Climate-Smart Land Management Decisions in a Changing Climate: Exploring Land Productivity and Livelihood Impacts in the Dabus Sub-basin of the Blue Nile River

Paulos Asrat Shiferaw

A Dissertation Submitted to the Center for Environment and Development Studies, College of Development Studies

Presented in Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Development Studies (Environment and Development Studies)

Addis Ababa University,
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Declaration

I, the undersigned, declare that this is my original work, has never been presented in this or any other University, and that all the resources and materials used for the dissertation, have been fully acknowledged.

Name: Paulos Asrat Shiferaw

Signature: Paulos Asrat

Date: May 29, 2018

Place: Addis Ababa

Date of submission: May 29, 2018

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

Supervisor name: Belay Simane

Signature:

Date: May 29, 2018

Dissertation Approval

Addis Ababa University

School of Graduate Studies

This is to certify that the dissertation prepared by Paulos Asrat Shiferaw entitled: "**Climate-Smart Land Management Decisions in a Changing Climate: Exploring Land Productivity and Livelihood Impacts in the Dabus Sub-basin of the Blue Nile River**" and submitted in fulfillment of the requirement for the Degree of Doctor of Philosophy (Environment and Development) complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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Ermias Teferi ______ May 29, 2018

Chairman, Examining Committee | signature | Date

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Dedication

To my late father, Asrat Shiferaw, for his unconditional love and support

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General Abstract

The objective of this research is to investigate autonomous climate-smart adaptation strategies and the impact of these strategies on the livelihood of the smallholder farmers in the Dabus Sub-basin of the Blue Nile River. The study is based on household and plot-level primary data collected from 734 farm households in the wet and dry lowland agro-climatic zones of the Dabus sub-basin. The LVI approach framed within IPCC is customized for the agro-ecology specific vulnerability analysis. The econometric models employed in this study are beyond a single regression equation that are based on smallholder farmers' utility maximizing behavior and customized into climate change adaptation and impact research. The models include the Heckman sample selectivity probit model, a two stage probit model, a bivariate probit model, the instrumental variable estimation method, the mean-variance approach, and the Propensity Score Matching Method. In the process, the research assessed vulnerability of smallholder farmers to climate change and variability; identified the factors affecting the use of different climate-smart agricultural practices as adaptation strategy; examined the interface among different climate-smart agricultural practices; and identified the impact of the climate-smart land management decisions on crop yield variability and productivity. Based on the results, the dry lowland agro-climatic zone is characterized by a higher exposure and sensitivity to climate stresses with a comparatively limited adaptive capacity as compared to the wet lowland, and this positioned it be more vulnerable to climate change and variability than the wet lowland. Adaptation to climate change in the area is proved to be a two-step process which requires that farmers first perceive climate change and respond in the second step through adaptation. Uses of some external inputs as adaptation strategy are proved to have a negative reciprocal causation on one another implying possibility of substitution between the strategies. Some climate-smart adaptation strategies are also interdependent in terms of sharing the resources at the disposal of the farm households. The study also revealed complementarity between short-term and long-term climate-smart agricultural practices. The climate-smart agricultural practices generally helped smallholder farmers to increase crop productivity through offsetting the production risk at plot and farm level. A positive increase in value of production is realized for those farmers who maintain the physical climate-smart land management practices for longer period. This calls for an intervention that motivate the farmers to make investment in a long-term climate-smart agricultural practices and an incentive mechanism that make them accept longer time horizons in terms of payoff periods. The findings of this study also verbalize that agro-climatic differences determine adaptation decision and hence location specific intervention is required to enhance farmers' use of climate-smart agricultural practices. Since climate-smart agricultural practices are knowledge and resource intensive, implementation of the practices could be challenged given the limited awareness and resource constraints of smallholder farmers. Hence, scaling up of the practices should be backed by both public and non-public investments to raise awareness and to provide technological support. Failure to do so would adversely affect crop productivity and sustainability of the smallholder agricultural production system.

Keywords: Climate change, climate-smart, adaptation, productivity, crop yield variability, impact

List of original papers

This dissertation is based on the following six original papers, which are listed from I –VI.

I) Asrat, P and Simane, B (2018a). Farmers' Perception of Climate Change and Adaptation Strategies in the Dabus Watershed, North-West Ethiopia, ***Ecological Processes*** (2018) 7:7 https://doi.org/10.1186/s13717-018-0118-8

II) Asrat, P and Simane, B (2018b). No regrets approach to climate change adaptation: Exploring causality and determinants of good agricultural practices in the Dabus Sub-basin, Blue Nile River, Ethiopia. ***Journal of Land Degradation and Development*** (In Press)

III) Asrat, P. and Simane, B. (2017a) Characterizing Vulnerability of Crop-Based Rural Systems to Climate Change and Variability: Agro-Ecology Specific Empirical Evidence from the Dabus Watershed, North-West Ethiopia. ***American Journal of Climate Cha****nge*, 6, 643-667. https://doi.org/10.4236/ajcc.2017.64033

IV) Asrat, P. and Simane, B. (2017b). Adapting Smallholder Agriculture to Climate Change through Sustainable Land Management Practices: Empirical Evidence from North-West Ethiopia, **Journal of Agricultural Science and Technology** A 7 (2017) 289-301 doi: 10.17265/2161-6256/2017.05.001

V) Asrat, P and Simane, B (2017c). "Adaptation Benefits of Climate-Smart Agricultural Practices in the Blue Nile Basin: Empirical Evidence from North-West Ethiopia." In: W. Leal Filho et al. (eds.). ***Climate Change Adaptation in Africa, Climate Change Management***, DOI 10.1007/978-3-319-49520-0_4 © Springer International Publishing AG 2017

VI) Asrat, P and Simane, B (2017d) Household and plot-level impacts of sustainable land management practices in the face of climate variability and change: empirical evidence from Dabus Sub-basin, Blue Nile River, Ethiopia, ***Agric & Food Security*** (2017) 6:6, 1DOI 10.1186/s40066-017-0148-y

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Abbreviation and Acronyms

ATT	Average treatment
BP	Bivariate probit
CIAT	International Centre for Tropical Agriculture
CRGE	Climate Resilient Green Economy
CSA	Climate Smart Agriculture
FaWCDA	Forestry and Wildlife Conservation and Development Authority
FGD	Focus Group Discussion
GCM	General Circulation Models
GDP	Gross Domestic Product
GHG	Green House Gas
IPCC	Intergovernmental Panel for Climate Change
IV	Instrumental Variable
GTP	Growth and Transformation Plan
GPS	Generalized propensity score
ha	Hectares
HDI	Human Development Index
LVI	Livelihood Venerability Index
m.a.s.l	Meters above Sea Level
mm	Millimeter
NNM	Nearest Neighbor Matching
PASDEP	Plan for Accelerated and Sustained Development to End Poverty
PCI	Per Capita Income
PPS	Probability Proportionate to Size
PSM	Propensity Score Matching
SLM	Sustainable Land Management
TSP	Two Stages Probit
2SLS	Two Stage Least Square
VA	Vulnerability analysis

Chapter One

1. General Introduction

1.1 Background of the Study

Climate change refers to any change in climate over time, whether due to natural variability or/and as a result of human activity (IPCC 2007a). It imposes constraints to development especially in rural livelihoods that depend on rain-fed agriculture (IPCC 2007b). In this regard, land degradation, being aggravated by climate change, has become a global environmental threat currently drawing wide-spread attention from the international community (Nhemachena and Hassen 2007). The coverage in terms of degraded area and its direct effects on the rural livelihood signals the severity of the problem. Globally, 24 percent of the land area has been degrading owing to climate-change induced factors, of which about one-fifth is cropland. In terms of population being directly affected, about 1.5 billion depend on these degrading areas for their livelihoods (Mengistu 2010; Bai et al. 2008).

In communities where livelihoods are tied with the primary sector (agriculture), climate remains a single important factor for the healthy functioning of the livelihoods (IPCC 2007a; IPCC 2007b). Climate change exacerbated the land degradation and this has an abysmal effect on agricultural productivity especially in developing countries where agriculture remains the largest sector in the economy both in terms of its contribution to the GDP and generating employment. It is estimated on a global scale that the annual loss of 75 billion tons of soil costs the world about USD400 billion per year, or approximately USD70 per person per year (Mengistu 2010).

In the Sub-Saharan Africa (SSA), agriculture contributes on average about 40 percent of exports, 30 percent of GDP, up to 40 percent of the foreign exchange earnings, and 70 to 80 percent of the employment (Commission for Africa 2016). However, agricultural productivity growth in the region is far below the growth required to meet food security and poverty reduction goals set in national and regional plans. The situation is even worse if one looks at the negative per capita growth rate of food production registered in the region due to climate change risks in the agricultural sector (FAO 2010a; IPCC 2007b). Various studies indicated that the continent of Africa is seriously threatened by climate change aggravated land degradation problems accounting for 65 percent of the total extensive cropland degradation of the world. Agricultural yield reduction in the continent due to cropland degradation ranges from 2 to 40 percent, with a mean loss of 8.2 percent (Mengistu 2010).

In agriculture based low-income African countries, reversing the deterioration of land productivity resulting from land degradation in the face of climate change, and ensuring adequate food supplies to the fast growing population is a formidable challenge. Among the livelihoods of such concern, Ethiopia in general and the Blue Nile Basin in particular serve as worthy examples. According to Simane et al. (2016) and Deressa (2011), Ethiopia is well characterized for its experience with climate related impacts. The country's geographic location, low adaptive capacity and overwhelming dependence on rain-fed agriculture make it among the most vulnerable to the climate hazards. The country is endowed with little choice to respond to the impacts of climate change and this low level of adaptive capacity could be reflected by the low level of social and economic development by all standards. Based on (UNDP 2016), it stood 174th out of 187 nations in terms of HDI and its PCI was USD630 in 2015, which makes it much lower than the SSA average of USD 1,165.

For Ethiopia, agriculture is the main stay of the economy accounting about 43 percent of the GDP and 90 percent of the export earnings. The sector also serves as the direct source of employment and livelihood for about 85 percent of the population in smallholder agriculture, which contribute about 95 percent of the agricultural GDP (Chanyalew et al. 2015). Since the main source of the economy is rooted on climate sensitive sector, an episode of a single climate event can relentlessly affect or even reverse any economic achievement in the past (IGAD-ICPAC 2007). Consequently, the economic performance of the country remains at the mercy of a climate and land degradation is among the major development challenges contributing to reduced economic output, lower growth potential, and increased poverty (Deressa et al. 2011). In effect, Ethiopia is losing five to nine percent of its agricultural output due to land degradation being aggravated by climate change (FAO 2010a; Mengistu 2010).

Empirical evidence has shown that smallholder farmers can adapt to climate change by using climate-smart land management practices through offsetting the negative effects of climate change at a plot, farm, or even landscape levels while providing local mitigation benefits. Hence, climate-smart land management practices can generate both private and public benefits and thus constitute important means of generating “win-win” solutions to addressing poverty, food insecurity and climate change risks (FAO 2010b; FAO 2009). In terms of private benefits, climate-smart agricultural practices can potentially lead to higher yields and greater resilience, thus contributing to enhanced food security and rural livelihoods. However, there is limited evidence that smallholder farmers have sustainably used the practice as an adaptation strategy (FAO 2010a) in SSA in general and in Ethiopia in particular. For example, a study in Ethiopia found that 31 percent of the farmers adopted sustainable land management (SLM) and water management practices to address perceived changes in rainfall and only 4 percent adopted water harvesting technologies (Yesuf et al. 2008).

Over the last two decades, the Ethiopian government and a variety of development partners have invested in a myriad of SLM programs on public and private lands. Moreover, the country’s plans such as Accelerated and Sustained Development to End Poverty (PASDEP), the five-year Growth and Transformation Plans (GTP-I and GTP-II), and the Climate Resilience Green Economy (CRGE-2011) also outlined the need to promote and invest in climate-smart agricultural practices that take into account the unique conditions of different agro-ecological zones with a goal of augmenting agricultural production and reducing climate change induced production risk (MoFED 2010). However, studies suggest that long-term maintenance of the land management measures is not common among the rural communities (Simane et al. 2016; Mengistu 2010; Tadesse and Belay 2004; Asrat et al. 2004; Shiferaw and Holden 1998). Thus, there is considerable interest in understanding the constraints to the wider adoption and sustainable use of these practices.

Climate-smart land management is generally comprised of a variety of farm practices that have multifaceted adaptation and mitigation functions: reduce production risk, increase productivity, augment food security, secure ecosystem functions, and enhance effectiveness of mitigation efforts (IFAD 2011; FAO 2010b). Therefore, expanding smallholder farmers’ adoption of the practices not only reduces risk from the extreme climate events (adaptation) but also contributes to reduced emission efforts (mitigation). Since these practices increase productivity and income, they enable continued and expanded investment in productivity enhancing agricultural technologies (FAO 2010b; Woodfine 2008; Pretty 2008).

Generally, climate-change has exacerbated land degradation problem in countries that heavily rely on exploitation of the land resources, like Ethiopia, is manifested in terms of complex relationships among poverty, population growth, the environment, climate vulnerability, adaptive capacity and livelihood impacts (Mengistu 2010; Reardon and Vosti 1995). To this effect, research interests that address the linkage in total or components of the inter-linkages, separately, are increasing from time to time particularly in land degradation prone African countries (McCarthy et al. 2011; Pretty 2008; Woodfine 2008; Lal 2004). Climate-smart land management strategies are becoming a new and expanding thrust in African policy research (McCarthy et al. 2011; FAO 2010b; Mengistu 2010). In view of this, there is a general consensus that the strategies can help to reduce production risk, enhance land productivity and ultimately improve rural livelihood. This necessitates assessing smallholder farmers' vulnerability to climate change and their adaptive responses through climate-smart land management measures, and the impact of the measures on land productivity, crop yield variability, and rural income. Such study is particularly relevant in Ethiopia as the country is among those in SSA reported to suffer severe climate-aggravated land degradation problems (Chanyalew et al. 2015; Deressa et al. 2011; IPCC 2007a).

Thus, the present study primarily focuses on farmers' decision to use climate-smart land management strategies for reversing climate-change persuaded land degradation problems, how the strategies are interlinked, and how these strategies affect welfare indicators such as vulnerability levels, adaptive capacity, crop yield variability, land productivity, and rural income in the face of changing climate episode in the Dabus Sub-Basin of the Blue Nile River, North-West Ethiopia.

The rationale and motivation for choosing the Dabus Sub-basin for this research emanate from three sources. One is a preliminary information the researcher has about the area that it is among the most important sub-basin of the Blue Nile River Basin but vulnerable to climate variability and change. Secondly, the sub-basin is the least researched part of the Blue Nile River Basin in terms of all disciplines of research including climate change. Third a preliminary assessment made by the researcher in the specific study sites and the Regional Climate Change Adaptation Plan of Action (BGNRS 2013) confirm that climate change prompted land degradation problems caused multiple impacts through a broad range of direct and indirect processes affecting a wide array of ecosystem functions and services leading to a decline in productivity and rural income and hence possess a challenge on the adaptive capacity of the smallholder farmers to climate hazards.

1.2 General Problem Description

Ethiopian is vulnerable to climatic change and the change is likely to increase the frequency and magnitude of natural disasters and extreme weather events (FAO 2010a). The country's subsistence agriculture, being the source of livelihood for the large majority of the population, is particularly vulnerable to climate change as smallholder farmers have inadequate resources to adapt to the change (Simane et al. 2016). The county's population that is more than doubled from about 40 million in 1984 projected to over 92 million in 2016 (CSA 2013; CSA 2008) just in 32 years makes it the second most populous country in Africa with a current annual growth rate of 2.6 percent (CSA 2008). On the other hand food gap increased since the early 1980s, though per capita food availability has remained relatively stable over the years owing to inflow of food aid. Agricultural growth rate has been increasing in the country over the years but with volatile production compared to most developing countries (Buni 2014; ATA 2013; Mengistu 2010). This defers the country's food production far behind the population growth and hence leads to food shortage (FAO 2013).

Thus, Ethiopia is confronted with the challenges of feeding its population. Food insecurity and pervasive poverty epitomize the country in the face of climate change as this ravage the livelihood of significant portion of the population (FAO 2014). The causes of food insecurity and poverty could be numerous. Specific causes including climate extremes, widespread land degradation, unsustainable agricultural practices, shrinking and fragmentation of land holding and ineffective agricultural policies are among the major ones (Nkonya et al. 2011; FAO 2010b).

Be it directly or indirectly, the land degradation problems in the country are related to climate change and variability prevailed overtime. Hence, land degradation problems in the face of climate change can be singled out as one of the most important environmental problems creating a formidable threat to the food self-sufficiency goals of the country. It is apparent that land degradation contributes to heightened production risk, a decline in crop productivity and rural food insecurity (Buni 2014; FAO 2014). Furthermore, decline in per capita land holding and fragmentation, unsustainable agricultural land use system, tenure insecurity and poverty are among the major causes of land degradation coupled with the vulnerability of smallholder agriculture to climate change and variability (Simane 2016; FAO 2010a).

An estimate based on remote sensing tools indicated that about 26 percent of the cropland area in Ethiopia has been degrading over the years 2003-2013 directly affecting the livelihoods of about 29 percent of the population (Buni 2014; ATA 2013). Based on FAO (2014) estimates for the period 2008-2014, the average yield was 1318 kg per hectare, which is less than 60 percent of that in other low-income countries and less than 40 percent of the world average. Available estimate of economic impact of cropland degradation also showed that it is among the factors that contribute to the country's structural food insecurity problem causing estimated reduction of food production by at least two percent annually (FAO 2013). This definitely has a consequence on the country's national income and in this regard, the cost of cropland degradation to the national economy is about one billion US dollars each year (Mengistu 2010). Various sources (Buni 2014; ATA 2013; FAO 2013; Hurni 1998) have also indicated land degradation as a major constraint to agricultural production in Ethiopia.

The problem of climate-change related land degradation is especially serious in the crop-based farming systems of the country (FAO 2014; Mengistu 2010) that cover about 46 percent of the land mass and account for 95 percent of the regularly cultivated lands. Furthermore, fragmentation and small size of holding are peculiar characteristics of subsistence farming affecting crop production and adaptive capacity in the country. In 2014/15 cropping season, for instance, about 84 percent the holders had a holding size of less than two hectares (CSA 2016) and this may affect productivity, land management decisions and rural livelihood thereof.

The Dabus sub-basin of the Blue Nile River, which is the focus of this particular study, is among the semi-arid areas of Ethiopia most vulnerable to climate change intensified land degradation problems. Based on the regional climate change adaptation plan of action (BGNRS 2013), climate variability and change poses a huge threat to farmers in the area, the stressful problems being land degradation, overwhelming reliance on small-scale agriculture, and water shortages. In the sub-basin, climate intensified land degradation problem varies across the agro-climatic zones but has commonly caused multiple impacts through a broad range of direct and indirect processes affecting a wide array of ecosystem functions and services. Among its direct effects is the loss of fertile soils (BGNRS 2013) that ultimately leads to vulnerability, production risk, decline in productivity and low income and hence possess a challenge on the adaptive capacity of the smallholder farmers to climate hazards. The regional sector-based Program of Plan on Adaptation to Climate Change (BGNRS 2013) also shows that cropland degradation in the sub-basin is rated to be the first source of vulnerability to climate change hazards in the agricultural sector and hence community and private land management strategies are considered as viable adaptation options.

Overall, the cropland degradation is singled out as one of the most important climate-change heightened problems creating a formidable threat to the food security goals of the country in general and to the study area in particular. It is apparent that land degradation contributes to rural food insecurity. In effect, the problem of poverty, resource depletion, and declining productivity co-exist with some sort of interrelationship and this reinforces vulnerability of the rural livelihood to climate induced factors (Simane et al. 2016; Nkonya et al. 2011; Camberlin 2009). This interrelationship is what is termed as the 'critical triangle' of development objectives (Mengistu 2010; Vosti and Readon 1997) the notion behind being poor farm households are compelled to apply unsustainable farming practices as immediate copying mechanism and this erodes their natural resource base, enhance vulnerability, reduce crop yields, lower adaptive capacity, and promote rural poverty.

In fact, the poverty-environment side of the 'critical triangle' is controversial. Many observers have conceptualized this side of the triangle as 'downward spiral' of declining soil fertility and increasing poverty. Others have challenged it by showing the possibility of striking heterogeneity in environmental (land) management by the rural poor, the success and outcome of adaptation being depend on the efficacy of polices (Mengistu 2010; Scherr 2000). The implication is that poverty may not necessarily lead to environmental/land degradation, and hence there are many other factors that condition poverty-environment interactions and outcomes in the agricultural sector. Though the causal link of poverty-environment is controversial, poor farmers whose livelihood depends on environmental resources are vulnerable and immediate victims of land degradation (Nkonya et al. 2011; Camberlin 2009).

In Ethiopia, climate-change persuaded land degradation contributes to crop production risk, variation in output, undermines household food security, and aggravated the economy-wide structural problem. The challenge is, therefore, how to reconcile the objectives of increasing agricultural production, reducing poverty and using the land resource sustainably, the targets that the country is trapped in given the prevailing climate change challenges in the agricultural sector. This requires a careful assessment of the nature of the linkage among land degradation, climate vulnerability, crop yield variability, productivity and rural poverty, which can also be translated into its 'dual' of the linkages among climate-smart land management strategies, adaptive capacity, agricultural productivity and improved rural livelihood. Effective decision against climate land degradation, vulnerability, crop production risk; low agricultural productivity first and foremost requires understanding of the underlying causes that arise out of a complex interplay of socio-economic and natural/environmental factors.

