0.064 (0.064)	0.005 (0.005)	0.065 (0.062)	0.005 (0.005)
Farm income (ln)	0.283 (0.274)	0.022 (0.021)	0.257 (0.272)	0.020 (0.021)
Non-farm income (ln)	-0.057 (0.029)*	-0.004 (0.002)	0.058 (0.029)**	-0.004 (0.002)
Crop value (ln)	-0.711(0.358)**	-0.054 (0.026)	-0.697(0.355)**	-0.053 (0.025)
Training	0.355 (0.264)	0.027 (0.02)	0.365 (0.257)	0.028 (0.020)
Extension contact	0.323 (0.12)***	0.025 (0.009)	0.317(0.121)***	0.024 (0.009)
Land market	-0.586(.221)***	-0.045 (0.017)	-.585(0.222)***	-0.044 (0.017)
Road distance	0.021 (0.031)	0.002 (0.002)	0.020 (0.031)	0.002 (0.002)
Community bylaws	-0.109 (0.281)	-0.008 (0.021)	-0.167 (0.290)	-0.013 (0.022)
Incentive	0.319 (0.307)	0.024 (0.023)	0.304 (0.302)	0.023 (0.023)
Farm location	-0.932(.254)***	0.071 (0.017)	-0.940(.251)***	0.071 (0.017)
Soil fertility index	1.198 (0.513)**	0.091(0.036)	1.264(0.509)**	0.096 (0.035)
Slope status of plots	0.434 (0.188)**	0.033 (0.014)	0.441 (0.184)**	0.033 (0.014)
Soil erosion	0.785(0.255)***	0.060 (0.021)	0.763(0.260)***	0.058 (0.021)
Constant	-2.590 (2.643)		-2.495 (2.630)	
Value equation				
Dependent variable	ln (SLM land size)		ln (SLM land size)	
Farming experience	-0.007 (0.004)*	-0.003 (0.001)	-0.007 (0.004)*	-0.007 (0.004)
Gender	-0.028 (0.136)	0.019 (0.047)	-0.043 (0.138)	-0.043(0.138)
Household size	-0.008 (0.014)	-0.002 (0.005)	-0.008 (0.015)	-0.008(.015)
Dependency ratio	0.003 (0.031)	0.002 (0.011)	0.003 (0.031)	0.003 (0.031)
Education level	-0.042(.008)***	-0.015 (0.003)	-0.042(.008)***	-0.042(.008)
Social network	-0.021 (0.134)	0.048(0.044)	-0.117 (0.164)	-0.117(.164)
Perception index	-0.167 (0.206)	0.044 (0.068)	-0.277 (0.225)	0.277 (0.225)
Cultivated farm size	0.439(.089)***	0.150 (0.032)	0.437(0.089)***	0.437 (0.089)
Livestock holding	-0.002 (0.013)	0.001 (0.004)	-0.003 (0.013)	-0.003(.013)
Farm income (ln)	-0.051 (0.076)	-0.010 (0.026)	-0.054 (0.077)	-0.054(.077)
Non-farm income (ln)	-0.006 (0.007)	0.001 (0.003)	0.007 (0.007)	0.007 (0.007)
Crop value (ln)	0.501(0.091)***	0.152 (0.033)	0.501(0.091)***	0.501 (0.091)
Training	0.209 (0.087)**	0.081 (0.030)	0.201 (0.087)**	0.201 (0.087)

Extension contact	-0.054 (0.031)*	-0.010 (0.011)	-0.059 (0.032)*	-0.059(.032)
Land market	-0.125 (0.064)*	-0.058 (0.023)	-0.117 (0.064)*	-0.117(.064)
Road distance	0.043(0.009)***	0.015 (0.003)	0.042(0.009)***	0.042 (0.009)
Community bylaws	0.239 (0.066)***	0.079 (0.024)	0.24 (0.066)***	0.24 (0.066)
Incentive	-0.038 (0.07)	-0.004 (0.026)	-0.036 (0.070)	-0.036 (0.07)
Farm location	0.032 (0.072)	-0.013 (0.024)	0.046 (0.073)	0.046(0.073)
Soil fertility index	-0.001 (0.130)	0.031 (0.046)	-0.021 (0.130)	-0.021(0.13)
Slope status of plots	-0.053 (0.048)	-0.007 (0.017)	-0.062 (0.049)	-0.062(.049)
Soil erosion	0.188 (0.114)*	0.085 (0.039)	0.178 (0.115)	0.178 (0.115)
Constant	-5.887(.756)***		-5.596(.797)***	
Observation	475		475	
/sigma ($\hat{\boldsymbol{\sigma}}$)	0.562 (0.020)***		0.563(0.021)***	
Log-likelihood	40.228		40.674	
Wald chi2 (22)	486.41(p=0.000)		465.21 (P = 0.000)	
Pseudo R^2	0.551		0.560	
Mills|Lambda (λ)			-0.165 (0.112)	
Athrho/$\hat{\boldsymbol{\rho}}$			-0.302(0.215)	
Vuong test	t = 5.37*** (p = 0.000)			