In order to combat the adverse effects of climate-change provoked land degradation, it is necessary for smallholder farmers to adopt climate-smart land management, among others, that result in reduced vulnerability and production risk, increased productivity and farm income that at the same time ensure sustainability of smallholder agriculture in the face of climate change. Climate-smart land management practices are pathways towards food security and enhancing resilience of livelihoods and ecosystems (FAO 2010b) and hence farmers can adapt to climate change by using these practices to offset the negative effects of climate change (Nkonya et al. 2011; World Bank 2010). In view of these, smallholder farmers in Ethiopia have already made some progress in implementing different land management strategies although the majority of the farmers are not using the practices despite the fact that climate change intensified land degradation deepens crop production risk, undermines farmland productivity and rural livelihood.

Impediments for the wider adoption of climate-smart land management practices can be multi-faceted including factors related to adaptive capacity in terms of livelihood assets, knowledge/awareness about climate change and adaptation options, and farm-related features. In this regard, it is necessary to assess how implementation of climate-smart land management strategies is related to the smallholder farmers' endowments of labor, capital, and natural resources. Other than these resources, land management decisions are believed to be related to income levels of the rural households, which is an indication that whether rural income levels determine or determined by land management investments. Moreover, the decision on different climate-smart land management practices are assumed to be interdependent; use of one land management strategy may hinder or foster use of other land management strategies. Therefore, it is necessary to make detailed analysis of the interrelationship among climate-smart land management decisions, crop yield variability, land productivity and rural livelihood.

In recent years, there are few studies which assessed vulnerability of smallholder farmers to extreme climate events in the Blue Nile Basin (Simane et al. 2016; Deressa et al. 2009). However, Ethiopia in general and the Blue Nile Basin in particular are characterized by considerable diversity in terms of agro-ecology, socio-economic setup, climate change and variability, environmental conditions, agricultural production systems, water resources and biodiversity. Given these diversities, aggregate assessment cannot capture the complexity of climate change vulnerability at agro-ecology level and may lead to blanket recommendations. In view of these, the present study aims at contributing to the vulnerability literature and to the building of agro-ecology specific resilience in Ethiopia by assessing location-specific vulnerability to climate change and variability. Consequently, the results of the study will be indispensable to ensure better targeting of agro-ecology specific adaptation measures and development interventions.

With regard to climate change adaptation, there are research undertakings (Deressa et al. 2011; Di Falco et al. 2011; Deressa et al. 2009), which focus mainly at a large scale and overlooked location-specific factors that drive perception and adaptation to climate change. However, the findings of these studies are highly aggregated and are of little help in addressing local peculiarities of perception and adaptation to climate change. As a result, there is a substantial deficit of location-specific information on the process of autonomous adaptation. Adaptation decision is location specific and influenced by key drivers such as socio-economic, environmental and institutional factors. Thus, there is a need to understand location-specific drivers of perception and adaptation so as to design relevant policy responses based on the accessibility of the adaptation measures. Understanding local perceptions and adaptive behavior provides better insights and information relevant to a policy that helps to address the challenge of sustainable agricultural development in the face of variable and uncertain environments. This study, therefore, responded to a paucity of empirical information regarding perception and adaptation to climate change.

Specific to the land resource management, much research has been conducted in Ethiopia in recent years. Several of these studies have sought to identify determinants and extent of land degradation, or factors affecting adoption of soil conservation measures, or extent of poverty and its determinants in relation to the land resources. Yet only few studies have systematically addressed the linkage between rural income, productivity and land management and notable exception to the best of the researcher's knowledge in this regard are Mengistu (2010), Bamlaku (2010), and Pender and Gebremedhin (2008) that investigated the cause and effects of rural livelihood and land management decisions in the eastern, central and northern parts of Ethiopia, respectively. However, solid empirical evidences that address climate change adaptation role of the land management practices, the linkage among the practices, and their livelihood impacts in terms of managing crop yield variability and augmenting productivity are very scant.

Given the dynamism of smallholder farming systems, household assets, vast geographical and agro-ecological diversity of the country, it is necessary to undertake studies using timely data in areas more or less representing the majority of the semi-arid parts of the country, which are peculiar in terms of land use and livelihood strategies. More importantly, previous research efforts did not adequately address how different land management strategies affect one another (causality) besides being affected by other factors. Furthermore, the systematic link among climate-smart land management decision, crop yield variability, land productivity and rural livelihood are not yet assessed by any of the previous research undertakings. The previous studies have also limitations in terms of the composition of land management practices being considered. In the same line, the literature on climate change has paid little attention to the role of climate-smart land management practices as adaptation strategy and overlooked agro-ecology specific factors that affect the implementation of the practices.

This study, therefore, responds to a paucity of empirical information regarding the indicated gaps using agro-ecology specific data at village, household and plot levels collected from four districts representing the two major agro-climatic zones of the Dabus Sub-basin of the Blue Nile River.

1.3 Study Objectives, Research Questions and Hypothesis

1.3.1 Study objectives

The major focus of this research is to explore how agro-ecology specific physical, human, natural, and social assets influence climate-smart land management decisions and the impact of the decision on land productivity and crop yield variability at household and plot level. It also investigates how the climate-smart land management practices are interlinked with one another.

Specifically, the study intends to address the following objectives:

1) Analyze agro-ecology specific famers' vulnerabilities to climate change hazards;
2) Identify agro-ecology specific determinants of farmers' perception and adaptation to climate change;
3) Investigate factors affecting famers' decision to use structural and non-structural climate-smart land management measures;
4) Explore the causality/interrelationship between different climate-smart land management practices and the underline factors affecting farmers' decision to use these practices;
5) Examine the link between climate-smart agricultural practices, crop yield variability and productivity; and
6) Determine household and plot level land productivity impacts of climate-smart land management measures.

1.3.2 Research Questions

i) How different/similar are the agro-ecologies in terms of vulnerability to climate change?
ii) What factors influence farmers' perception of climate change and adaptive decisions?
iii) What factors determine farmers' decision to use climate-smart land management practices?
iv) How is the proximate causal link among different climate-smart land management practices?
v) How do climate-smart land management practices affect crop yield variability at plot-level?
vi) How do climate-smart land management practices affect crop productivity at plot-level?

vii) What is the household and plot level land productivity impact of climate-smart land management practices?

1.3.3 Research hypothesis

The key interests of this study are outcome variables that include crop productivity, crop yield variability, and decision (choice) variables that include different climate-smart land management strategies. The study also explored the proximate causal link between the decision variables and the underlying determinants. Based on these general premises, the following core hypotheses are formulated:

1) Climate vulnerability factors (exposure, sensitivity and adaptive capacity) are influenced by agro-ecology specific factors.
2) Crop productivity (in terms of value of output per hectare) is positively affected by the use of climate-smart management practices.
3) Crop yield variability is negatively influenced by climate smart land management practices.
4) There is a reciprocal causation between different climate smart land management practices.
5) There is a link among climate-smart agricultural practices, crop productivity and crop yield variability.

1.4 Significance of the Study

This study provides useful empirical information to policy makers, researchers, academicians and various other stakeholders regarding climate-change land degradation problems and the adaptive role of climate-smart land management practices thereof. It offer agro-ecology specific policy recommendations targeted to smallholder farmers in degraded and degradation-prone areas of the country owing to climate-change-induced factors, and pinpoints existing opportunities and potential priorities for necessary interventions including public investment that aims at enhancing autonomous climate-change adaptation. It helps policy makers to come up with relevant policies that gear to reducing climate change impacts through enhancing adaptive capacity, increased agricultural productivity and rural income, and at the same time conserving land resources sustainability.

This study customized the notion of the “critical triangle” (Vosti and Reardon 1997) of development objectives and the ‘downward spiral’ (Scherr 2000) of declining soil fertility and increasing poverty into land degradation-vulnerability- adaptation-impact relationships. The study also makes a methodological contribution in terms of customizing and applying advanced econometric models into climate change adaptation studies that link land resource management-crop yield variability-and land productivity as it entirely employs beyond single equation regressions. Besides, the study pinpointed some gaps and limitations that future studies need to address. It can also serve as a case study to researchers and development actors to replicate similar or related studies by building on its limitation and produce recommendations of more robust and broader applicability.

Based on the extent of implementation of its recommendations by decision makers, the study is expected to ultimately benefit the vulnerable rural poor that are toiling for their livelihood on climate sensitive subsistence agriculture which is either tormented by climate change impacts or prone to the impacts.

1.5 Scope and Limitation of the Study

Owing to the constraints of time and financial resources, this study has its own limitation. It is limited to a one-shot survey of cross sectional data collected from respondents. As a result overtime trends of important variables and their dynamic linkage is not addressed, although efforts were made to draw inferences about long-term behavior of some variables.

Quantitative aspects of land degradation in terms of soil nutrient inflows and outflows and measurement of the extent of degradation in general are beyond the scope of this study. Rather the study focuses on the strategies for reversing climate-change intensified land degradation trends and the effect of these strategies on smallholder farmers’ adaptive capacity, agricultural productivity, and crop yield variability. The study is also limited to soil degradation component of the broader concept of land degradation. It does not address a broader aspect of land degradation, such as biodiversity. Furthermore, this study focuses on crop productivity and related crop yield variability though the outcome generally is applicable to agricultural productivity and risk. The analysis is made at household and plot level under the existing land tenure system. Collective decisions affecting climate vulnerability, adaptation strategies and land management decision at landscape and community level is not addressed in this study, except in the case when community level strategies are strongly linked to household level strategies.

Despite these limitations, the study makes substantial addition to the existing knowledge pool on climate change vulnerability, climate change perception and adaptation decision, climate-smart land management practices, and the overall impact of these on rural livelihood.

1.6 Study Area Description

The study area description relied on data from secondary sources, FGD and key informant interviews. The secondary data were obtained from the regional bureaus, woreda level offices, statistical abstracts and bulletins of the Central Statistical Agency of Ethiopia. Climate related data were obtained from different metrological stations in the study area and the central office of the Ethiopian National Meteorological Agency. The key informant interviews and FGDs were made at institution level (region, woreda, and sector offices) and at community level in the specific study sites.

1.6.1 Regional overview

The study area is in the Benishangul Gumuz National Regional State (BGNRS). The region is one of the nine Federal States in Ethiopia and located in the North-west part of the country at $9^{o}17'$ to $12^{o}6'$ N latitude and $34^{o}10'$ to $37^{o}4'$E longitude (Figure 1). It has a total land area of about 50,380 km^2. The elevation in the region ranges from 580 to 2,731 m.a.s.l. Based on the traditional agro-ecology classification, the major part of the region (about 75 %) is lowland, 24% is midland and the remaining 1 % is highland (BoFED 2007). Based on CSA (2013), the total population of the BGNRS is 670,847.

The topography of the region is composed of dominantly plain lowlands and few gorges created by the Blue Nile (Abay) River and its main tributaries namely Dabus, Beles, Anger and Didesa along their courses. Abay River cuts the region into two parts with the northern half comprises Metekel zone and the southern half comprises Assosa and Kamashi zones as well as the Mao-Komo special woreda (IPS 2012b). The region is endowed with fertile land and forest resources that include the lowland bamboo and incense (IPS 2012a). Based on the Ethiopian National Meteorological Service

Agency (NMSA) (2016), the annual rainfall in the region ranges from 800-1200 mm, and it extends from May to October, although there is a tendency to be erratic during recent years.

Livestock production is an important means of livelihood in the region next to crop production. It is important sources of food, cash, and assets to buffer against shocks. Based on CSA (2016), the Region had 350,399 cattle, 314,277 goats, 102,289 sheep, and 961,196 poultry. The available evidence on the regional land use (BoLA 2016) indicates that out of the 249,856 ha of the total land area, grazing land accounts for 20%. However, this potential is seriously constrained due to the prevalence of various livestock diseases. Apiculture is also another economically important livelihood option in the region. The vast vegetation cover of the region (about 223,980 ha) coupled with the favorable climate makes it suitable for apiculture.

The BGNRS is endowed with important mineral resources. The annual report (BoWME 2016) confirms that the region has a potential for gold and base metals such as zinc, lead, copper, and considerable reserves of marble, silica and clay. Traditional gold mining is an important economic activity in the region widely practiced by the indigenous people mainly to finance food purchase in the major food gap months and to meet immediate household cash needs for other purposes.

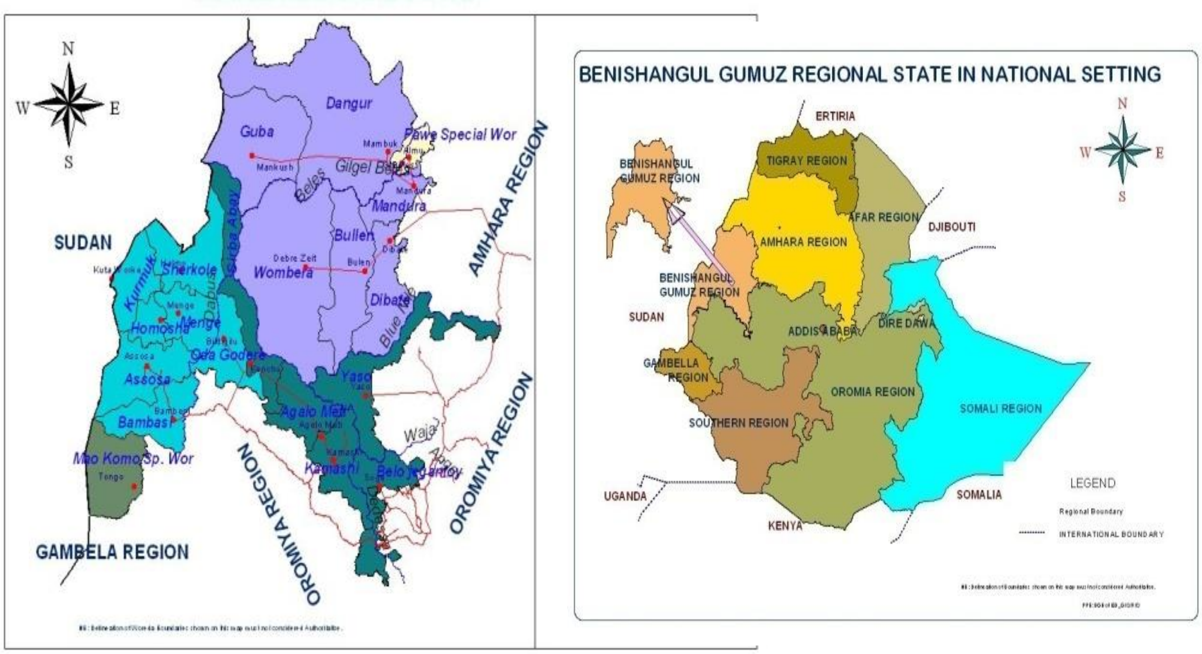


Figure 1 Administrative map of the BGNRS and its location in the national setting

Handcraft is another important economic activity in the region (SID-Consult 2014). Several handicraft products are made from clay, wood, iron, and bamboo both for home use and market. Basketry products from bamboo and palm leaves and pottery are produced mainly for market. According to SID-Consult (2014), handicraftsmen among the indigenous ethnic groups are respected and many seek to acquire the skills, which is in contrary to the segregation and marginalization attributed to the practitioners in other parts of Ethiopia in the past. This provides an opportunity to expand handicraft activities as a strategy for livelihood diversification.

1.6.2 Dabus sub-basin of the Blue Nile River

The Dabus River is one of the major tributaries of the Blue Nile River. It starts south of the BGNRS (in Begi woreda of Oromia National Regional State) and flows towards north. The lower and middle parts of the Dabus sub-basin fall in the BGNRS. The sub-basin is characterized by contrasting differences in climatic condition, soil, and human activities across the traditional altitude zones (IPS 2012b; BoFED 2007).

The sub basin has an area of 21,030 km^2. The altitude ranges between 580 and 2731 m.a.s.l. Based on Hurni (1998), the sub-basin is characterized by two agro-climatic zones: dry lowland and moist/wet lowland (Figure 2). Based on NMSA (2016a), the rainfall in the sub-basin varies between 970 and 1985 millimeters. The maximum and minimum temperature varies between 20^0C -35^0C and 8^0C- 20^0C, respectively. The slope gradient of the Dabus Sub-basin varies from flat to steep slopes and the slope is ranges from zero to 80 percent. The dominant soil types include Alisols, Nitisols, Cambisols, Leptosols, and Fluvisols with the occurrence of Vertisols and Acrisols (Aster and Sileshi 2009). The middle and lower part of the Dabus sub-basin covers 19,291 km^2 (about 92% of the Dabus sub-basin) and is characterized by the wet and dry lowland agro-climatic zone. It encompasses 8 woredas (districts), namely Assosa, Bambasi, Homosha, Mengie, Kurmuk, Sherkole, and Oda Bildigilu woredas and Mao Kome Special woreda with an estimated population size of 319,428 and 70,984 households (CSA 2013; CSA 2007).

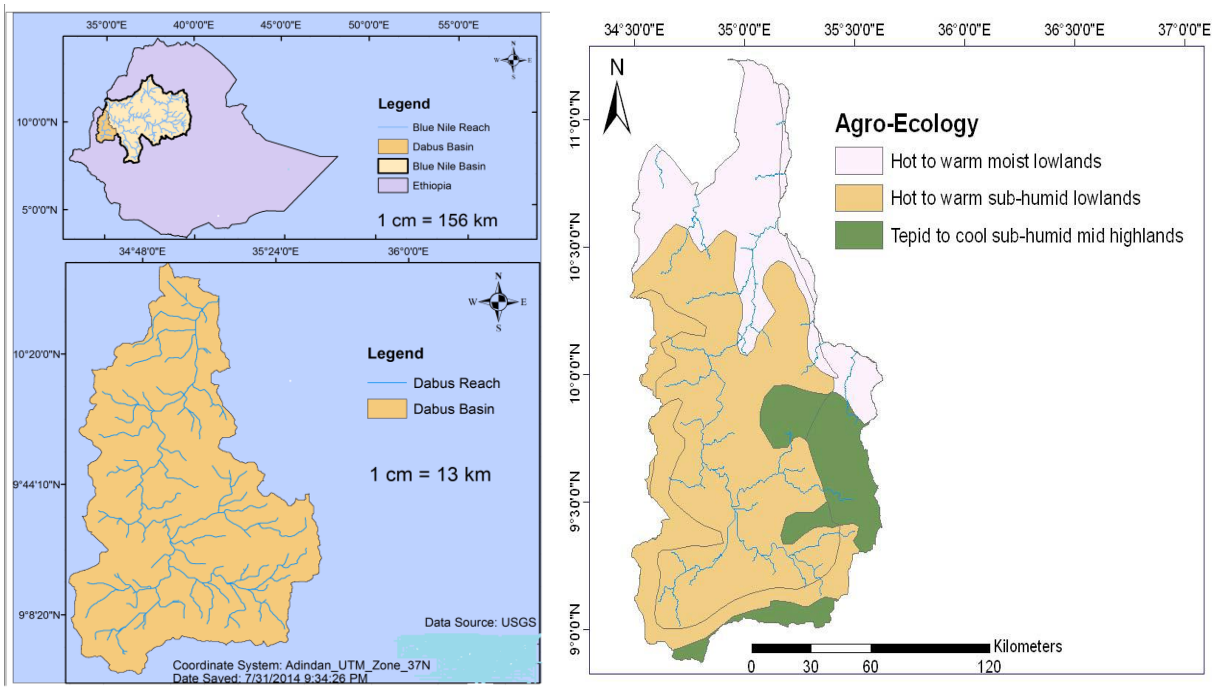


Figure 2 Map of the research area and agro-climatic zones

Agriculture is the main economic activity and source of livelihood in the Dabus sub-basin. The farming system is characterized by a mixed crop-livestock production. A considerable part of the sub-basin is cultivated and is dominated by maize-sorghum and maize-sorghum-perennial complex (Aster and Sileshi, 2009). The sub-basin is among the most vulnerable lowland agro-climatic zones to climate variability and change in Ethiopia (BGNRS 2013). Climate variability and change poses a huge threat to the farmers in the area, the stressful problems being overwhelming reliance on small-scale agriculture, land degradation, and water shortages. The level of climate change impacts varies across the moist and dry lowland parts of the sub-basin. However, the two parts have commonly caused multiple impacts that affect a wide array of ecosystem functions and services and hence pose a challenge on the adaptive capacity of smallholder farmers to climate hazards. The direct effects of climate change in the sub-basin include the loss of fertile soils, enhanced crop production, a decline in productivity and the cumulated effect of these distress the livelihood of the smallholder farmers and their adaptive capacity thereof (BGNRS 2013).

1.6.2.1 Agro-climatic zones in the Dabus sub-basin

Moist lowland

The moist/wet lowland agro-climatic zone encompasses Assosa, Bambasi, and Homosha woredas. The minimum and maximum temperatures range from 20-25^{0}C in May to October and 35- 40^{0}C in November to April (NMSA 2016b). The rainy season is unimodal and it spans from May to October with annual rainfall in a range of 900- 1200 mm. The topography is characterized by plains and undulating land. The vegetation type includes bamboo forest and bush scrub. The major river is Dabus with its tributaries that include Chankur and Keteb.

The area is characterized by a mixed farming system the main economic activities being crop and livestock production (Aster and Sileshi 2009). Wild food gathering is also common among the indigenous people in the area. Keyida (a climbing plant with a tuber), Kuntsu (Bamboo-shoot) and Tsirgun (mushroom) are common wild foods collected and consumed by the poorer wealth groups. Gold, marble, gum Arabic, bamboo and wild foods are the natural resources with significant economic importance.

This agro-climatic zone has high crop production potential, although food deficits do occur in part as a result of climatic factors ((BoARD 2016). Sorghum, maize, sesame, finger millet, Niger seed and groundnut are the main crops grown. Sorghum, maize and finger millet are grown for home consumption. Sesame and sorghum are the main crops grown for market. Oxen plow and hand hoe are the two methods used to prepare crop fields. Weeding and harvesting of crops are the most labor demanding tasks. Agricultural inputs such as fertilizer, improved seed and pesticides are utilized in this area though the level of use is very minimal. Army worm, bollworm, termites, stalk borers, late blight, smut and weed (striga) are the main challenges that constrain crop production in the agro-climatic zone (BoARD 2016). Cattle, goats and sheep are the main livestock reared. Trypanosomiasis (on cattle/shoats), pasteurellosis (on shoats), and brucellosis (on cattle/goats) are the main diseases affecting livestock production.

Seasonal calendar in the moist lowland

The cropping season starts with clearing and preparation of farmland in April followed by planting of maize and sorghum in May/June (Figure 3). Sorghum and maize are long cycle crops grown from June to January. Weeding and harvesting are the laborious activities from July to

August and November to January, respectively. For agricultural households, food purchases peak from June to August, when stocks are running out before the new harvest. Wild food collection is also common from March through July by the indigenous people. Agricultural labor during the weeding and harvesting periods provides income for poorer households.

Wealth is linked to family size, land holding, crops cultivated and livestock ownership. The middle and better off groups have more working family members. The poor rent out and the better-off and middle households rent in agricultural land. The cultivated land for better-off households is 4-6 ha while the poorer households cultivate 0-2 ha. All wealth groups cultivate sorghum, maize, finger millet, haricot beans, Niger seed and sesame. The major constraints to increasing crop production for all wealth groups are climate factors and lack of capital to purchase inputs. Shortage of grazing land depends on farmers' origin. Those indigenous to the area have access to sufficient grazing land, while settlers to the area usually face shortage.

The better-off and middle farmers cover most of their annual food needs from own crop production and livestock produce, while poorer households purchase more food and consume wild foods. Poorer households less likely consume livestock products from their own production.

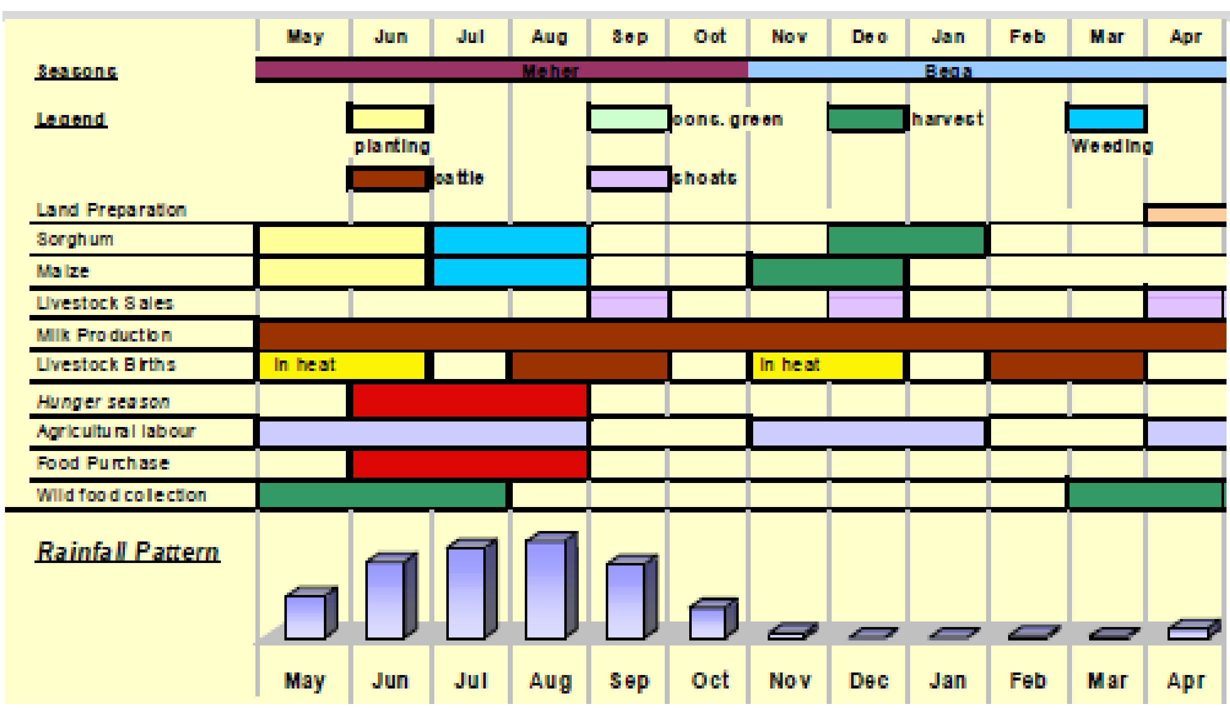


Figure 3 Seasonal calendar in the wet lowland agro-climatic zone

Climate-change hazards and coping strategies in the wet lowland

Climate change induced hazards such as livestock disease, crop pests, and land degradation are chronic in affecting the livelihood of smallholder farmers every year in the wet lowland agro-climatic zone. To overcome the impacts of such hazards on their livelihood, farmers in the area adopt different strategies that include crop and livestock diversification, soil and water management practices, use of improved agricultural inputs, and diversifying livelihood options in to non-farm activities.

Dry lowland

The dry lowland agro-climatic zone is characterized by undulating hills and plains. The altitude ranges from 500 – 900 meters above sea level. A maximum temperature of 38-43 ^{0}C is reached in March and a minimum temperature of 26- 30 ^{0}C occurs in August. The vegetation in the area consists of acacia, bamboo and grasses. The rainy season spans May to mid-October during which the agro-climatic zone receives 700-900 mm of rainfall (NMSA 2016a). This agro-climatic zone encompasses Mengie, Kurmuk, Sherkole, Oda Bildigilu woredas and Mao Kome special woreda. It is sparsely populated, with a population density estimated at about 11 person/ km^2 (CSA 2013).

This area is particularly endowed with natural resources including marble, gold, sandstone, wild foods, fruits and Gum Arabic. The main categories of livelihood are crop and livestock production. Crop production is mainly depend on oxen plow and hand hoe cultivation (BoWME 2016). The area is also known for traditional gold mining and wild food collection. The traditional gold mining is an important source of supplementary income for the farming community. The typical wild foods in the area include Yecha, Mujua and Agangulesh (Baobab).

Despite the production potential, this agro-climatic zone is food deficit each year and households turn to wild food collection, and off-farm employment to finance food purchase (BoLA 2016). The main food crops grown are sorghum, maize, sesame, groundnut and pulses. The agricultural activities that require most labor are land preparation, weeding and harvesting. Better-off and middle farm households may hire labor for weeding and harvesting activities. The main crop production constraints are terminal moisture stress, late start of rainfall, cropland degradation, lack of agricultural inputs, pests and disease and wild animals' attack on crops. Crop pest and disease in the area include boll worm, stalk borers, termites, leaf blight and smut. Wild animals such as monkey, apes and wild pigs also challenge the crop production activity. The Striga is the most common parasitic weed that challenges sorghum production (BoARD 2016). The main livestock reared in this agro-climatic zone are cattle, goats, donkeys and poultry. Free grazing is the main livestock feed source in the area supplemented by crop residue to a lesser extent. Trypanosomiasis is the main livestock disease in the area and it poses a critical challenge on cattle production (BoARD 2016).

Activity calendar in the dry lowland

In the dry lowland agro-climatic zone, there are four locally defined seasons (Figure 4) in relation to the sources of food grain and other livelihood activities in the year round (*Fona* from June-August, *Rajib* from September-November, *Gasir* from December-February, and *Showal* from March to May). The consumption season starts in November and ends in October. Agricultural activities begin in May with clearing and preparation of crop fields. Sesame is a short cycle crop grown from June to October. Sorghum and maize are long cycle crops grown from May to December. The planting and weeding periods for sorghum and maize are May to June and July to August, respectively. The harvesting period for sorghum and maize is November-December.

Food purchases are most common from June to October when food grain stocks run low in advance of the coming harvest. This time is a critical food shortage season, which also coincides with human and livestock diseases prevalence in the area. Wild foods are collected in May and from September to April. On the other hand, mining is a year round activity parallel to the other livelihood activities. Wealth is differentiated by livestock ownership as well as household size. All wealth groups cultivate sorghum, maize, sesame and haricot beans. All but the very poorest households also cultivate groundnuts. There is no experience of land renting in/out in this agro-climatic zone. Household size increases with relative wealth meaning that middle and better-off households have more working family members (9-11) while the poorest households have as few as three members.

The main source of food is from own production with all households fulfilling more than half of the annual food need from this source. Food purchase and wild food collection also contribute to household food supply. The annual food need covered through purchase decreases across the wealth groups and is in the range of 20-35% for the poorer households. The poor and the very poor households cover 5-15% of their annual food requirement through wild roots/ fruits collection. Livestock and crop sales are key sources of income for all households. Sesame is serving as an important cash crop for all household categories complemented by groundnuts. Gold mining is significantly contributing to households' income for all wealth groups. Farm households also generate income through the sale of wild roots and fruits.

Climate-change hazards and coping strategies in the dry lowland

The chronic climate-induced hazards affecting the livelihood of smallholder farmers in the dry lowland agro-climatic zone include moisture stress, land degradation, poor land productivity, crop and livestock disease, crop pests and erratic rainfall. In response to these hazards, smallholder farmers practice different coping and adaptation strategies that include land water conservation measures, wild food collection, livelihood diversification, use of improved agricultural inputs and agronomic practices.

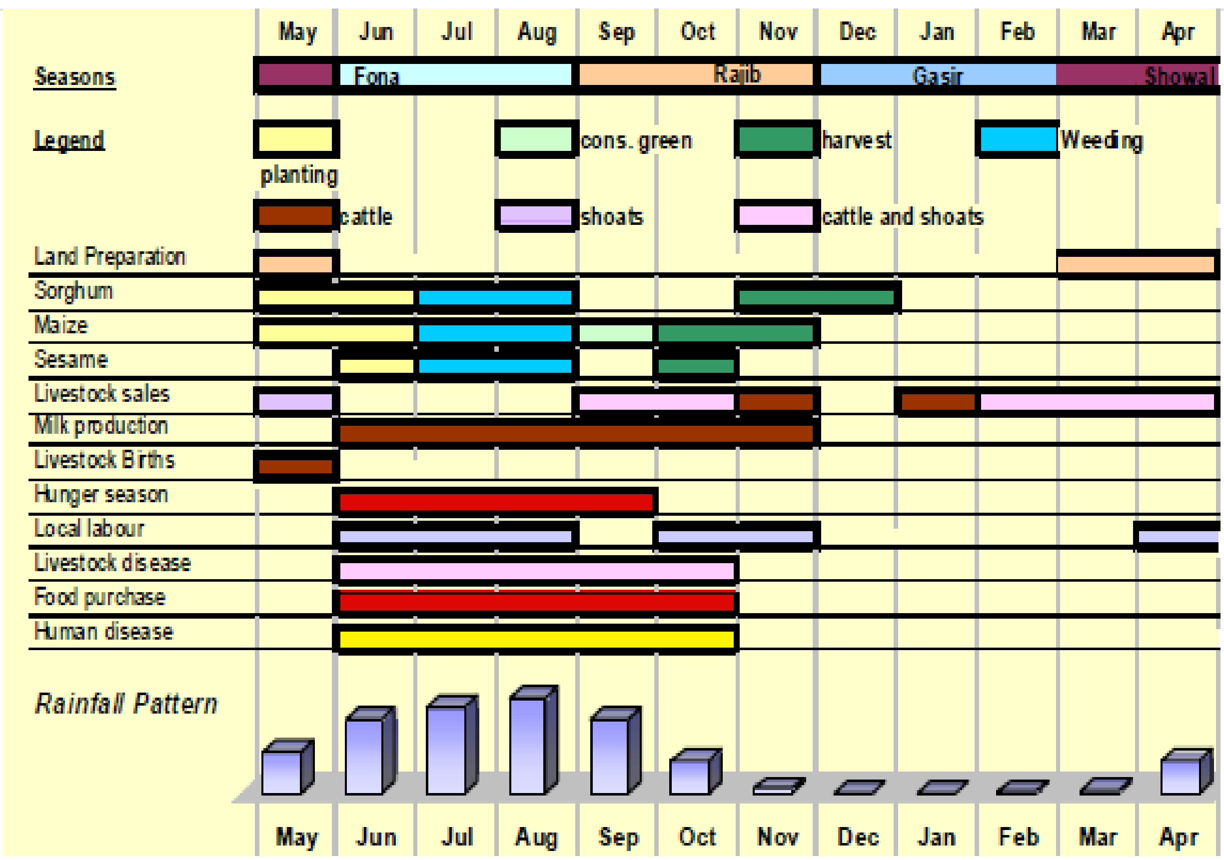


Figure 4 Seasonal activity calendar in the dry lowland ago-climatic zone

1.6.2.2 Climate in the Dabus sub-basin

The rainfall in the Dabus sub-basin is characterized by a mono-modal pattern (*i.e.* a single rainfall maximum per year) and the length of the rainy season decreases from south to north. Based on NMSA (1996) classification of rainfall regimes, the sub-basin lies in the B2 zone, which is characterized by a wet season that extends from April/May to October/November. In the area, the altitude has a considerable influence on the amount of precipitation. For example, Assosa, with an altitude of 1550 m.a.s.l, has an average annual precipitation of 1,275 mm, whereas Kurmuk, with an altitude of 700 m.a..s.l. only receives 860 mm rainfall (NMSA 2016a). However, the spatial distribution of the rainfall stations in the sub-basin is uneven to carry out a proper correlation between altitude and rainfall. Figure 5 depicts the cumulative annual precipitation in the sub-basin based on the data from the available rainfall stations (1996-2016).

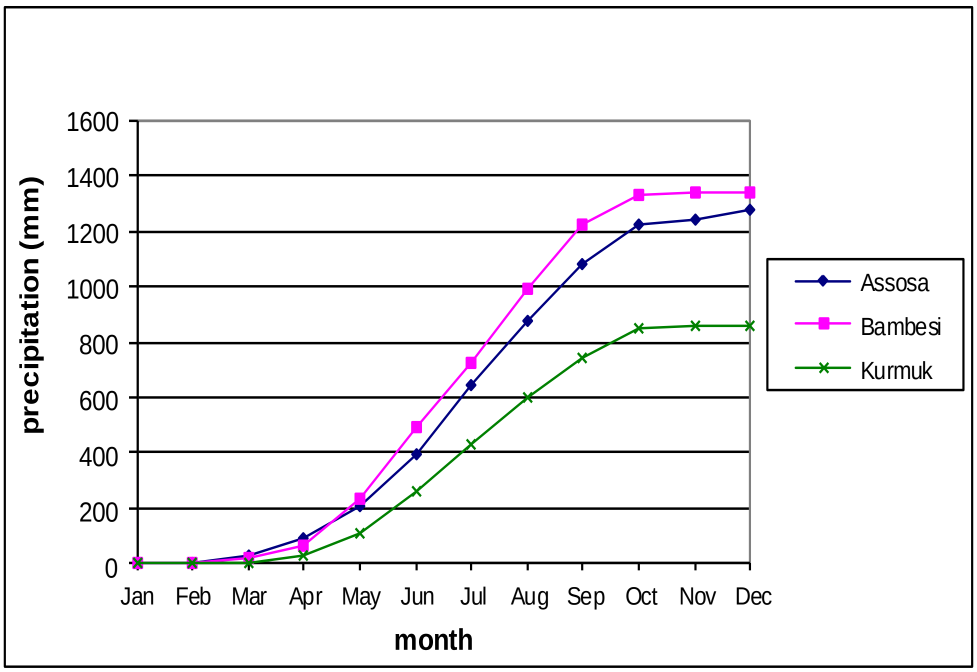


Figure 5 Cumulative annual precipitation in the study area

Source: Assosa, Bambasi and Kumruk Meteorological stations (1996-2016).

Figure 6 depicts the mean monthly rainfall for the three stations namely, Assosa (31years record), Bambasi (25 years record), and Kurmuk (20 years record). It also shows the monthly rainfall pattern in the area signifying the erratic nature of rainfall. The monthly total, distribution and timing (beginning and ending) of the rainfall are also irregular.

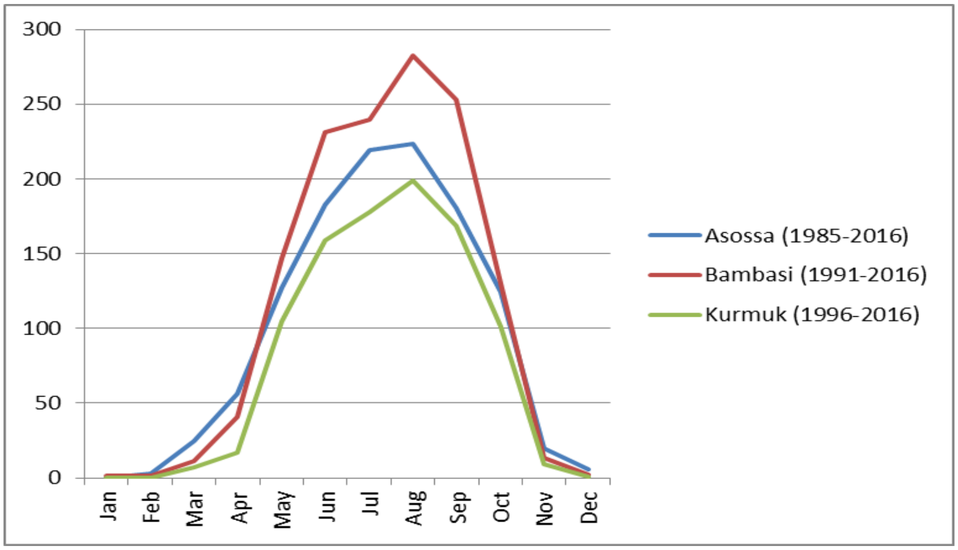


Figure 6 Mean monthly rainfall (mm)

Source: Assosa, Bambasi and Kumruk Meteorological stations (1985-2016).

$$RC = \frac{MMRF}{MARF\left(\frac{1}{2}\right)}$$

RC=Rainfall coefficient

MMRF= Mean monthly rainfall over a certain year

MARF= Mean annual rainfall

Based on Daniel (1974) the following designation of the rainfall of the study area is made:

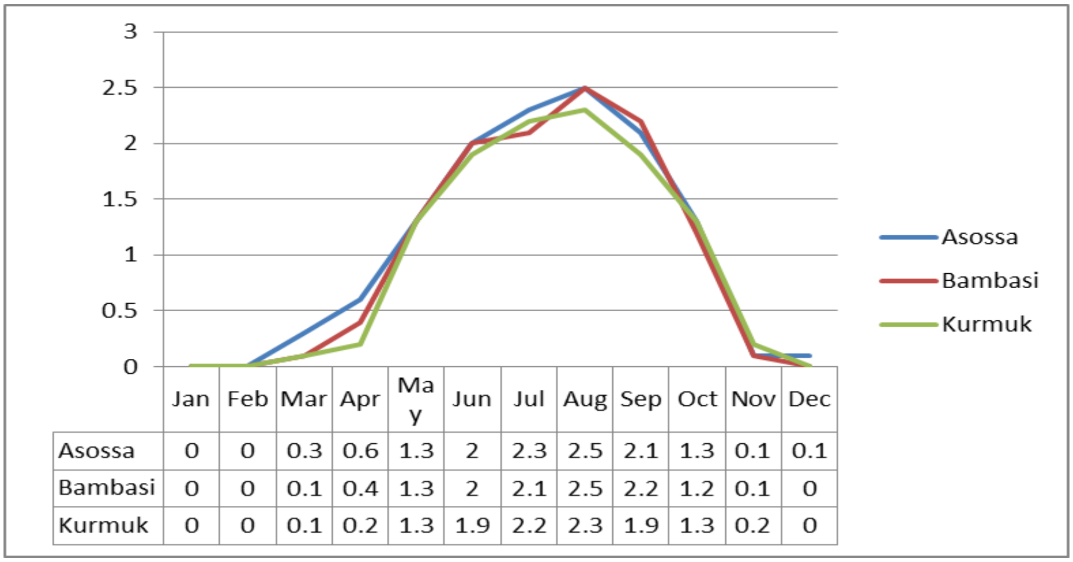
RC= >1 implies extremely rainy months

RC=0.8 –1 implies distinctly rainy months

RC=0.6-0.8 implies rainy months

RC= < 0.6 implies dry months

Accordingly, it can be shown that, the rainfall of the Dabus sub-basin is unimodal and it obtains high rainfall from May to October (Figure 7) and the highest rainfall occurs in August.



	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Asossa	0	0	0.3	0.6	1.3	2	2.3	2.5	2.1	1.3	0.1	0.1
Bambasi	0	0	0.1	0.4	1.3	2	2.1	2.5	2.2	1.2	0.1	0
Kurmuk	0	0	0.1	0.2	1.3	1.9	2.2	2.3	1.9	1.3	0.2	0

Figure 7 Rainfall coefficients of the Dabus sub-basin
Source: Assosa, Bambasi and Kumruk Meteorological stations (1996-2016).

The temperature of the Dabus sub-basin reaches a daily minimum of 20-25°C in the rainy season and rises to 35-40°C in the dry season. The hottest period is from February to April. The minimum temperatures range from 12°C to 20°C, depending on season and altitude. Figure 8 shows the course of average temperature in the sub-basin over the year.