Notes: ***, ** and * are significant at 1%, 5% and 10% probability level.
The robust standard errors indicated in parentheses
Wald test of independent equations (rho=0): chi2 (1) = 1.97; Prob > chi2 = 0.160
Source: Own computation from the household survey data, 2022

Appendix Table 8 List and prioritized SWC measures implemented at the study areas

SWC measures	Arbegona	Malega	Boloso Bombe	Boloso Sore	Hulbareg	Dalocha	Average score point (%)	Rank
No of FGDs	4	4	4	4	4	4		
Number of discussants	46	40	38	40	40	36		
			Applied SWC measures in Percent (%)					
Level soil bund with trench	71.74	62.50	84.21	80.00	85.00	91.67	79.19	3
Level *Fanya juu*	86.96	75.00	86.84	85.00	80.00	80.56	82.39	2
Bench terrace	89.13	70.00	89.47	82.50	55.00	50.00	72.68	4
Indigenous SWC	93.48	90.00	86.84	90.00	80.00	83.33	87.28	1
Stone faced soil bund	0.00	0.00	2.63	2.50	7.50	8.33	3.49	7
Check dam	4.65	5.00	5.26	7.50	7.50	5.56	5.91	6
Trench bund	4.35	7.50	7.89	7.50	5.00	5.56	6.30	5
Conservation agriculture	2.17	2.50	0.00	2.50	0.00	0.00	1.20	8

Source: Own computation from the FGDs, 2022

Note: On average 40 selected FGD discussants were participated at each woreda of the study areas.

Appendix Table 9 Estimated propensity score and matched observations

Analysis level	Description	Observations	Estimated propensity score			
			Mean	Std.dev.	Smallest	Largest
Household level	No. of households in the common support	473	0.770	0.204	0.0761	0.9999
	Treated	365	0.826	0.153	0.0761	0.9999
	Non-treated	110	0.572	0.248	0.0169	0.9744
	Number of on-support	420 (88.42%)				
	Number of off-support	55 (11.58%)				
	Treated	55				
	Non-treated	0				
Plot level	No. of plots in the common support	1172	0.752	0.203	0.0943	0.9999
	Treated	857	0.808	0.168	0.0943	0.9999
	Non-treated	315	0.574	0.218	0.0413	0.9845
	Number of on-support Plots	1172 (93.24%)				
	Number of off-support	85 (6.76%)				
	Treated	85				
	Non-treated	0				

Source: Own computation, 2022

Appendix Table 10 Impacts of SLM on value of crop produced (ESR model result)