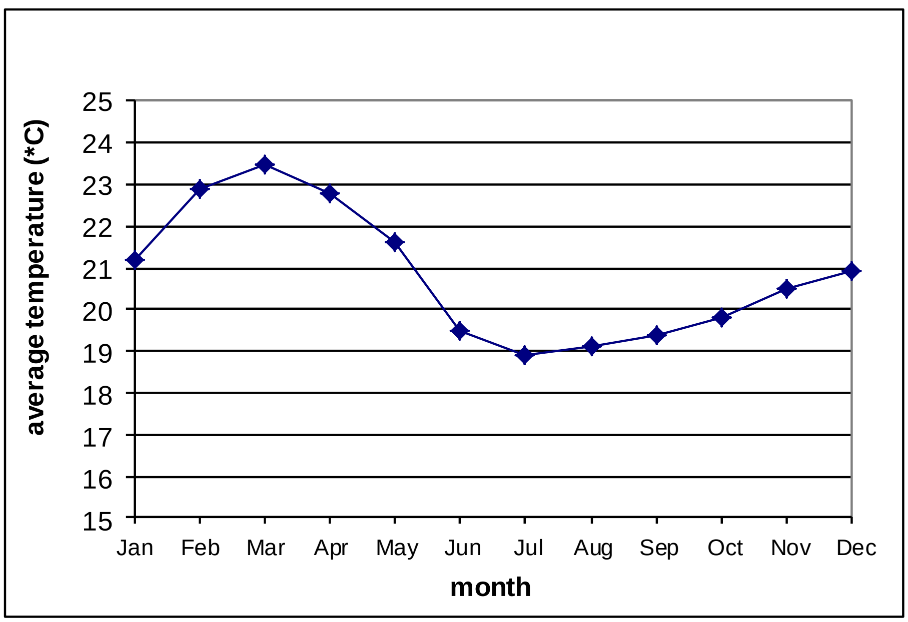


Figure 8 Seasonal course of the average temperature of the study area
Source: Assosa, Bambasi and Kumruk Meteorological stations (1996-2016).

The mean monthly temperature was computed based on the data from the three stations (1996-2016). The data shows that the lowest temperature occurs in August while the maximum occurs in the month of January (Figure 9). However, it can be observed that variation of the mean monthly temperature is small.

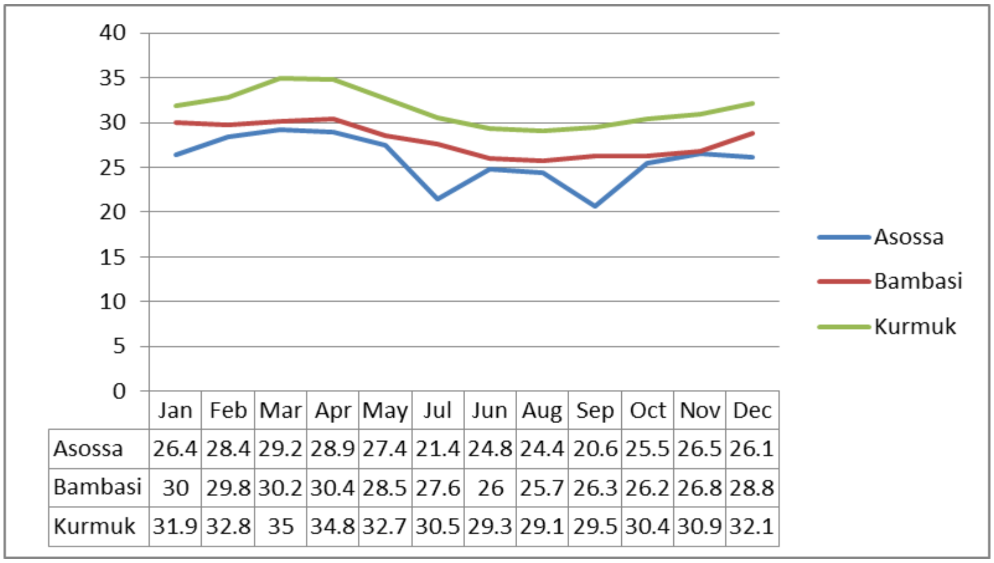


Figure 9 Mean monthly temperatures (^{0}C) in the Dabus sub-basin
Source: Assosa, Bambasi and Kumruk Meteorological stations (1996-2016).

1.6.2.3 Population size and spatial distribution in the Dabus sub-basin

Based on CSA (2013), there were 319,428 people in the Dabus sub-basin (70,984 households). The average family size for the study location is 4.5 persons per household (Table 1.1) and this is very close to the national average of 4.8 persons.

Table 1.1 Population size and density in the Dabus sub-basin

Woreda	**Population**	**Area (Km2)**	**Population density**
Menge	47,677	2407.4	19.80
Kurmuk	24,402	2322.4	10.51
Assosa	106,128	3205.4	33.11
Bambasi	55,247	2809.4	19.67
Sherkole	28,779	4104.4	7.01
Oda Buldiglu	27,657	1,518	18.22
Homosha	12,097	679	17.82
Mao-Komo Spe. Woreda	17,441	2,245	7.77
Total	**319,428**	**19,291**	**16.56**

Source: Statistical Abstract (CSA 2013)

1.6.2.4 Economic mapping of the Dabus sub-basin

In conformity with the agricultural nature of the economy, majority of the population is in agriculture (88%) with some degree of diversification into non-farm activities including mining, crafts, and trade. The main source of income is crop production constituting 50% of the total income followed by livestock raising (20%), mining (17%) and non-timber forest products (13%) (IPS 2012a; IPS 2012b).

Crop production

About 95,000 ha of land were cultivated during the 2016 cropping season in the study woredas (BoARD, 2016). Sorghum, maize, haricot beans and sesame are grown in all of the study woredas. Sorghum and maize covered about 52% of the total cultivated land. The land allocated to sesame and millet accounts about 20 and 12%, respectively. Niger seeds, haricot beans and groundnuts are also important crops grown on 10%, 5% and 4% of the cultivated area, respectively. The land allocation pattern confirms that food crops have taken the lion share occupying about 71% of the cultivated area. The productivity of food crops shows considerable variation among the study woreds, the smallest yield being recorded in Mengie and Shirkole woredas owing to moisture stress and low use of agricultural technologies. On the other hand, Assosa, Bambasi, Homosha and Oda Buldiglu woredas experienced a relatively higher yield owing to the favorable rainfall and better use of agricultural technologies.

Table 1.2 shows the relative importance of the crops produced in the sampled woreadas based on secondary data and the results of the FGDs held the respective woredas. Cereals are the most important crops taking a rank of 1-2 in all the sampled woredas, while oil seeds, particularly sesame, are the second most important crops. The oil crops are grown mainly for market. However, the yield level of these crops is generally low with an average of 4qt/ha. Sesame is the most important oil crop grown followed by Niger seed.

Mango is the major fruit tree grown followed by other fruit trees like papaya, banana, orange, lemon and avocado. The FGD results indicated that about 80% of the farm households in the area own mango trees with an average of 7 trees per household, the maximum number being 100 trees per household. Some big mango trees set up to 3,000 fruits per a tree per year indicating the good potential for expanding mango production and processing in the area.

Table 1.2 Relative importance of crops produced in the sampled woredas

Crop type	Assosa	Bambasi	Sherkole	Mengie
Sorghum	1	2	1	1
Maize	2	1	4	2
Sesame	3	3	2	3
Groundnut	6	4	5	4
Haricot beans and soybeans	5	7	3	6
Finger millet	10	10	7	7
Fruits/mango	7	6	9	8
Niger seed	8	8	8	5
Tef	4	5	10	10
Vegetables	9	9	6	9

Livestock rearing

Livestock rearing is the second most important livelihood activity in the Dabus sub-basin. The study woredas account for 17% of the region's goats, 15% of the sheep, 15% of the poultry and 8% of the donkey population (CSA, 2016). Availability of grazing land provides a good feed opportunity during the rainy season. However, the livestock production follows an extensive traditional system with limited veterinary services and supplementary feeding. Disease and feed shortage during the dry season constrain livestock production in the area. The FGDs held in the sampled woredas revealed that livestock disease reduced the number of oxen available for traction and constrained modernization of the crop farming. Oxen shortage coupled with lack of knowledge in using oxen plow induced most of the indigenous people to use hoe for land preparation and planting.

Traditional gold mining

A study by (SID-Consult, 2014) indicated that about 70% of the households in Sherkole and Mengie woredas depended on the traditional gold mining as an alternative source of livelihood. The FGDs held for in these woredas also confirm that about 60% of the households in Sherkole woreda (Figure 10) and 50% in Mengie woreda (with some variations among the rural kebeles) participated in gold mining during the dry season. However, the contribution of gold mining to the livelihoods of the community has been low since the amount of gold mined is very low compared to the efforts exerted. Based on the FGDs, the income from gold mining in Mengie woreda is about Birr 160 per week, but this income accrue to only about one-third of the people involved in the gold mining. The rest earned as low as Birr 35 per week. In Sherkole, the miners reported less success with an average weekly income of birr 30.

Figure 10 Artesian gold mining and washing (Sherkole)

Bee keeping

The Dabus sub-basin is very rich in its flora diversity favorable for apiculture. The existence of tree species appropriate for honey production in the area favored bee colonies to produce honey even without beehives. As a result, the indigenous people commonly hunt for such forest honey to supplement their livelihood. Despite this immense potential, the traditional beekeeping practice constrained the production level and hence the contribution of beekeeping to household income is very minimal. The honey yield in the area from the traditional beehives ranges between 5-8 kg per year per beehive (BoARD, 2016).

Forest products

Based on BoLA (2016), the forest vegetation cover of the Dabus sub-basin consists lowland bamboo (Oxytenanthera abyssinica), dense forests, riverine forests, broad-leaved deciduous woodlands, acacia woodland, boswellia woodland, bushland, and shrubland. Forest products can be classified into wood forest products (major forest products) and non-wood forest products (minor forest products) (SID-consult 2014). The wood forest products include industrial wood, construction wood, timber, fuel wood and charcoal. The non-wood forest products consist of bamboo products, forest honey and wax, gums and incense, resins, spices and medicinal plants.

Farm households in the area depend heavily on the woody biomass as source of light and energy supply. The indiscriminate cutting of trees for such purposes is causing a decline of the forest resources and exposing the area to land degradation. The traditional charcoal production in the area, which is reported to have a low conversion efficiency of 15% (BoARD, 2016), is also inducing a mounting pressure on the forest resources. The demand for construction wood and timber is also increasing over years as most of the construction activities in the area depend on forest products. Light construction activities also largely depend on the lowland bamboo.

Non-wood forest products are very common in the area although the use of these resources is largely limited to household consumption. The region is the only location in the country known for the lowland bamboo and this resource has got an enormous importance for the society in the area. It is a multipurpose resource used for fuel wood, construction, animal fodder, human food (bamboo bud/shoots), as a raw material for making house utensils and catchment rehabilitation. The other category of non-wood forest products are gums and incense. These are collected from several trees and shrubs, notably, Acacia senegal, Boswellia paprifera, Commiphora erythraea and Commiphora abyssinica (BoARD, 2016). Key informants in the study area indicated that, the exploitation of incense was started in 1976 by the Forestry and Wildlife Conservation and Development Authority (FaWCDA). Later, the Natural Gum Processing and Marketing Enterprise was established to exploit the resource though the success is not to the expected level.

Mengie and Sherkole woredas are endowed with good source plants of incense (Figure 11). Harvesting of incense has been granted to private business (investors) who employ laborers from other parts of the country. The investors have been operational in the area since 2009/10 being granted up to 20,000 ha of land with a planned production level of 1qt/ha and estimated production of 30,000 qt per annum (BoARD, 2016). In addition to private companies, the state owned Ethiopian Gums and Incense Enterprise has been also collecting incense from the potential woredas. However, there have been conflicts between the indigenous people and the company/collectors (laborers) on ownership of the trees in many instances and this constrained the harvesting practice.

Figure 11 Incense collection and sorting (Shirkole)

Lowland Bamboo

The lowland bamboo has considerable economic importance in the in the study locations. This forest type is common in the altitude range from 700-1700 m.a.s.l and requires a minimum annual rainfall of at least 700 mm. The lowland bamboo area mapped in the BGNRS was 300,823 ha. However, the total area of the bamboo forest in the region is estimated at 440,000 ha (BoARD, 2016). Table 1.3 depicts the estimated lowland bamboo area in the region. As can be seen from the same Table, considerable lowland bamboo area (about 148,000 ha) is recorded in woredas within the Dabus sub-basin.

The settlement program in the area during the 1990s seriously affected the lowland bamboo resource. Based on the key informants and experts opinion, more than 240,000 hectares of bamboo forest has been destroyed in Assosa settlement area alone during the settlement program. The observation made in the area and BoARD (2016) confirms that there is also a mounting pressure on the remaining natural bamboo, being threatened by agricultural expansion, shifting cultivation, and land clearing through burning that ultimately leads to forest fire.

Table 1.3 Estimated lowland bamboo area in BGNRS and in the study woredas

Woreda	Total Area (ha)
Assosa	77,947
Bambasi	64245
Mengie	3544
Sherkole	2345
Dibate	14,200
Mandura	21,509
Bulen	40,316
Guba	7,757
Dangur	27,612
Kamashi	43,723
Pawe	53,830
Total	**440, 416**

Source BoARD (2016)

Based on the FGD held in the study woredas, the lowland bamboo has many unique features. It is the fastest growing perennial plant. Once the rhizome-root system is well established, new bamboo shoots attain full height (6-8m) and a diameter of (4-8 cm) within 2-3 months. The plant matures and be ready for utilization after 2-3 years. It sets flowers towards the end of its life time (14 to 50 years in some species) and then dies soon after (Figure 12)

Bamboo products are used locally for different purposes including house construction, fencing, and construction of cattle barns, furniture, baskets, grain stores, tools, and firewood (BoARD 2016). The FGDs held in the area pointed out that bamboo shoots are used for food during food gaps between June and August. The stem sheath (thin silvery) is extensively used for roofing and the construction of traditional beehives while the hollow bamboo is used for making traditional musical instruments. The stem (culms) cut into small pieces to make coffee cups and water jars. Based on the key informants, the rate of deforestation of other tree species would have been drastically increased in the absence of bamboo. Thus, bamboo conservation should be the major part of the natural resource management component in the Dabus sub-basin.

Figure 12 Flowered lowland bamboo (Assosa)

1.7 General Conceptual Framework

Reconciling the three objectives of increasing production, reducing vulnerability of the rural poor (subsistence farmers) and using natural resources sustainably in the face of changing climate is a challenging target that developing countries are trapped in (Nkonya et al. 2011; Deressa 2011; Mengistu 2010). These are what Vosti and Readon (1997) call the *critical triangle of development objectives*. It is generally proved that land degradation problems in terms of decline in soil fertility results in low productivity, among other consequences, and in turn contributes to vulnerability of rural livelihoods to climate change induced hazards. This vulnerability to climate change induced risks is evident in Sub-Saharan Africa (Way 2006) where vulnerability is indicated as possible consequence of land degradation.

Conversely, vulnerability may also contribute to land degradation if subsistence farmers lack the ability or the incentive to invest in conserving and managing their land (Nkonya et al. 2011; Nkonya et al. 2006, Cleaver and Schreiber 1994) and over use the land resource to survive (as coping strategy). This makes the land more impoverished, which further impoverishes the already poor and vulnerable people. Supporters of this thought argue that if policy makers want to address the land degradation issue, then they must first address the vulnerability of the rural poor (Nkonya et al. 2011; Nkonya et al. 2006).

Consequently, the notion of the *down spiral of land degradation and vulnerability* may hold for smallholder farmers with scanty resources. This circular/spiral relationship indicates that land degradation leads to more vulnerability which in turn leads to further degradation (Nkonya et al. 2011; Way 2006; Prakash 1997). According to this argument, vulnerable people are forced to degrade landscapes in response to climate induced hazards and other factors such as population growth and economic marginalization.

Contrary to this notion, there are also empirical evidences (Scherr 2000; Way 2006) based on the argument that the poor and vulnerable are not always responsible for degradation, but they have interest in conserving their land, for they already know the consequences of degradation. A study on livelihood strategies (Scherr 2000) revealed that subsistence farmers may have limited resources; they still have considerable capacity to adapt to environmental degradation, either by mitigating its effects on their livelihoods or by rehabilitating degraded resources. There is also a relatively similar argument that vulnerable people are able to adopt protective mechanisms (adaptation strategies) through collective action to reduce the impacts of environmental/climate change (Nkonya 2008; Forsyth et al. 1998). Further, people (whether vulnerable or not, poor or rich) may choose to degrade natural resources while investing in other assets that yield higher returns (Nkonya 2008), a process of substituting one type of capital for another which may lead to improvement in livelihoods.

In effect, studies revealed striking heterogeneity in environmental management by subsistence farmers, their success in adapting to environmental/climate changes and the efficiency of external factors (policies, institutions, environmental variables, technologies) in influencing the outcomes (Nkonya et al. 2011; Mengisu 2010; Nkonya 2008; Way 2006; Tchale et al. 2004; Asrat eta al. 2004). Hence, *poverty-environmental interaction side of the critical triangle* poses more controversial research challenges.

In whatever direction or degree of complexity of *poverty-land degradation linkages*, poor people are more vulnerable to the negative consequences as they lack sufficient asset base to adapt to its effects (Nkonya et al. 2011; Mengisu 2010). Hence, enhancing sustainable land use practices among subsistence farmers is widely recognised as a critical aspect in addressing vulnerability (Nkonya 2008; Tchale et al. 2004) through increasing agricultural productivity and reducing production risk. In line with this, creating a loop that can reduce both vulnerability of subsistence farmers and land degradation (‘win-win’ situation) is possible (Nkonya et al. 2011; Way 2006; Scherr 2000; Forsyth et al. 1998).

The possible link among vulnerability, climate-smart land management, land degradation, and productivity is illustrated in Figure 13. The conceptual framework is presented to show the general relationship among the core concepts of this study. Further, this conceptual framework is cascaded to various analytical frameworks in the subsequent chapters to address each of the specific issues of the research piece by piece. The conceptualization of the framework is substantiated by empirical evidences from Simane et al. (2016), Nkonya et al. (2011) Mengistu (2010), Petermann (2008), Nkonya et al. (2008), IPCC (2007b), IPCC (2007c), Adger (2005), Way (2006), Asrat et al. (2004), Scherr (2000), and Vosti and Readon (1997). Accordingly, the possible link among farm households’ vulnerability, land degradation, climate smart land management decision, and agricultural productivity as well as the role of various factors (technological, institutional, environmental and policy) affecting these relationship is illustrated Figure 13.

Climate smart land management decisions directly affects agricultural productivity, vulnerability and land degradation and the direct effect of land degradation on agricultural productivity is evident. Moreover, land degradation directly contributes to vulnerability as it reduces availability of valuable environmental goods and services important to the livelihood of subsistence farmers. Further, the level and type of land degradation may dictate the type of land management strategies to be adopted. Agricultural productivity determines vulnerability status of households. Thus, improving agricultural productivity is a means for enhanced availability of food, rural income and other livelihood assets for farm households. These relationships occur in a wider environment of a given location. Hence, the core components (climate-smart land management decisions, land degradation, vulnerability and productivity) and their interrelationships can further be affected and conditioned by climate change and variability (exposure, sensitivity, and physical characteristics), policies and programs, availability of appropriate technologies, and institutions.

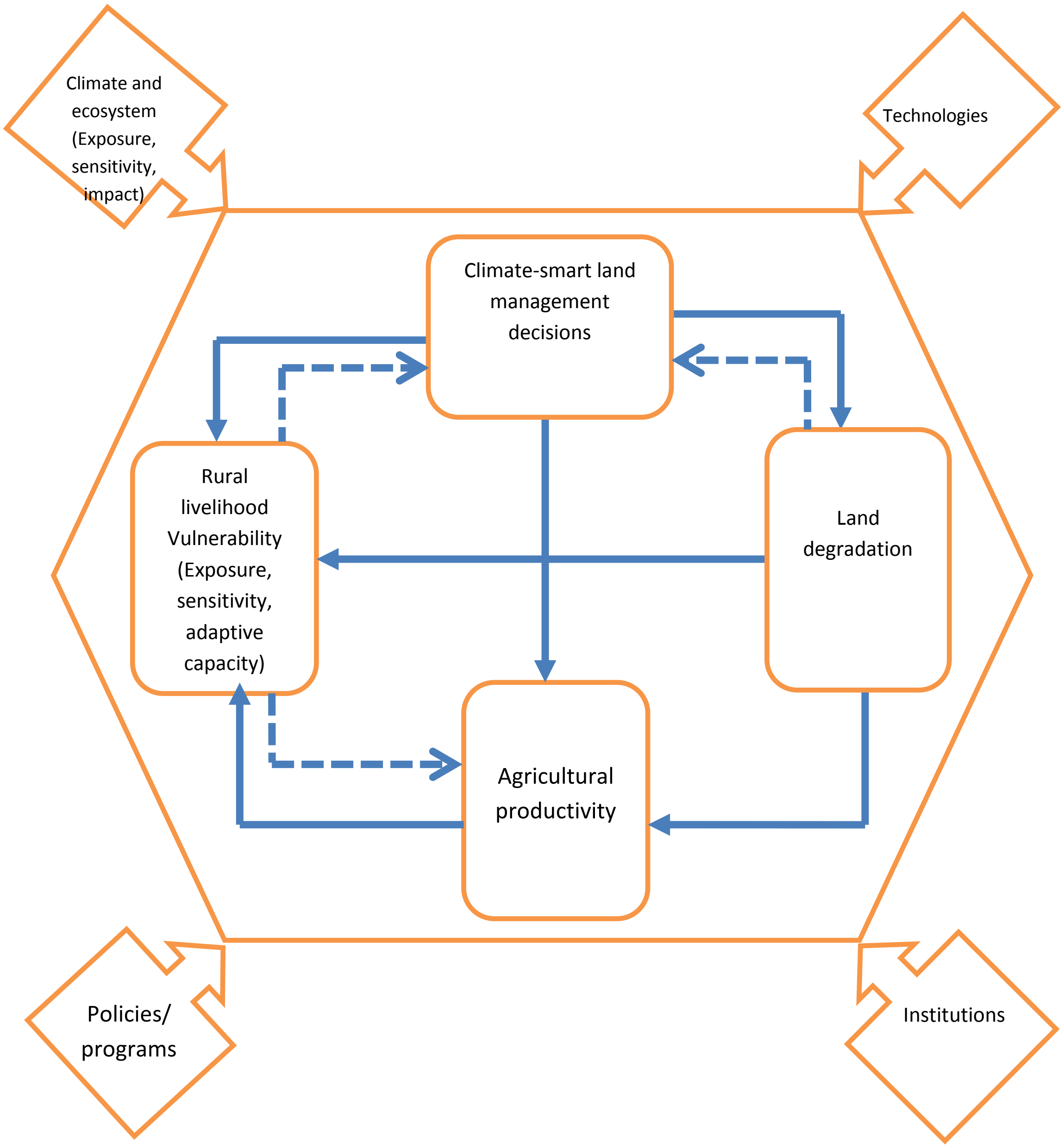


Figure 13 Causal-link among vulnerability, adaptive capacity, land management decision and productivity

The factors which are assumed to affect climate-smart land management and input use decisions also affect crop productivity and income of the farm household. Crop productivity and income are assumed to be affected by land management decision and input use. Conversely, crop productivity is assumed to affect income, and income affects land management decisions. Here, the key interest are outcome variables (crop productivity and farm income) and choice (decision) variables that include different climate-smart land management strategies and associated household and plot-level factors as well as environmental, institutional and technological factors (Figure 14).

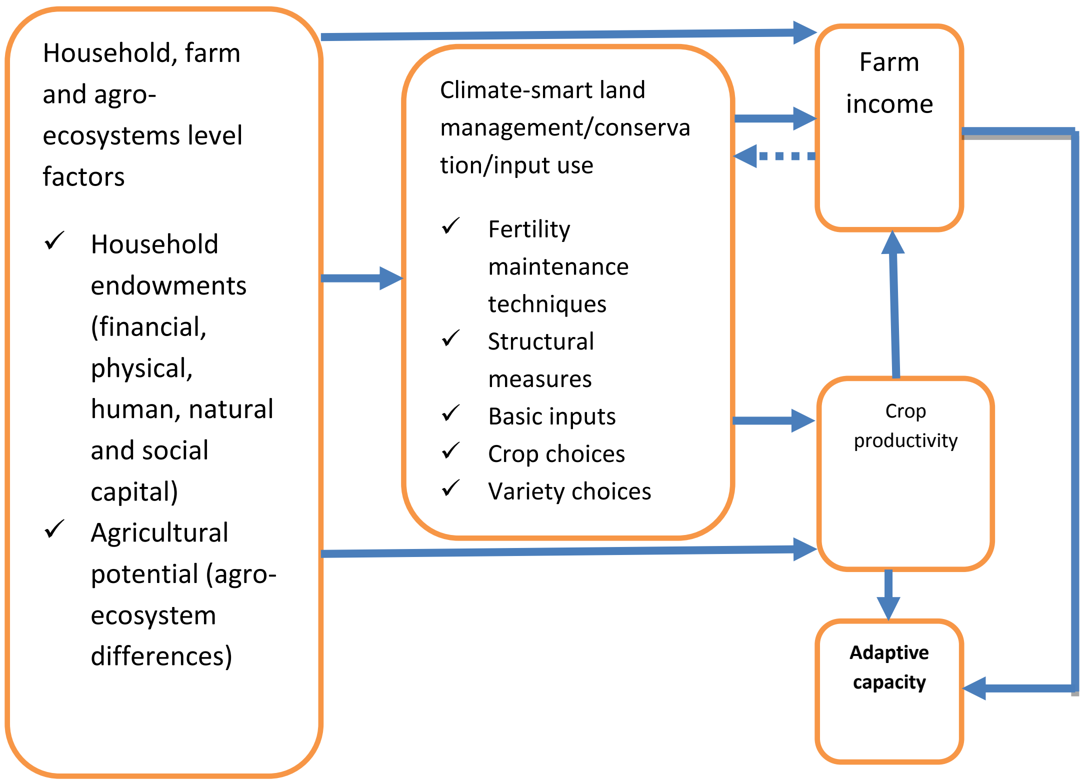


Figure 14 Analytical framework for climate-smart land management decision and impact

1.8 General Methodological Approaches

1.8.1 Types and sources of data

A cross-sectional household survey conducted in November and December 2016 enumerated 734 farm households, who are spatially distributed in the wet lowland and dry lowland agro-climatic zones of the Dabus sub-basin. The study employed a mixed approach and hence the types of data collected were both qualitative and quantitative in nature. The qualitative data largely depends on information obtained through key informant interview, focus group discussion, observation, community resource mapping and document review. The quantitative data was generated from household survey and secondary sources. Household survey instruments (structured questionnaire and semi-structured questionnaire) were employed.

Key informant interviews: Key informant interview was particularly used to generate in-depth information pertinent to climate trends over time, land use changes, coping strategies, adaptation measures, land productivity trends, and crop yield variability. For these purposes, a total of 36 key informant interviews were conducted.

Focus group discussions: Participants for FGD were selected based on their age, gender, primary activity, knowledge of the area, knowledge of major changes in relation to land use, land management, and climate change/variability. Two focus group discussions were held per a study kebele and the total numbers of focus group discussions held were 24.

Secondary data: This includes information on the agro-ecologies of the study area, rainfall data, temperature data, land use data, crop production data, livestock data, population data and other pertinent issues related to the study objectives.

Household survey: Household and plot level data were collected and used to understand the social, economic and demographic characteristic of the study population as well as to understand the level of vulnerability, adaptation options, perceptions about climate change and variability, the role of climate smart land management practices as adaptation measures, land productivity, yield variability and livelihood impacts.

1.8.2 Sampling Design

Sampling for qualitative data set: In order to identify the sample units (participants) for the qualitative data set a non-probability sampling approach was used. These include intensity sampling, stratified purposive sampling, and criterion based judgment sampling.

Sampling for quantitative data set: For the quantitative data set, a statistically proven approach and a rule of thumb were applied to determine the minimum sample size to be drawn considering the distribution and size of the population of the study area. The two agro-climatic zones of the Dabus sub-basin (Moist-low-land and dry lowland) were purposefully included to ensure representation of the sub-basin.

In the sampling process, the study followed a multi-stage sampling procedure combining purposive and random sampling techniques. In the first stage, 8 *Woredas* (districts) in the middle and lower part of the Dabus sub-basin were stratified into the two agro-climatic zones (wet lowland and dry lowland). In the second stage, four woredas (Assosa and Bambasi from the wet lowland; Mengie and Sherkole from the dry lowland) were randomly selected to represent the agricultural production systems, climate vulnerability and adaptation responses, land management practices, crop productivity and crop yield variability in the study area. In the third stage, 3 *Kebeles* (the smallest administrative unit) were randomly selected from the four sampled woredas and hence a total of 12 rural Kebeles were included in the study. Finally, 734 farm households were randomly drawn from the selected Kebeles on the basis of probability proportional to size (PPS) sampling procedure.

Sample size determination for the study was made following Cochran (1977), Daniel, (1999) and Kothari (2004) given the study population. However, the sample size from this approach is valid only if simple random or systematic random sampling methods are applied. Multistage sampling requires a larger sample size to achieve the same precision. The present study followed a multistage sampling procedure, and hence the calculated sample size is adjusted through a design effect based on Cochran (1977) and Daniel (1999). Previous studies of such type (Daniel 1999) estimated a design effect in a range of 1.5-2. Based on this consideration and observation made on the study population, a design effect of 1.5 is used.

$$n = \frac{NZ^2 P(1-P)}{d^2(N-1) + Z^2 P(1-P)}$$

Where:

n = sample size of household units with finite population correction,

N = total number of farm household units (population size),

Z = Z statistic for a level of confidence (Standardized normal variable that its value correspondence to 95% confidence interval which is equal to 1.96),

P = farm household units variable in terms of percentage (Expected proportion in proportion of one),

1-P= non-farm households, and

d = allowable error or precision {0.5*(1-P)}

Given the population of the study area and using the above formula, the minimum sample size for a reliable result was found to be 489. However, cluster and multistage sampling methods require a larger sample size to achieve the same precision. Therefore, the calculated sample size using the above formulae needs to be multiplied by the design effect (*deff*) (Cochran 1977; Daniel 1999). For example, in immunization coverage cluster surveys, the design effect has been found to be approximately two (Macfarlane 1997). This means that such cluster sampling requires double the sample size of the above calculation. Since this particular study used multistage sampling procedure, it is worthy to estimate a design effect to increase the precession. Based on this consideration and the observations made about the study population during a pilot survey conducted in the study area by the researcher, the minimum sample size determined using the above formulae is adjusted through the design effect (1.5) and increased to 734.

1.8.3 Data analysis techniques

Information from the qualitative data set was used to triangulate and substantiate the quantitative data. It is also used capture commonality and divergence across the study locations (before and after the quantitative survey) in terms of the variables of interest in a sequential-embedded approach. More importantly, the qualitative data set from the FGD is used to describe the study area along with information obtained from the secondary data sources.

The quantitative data analysis techniques incorporate descriptive statistics, indexed approach, and econometric models. The descriptive methods are used to reveal the farm households' social, economic and demographic characteristics. Moreover, descriptive tools are applied to compare the two agro-climatic zones of the study area in terms of the variables of interest that include: households' perceptions of climate shocks and long-term changes, the effects of the shocks and changes, responses towards those shocks and changes (adaptation measures), the impacts of the responses, and the constraints in implementing the responses.

The Livelihood Venerability Index (LVI) framed within the United Nations Intergovernmental Panel for Climate Change (IPCC) is customized based on (Simane et al. 2016; Entwire et al. 2013; Mohan & Sinha 2010; Hahn et al. 2009), and contextualized for the agro-ecology specific vulnerability analysis in this study.

The econometric models employed are customized from technology adoption studies into climate change adaptation and impact analysis made in this study. The econometric models are advanced models as most of them are beyond a single regression equations. They basically take into account the nature of the dependent variables, dependence of the error terms across equations (simultaneity problem), the correlation of the error terms to one or more independent variables in the models (endogeneity problem) and other econometric considerations.

In this respect, the Heckman sample selectivity probit model is employed to identify the determinant factors that influence perception and adaptation of smallholder farmers. The probit model is used to assess factors that determine farmers' use of different set of land management based adaptation strategies. On the other hand, two sets of econometric models are employed to examine the causality between different climate smart land management practices and factors affecting farmers' decision to use these practices. A two stage probit model is used to determine a reciprocal causation between use of external inputs as a land management strategy and factors affecting their use thereof. Likewise, a bivariate probit model is used to analyze the interrelationship between modified agricultural practices as a land management strategy and factors affecting the decision to use the practices at household and plot level.

In order to assess the impact of climate-smart land management practices on crop productivity, the Propensity Score Matching (PSM) method is employed. Parallel to this, the mean-variance method of Just and Pope (1979) is applied to assess the effect of climate smart agricultural practices on crop yield variability at plot level. Moreover, the Instrumental Variable (IV) estimation method was employed to assess the relationship between climate smart agricultural practices and crop productivity at plot level. Detailed specifications of the analytical tools and the econometric models are provided in the respective chapters.

1.9 Organization of the Study

This PhD dissertation is organized into eight chapters. Chapter one presents the general problem description, general methodological approach, the study area description, the conceptual and empirical frameworks that guided the study and the study design. Chapter two, Chapter Three, Chapter Four, Chapter Five, Chapter Six and Chapter Seven form the core of this study presenting the main results and conclusions. These chapters stand "independent" each consisting of chapter introduction, analytical framework/methodology, empirical results and discussions, and chapter summary. Chapter Two addresses the vulnerability of crop-based rural systems to climate change and variability. Chapter Three deals with agro-ecology specific determinants of perception and adaptation to climate change. Chapter Four details the determinants of farmers' decision to invest on structural and non-structural land management measures. Chapter Five specifically deals with the causality and interdependence among different climate-smart agricultural practices including manure application, fertilizer application, conservation tillage and intercropping activities; and investigate the factors associated with the decision to use these practices. Chapter Six investigate the link among climate-smart agricultural practices, crop yield variability and productivity as well as determinates of productivity. Chapter seven is devoted to the analysis of household and plot-level impacts of climate-smart land management measures. Finally, Chapter Eight synthesises the main findings of the core chapters of the study and their potential policy implications.

Chapter Two

2. Characterizing Vulnerability of Crop-based Rural Systems to Climate Change and Variability: Empirical Evidence from the Dabus Sub-basin, North-west Ethiopia

Abstract

Climate change is impacting climate sensitive rural livelihood systems. Exposure, sensitivity, and adaptive capacity of agricultural livelihoods to climate variability and change differ across agro-climatic zones and these pose a challenge to climate resilient development strategy. This study assesses agro-climatic zone based vulnerability of smallholder farmers to climate change and variability in the Dabus sub-basin based on a survey of 734 farm households complemented with focus group discussion and key informant interviews. Recognizing the physiographic and climatic diversity that exists across agro-climatic zones in the study area, Livelihood Vulnerability Index (LVI) framed within the United Nations IPCC vulnerability framework (LVI-IPCC) is adapted to assess vulnerability in two local agro-climatic zones, namely wet lowland and dry lowland. For each agro-climatic zone, exposure, sensitivity and adaptive capacity indices as well as the LVI-IPCC vulnerability score was calculated. The result shows that the dry lowland agro-climatic zone has a relatively higher exposure and sensitivity to climate stresses with a comparatively limited adaptive capability. On the other hand the wet lowland exhibits intermediate vulnerability with a relatively lower perceived exposure and higher adaptive capacity. Higher exposure relative to adaptive capacity resulted in a positive LVI-IPCC score in the dry lowland and positioned it in more vulnerable level than the wet lowland. A higher adaptive capacity relative to exposure unveils a negative LVI-IPCC score for the wet lowland and positioned it in a moderate vulnerability category. In line with the findings, there is a need to set agro-climatic zone specific priorities for intervention that is most needed to cop up with the effects of climate variability and change in each agro-ecology. Climate risk exposure levels can be reduced through timely provision of climate specific information and early warning systems aimed at enhancing preparedness of farm households to extreme events. It is also crucial to expand infrastructural facilities such as market, health services, and veterinary services so as to enhance adaptive capacity. Supporting alternative livelihood options and enhancing water harvesting practices for supplementary irrigation also call policy attention.

Keywords: *Climate change, exposure, sensitivity, adaptive capacity, vulnerability, agro-climatic zone*

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2.1 Introduction

Based on the predication made by the Intergovernmental Panel on Climate Change (IPCC), the expected increase in global temperature in the next two decades is between 0.3 and 0.7 °C (IPCC 2007c). Based on this prediction, Collins et al. (2013) and Kirtman et al. (2013) revealed an increase of temperature between 0.3–4.8 °C by the end of the 21st century depending on emission scenarios. The increase in temperature is also evidenced by an increase in frequency of extreme events such as drought, floods and emergence of different crop and animal pests and diseases. The changes have also been manifested through increase in duration of hot days, hot nights, and heat waves. These variability and change in climate have already made Africa most vulnerable owing to its high reliance on climate sensitive sector and low adaptive capacity (Adger 2007) putting about 600 million Africans at the risk of water stress, extensive floods, drought, and famine. Sub-Saharan Africa will be the most vulnerable part as these risks will cause a reported decline of 10-20 percent in crop yields by 2050, which will also lead to a significant decline in crop revenue (Lobell et al. 2011a; IPCC 2007d).

Based on IPCC (2007a), vulnerability to climate change is the extent to which a system or community is prone or at risk and unable to deal with the negative effects of climate change and variability. Vulnerability is not a static concept, it varies in space and time; and its level also depends on the rate of change of climate and the extent to which the system is exposed, its sensitivity and adaptive capacity. Based on Simane et al. (2016), sensitivity refers to the extent to which a system is either negatively or positively, directly or indirectly affected by climate change and variability. Adaptive capacity on the other hand is the ability of a system to reduce/moderate the potential effects of climate change and variability by either taking advantages of existing opportunities or undertaking measures to deal with its consequences.

As part of Sub-Saharan Africa, the livelihood of about 85 percent of the labor force in Ethiopia is dependent on the climate sensitive sector, agriculture, and this sector also contributes 40 percent of the country's GDP (Conway and Schipper 2011; Cooper et al. 2008; Thomas et al. 2007). In line with this, Von (2007) estimated that a 10 percent decrease in the main season rainfall from the long-term average causes a 4.4 percent decrease in the national food production. If this situation left unmanaged, it may end up in a decline of the country's GDP growth projected in the range of 0.5 to 2.5 percent annually (World Bank 2010; EPA 2011). Generally, the heavy reliance on the climate sensitive sector, unsustainable pattern of land use practices, and lack of necessary capital to invest in adaptation options exacerbate the consequences of climate change in Ethiopia (Patt et al. 2009a).

There are some studies which assessed vulnerability to extreme climate events in Ethiopia. Deressa et al. (2009) have used national data and employed “vulnerability as expected poverty” approach to develop an index that determines the vulnerability levels of smallholder farmers to climate extremes. On the other hand, Simane et al. (2016) have used Livelihood Vulnerability Index (LVI) and LVI-IPCC framework to determine smallholder farmers’ vulnerability to climate change impacts in the high land agro-ecosystems. However, to the best of the researchers’ knowledge, no previous agro-ecology specific studies on vulnerability to climate change impacts have been conducted in the country in general and in the lowland agro-ecologies in particular.

Considerable diversity is prevailing in Ethiopia in terms of agro-ecology, socio-economic set up, climate change and variability, environmental conditions, agricultural production systems, water resources and biodiversity (Simane et al. 2016; Deressa et al. 2009). Given this diversity, aggregate assessment cannot capture the complexity of vulnerability at agro-ecology level and may lead to blanket recommendations (Simane et al. 2016). The present study, therefore, adds to the vulnerability literature and contributes to the building of agro-ecology specific resilience in Ethiopia by assessing agro-ecology specific vulnerability to climate change and variability. The results of the study are indispensable to ensure better targeting of agro-ecology specific adaptation measures and development interventions.

2.2 Methodology

2.2.1 Analytical framework

Vulnerability analysis (VA) is employed to systematically understand how socio-ecological systems are affected by a source of harm. In climate change adaptation research, vulnerability assessments are used to understand how the effects of climate change may harm a given system, providing a basis for devising measures that will minimize or avoid this harm (Simane et al. 2016; Deressa at al. 2009; Patt et al. 2009b). Attempts at developing a one-size-fits-all definition of vulnerability have generally been dismissed and most researchers agree that it is more important to define the term within the context of a specific analysis than seeking a single theoretical definition (Wolf 2011). Clarifying the 'what' in vulnerability assessments, vulnerability of what (e.g. people, regions, ecosystems, economic sectors) and vulnerability to what (e.g. temperature extremes) is a first step to framing a vulnerability assessment. Füssel (2007) identified four aspects in describing a vulnerable situation:

System: The social/socio-ecological system being threatened by a hazard (e.g. geographic region, agro-ecology, agro-ecosystem, economic sector).

Attribute of concern: A valued features within the vulnerable system that may be harmed by a hazard (e.g. specific crop, human health)

Hazard: Potentially damaging influence /stress that may adversely affect a valued attribute of a system

Temporal reference: The time period of interest, including whether it is a current vulnerability or future vulnerability that is being assessed.

In recent days, the overarching goal of climate change vulnerability assessments is to inform policies that will facilitate adaptation. Different authors have identified a range of purposes for assessing vulnerability (Hinkel 2011; Patt et al. 2009a; Füssel and Klein 2006): setting mitigation targets, allocating resources, designing adaptation polices, monitoring adaptation polices, raising awareness about climate change, and conducting scientific research. Moreover, vulnerability assessments can support two distinct but related processes for developing adaptation policies (Preston et al. 2011):

Problem orientation: where the aim is to build an understanding of the nature of vulnerability, including its magnitude and extent, causes and effects, as well as the institutional and governance context within which it exists.

Decision-support: where the aim is to identify and select strategies for managing vulnerability. More recently, it has also been acknowledged that vulnerability analysis can provide a basis for monitoring and evaluation of adaptation.

Figure 15 portrays the analytical framework employed to assess climate change induced livelihood vulnerabilities in the study area. This analytical framework is cascaded from the general conceptual framework developed for this study and more elaborated here to depict the link among vulnerability, climate change impact, and adaptive capacity.