Variables	First stage (selection)		Second stage ESR estimation					
			User			Non- user		
	Coef.	Rob. Std.err	Coef.	Rob. Std.err	t	Coef.	Robust Std.err	t
Gender	0.409	0.385	0.102	0.075	1.37	-0.129	0.151	-0.86
Household size	-0.024	0.053	0.006	0.009	0.74	-0.008	0.025	-0.34
Educational level	-0.032	0.025	0.011**	0.005	2.12	0.032**	0.013	2.50
Farmingexperience	-0.006	0.013	-0.002	0.002	-0.87	0.005	0.005	1.03
Active family size	-0.004	0.068	0.001	0.013	0.07	0.002	0.027	0.08
Livestock holding	0.034	0.060	0.009	0.007	1.20	0.029	0.030	0.97
Cultivated land	0.503 *	0.256	.578***	0.041	14.2	0.573***	0.176	3.25
Off-farm income	-0.222	0.190	0.020	0.038	0.52	-0.032	0.111	-0.29
Crop choice	2.827***	0.371	0.124*	0.075	1.65	0.348	1.197	0.29
Extension service	0.533	0.335	0.072	0.117	0.62	0.121	0.153	0.79
Fertilizer use	1.041***	0.297	0.016	0.154	0.10	0.148	0.209	0.71
Improved seed use	0.250	0.320	0.054	0.054	0.98	-0.156	0.135	-1.15
Incentive	-0.166	0.232	-0.047	0.049	-0.97	-0.036	0.115	-0.31
Main road distance	-0.013	0.032	-.019***	0.006	-3.03	-0.024	0.015	-1.54
Market distance	0.037	0.027	0.005	0.006	0.94	0.009	0.014	0.67
Plot distance	0.492	0.406	0.112***	0.039	2.83	0.125	0.270	0.46
Farm plot location	0.598***	0.195	0.089**	0.044	2.04	0.076	0.150	0.51
Erosion severity	0.490 **	0.173	0.053*	0.032	1.66	-0.047	0.136	-0.35
Slope index	0.244	0.512	.249***	0.086	2.90	0.085	0.271	0.31
Degraded infertile soil proportion	0.257	0.418	-0.102	0.068	-1.49	0.121	0.217	0.56
Land certificate	-0.145	0.382	0.102	0.079	1.28	-0.016	0.166	-0.10
Agro ecology	-0.134	0.330	-.521***	0.061	-8.57	-.561***	0.167	-3.35
Perceived rainfall intensity	0.359**	0.148	-0.038	0.025	-1.54	-0.056	0.098	-0.57
Inverse mills ratio			0.085	0.106	0.80	-0.088	0.349	-0.25
Constant	-4.119***	1.004	9.345***	0.283	32.9	9.643***	0.485	19.87
No.of observations	475		365			110		
Wald chi2(23) value	191.08							
F(24, 340)			39.12					
Prob > chi2/F	0.0000		0.000			0.000		
Pseudo R2	0.558		0.720			0.621		
Root MSE			0.327			0.426		
Log likelihood	-113.61							

Note: ***, ** and * indicates significant at the 1%, 5% and 10% probability levels, respectively.
Source: Own computation from field survey, 2022.

Appendix Table 11 Impacts of SLM on farm income (ESR model result)

Variables	First stage (selection)		Second stage ESR estimation					
			User			Non- user		
	Coef.	Rob. Std.err	Coef.	Rob. Std.err.	t	Coef.	Rob. Std.err.	t
Gender	0.409	0.385	0.065	0.124	0.52	-0.191	0.257	-0.74
Household size	-0.024	0.053	-0.012	0.014	-0.90	0.009	0.031	0.29
Educational level	-0.032	0.025	0.006	0.008	0.75	0.048	0.021	2.25
Farmingexperience	-0.006	0.013	-0.002	0.004	-0.48	-0.004	0.008	-0.52
Active family size	-0.004	0.068	0.012	0.019	0.61	0.006	0.046	0.12
Livestock holding	0.034	0.060	0.073***	0.013	5.80	0.165	0.044	3.79
Cultivated land	0.503 *	0.256	0.483***	0.062	7.81	-0.015	0.238	-0.06
Off-farm income	-0.222	0.190	-0.004	0.056	-0.08	0.091	0.158	0.58
Crop choice	2.827***	0.371	0.033	0.109	0.31	-2.744	1.740	-1.58
Extension service	0.533	0.335	-0.122	0.115	-1.06	0.033	0.201	0.17
Fertilizer use	1.041***	0.297	-0.195	0.281	-0.69	-0.432	0.330	-1.31
Improved seed use	0.250	0.320	0.074	0.094	0.79	-0.075	0.242	-0.31
Incentive	-0.166	0.232	0.015	0.077	0.20	0.377	0.167	2.26
Main road distance	-0.013	0.032	-0.025**	0.011	-2.37	-0.044	0.028	-1.59
Market distance	0.037	0.027	0.004	0.008	0.49	0.026	0.021	1.27
Plot distance	0.492	0.406	0.150***	0.054	2.79	0.314	0.495	0.64
Farm plot location	0.598***	0.195	0.080	0.064	1.24	-0.062	0.216	-0.29
Erosion severity	0.490 **	0.173	0.042	0.044	0.96	-0.351	0.211	-1.66
Slope index	0.244	0.512	0.124	0.139	0.89	-0.220	0.369	-0.60
Degraded infertile soil proportion	0.257	0.418	-0.096	0.119	-0.81	0.553	0.377	1.47
Land certificate	-0.145	0.382	0.349***	0.113	3.10	0.474	0.230	2.06
Agro ecology	-0.134	0.330	-.225***	0.083	-2.71	-0.631	0.255	-2.48
Perceived rainfall intensity	0.359 **	0.148	0.027	0.035	0.76	-0.100	0.145	-0.69
Inverse mills ratio			0.137	0.156	0.88	-0.692	0.577	-1.20
Constant	-4.119***	1.004	8.839***	0.423	20.91	9.501***	0.822	11.56
No.of observations	475		365			110		
Wald chi2(23) value	191.08							
F(24, 340)			14.01					
Prob > chi2/F	0		0			0		
R-squared	0.558		0.544			0.503		
Root MSE			0.494			0.622		
Log likelihood	-113.61							