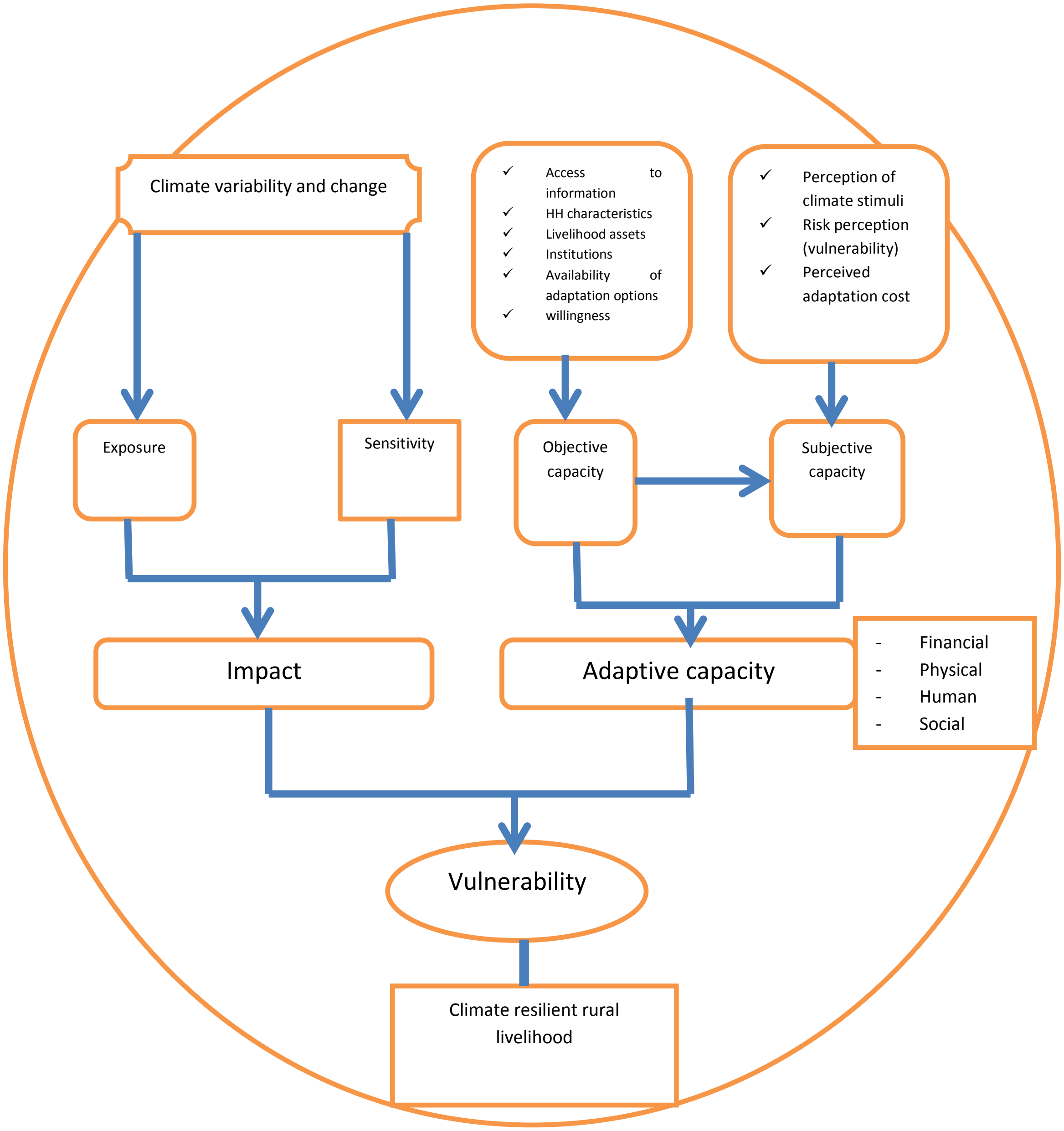

Figure 15 Analytical framework for understanding climate vulnerabilities of smallholder farmers

2.2.2 Defining vulnerability profiles

Hahn et al. (2009) developed and demonstrated the LVI and LVI-IPCC applying to two geographical locations (villages) in Mozambique. For this purpose, they defined seven major components of vulnerability that map onto the three IPCC contributing factors to vulnerability (exposure, adaptive capacity, and sensitivity). Simane et al. (2016) adopted this framework for Choke Mountain in the Northern highlands of Ethiopia and modified the number of the major components into eight in order to match the conditions and constraints facing agricultural households in their study location. In the present study, the framework being followed by Hahn et al. (2009) and Simane et al. (2016) are customized and adjusted to the context of the two agro-climatic zones in the Dabus sub-basin. Accordingly, we defined 12 major components that include natural resource, natural disaster, climate change and variability, land use system and sustainability, agriculture, income/wealth, technology, infrastructure, livelihood, knowledge/skill, socio-demographic, and social network.

Each profile is defined by a set of indicators with a hypothesized relationship with climate vulnerability. The indicators used in this study were generated based on review of previous vulnerability studies, secondary data, qualitative data and observation made in the study location. The 12 major vulnerability indicators/profiles were then mapped onto the three IPCC contributing factors to vulnerability following Hahn et al. (2009) and Simane et al. (2016). Each of the profiles (except the climate change and variability component) is associated with one of the five forms of capital used in the Sustainable Livelihoods Approach (Campbell et al. 2011)

A cross-sectional survey was conducted in November and December 2016 engaging 734 farm households from the two agro-climatic zones (wet lowland and dry lowland) of the Dabus sub-basin drawing 367 households from each. A survey questionnaire used to collect the data was designed in such a way that it addresses issues related to the 12 major components. Corresponding to these major components, the questionnaire addresses 37 indicators (sub-components). The 12 major components along with the associated 37 indicators are portrayed in Table 2.1. The data from household survey were triangulated with qualitative data from focus group discussions, key informant interviews, field observations and secondary sources. Moreover, the climate data that is used to assess exposure level were obtained from proxy stations of the National Meteorological Service Agency in the study area.

Table 2.1 Major components and sub-components vulnerability

LVI-IPCC factors	Capital forms	Major components/profiles	Sub-components/indicators
Exposure	Natural	Natural resource	% of household heads (HHs) that depend on natural resource for cash/food
			% of HHs with inconsistent water supply
			Average time taken to reach water source (hours)
			Inverse of the average liters of water per HH per day
		Natural disaster	Number of extreme events in the last 10 years
			Number of extreme crop disease/pest outbreak in the last 10 years
			Number of extreme livestock disease outbreak in the last 10 years
			% of HHs that didn't receive warning on pending extreme events
		Climate change and variability	Mean SD of monthly average of average max daily T^0 (30 years average).
			Mean standard deviation (SD) of monthly average of average min daily T^0 (30 years average)
			Mean SD of monthly average precipitation (30 years average)
			% HHs that did not perceived decreasing trend in precipitation
			% HHs that did not perceived increasing trend in temperature
Sensitivity		Land use and sustainability	% of HHs with non-suitable cultivated land (fertility, slope)
			% of HHs not practicing soil and water conservation
			% of HHs not practicing irrigation
		Agriculture	No. of months HH cannot fulfill food requirement from own production
			Average crop diversity index [1/ (no. of crops grown + 1)]
Adaptive capacity	Financial	Income/wealth	Annual income (sales of crop, livestock and off-farm income) (Birr) (inverse)
			Livestock in total livestock unit (TLU) (inverse)
			Cultivated farm size (ha) (inverse)
	Physical	Technology	% of HHs not using farm chemicals
			% of HHs not using fertilizer
			% of HHs not using improved seed
		Infrastructure	Average time to reach market (walking hours)
			Average time to reach human health facility (walking hours)
			Average time to reach veterinary service facility (walking hours)
	Human	Knowledge/skill	% of HH heads with no formal education
			% of HH heads not received climate specific extension advise/training
		Livelihood	Livelihood diversification [1/ (no. of livelihood activities + 1)]
			% of HHs that majorly depend on agriculture as source of income
	Social	Socio-demographic	Adult equivalent ratio (inverse)
			Dependency ratio
			Farm experience (inverse)
		Social networks & external support	Average receive: give ratio
			Average borrow: lend ratio
			% of households that receive government/NGO assistance in a year

2.2.3 Approaches to measuring vulnerability

Vulnerability can be analyzed either on the basis of risk hazard or social constructive frameworks (Simane et al. 2016; Ribot 2009). The risk hazard model tends to assess several possible impacts of a single climatic event whereas the social constructive model tends to emphasis the several possible causes of a single climatic event. Application of the risk hazard model generally emphasis exposure and sensitivity to environmental stressors and operates from the hazard to the impact (Turner et al. 2003).

In the risk hazard approach, several methods have been developed for aggregating indicators and computing an index, and key among them are the gap method and the weighting method. The gap method assesses vulnerability based on the deviation of farmers' current condition from predetermined level in the absence of climate change and variability. The weighting method on the other hand is based on valuing the importance of each indicator in terms of contributing to making the farmers vulnerable to climate change and variability (Simane et al. 2016; Hahn et al. 2009). In another perspective, econometric methods and indicators approaches can be employed to measure vulnerability to climate change and variability (Deressa et al. 2009). The indicator approach involves selection of indicators that a researcher considers to account for vulnerability. However, the weakness of this approach is that there could be some level of subjectivity in choosing the various indicators. Since the focus of the present study is on valuing the importance of various indicators, it opts for the balanced weighting approach to compute the LVI.

"Vulnerability as expected poverty" approach was used by Deressa et al. (2009) to measure farmers' vulnerability to climatic extremes with a particular reference to drought and floods. They estimated the probability that a given set of shocks will move a household's consumption below the consumption poverty line or force the consumption level to remain below a given minimum if the consumption is already below this level. However, this approach captures vulnerability as expected poverty (the tendency to be poor in the future as a result of climate extremes) and hence only measures future and not current vulnerability. An aggregate vulnerability index was developed by Gbetibouo (2009) to determine the level of vulnerability of the farming sector to climate change and variability. This approach selects and aggregates a number of variables that together serve as a proxy for vulnerability. Nevertheless, development of the aggregate index requires secondary data on both macroeconomic (such as agricultural GDP) and microeconomic (household level farm income) indicators, which is not readily available at agro-ecology level.

In view of this, the present study adopted the indicator (composite index) approach in measuring the vulnerability of smallholder farmers to climate change and variability based on the livelihood vulnerability index (LVI) developed by Hahn et al. (2009). This approach uses household level primary data (except data for precipitation and temperature) and takes into account several variables to capture the level of exposure to climate hazards, adaptive capacity and sensitivity to climate change impacts. Unlike the other techniques, this approach not only addresses future susceptibility but also the current vulnerability, which is useful for current adaptation planning. Therefore, LVI framed within the Livelihood Vulnerability Index-Intergovernmental Panel for Climate Change (LVI-IPCC) is contextualized and used to assess agro-ecology specific smallholder farmers' vulnerability to climate change and variability in the study area.

2.2.4 Livelihood vulnerability index

Since the 12 indicators used in this study are measured on a different scale, they have to be first standardized as an index. The equation used for this standardization is adapted from that used in the Human Development Index (UNDP 2007) as also used in Hahn et al. (2009) to calculate the LVI in Mozambique and in Simane et al. (2016) for the calculation of LVI to assess vulnerability of smallholder farmers in the highland agro-ecosystems of Ethiopia. The current vulnerability analysis involves calculation of a balanced weighted average LVI (composite index), in which each major component contributes equally to the overall index. Accordingly, first the raw data is transformed into appropriate measurement units such as percentage, ratio and indices and then the indicators measured in different scale are standardized (equation 2.1).

$$lvi = \frac{S_a - S_{\min}}{S_{\max} - S_{\min}} \qquad (2.1)$$

Where lvi is the standardized value for the indicator, S_a is the observed (average) sub-component indicator for agro-ecology a, and S_{min} and S_{max} are the minimum and maximum values, respectively for the indicator across the two agro-ecologies. Then, the sub-component indicators are averaged (equation 2.2) to obtain the index of each major component.

$$M_a = \frac{\sum lvi}{N} \qquad (2.2)$$

where M_a is one of the 12 major components for agro-climatic zone a; index Ivi represents the sub-components indexed by i, that make up each major component and "N" is the number of sub-components in each major component. Equation 2.3 combines the weighted averages of all the major components to generate the LVI score. The number of indicators of which it is compressed to determine the weights of each major component is WM_i. Values for each of the 12 major components for an agro-climatic zone are calculated and averaged (equation 2.3) to obtain the agro-climatic zone level LVI:

$$LVI_a = \frac{\sum_{p=1}^{12} WM_i M_{ai}}{\sum_{p=1}^{12} WM_{ai}} \quad \text{……………… (2.3)}$$

Where, LVIa is the LVI Index for agro-climatic zone a.

Based on the above three equations, the major components of LVI are calculated following the LVI-IPCC vulnerability categorization in to Exposure (E), Sensitivity(S) and Adaptation (A) as stated in equation 2.4):

$$CF_a = \frac{\sum_{p=1}^{f} WM_i M_{ai}}{\sum_{p=1}^{f} WM_{ai}} \quad \text{……………… (2.4)}$$

where, CF_a, is the LVI-IPCC defined contributing factors for agro-climatic zone a, M_{ai} are the major components for the agro-climatic zone a indexed by i, WM_i, are the weights of each major components, f is the number of the profiles associated to the contributing factors and p is indexed to the profiles associated with the CF. Finally, the LVI-IPCC is computed using equation 2.5.

$$LVI - IPCC_a = (E_a - A_a) * S_a \quad \text{……………… (2.5)}$$

where, LVI-IPCCa is the LVI for agro-climatic zone a, expressed using the IPCC vulnerability framework, E_a is the calculated exposure score for agro-climatic zone a, A_a is the calculated adaptive capacity score for agro-climatic zone a and S_a is the calculated sensitivity score for agro-climatic zone a. The LVI-IPCC is scaled from −1 (least vulnerable) to 1 (most vulnerable) and is best understood as an estimate of the relative vulnerability compared to the population in the agro-climatic zone.

2.3 Results and Discussion

2.3.1 Vulnerability index components and sub-components

Livelihood vulnerability has economic, political, social, demographic and institutional dimensions (Adger 2007; Sullivan 2002). As a result, practical assessment of livelihood vulnerability is very complicated and their applicability is also context specific. Therefore, the present research only focuses on the major factors (major components and sub-components) that are related to different livelihood assets at household level. The major components and the sub-components used to construct the LVI were selected based on primary data generated through household survey, focus groups discussion, key informant interview, expert opinion, and field observation.

The study adopted the risk hazard model to assess agro-ecologically classified vulnerability of smallholder farmers to climate variability and change. It valued the importance of various indicators and applied the balanced weighting approach to compute the LVI. Accordingly, the vulnerability index is derived for the two agro-climatic zones of the study area based on the IPCC definition of vulnerability to climatic impacts making use of the 12 major components aligned to the three vulnerability contributing factors (exposure, sensitivity and adaptive capacity). The exposure category consists of three major components namely natural resource, natural disaster and climate variability and change. In the adaptive capacity category, seven major components including finance, technology, infrastructure, livelihood, socio-demographic, social net-work and knowledge are considered. Agriculture, land use system and sustainability are included in the sensitivity category. The major component is made up of 37 indicators, which are standardized as index since each of them is measured on a different scale.

2.3.2 LVI-IPCC contributing factors and indexed components

This section describes the LVI-IPCC contributing factors, the major components and the indicators along with comparing the calculated indices between the two agro-climatic zones of the study area. The indices for the major components, sub-components and contributing factors are relative values and hence compared between the two agro-climatic zones within the sample only.

2.3.2.1 Exposure

The exposure factor consists of three major components that fall in the natural capital category. These major components are climate change and variability, natural resource, and natural disaster, which in turn comprise 13 sub-components/indicators.

Natural resource component

This major component is composed of four indicators. In terms of access to water, the dry lowland agro-climatic zone has the highest percentage (63%) of households without consistent water supply compared to 30 percent for the wet lowland. The average time taken to reach the nearest water source is higher in the dry lowland (about an hour) compared to 0.5 hour in the wet lowland. As water is usually sourced by women and young girls, distant water sources imply mounted pressure on the female household members. In terms of keeping water stock for future use, households in the wet lowland are better as reveled by the calculated inverse liters of water stored per household per day, which is 0.018 for the wet lowland compared to 0.042 for the dry lowland.

Comparatively more households in the dry lowland (35%) depend on forest products as food and cash source compared to 12 percent in the wet lowland. Exposure varies positively with the level of contribution of the natural resources to livelihoods and this is in line with Bankoff et al. (2004), who reported a strong association between dependence on natural capital and vulnerability to climate change risks. Moreover, large dependence on the natural resource may divert farmers' attention away from the regular farm activities and enhance their exposure to climate change induced risks. Considering the four indicators, the calculated vulnerability index for the natural resource component shows that the dry lowland is more vulnerable (with a score of 0.219) compared to the wet lowland (with a score of 0.152) (Table 2.3).

Natural disaster component

This major component is composed of four indicators. Intermittent drought is the typical extreme climate event that induces vulnerability of the farming community in both the wet lowland and dry lowland agro-climatic zones. In this regard, farm households in the dry lowland faced more frequent challenge (7 times) in the past 10 years compared to those in the wet lowland who faced the challenge 3 times. In terms of major crop disease/pest outbreaks, households in the dry lowland faced the challenge 4 times in the past 10 years compared to 3 times in the wet lowland. The other challenge is livestock production risk (disease), which has been prevalent 4 times in both agro-climatic zones in the last 10 years.

In both agro-climatic zones, about 76 percent of the respondents did not receive any warning about pending extreme events that could have helped them to adequately respond. This lack of information increases their exposure risk to natural disaster. Disaggregating this proportion into the respective agro-climatic zones entails that lack of information about extreme events is more prevalent in the dry lowland where 88 percent of the respondents did not receive any warning compared to 64 percent in the wet lowland. Considering the four indicators, the vulnerability index for the natural disaster major component is higher for the dry lowland (0.324) as compared to the wet lowland (0.186) (Table 2.3).

Climate change and variability component

Farmers' perception of the overtime changes (precipitation and temperature) along with climate data are the indicators used in this major component. This is line with previous studies (Simane et al. 2016; Deressa et al. 2009), which indicated that elements of the natural capital are important determinants of smallholder-farmers' exposure to climate risks. In the present study, about 52 percent of the respondents perceived that temperature has increased over the last 20-30 years, with a slightly higher perception of increasing temperatures in the wet lowland agro-climatic zone (62 %) compared to 42 percent in the dry lowland. This is consistent with the metrological data that witnessed the wet lowland agro-climatic zone has experienced more variable precipitation and variation in both maximum and minimum daily temperature (Table 2.2). The meteorological temperature records in the study area have shown linearly increasing trends in the average monthly maximum temperature since 1985 on an average of 0.4 °C per decade.

With regard to precipitation, a decreasing trend is perceived by 64 percent of the respondents. This perceived change is different between the two agro-climatic zones with a relatively more perception of decreasing precipitation in the wet lowland (68%) as compared to 60 percent in the dry lowland. The changes in precipitation are apparently accompanied by late on set, early exit (terminal moisture stress) and sometime with prolonged rainfall in both agro-climatic zones. The difference in perception concerning the trends of temperature and precipitation is plausible given the spatial and temporal variability of these climate variables across the two agro-climatic zones.

However, these changes in precipitation are little supported by measurements as most of them show no change or small change only. Shortfall of farmers perception with measurements may be attributed to the fact that increasing temperature with steady precipitation level may cause water stress for agricultural activities and hence cause farmers to believe that precipitation is decreasing overtime. This is in line with Simane et al. (2016) who reported farmers' perception of a precipitation shortfall with objective measurements reflecting a climatic signal of increasing water stress when steady precipitation is associated with rising temperature.

Considering the farmers' perception and substantiating it with objective records, the vulnerability index for the climate change and variability component is higher for the wet lowland agro-climatic zone (0.379) compared to the corresponding index for the dry lowland (0.331) (Table 2.3). As the calculated indices for climate change and variability major component in both agro-climatic zones are positive, it is apparent that the main livelihood source (agriculture), which is climate-sensitive, is highly exposed to risks.

Table 2.2 Precipitation and monthly average temperature

Agro-climatic zone	Altitude (masl)	Area (%)	T^0 (^oC)		Annual precipitation (mm)
			Min	Max	
Wet lowland (LL)	900-1500	56	20	31	900-1200
Dry lowland (LL)	589-900	38	26	38	700-900

On the basis of the three major components and the corresponding indicators, the exposure assessment reveals high score (0.291) for the dry low land agro-climatic zone as compared to (0.239) for the wet lowland justifying high exposure level of the dry lowland to the risk of climate change and variability (Table 2.3). Although the exposure score for the wet lowland is comparatively low, it is still in the high vulnerability range implying that agricultural production system in both agro-climatic zones is at risk.

Table 2.3 Exposure LVI along with indexed major and sub- compeonts

Sub-component (indicators)	Wet LL	Dry LL	Major component	Wet LL	Dry LL
% of HHs that depend natural resource for cash/food	0.146	0.306	Natural resource	0.152	0.219
% of HHs with inconsistent water supply	0.269	0.431			
Average time taken to reach water source (hours)	0.175	0.098			
Inverse of the average liters of water per HH per day	0.018	0.042			
Number of extreme events in the last 10 years	0.208	0.279	Natural disaster	0.186	0.324
Number of extreme crop disease/pest outbreak (last 10 years)	0.130	0.240			
Number of extreme livestock disease outbreak (last 10 years	0.149	0.289			
% of HHs not receive warning on pending extreme events	0.257	0.488			
% HHs that don't not perceived increasing trend in temperature	0.421	0.384	Climate change and variability	0.379	0.331
% HHs that don't perceived decreasing trend in precipitation	0.344	0.286			
Mean SD of monthly average precipitation (30 years average)	0.369	0.296			
Mean standard deviation of monthly average of average maximum daily temperature (30 years average).	0.324	0.298			
Mean standard deviation of monthly average of average minimum daily temperature since (30 years average)	0.441	0.386			
Exposure LVI				**0.239**	**0.291**

2.3.2.2 Sensitivity

The sensitivity contributing factor constitutes two major components that fall in the natural capital category, namely agriculture and land use and sustainability components, which in turn consist of five indicators.