Note: ***, ** and * significant at the 1%, 5% and 10% probability levels, respectively.
Source: Own computation from field survey, 2022.

Appendix 2: Household Survey Questionnaire

Smallholder Farmers Participation in Sustainable Land Management Practices and Its Impact on Crop Production and Farm Income in Densely Populated Areas of Southern Ethiopia

PhD Dissertation

Household Survey Questionnaire

Household head name ---------------------------

Questionnaire no. ------------------------------

Instruction for enumerators

1. Introduce yourself and inform the purpose of the study to the respective respondents
2. Before starting the interview check whether the respondent is sample farmer or not
3. Check the questionnaire pages before starting interview and use pencil to fill the response
4. Read, understand, ask each question and write the responds on the blank spaces provided
5. Don’t fill on the shaded blank cell
6. At the end of the interview acknowledge the respondent politely.

General information

Classifying information	Response(Answer)		
Respondent name if different from HH head		Phone no. (Mobile):	
Name of the enumerator		Sig.	Date of the interview
Zone			
Sample woreda name			
Sample kebele Name			
Geo-reference information (coordinates)	Altitude (m asl)	Latitude (N)	Longitude (E)
Wealth status of the household head	Poor	Average	Rich
Agro-climatic zone (traditional)	High land (*dega*)	Midland (*woinadega)*	Low land (*kola*)
Participant in SLMP-II (2013 to 2018)	-------- Yes	-------- No	(tick X)

Part I. Demographic and socioeconomic characteristics of sample households

1. Sex of the household head (respondent) ----------- 1. Male, 0. Female
2. Age of the respondent ------------------ (Yrs.)
3. Marital status -------------- 1. Single, 2. Married, 3. Divorced, 4. Widowed, 5.Widower
4. Family size in number and gender in year 2020

Age category	Male	Female	Total	Hired farm labourer	Sex
Below 10 years					
10 to 14 years					
15 to 64 years					
Above 64 years					
Total family size					

5. Attended education level of the sample farm household in years of schooling ------------
6. Social position of the respondent in the *kebele* --------- 1. Simply member, 2. Model farmer, 3. *Kebele* council member, 4. Religious leader, 5. Elder (recognized), 6. Committee member, 7. Other
7. Major occupation of the household head ------- 1. Farming, 2. Business man, 3. Other (specify) ---
8. What is your major livelihood source? ----- 1. Crop production, 2. Animal rearing, 3. Mixed (crop and livestock), 4. Off-farm activity, 5. Non-farm activity, 6. Other (specify) ---------------------
9. What is your second major livelihood activity? ----- 1. Crop cultivation, 2. Animal rearing, 3. Off-farm activity, 4. Non-farm activity, 5. Other (specify) ------------------------------------
10. Have you/ family member involved in off-farm/non-agricultural activity? 1. Yes, 0. No.
11. If yes, what was the activity (multiple answers possible)? - 1. Fuel wood sale, 2. Casual labour, 3. Charcoal making, 4. Sale of grass, 5. Pity trade, 6. Handicraft, 7. Broker, 8. Employee, 9. Other----
12. The income obtained in off-farm/non-agricultural activity in 2020 (2011/12) ------- ETB
13. For how many years the household head living in this *kebel*e? ---------------------- years
14. Farming experience of the sample household head in years ----------- or since ----------E.C.
15. Land ownership and use right status ---- 1. State, individual titled, 2. State, non-titled (family), 3. State, non-titled (rent in), 4. State, non-titled (share in), 5. State (communal) 6. Other ----------------
16. If state and titled, do you have land certificate? ------------- 1.Yes, 0. No

Part II. Institutional and social services affecting households' participation of SLM

1. Have you got extension advice on SLM particularly on SWC for the last five years? ---1. Yes, 0. No
2. If yes, would you tell us the average number of extension contacts within a month?--- days
3. Have you got training on SLM particularly on SWC measures in the last five years? ---1.Yes, 0. No
4. If yes, on average for how many days you took annually? ---------- days/year
5. Have you received a credit service for SWC measures over the last five years?1.Yes, 0. No
6. If yes, on average how much you got annually during 2013 -2018? ---------------- Birr
7. Was there community bylaws to implement SLM specifically on-farm SWC? 1. Yes, 0. No
8. If yes, could you tell us the community bylaw that was enforced? -----------, -----------------
9. Was there a community bylaw to maintain on-farm SWC in the last five years?1.Yes, 0.No
10. If yes, could you tell us the bylaws that enforced to maintain on-farm SWC?-------, ---------
11. Was there NGOs/project involvement in introducing and applying on-farm SWC measures? --- 1. Yes, 0. No
12. If yes, name of the NGOs/project -----------, --------, Project benefit -------, ------------------
13. Have you participated in land rental market for the last five years? ------ 1. Yes, 0. No
14. If yes, what was the land rental market you involved? ----- 1. Land rent in, 2. Land rent out, 3. Crop share in, 4. Crop share out, 5. Others --------------------------
15. If yes to question 13, why you participated? --
16. Would you tell us your accessibility to the following services?

Institutional, social and infrastructural service type	Accessibility 1. Yes, 0.No	If yes, distance in		Additional Notes
		Minutes	km	
Rural road (all weathered and dry season)				
Main market (woreda and nearby markets)				
Extension office (FTC)				
Rural credit (specify ---------------------)				
Health service				
Formal education (schooling)				

Part III. Biophysical attributes of farm households farm plots

1. Framing system of the *kebele* where the household located------ 1. Crop. 2. Livestock, 3. Mixed
2. Farm plot location of the household in a watershed --- 1. Upper, 2. Downstream
3. Would you tell us the current (2020) land use of your owned & managed farm land (titled) info?

Land use type	Area in *timad*[16]	No. of plot	Plot* Name	Plot Size (*timad*)	Distance from homestead	
					Walking minutes	Km
Total cultivated land						
Annual cropping						
Perennial cropping						
Trees and shrub cropping						
Grazing land						
Forest/woodlands						
Other use (specify)						
Total						

*Consider only cultivated plots utilized for cropping

4. The average fertility level of farm plots (¾th or 75% of the plots owned & managed) -------
   1. Less fertile and degraded (infertile), 2. Moderately fertile, 3. Highly fertile
5. Proportion of owned and managed farm plot with respect to slope gradient

Slope gradient	Slope		No. of plots	Average proportion from the whole	
	Degree	Percent		In %	*Timad*
Flat to gentle (0-5%)	1-3	2-5			
Moderate (6-30%)	5-17	8-30			
Steep slope(>31- 0%)	31-45	60-100			

6. Soil quality of owned plot (in terms of fertility, depth, workability) 1. Poor, 2. Moderate, 3. Good

[16] *Timad* is a local unit to measure area of farmland, 1 *timad* is equivalent to 0.25 ha

7. The top soil texture type of majority of the farm plots ------- 1. Sandy (coarse/light), 2. Loamy silty (medium), 3. Clay (fine/heavy) 4. Clay loamy, 5. Clay sandy, 6. Other (specify) -------------------
8. The average soil depth of the main farm plots - 1. Very shallow (0-20 cm), 2. Shallow (21-50 cm), 3. Moderately deep (51-80 cm), 4. Deep (81-120 cm), 5. Very deep (> 120 cm)
9. Type of owned farm plots in terms of water source (>50%) -- 1.Rainfed, 2.Irrigated 3. Mixed (1&2)

Part IV. Farmers' perception about the role of SLM practices

1. Did you perceived land degradation problems of land resources (soil, vegetation and water) in your owned managed farm plots?--- 1. Yes, 0. No

2. If yes, would you tell us the detail of land degradation occurring in your farmland?

Land degradation type	Presence 1.Yes, 0.No	Since when[17]	Causes [18]	Severity 1.high, 2.Medium, 3. Low	Impacts[19]
Soil erosion					
Loss of top soil					
Gulley erosion					
Landslide					
Offsite erosion including flooding[20]					
Physical soil deterioration					
Compaction					
Water logging					

[17] 1. > 50 years , 2. 25-50 years, 3. < 25 years, 4. < 7 years (2013 to 2018)