Land use and sustainability component

Land degradation problems are prevalent in both agro-climatic zones with varying degree of intensity owing to extensification, incursion into forest areas, unsustainable land use practices and cultivation of fragile land. In this regard about 44 percent of the respondents in the wet lowland owned non-suitable cultivated land compared to 38 percent in the dry lowland. In response to these, farmers used different soil fertility management practices that include physical soil conservation measures and agronomic practices. Physical soil conservation measures are non-scale neutral and their application mostly requires larger plot size. Population pressure in the wet lowland poses a dwindling farm size per household and challenges the application and economic feasibility of physical soil conservation measures implying that land fragmentation further induces vulnerability of smallholder agriculture to climate risks.

Famers also use non-physical soil conservation measures as a substitute or as a complement to physical soil conservation measures. The none physical measures largely constitute different agronomic practices, which are scale neutral and can be indiscriminately applied to both small and large farm plots without land shrinking effect. These measures are practiced by 60 percent and 49 percent of the respondents in the wet lowland and dry lowland agro-climatic zones, respectively. The comparatively low use of both types of soil conservation measures in the dry lowland contributed to increased sensitivity of farm households to climate change and variability risks in this agro-climatic zone.

Dependence on rain-fed farming is the major feature of agricultural livelihood in both agro-climatic zones. However, scattered traditional irrigation practices are witnessed among the farm households in both agro-climatic zones depending on land suitability, experience and water access. In this regard about 17 percent and 8 percent of respondents in the wet and dry lowland respectively practiced traditional irrigation. In this regard, less use of irrigation is positively associated to sensitivity to climate change risks and hence farm households in the dry lowland are more sensitive. Considering the three indicators, the vulnerability index for land use and sustainability component is higher for the dry lowland (0.366) compared to the corresponding index for the wet lowland (0.328) (Table 2.4).

Agriculture

This component is composed of two indicators that include food self-sufficiency from own production and crop diversification. The two agro-climatic zones are characterized by a mixed crop-livestock system with some level of variation in the dominant crop types grown. The average number of months that a household unable to fulfill food requirement from own production in a year varies between the two agro-climatic zones. It is 4.8 months in the dry lowland compared to 2.5 months in the wet lowland, signifying more sensitivity of farm households in the dry lowland to climate stresses.

Crop diversification is prominent in both agro-climatic zones owing to dualistic nature of subsistence agriculture that aimed at fulfilling multiple household requirements and as risk spreading strategy. However, crop diversification in the dry lowland is limited to few crop types compared to the wet lowland owing to less experience in the crop sector, environmental factors and comparative importance of the livestock sector. Accordingly, the calculated inverse crop diversification indices are 0.17 and 0.25 for the wet and the dry lowland, respectively.

When the two sub-components are averaged, the overall index for the agricultural component is slightly higher in the dry lowland (0.244) as compared to the wet lowland (0.152) implying less sensitivity of the wet lowland agro-climatic zone in relation to this major component. Therefore, given the two major components and the corresponding indicators, the sensitivity assessment reveals a high score for the dry lowland (0.293) as compared to the wet lowland (0.221). This result justifies high sensitivity of the dry lowland ago-climatic zone to the risk of climate change and variability (Table 2.4).

Table 2.4 Sensitivty LVI and corosponding major and sub- compeonts

Sub-component (indicators)	Wet LL	Dry LL	Major component	Wet LL	Dry LL
% of HHs with non-suitable cultivated land (fertility, slope)	0.396	0.226	Land use and sustainability	0.328	0.366
% of HHs that do not practice any soil & water conservation	0.124	0.286			
% of HHs not practicing irrigation	0.464	0.586			
Number of months a HH cannot fulfill food from own production	0.136	0.238	Agriculture	0.152	0.244
Average crop diversity index [1/ (no. of crops grown + 1)]	0.167	0.250			
Sensitivity LVI				**0.221**	**0.293**

2.3.2.3 Adaptive capacity

The adaptive capacity is composed of seven major components that fall in different capital forms (financial, physical, human and social). The major are income/wealth, livelihood, technology, infrastructure, knowledge/skill, socio-demographic, and social network. These major components encompass 19 sub-components.

Livelihood

The livelihood major component is made up of two sub-components that include agricultural livelihood diversification and proportion of households that solely depend on agriculture. Excessive dependence on agriculture as a source of food and cash is hypothesized to decrease the adaptive capacity of farm households to climate shocks. More dependence on agriculture is the major feature of the wet lowland agro-climatic zone, where involvement in non-farm/off-farm activities is only practiced by 24 percent of the respondents as compared to 56 percent in the dry lowland. The more a household is engaged in non-farm activities, the more the chance to cope with the livelihood shocks that emanate from climate effects in agriculture in the short run. On other hand, more involvement in non-farm activities may divert attention away from the major source of livelihood and may end up with enhanced vulnerability in the long run unless the proceeds from non-farm activities are re-invested in agriculture. Therefore, the role of off-farm/non-farm activities for adaptation in stallholder agriculture is indeterminate and may depend on a household's allocation decision on the proceeds from these sources.

The other indicator in the livelihood major component is the agricultural livelihood diversification index. For the households in the wet lowland, this index is mainly determined by crop and animal raring livelihood activities. The same index for the dry lowland is profoundly complemented and supplemented by off-farm/non-farm activities and the use of forest products. Consequently, this difference in agricultural livelihood diversification between the two agro-climatic zones is implied by an inverse index of 0.124 for the dry lowland compared to 0.112 for the wet lowland. Therefore, when the sub-components are aggregated, the calculated indexes for the livelihood competent are 0.134 and 0.145 for the wet and the dry lowland agro-climatic zones, respectively (Table 2.5).

Income/wealth component

The wealth profile is composed of three indicators, namely cultivated land size, livestock size (in TLU) and annual cash income from diversified sources (sale of crop/livestock, and off-farm). Comparing households in terms of total land holding size, the average for the wet lowland is 6.6 hectares, while it is 5.8 hectares for the dry lowland. In terms of cultivated land size, it is 1.68 hectares in the wet lowland while it is one hectare in the dry lowland, which is very close to the national average of 1.22 hectares (CSA 2012). However, vulnerability and adaptive capacity are more attributed to cultivated land size, utilization and productivity than the absolute land holding. Accordingly, vulnerability level inversely varies with cultivated land size owing to the opportunity it provides for crop diversification and implementation of soil conservation measures.

When the two agro-climatic zones are compared in terms of annual cash income (crop enterprise, livestock and off-farm), households in the wet lowland on average generated Birr 4185 compared to Birr 4338 in the dry lowland. However, households in the wet lowland generated much of the income from crop enterprise while livestock sale and non-farm/off-farm activities are important income sources in the dry lowland. Similarly, the two agro-climatic zones are compared in terms of livestock holding (in TLU). Accordingly, per capita livestock holding is higher in the dry lowland agro-ecology (5.57 TLU) compared to 3.37 TLU in the wet lowland. In line with this, the inverse average livestock unit (TLU) LVI score is 0.014 for the dry lowland compared to 0.112 for the wet lowland. Therefore, considering the indicators that constitute the income/wealth component, the dry lowland has less adaptive capacity with a calculated index of 0.146 as compared to 0.187 for the wet lowland (Table 2.5).

Technology component

The two agro-climatic zones are different in terms of the technology profile. The wet low land is better in terms of number of users of agricultural inputs attributed to better farming experience, access to credit and extension services, and a relatively favorable climatic for crop production. However, in both agro-climatic zones the use level of the technologies is by far low compared to the recommended rate (BGNRS 2013) for most of the inputs. In the wet lowland, about 65 percent of the respondents reported use of fertilizer compared to 28 percent for the dry lowland. In the present study, the use of chemical fertilizer is positively and significantly associated with farm experience whereas it is negatively correlated with livestock ownership (p-value=0.000). This is in contrast with Simane et al. (2016) who reported a positive relationship between fertilizer use and livestock holding. The negative relationship may indicate complementarity between fertilizer and manure where large livestock holding induces more use of manure and less use of chemical fertilizer.

In terms of users of improved seed, it is higher for the wet lowland (44%) compared to 18 percent for the dry lowland. Parallel to this, large proportion of the respondents (68) reported use of different farm chemicals (mainly herbicides and insecticides) in the wet lowland as compared to 34 percent in the dry lowland. Therefore, given the three indicators for the technology profile, the dry lowland has less adaptive capacity with an index of 0.342 as compared to the wet lowland with an index of 0.448 (Table 2.5).

Infrastructure component

Three indicators are included in the infrastructure major component (access to human health facilities, veterinary services and market). Considering distance from dwelling area as an reference point, access to these infrastructural facilities slightly varies between the two agro-climatic zones with a comparatively lower access in the dry lowland. On average, it takes 3 hours to reach the nearest health facility in the dry lowland agro-ecology as compared to an hour in the wet lowland. Less access to health facilities in the dry lowland is further justified by the prevalence of major human health risk in the area (malaria), which is reported by 43 percent of the respondents in this agro-climatic zone as compared to 24 percent in the wet lowland. The high prevalence in the dry lowland is mainly attributed to lack of easy access to health facilitates (as reported by 76 % of the respondents) coupled with mounting temperature and untimely rain (as reported by 65 % of the respondents), which creates conducive environment for the hatching of the malaria vector.

Lack of access to health facilities is also aligned to vulnerability as evidenced by the fact that 44 percent of the respondents in the dry lowland reported family members missed either work or school in the past one year due to illness and lack of timely treatment. The corresponding proportion for the wet lowland is 18 percent revealing that households in this agro-climatic zone are comparatively less vulnerable to health risk owing to better access to health facilities.

Better access to veterinary services is hypothesized to reduce the risk associated with livestock disease outbreak and hence reduces the vulnerability of smallholder farmers. In this regard, households in the wet lowland are relatively better off in terms of access to veterinary services as it takes on average an hour to reach the nearest veterinary service point as compared to 2 hours in the dry lowland. In terms of market access, households in the dry lowland are expected to travel on average for two hours to reach the nearest market point as compared to 1.2 hours for the wet lowland, which signifies higher vulnerability in the dry lowland.

Generally, inadequate access to infrastructural facilities induces vulnerability of smallholder farmers to climate risks and in effect leads to low agricultural production and less adaptive capacity. When the three indictors in the infrastructure component are aggregated, the dry lowland agro-climatic zone has lower adaptive capacity with an index of 0.183 as compared to the wet lowland with an index of 0.286 (Table 2.5).

Socio demographic profile

This major component consists of three indicators that include adult equivalent ratio, dependency ratio and farm experience. In terms of adult equivalent ratio, a household in the wet lowland has an average of 3.04 as compared to 2.96 for the dry lowland. Higher adult equivalent imply high labor endowment at the disposal of a farm household to accomplish various agricultural activities signifying the role of the demographic variables for climate change adaptation (Simane et al.

2016; Deressa et al. 2011). Labor endowment is also an important source of social capital in the rural economies, indicating the potential of a farm household for labor exchange and involvement in communal activities.

A large family size may also stress household's adaptive capacity in the form of disguised unemployment particularly when the available livelihood options are limited and unable to engage all members of a household. Consequently, large family size may contribute to households' vulnerability to climate change induced risks in the case of limited livelihood options and when land to labor ratio is very low. Therefore, the role of a large family size for adaptation to climate risks is feasible where labor to land ratio is lower or where there is an opportunity to engage the family members in a diversified livelihood options. In terms of dependency ratio, it is higher in the wet lowland (2.07) compared to the dry lowland (1.47) indicating that the economically active labor in the wet lowland is expected to feed more mouths than the case in the dry lowland. This may impose a strain on the available resources thereby reducing resilience to climate change and variability.

Farming experience is the other indicator used in the socio-demographic major component. It is expected that faming experience provides the opportunity to moderate vulnerability to climate change impacts through adjustments in terms of planting dates, choosing crop types/varieties, and applying farm management practices (Gutu et al. 2012; Patt et al. 2009b). In this regard, the household heads in the wet lowland have longer farming experience (17.87 years) than those in the dry lowland (13.01years). Therefore, farm households in the wet lowland have better chance of making possible adjustments to anticipated impacts of climate change/variability.

Generally, the indicators used in the socio-demographic component have the potential to influence farmers' decision to adjust agricultural practices in response to climate change as also implied in the findings of Nhemachena and Hssan (2007) and Maddison (2007a). Considering the three indicators that constitute the socio-demographic component, households in the dry lowland revealed lower adaptive capacity index (0.223) compared to 0.234 for the wet lowland (Table 2.5).

Knowledge/skill component

Education and training have the potential to influence farmers' decision and favorably contribute to climate change adaptation. In the wet lowland agro-climatic zone, about 38 percent of the respondents had access to different training opportunities in relation to climate related issues, while the corresponding proportion for the dry lowland is 21percent. In terms of literacy level, about 42 percent of the respondents in the wet lowland have formal education compared to 29 percent in the dry lowland. Considering the two indicators that constitute the knowledge/skill component, the dry lowland agro-climatic zone is more vulnerable with a lower adaptive capacity score of 0.194 as compared to the wet lowland with a score of 0.278 (Table 2.5).

Social network and external support

Variation is prevalent between the two agro-climatic zones in terms of the social network profile indicators such as borrowing/lending and receiving/giving ratios. However, for other types of social network indicators the difference between the two agro-climatic zones is not statistically significant and hence omitted for brevity. Consequently, the wet lowland revealed a higher borrowing-lending ratio as well as a higher receiving-giving ratio showing that households in this agro-climatic zone borrow and receive (in support) more from family and friends relative to the number of times they lent money or provided assistance in the past. Based on Hahn et al. (2009), households that borrow/receive money more than they lend/give are more vulnerable. However, considering only these ratios without taking into account receiving assistance from other sources (government/NGOs) may overstate the vulnerability of household in the wet lowland while understating the same in the dry lowland. This is because; the number of times (in a year) that households in the dry lowland receive assistance through other channels is considerably high (44%) while it is only 6 % in the wet lowland. Considering the higher external (government/NGO) support provision in the dry lowland in generating the index for the social network component, the adaptive capacity index is lower for the dry lowland (0.203) as compared to the wet lowland (0.272).

Therefore, given the seven major components and the corresponding indicators, the adaptive capacity assessment reveals lower score for the dry low land (0.201) compared to 0.255 for the wet lowland (Table 2.5).

Table 2.5 Adaptive capacity and indexed major and sub-compeonts

Sub-component (indicators)	Wet LL	Dry LL	Major component	Wet LL	Dry LL
Annual income (crop, livestock, off-farm) (inverse)	0.023	0.023	Income/wealth	0.187	0.146
Livestock (TLU) (inverse)	0.034	0.042			
Cultivated farm size (ha) (inverse)	0.50	0.373			
% of households not using farm chemicals	0.425	0.385	Technology	0.448	0.342
% of households not using fertilizer	0.415	0.246			
% of households not using improved seed	0.505	0.396			
Average time to market	0.219	0.168	Infrastructure	0.286	0.183
Average time to human health facility	0.284	0.178			
Average time to veterinary service facility	0.354	0.204			
% of household heads with formal education	0.268	0.164	Knowledge/skill	0.278	0.194
% of HH heads received climate specific advise/training	0.288	0.224			
Agri. livelihood diversification [1/ (no. of agricultural livelihood activities + 1)]	0.125	0.064	Livelihood	0.134	0.145
% of HHs more dependent on agri. as source of income	0.142	0.225			
Adult equivalent (inverse)	0.158	0.144	Socio-demographic	0.234	0.223
Dependency ratio	0.218	0.314			
Farm experience (inverse)	0.326	0.212			
Average receive: give ratio	0.212	0.264	Social networks and external support	0.272	0.203
Average borrow: lend ratio	0.162	0.243			
% of HHs that receive Gov./NGO assistance in a year	0.442	0.102			
Adaptive capacity LVI				**0.255**	**0.201**

2.3.3 Practical implication of the Livelihood Vulnerability Index

The LVI-IPCC contributing factors, the major components and the sub-components are combined together on the basis of the balanced weighted average contextualizing the approaches used in Simane et al. (2016), Hahn et al. (2009), and Sullivan et al. (2002) to construct the LVI. In this approach, each sub-component contributes equally to the overall index although each major component is comprised of different number of sub-components. The calculated LVI and LVI-IPCC indices are in line with the pattern provided in the focus groups discussion, key informant interviews, household survey and secondary data in reference to the trends of exposure, sensitivity, adaptive capacity and overall vulnerability to climate risks in the two agro-climatic zones of the study area. This implies that the LVI and LVI-IPCC could arguably capture the main features of the study population in terms of exposure, sensitivity and adaptive capacity.

The 12 major components that yield the LVI scores are elements of either of the five capital forms (natural, human, social, financial and fiscal) and are grouped into the contributing factors namely exposure, sensitivity and adaptation capacity in order to compute the LVI-IPCC.

Exposure is made up of the scores of three major components; sensitivity is composed the scores of two major components; while adaptive capacity is made up of the aggregated scores of seven major components. The LVI-IPCC is on a scale from −1 (least vulnerable) to 1 (most vulnerable) and it is evident from the LVI-IPCC index that high values of exposure relative to adaptive capacity yield positive vulnerability scores while low values of exposure relative to adaptive capacity yield negative vulnerability scores. The sensitivity factor plays a role of a multiplier in such a way that a high sensitivity leads to a higher/lower LVI-IPCC score depending on the relative magnitudes of exposure to adaptive capacity.

In the LVI assessment, use of the sub-components/indicators and indices somehow helped to simplify a complex reality. However, directionality of the indicators is arguable and context specific. For instance, the large family size (converted to adult equivalent ratio) implied increased adaptive capacity or reduced vulnerability to climate impacts; however a different result may arise in a different context or location. Considering similar components and indicators in both agro-climatic zones, the LVI values confirmed that the two zones are different in terms of vulnerability level where the dry lowland is more vulnerable than the wet lowland with comparatively higher exposure and sensitivity scores and lower adaptive capacity score.

Table 2.6 portrays the scores for the LVI-IPCC contributing factors indicating that the dry lowland has higher exposure with a score of 0.291 compared to the wet lowland which exhibited a score of 0.239. Similarly, the dry lowland is lower in terms of adaptive capacity with a score of 0.201 compared to 0.255 for the wet lowland. Besides, the dry lowland is more sensitive to climate change and variability impacts (with a score of 0.293) than the wet lowland (with a score of 0.221). This shows that exposure exceeds adaptive capacity in the dry lowland and resulted in a positive LVI-IPCC score (0.026) which positioned this agro-climatic zone in a more vulnerable level than the wet lowland which unveil a LVI-IPCC score of -0.004. However, since the LVI-IPCC scores for the wet lowland is very closer to the midpoint (0) of the extreme vulnerability scales (+1 & -1), this agro-climatic zones is positioned in a moderate vulnerability category.

Table 2.6 Indexd major compeonts, contributig factors and the overall LVI-IPCC

Indexed major compnts by agro-ecology			LVI-IPCC contributing factors	Wet LL	Dry LL	Average
Major components	Wet LL	Dry LL	Exposure	0.239	0.291	0.265
Natural resource	0.152	0.219				
Natural disaster	0.186	0.324				
CC change/ variability	0.379	0.331				
Land use/ sustainability	0.328	0.366	Sensitivity	0.221	0.293	0.257
Agriculture	0.152	0.244				
Income/wealth	0.187	0.146	Adaptive capcity	0.255	0.201	0.228
Technology	0.448	0.342				
Infrastructure	0.286	0.183				
Knowledge/skill	0.278	0.194				
Livelihood	0.134	0.145				
Socio-demographic	0.234	0.223				
Social network/support	0.272	0.203				
LVI-IPCC= [Exposure-Adaptive capacity]*Sensitivity				**-0.004**	**0.026**	**0.010**

The vulnerability scores of the 12 major components are summarized in a spider diagram (Figure 16), which ranges between 0 and 0.5. The diagram revealed that the dry lowland is more vulnerable in 10 of the 12 (92%) major components except for climate change/ variability and livelihood major components. This causes the dry lowland agro-climatic zone to be more exposed and sensitive to climate change and variability impacts with a lower adaptive capacity as compared to the wet lowland.

In terms of the contribution of the major components to the overall vulnerability score, natural disaster and climate variables (precipitation and temperature) components are the primary and secondary determinates of exposure in both agro-climatic zones. Among the two major components included in the sensitivity factor, land use system/sustainability is found to be the primary determinant of sensitivity to climate change risks in both agro-climatic zones. Technology, infrastructure, knowledge/skill, social network, and socio-demography are important determinants of adaptive capacity in the wet lowland in that order of importance. Similarly, technology, socio-demography, social network, and knowledge/skill are fond to be important in determining adaptive capacity in the dry lowland in that order of importance.