[18] 1. Agricultural expansion/population pressure 2. Tenure change/problems, 3. Inappropriate land use/farming Practice, 4. Expansion for investment, 5.Need for fuel and construction wood, 6. Frequent farming, 7. Rugged topography nature of the farmland and excessive rainfall, 8. Others --------------------. -------------------------------, -------------------------------

[19] 1. Crop yield decline, 2. Reduced animal herds, 3. Loss of asset, 4, Reduced water availability, 5. Loss of human lives, 6. Farmland became totally unproductive/abandoned, 7. Exposes the land to be stony and dry, 8. *Others* --

[20] Deposition of sediments, downstream flooding and pollution of water bodies

Chemical soil degradation					
Fertility decline					
Salinization/alkalinization					
Acidification					
Biological degradation					
Deforestation					
Reduce of vegetation cover					
Overgrazing					

3. Have you taken any measure to alleviate the problems you faced? 1. Yes, 0. No
4. If yes, what type of measures you took? 1. Traditional SWC measures, 2. Improved SWC measures, 3. Combination of both measures, 4. Traditional, Improved SWC and enclosing areas, 5. Other ----
5. Do you perceive that SLM practices specifically SWC measures are important in combating land degradation, and reducing soil erosion there by improving land productivity? ----- 1. Yes, 0. No.
6. Would you tell us your perception about the positive role of SLM specifically SWC measures and its negative effects on your farm land during 2013-2018?

SLM Role	Perception level [21]
SLM specifically SWC measures prevent and reduce land degradation, rehabilitate land resources (soil, vegetation and water)	
SLM specifically SWC improves production (crop, fiber, fodder)	
SLM reduces risk of disasters (flood, drought, landslides)	
SLM effect	Perception level[22]
SLM specifically SWC creates difficulty during ox ploughing	
SLM specifically SWC harbors rodents and other insects	
SLM specifically SWC competes cultivated land	

7. Would you please tell us your perception about the biophysical plot attributes of your owned plots?

[21] 1. Disagree (low perception), 2. Indifference (medium perception), 3. Agree (high perception)

[22] Agree (low perception), 2. Indifference (medium perception), 3. Disagree (high perception)

Attributes	Biophysical attributes for main farm plots	Respond1: Yes, 0.No	Area in *Timad*	Proportion in %
Slope	Owned farm plots have flat to gentle slope			
	Owned farm plots have moderate slope			
	Owned farm plots have steep slope			
Soil fertility	Owned farm plots have high fertility level			
	Owned farm plots have moderate fertility			
	Owned farm plots have low fertility (degraded infertile)			
Soil depth	Owned farm plots have shallow soil depth			
	Owned farm plots have medium soil depth			
	Owned farm plots have deep soil depth			
Soil color	Do you perceive your farm plot top soil color?		If yes, type of color--	

8. How was soil erosion severity in your owned farm plots during 2013-2018 (respondent's personal perception)? ----- 1. Low, 2. Moderate, 3. High
9. How was soil fertility decline severity in your owned farm plots? ----- 1. Low, 2. Moderate, 3. High
10. If your answer to Q8 and Q9 is moderate and high, what was your perceived indicators for low soil fertility? ------ 1. Declined crop yield/performance, 2. The soil demands high fertilizer, 3. The Soil became unresponsive and stony, 4. Low crop yield and high fertilizer demand, 5. Other ---------------
11. Do you perceive that incentive mechanisms (either in cash or kind) can encourage farmers to involve and implement SLM practices specifically on-farm SWC measures efficiently? -------- 1. Yes, 0. No
12. If yes, which incentive mechanisms you perceive the best? ------- 1. Cash incentive, 2. Kind (farm implements), 3. Kind (food grain and edible oil), 4. Kind (poultry, bull, ram, improved forage) 5. Certificate of recognition, 6. Other -----------------------------------

Part V. **Farmers' participation decision in SLM practices**

1. Have you participated in SLM particularly on-farm SWC measures for the last five years continuously in your owned managed farm plot? -------- 1. Yes, 0. No
2. If you are user of SLM practices, in how much of your owned farmland you applied on farm-SWC? 1. In 25% of plots, 2. In 50% of plots, 3. In 75% of plots, 4. In all the plots (100%), 5. In < 25% of plots, 6. In 37.5% of plot

3. If yes, to equation 1 how much farmland you allocated for on-farm SWC? ---- *timad*
4. What contributes for participation and less/no participation decisions (i.e., participation and land allocation for SLM)?
   a. Soil erosion severity experience on owned farm plots ------------- 1. High, 2. Low/less
   b. Farmers' perceptions and attitudes to SLM functions/role --- 1. Positive, 2. Negative
   c. Access to/provision of extension advice on SLM ------------------ 1. Yes, 0. No
   d. Skill training on SLM functions and importance --------- 1. Yes, 0.No
   e. Presence of functional and enforced community bylaws ------- 1. Yes, 0. No
   f. Availability of incentive mechanisms to implement on-farm SWC 1.Yes, 0.No
   g. Location of the plots in the watershed being ---- 1. Downstream, 2. Upper stream
   h. Higher proportion of farm plots' fertility being- 1. Less to medium 2. Medium to high
   i. Higher proportion of owned farm plots slope to be --- 1. Steep, 2. Flat to moderate
   j. Positive shared experience/social network from nearby neighbor farmers1. Yes, 0. No
   k. Selection process is biased i.e., selection is with interest of kebele's council members 1. Yes, 2. No
   l. Size of farmland determines on-farm SWC measures implementation --- 1. Yes, 0. No
      i. If yes, what contributes for participation? ---------- 1. Relatively large farm size, 2. Small farm size, 3. Medium farm size, 4. Medium to large farm size
      ii. If no, what contributes for no/less participation? ---- 1. Relatively large farm size, 2. Small farm size, 3. Medium farm size, 4. Small to medium farm size

Part VI Farmers' choices of SLM practices

1. Which SLM measures you were applying in your managed land over the last five years (2013-2018)? **(**multiple answers possible**)** ---- 1. Agronomic measures, 2. SWC structural measures, 3. Reforestation and afforestation measures, 4. Integrated soil fertility management, 5. Others ----------
2. If you were using SWC structural measures, would you tell the major integrated SWC measures applied in your cultivated farm land over the last five years?

SWC types	Applied 1. Yes, 0. No	Rank from more to less preferred as 1st, 2nd, 3rd, 4th, 5th …	Supported with stabilizers? (1. Yes, 0.No)
Level *Fanya juu*			
Level soil bund with trench			
Stone faced soil bund			
Bench terrace			

Check dam			
Trench			
Micro basin			
Hill side terrace			
Conservation agriculture			
Forage/grass strip			
Traditional SWC[23]			
Graded soil bund			
Integrated SWC (bund, stabilizer, and others)			

3. Would you tell us your farm plots applied with on-farm SWC measures over the last five years**?**

Plot Id	Local name	1st	2nd	3rd	4th	If yes, age of SWC
		1.Yes, 0.No	1.Yes, 0.No	1.Yes, 0.No	1.Yes, 0.No	

4. What are the biophysical and cost attributes that contributed for the adoption and applying preferred SWC measures (referring to question 3)?

Attributes of plots	1st	2nd	3rd	4th	Remark
	1.Yes, 0.No	1.Yes, 0.No	1.Yes, 0.No	1.Yes, 0.No	
Soil erosion severity level					
Low					
Moderate					
High					
Soil Fertility level					
Degraded infertile					
Moderate					
High (fertile)					
Slope gradient					
Flat to gentle					
Moderate					
Steep					
Rainfall intensity (perceived)					
Low					
Moderate					
High					

[23] *Traditional SWC includes contour farming, cutoff drain/waterway, manure, crop residu, mulching, plantation and others*

Agro ecology type					
Highland					
Midland					
Lowland					
Labour demand					
High labour intensive					
Less intensive					
Costs (material, time)					
Highly Costive					
Less costive					

5. Did you consider annual crop preference as a criterion to choose on-farm SWC?- 1. Yes, 0. No
6. Did you consider perennial crop preference as a criterion to choose on-farm SWC?- 1. Yes, 0. No
7. If yes, to Q5 and/or Q6, list annual and perennial crops preferred and supported with SWC in 2013- 2018.

Annual crop type[24]	1st	2nd	3rd	4th
	1.Yes, 0.No	1.Yes, 0.No	1.Yes, 0.No	1.Yes, 0.No
Perennial crops[25]				

Part VII Impacts evaluation of SLM Practices

1. Are you beneficiary in using SLM in your farm plots? --- 1.Yes, 0. No, **if no skip to Q3**

2. If yes, mention the type of benefits you gained from SLM for the last five years?
   a. Soil erosion on the farm plots reduced ------------ 1. Yes, 0. No
   b. Soil fertility of owned farm plots enhanced ------ 1. Yes, 0.No
   c. Crop yield had shown increment ------------------- 1. Yes, 0. No
   d. Livestock production (animal herds) increased ---- 1. Yes, 0.No
   e. Farm income of household increased --------------- 1. Yes, 0.N0
   f. Water recharging capacity of farm land has shown increment ------ 1. Yes, 0.No
3. Had you benefited of other projects than the SLMP-II during 2013 to 2018 in LM? --1. Yes, 0. No
4. If yes, mention the project (s) and the type of benefit you got from the project?
   a. Project name ----------------------, ------------------------, ---------------------------
   b. Benefit type gained ---------------------------------, ----------------------------, ----------

---

[24] Maize, *tef*, wheat, barley, sorghum, haricot bean, faba bean, field pea, pepper, onion, cabbage, carrot, potato, taro, sweet potato, ginger, forage and others -------------------, --------------------, ---------------------

[25] Coffee, *enset*, bamboo, chat, mango, avocado, banana, other fruit (s) -----------------------------, ---------------------

5. Crop type, parcel name, application of SWC, area cultivated, yield, and sale of crop produce in 2020 (2011/12) production year.

Crop type	Plot no.	Cultivated area (*Timad*)	Supported SWC measures (tick √)	Measure Name[26]	Yield (Qt)			Marketed quantity in Qt and annual total sale in ETB			Additional note
Cereals					*Beleg*	*Meher*	Total	Quantity	Unit price	Total sale	
Maize											
Tef											
Wheat											
Barley											
Sorghum											
Pulses											
Common bean											
Faba bean											
Field pea											
Root crops											
Sweet potato											
Taro											
Potato											
Perennials											
Coffee											
Enset											
Chat											
bamboo											
Fruits											
Vegetables											
Ginger											
Cabbage											
Total											

[26] . Level Fanya juu, 2. Level soil bund with trench, 3. Stone faced soil bund, 4. Bench terrace, 5. Check dam, 6. Trench, 7. Micro basin, 8. Conservation agriculture, 9. Forage plantation, 10. Grass strip plantation, 11. Traditional SWC (contour farming, cutoff drain, manure, mulching, others----------------, -----)

6. Would you tell us the animals herd and products you owned and sale in market in 2020

Animals type	Owned number	Soled animals		Total sale in Birr
		Number	Price	
Ox				
Cow				
Bull				
Heifer				
Calf				
Sheep				
Goat				
Donkey				
Horse				
Mule				
Poultry				
Bee colony (in beehives number)				
Sale of milk and milk products				
Sale of eggs				
Sale of forage grass				
Total income (sale of animal & its products)				

7. What were the sources of forage/feed during 2013 to 2018? ----1. Natural grazing 2. Zero grazing (cut and carry), 3. Crop residues, 4. Grazing + forage, 5. Forage only
8. Have you applied compost/manure in your farm plots during 2013 to 2018? 1. Yes, 0. No
9. Have you applied chemical fertilizer over the last five years? ----------- 1. Yes, 0.No
10. If yes, how was the trend of fertilizer use? ---1. Increasing, 2. No difference, 3. Decreasing
11. If yes, to Q9, which type of your farm plots demands high fertilizer? -- 1.Plot with SWC measures, 2.Plot with no SWC measures 3. Plot that was frequently cultivated 4. Other---
12. Have you used improved seed over the last five years? ----------- 1. Yes, 0.No
13. If yes, how was the trend of using ? ----1. Increasing, 2. No difference, 3. Decreasing

Part VIII Hypothetical Questions (*ask Q1 to Q4 SLM participant and Q3 & Q4 both)*

1. What would happen if you were not participating in SLM specifically on-farm SWC measures in your managed plots?-- 1. My plots of farmland were fully threatened severely with soil erosion, 2. I would have been in risk of food grain deficit, 3. Nothing happened
2. If non-participants of SLM would have involved in the project, do you think that their crop production and farm income would showed increment during 2013-2018? 1. Yes, 0. No.
3. What would happen if you were not applying improved on-farm SWC measures in your owned plots? -- 1. Business will go as usual (I use traditional SWC measures), 2. My farmland would be in risk of fast deterioration, 3. I would leave and migrate to other areas
4. If the land degradation will go in its current fast track, what will happen to the environment and land resources you are living in? ---------------------, ------------------------

Thank you for your time and collaboration in offering us valuable information!!