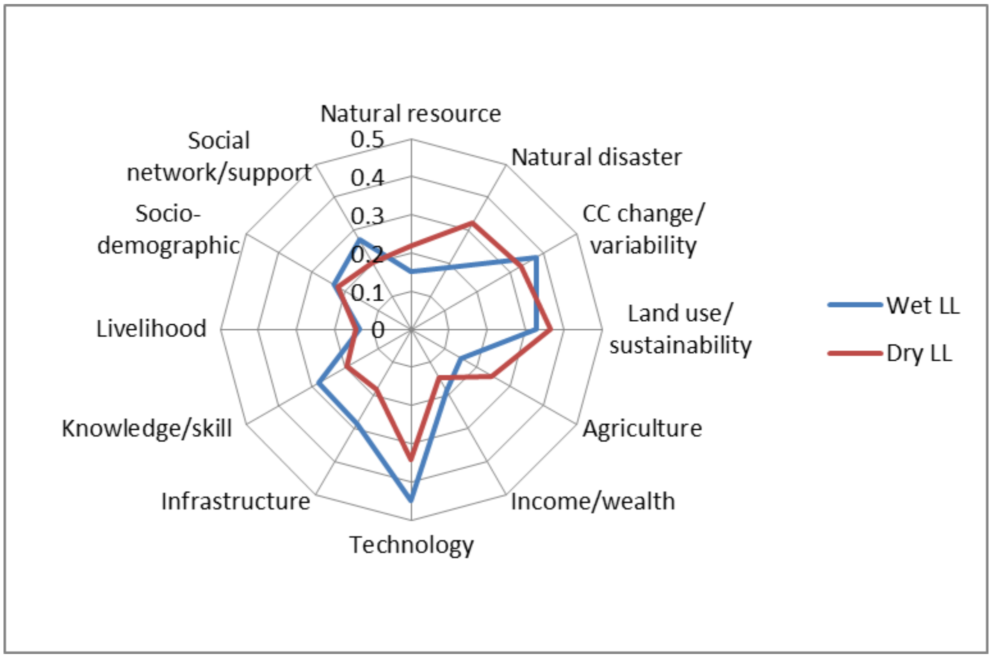

Figure 16 Vulnerability diagram of major components

The vulnerability triangle (Figure 17) portrays that the dry lowland agro-climatic zone is more exposed, more sensitive and exhibit a comparatively lower adaptive capacity to climate change/variability impacts as compared to the wet lowland.

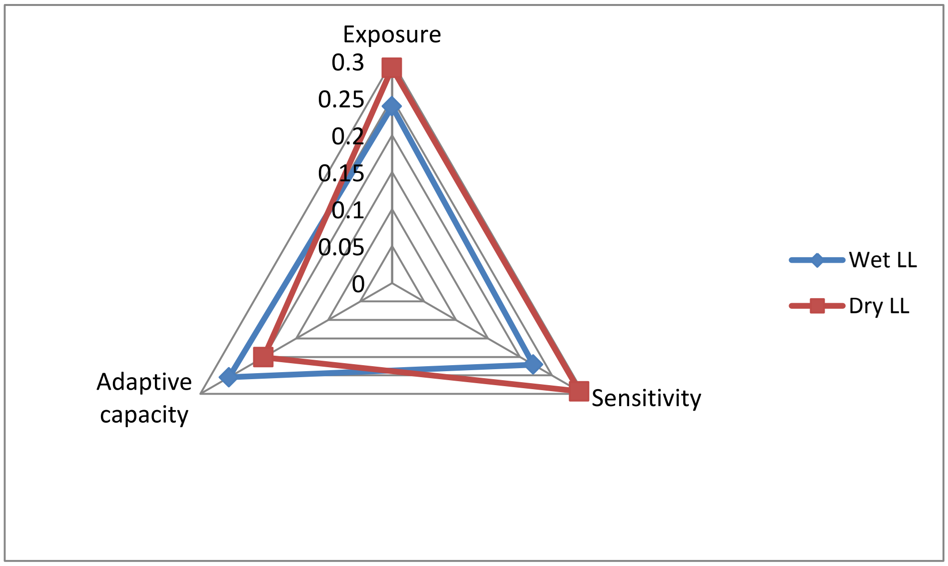

Figure 17 Vulnerability triangle of LVI-IPCC contributing factors

2.4 Conclusions and Recommendation

Vulnerability analysis is an essential step towards designing effective adaptation that takes into account perceived exposure, sensitivity and adaptive capacity. Agro-ecology specific vulnerability analysis captures spatial variation in vulnerability profiles and hence helps to systematically design context specific adaptation strategies. The present study used the LVI-IPCC framework to assess agro-ecology specific vulnerability to climate change/variability impacts at household level in the Dabus sub-basin of the Blue Nile River. The study area is characterized by diverse environmental, social, demographic and economic factors and hence the LVI-IPCC is aggregated at agro-climatic zone level to captures the diversity in the sub-basin.

The result shows that the dry lowland agro-climatic zone has a higher exposure and sensitivity to climate stresses with a comparatively limited adaptive capacity as compared to the wet lowland. On the other hand the wet lowland exhibits intermediate vulnerability with a relatively lower perceived exposure and higher adaptive capacity. Higher exposure relative to adaptive capacity resulted in a positive LVI-IPCC score and this positioned the dry lowland in a more vulnerable level than the wet lowland. Conversely, a higher adaptive capacity score relative to exposure unveil a negative LVI-IPCC score for the wet lowland and situated it in a moderate vulnerability category.

The LVI-IPCC framework analysis also revealed the prominent factors that induce exposure and sensitivity to climate risks as well as the barriers that stress adaptive capacity. In this regard, natural disaster and climate variables are found to be the major factors that induce exposure to climate risks in both agro-climatic zones. Likewise, lack of sustainable land use system influences sensitivity of smallholder farmers to climate risks in both agro-climatic zones. The result also indicated the importance of agricultural technologies, infrastructure, knowledge, social network and socio-demographic factors in determining adaptive capacity in both agro-climatic zones with a slightly different relative importance.

The findings of the study have important policy relevance for enhancing smallholder farmers' adaptive capacity to climate change and variability. The indices developed are useful to set location specific priorities for intervention that is most needed to cope up with the effects of climate variability and change. Both agro-climatic zones should be given attention in terms of climate specific extension/ training opportunities and agricultural input supply. Climate risk exposure levels can be reduced through timely provision of climate specific information aimed at enhancing the preparedness of farm households to extreme events. It is also crucial to avail infrastructural facilities such as market, health and veterinary services so as to enhance adaptive capacity.

The specific interventions that may call for policy attention include supporting alternative livelihood options based on available resources, water harvesting for supplementary irrigation, and early warning system on extreme events. Parallel to this, improving the literacy level of smallholder farmers through informal education programs based on the experience from other parts of Ethiopia is essential in this regard.

Finally, since the present analysis is at agro-ecology level, it can only provide an indicative vulnerability and hence more detail agro-ecosystem specific vulnerability analysis should be made in the Dabus sub-basin through further research. In the LVI assessment, use of major components, sub-components and indices somehow helped to simplify a complex reality. Nevertheless, directionality of most of the indicators used in any LVI assessment is context specific and arguable. Indicators that revealed increased adaptive capacity or reduced vulnerability to climate impacts in a given context may show a different result in a different context or location.

Chapter Three

3. Farmers' Perception of Climate Change and Adaptation Strategies: Agro-ecology Specific Analysis in the Dabus Sub-basin of the Blue Nile River

Abstract

This study is aimed at analyzing farmers' perception and adaptation to climate change in the Dabus sub-basin. It is based on analysis of data collected from 734 randomly selected farm household heads substantiated with Focus Group Discussions and field observations. The study employed descriptive methods to assess farmers' perception of climate change, local indicators of climate change and types of adaptation measures exercised to cop up with the risk. The study also employed the Heckman sample selection model to analyze the two-step process of adaptation to climate change which initially requires farmers' perception that the climate is changing prior to responding to the changes through adaptation measures. Based on the model result educational attainment, the age of the head of the household, the number of crop failures in the past, and changes in temperature and precipitation significantly influenced farmers' perception of climate change in the wet lowland agro-climatic zone of the study area. In dry lowland condition, farming experience, climate information, duration of food shortage, and the number of crop failures experienced determined farmers' perception of climate change. Farmers' adaptation decision in both agro-climatic zones is influenced by household size, gender of household head, cultivated land size, education, farm experience, non-farm income, income from livestock, climate information, extension advice, farm-home distance and number of parcels. However, the direction of influence and significance level of most of the explanatory variables vary between the two agro-climatic zones. Hence, in line with the findings, any intervention that promotes the use of adaptation measures to climate change may account for location-specific factors that determine farmers' perception of climate change and adaptive responses thereof.

Keywords: climate change, perception, adaptation, Heckman sample selection model, agro-climatic zone

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3.1 Introduction

Agricultural sector in Sub-Saharan Africa it is predicted to be negatively impacted by climate change (Deressa 2006; Moussa et al. 2006; Jain 2006) and the effect will induce substantial welfare losses especially for smallholders whose main source of livelihood derives from agriculture. Hence, there is a need to neutralize the potential adverse effects of climate change if welfare losses to this vulnerable segment of the society are to be averted (Hassan et al. 2008; Molua et al. 2006; Mano et al. 2006). In Ethiopia, climate change features such as drought, flood, and land degradation are among the major factors responsible for the low agricultural productivity (Yirga 2007). These coupled with heavy reliance on traditional farming techniques and poor complementary services (such as extension, credit, marketing, etc.) reduce the adaptive capacity or increase the vulnerability of smallholder farmers to climate change, which in turn affects the performance of the already weak agriculture (Deressa 2011).

Climate variability and change also pose a huge threat to the smallholder farmers in the Dabus sub-basin (the study area) due to overwhelming reliance on climate-sensitive small-scale agriculture, which could also be worsened by prevailing social and economic challenges (BGNRS 2013). Agricultural production is apparently affected by climate-related shock in the area, which is usually manifested by the occurrence of pest and disease infestations as well as land degradation. In this regard, adaptation appears to be an efficient and friendly way for farmers to reduce the negative impacts of climate change (Füssel et al. 2006).

Following IPCC (2007c), adaptation to climate change refers to the adjustment in the natural or human systems in response to actual or expected climatic stimuli or its effects, which moderates harm or exploits beneficial opportunities. Adaptation can be implemented by the smallholder farmers themselves (autonomous adaptation) or by the governments’ policies aimed at promoting appropriate and effective adaptation measures (planned adaptation). However, in order to implement appropriate interventions, there is a need to understand location-specific opportunities, challenges and the key drivers behind adaptation. Adaptation can be effected at different scales: individual/farm-level, national level or international level (Semenza et al. 2008). Although there is some autonomous adaptation at farm-level, it is usually inadequate and requires the intervention of different institutions (Simane et al. 2016; Maddison 2007b).

Moreover, adaptation at national or international level entails an understanding of the process of location-specific autonomous adaptation at farm-level (Bryan et al. 2009).

Studies (Deressa et al. 2009; Mideksa, 2009; Bryan et al. 2009) show that improved crop varieties, agroforestry practices, soil conservation practices, irrigation practices and adjusting planting dates are the most important adaptation strategies by the smallholder farmers. However, adaptation decision is location specific and influenced by key drivers such as socio-economic, environmental and institutional factors. Based on Deressa et al. (2011) adaptation at farm-level involves two stages: perceiving a change in climate and deciding whether to adopt or not (including which adaptation strategy to use). Nevertheless, perception is not a sufficient condition for adaptation since farmers who have perceived the change in climate may not adapt or the nature of their adaptation response may vary as a result of a complex interplay among social, economic, environmental and institutional factors (Maharjan et al. 2011; Mertz et al. 2009; Maddison 2007a).

Thus, there is a need to understand location-specific drivers of perception and adaptation to climate change among smallholder farmers. This helps to design appropriate policy responses based on the vulnerability and sensitivity level of each location as well as the accessibility of the adaptation measures (Simane et al. 2016). In this regard, there is a substantial deficit of location-specific information on the process of autonomous adaptation in the developing world including Ethiopia (McSweeney et al. 2010). There are few research undertakings (Deressa et al. 2011; Di Falco et al. 2011; Deressa et al. 2009), which focus mainly at a large scale (country level, region level, and basin level) and overlooked location-specific factors that drive perception and adaptation to climate change. The findings of these studies are highly aggregated and are of little help in addressing local peculiarities of perception and adaptation to climate change.

Understanding local perceptions and adaptive behavior provides better insights and information relevant to a policy that helps to address the challenge of sustainable agricultural development in the face of variable and uncertain environments (Simane et al. 2016). This study, therefore, responded to a paucity of empirical information regarding the indicated gaps of knowledge addressing threefold purposes: (i) investigate farmers' perception and adaptation to climate change in the Dabus sub-basin (ii) investigates location-specific social, economic, environmental and institutional factors that influence farmers' perception and adaptive decision, and (iii) compares the wet and dry lowland agro-climatic zones of the study area in terms of perception and adaptation to climate change.

3.2 Methodology

3.2.1 Analytical framework for climate change perception and adaptation

Figure 18 portrays the links among the factors that affect the adaptation strategy of smallholder farmers to climate variability/change based on the general conceptual framework of this study.

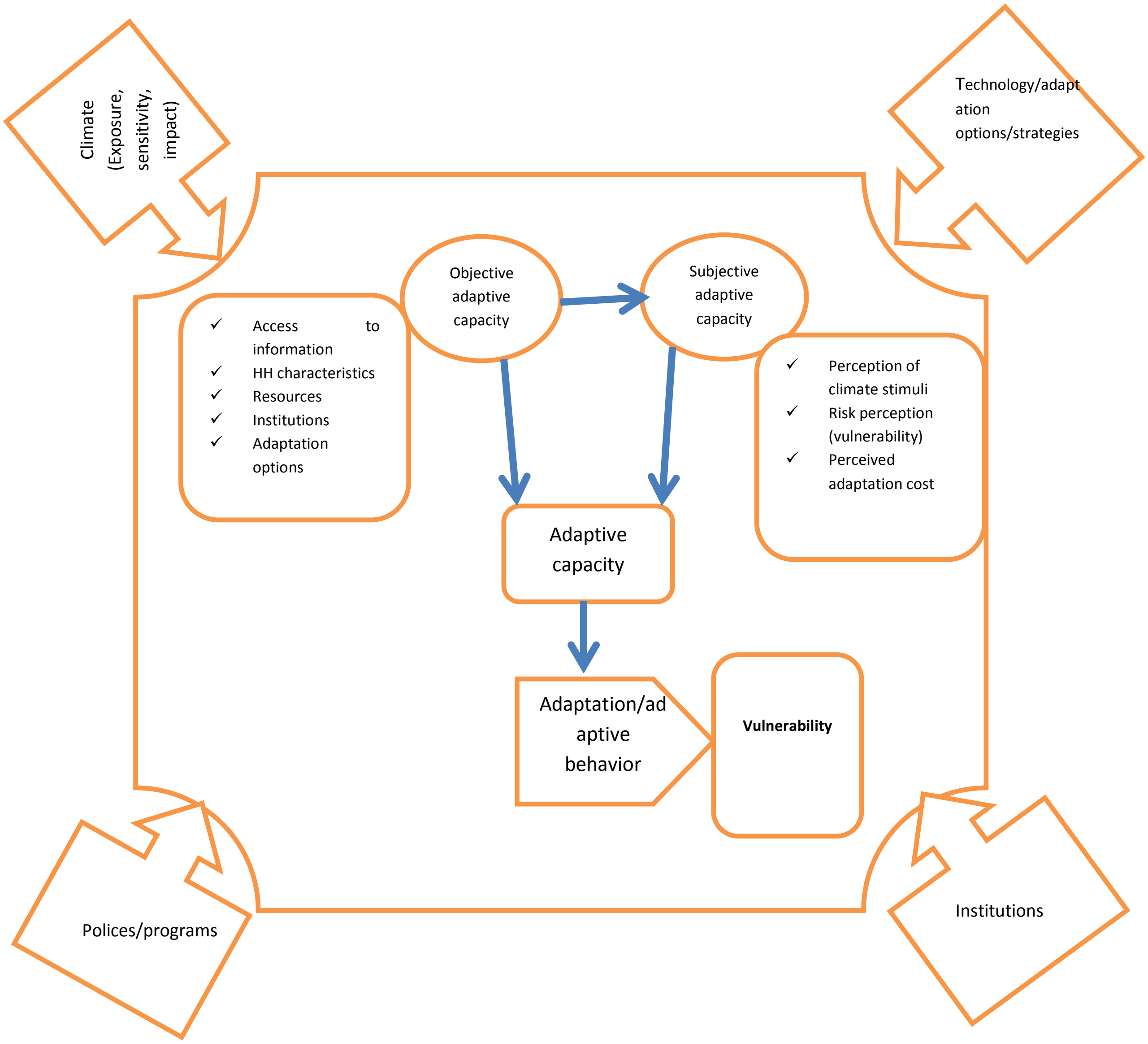

Figure 18 Analytical framework for CC perception and adaptive behavior of smallholder farmers

The framework is structured on the assumption that there are various driving forces behind farm households' adaptation decisions and choice of adaptation strategies to climate variability and change. Some of the influencing factors that lead to adaptation strategies are differentiations in gender and social groups, resources, assets, institutions, environment and perceptions. Based on Abate (2013), the overall adaptive capacity depends on subjective and objective adaptive capacities. Subjective adaptive capacity is a function of perception of climate stimuli, risk (vulnerability) perception, perception of adaptation cost, whether the perception is optimist or pessimist about the consequences. On the other hand objective adaptive capacity depends on household characteristics, livelihood assets, institutions, adaptation options, agro-ecologies, willingness and being pessimist or optimist about the consequences.

3.2.2 Data source and methods of data collection

The data for this study were collected from both primary and secondary sources. The primary source is a cross-sectional survey data collected from 734 farm households. The primary data majorly include demographic, socioeconomic, institutional, and biophysical attributes of the respondents. The data also include information on farmers' perception of the patterns of temperature and rainfall over the past 20 years, the impacts of the perceived changes, responses made to the perceived changes, and challenges faced in responding to the changes. Survey questionnaires, focus group discussion, and field observation were the data collection methods employed. Household-level data were collected through an open and close-ended survey questionnaire. Twenty four FGD, each comprising ten persons, were also carried out to complement the responses acquired through the survey questionnaire. The primary data were substantiated by data obtained from secondary sources.

3.2.3 Method of data analysis

The data was analyzed using descriptive statistics and econometric model (Heckman’s sample selection model). The descriptive statistics were employed to describe farmers’ perception of climate shocks, responses implemented to address the shocks, and the constraints faced in implementing the responses. The Heckman’s sample selection model was employed to analyze the two-step processes of adaptation to climate change.

3.2.3.1 Model specification

Based on Heckman (1976), when a farmer's decision process about the adoption of a new technology requires more than one step, models with two-step regressions, such as the

Heckman's sample selection, are appropriate to correct for selection bias generated during the decision-making processes. The Heckman's sample selection model is based on farmer's utility or profit-maximizing behavior and the assumption is that a farmer uses a new technology only when the perceived utility or profit from using the new technology is significantly greater than the traditional or the old method.

Similar to technology adoption, adaptation to climate change is a two-step process that involves perceiving that the climate is changing, and then responding to the change through adaptation measures (Deressa et al. 2011). Therefore, the Heckman probit selection model is employed in this study to investigate the determinants of perception and adaptation to climate change. The first stage of the model (the selection model) considers whether a farmer perceived a change in climate and the second-stage of the model (outcome model) explore whether the farmer adapted to climate change conditional on the first stage.

In the two-stage process, the second stage of adaptation is a sub-sample of the first. Thus, it is likely that the second stage sub-sample (that includes those who perceived and responded to the change) is non-random and necessarily different from the first (which included those who did not perceive climate change), and this creates a sample selection bias (Deressa et al. 2011). Therefore, the Heckman two-step maximum likelihood procedure was used to correct for this selection bias. The underlying relationship in the Heckman's sample selection model consists of a latent equation given by:

$$y_j = x_j \beta + u_{1j} \quad \text{(3.1)}$$

Such that we observe only the binary outcome given by the probit model as

$$y_i^{probit} = (y > 0) \quad \text{(3.2)}$$

The dependent variable is observed only if *j* is observed in the selection equation

$$y_i^{select} = z_j \delta + u_{2j} > 0 \quad \text{(3.3)}$$

$u_1 \sim N(0, 1)$

$u_2 \sim N(0, 1)$

$corr(u_1, u_2) = \rho$

Where y_j^{select} is whether a farmer has perceived climate change or not, z is an m vector of regressors, which include different factors hypothesized to affect the perception; δ is the parameter estimate, u_{2j} is an error term and u_1 and u_2 are error terms, which are normally distributed with mean zero and variance one. Thus, equation 3.3 is the first stage of the Heckman's two-step model which represents farmers' perception of the changes in climate. Equation 3.1 is the outcome model which represents whether the farmer adapted to climate change, and is conditional upon the perception model. When the error terms from the selection and the outcome equations are correlated ($\rho \neq 0$), the standard probit techniques yield biased results (Deressa et al. 2011; Van de Ven & Van Praag 1981). Thus, the Heckman probit (heckprob) provides consistent and asymptotically efficient estimates for all parameters in such model.

The dependent variable for the selection equation is whether a farmer has perceived or not the climate change. The explanatory variables include socio-demographic, environmental and institutional factors selected based on hypothesized relationships described in literature on factors affecting the awareness of farmers to climate change or their risk perceptions (Simane 2016 et al. 2016; Maharjan et al. 2011; Deressa et al. 2011; Deressa et al. 2009) and field observations made in the study area. In the case of the outcome model, the dependent variable is whether a farmer has adapted or not to climate change. The explanatory variables are chosen based on the climate change adaptation literature (Simane 2016 et al. 2016; Deressa et al. 2011; Maharjan et al. 2011; Deressa et al. 2009; Hassan and Nhemachena 2009) and the field observations made in the study locations. The hypothesized explanatory variables for the Heckman's two-step model used in this study are described in the section that presents the empirical model results (Tables 3.6 & 3.7).

3.3 Results and Discussion

3.3.1 Farmers' perception of climate change

The descriptive analysis indicated that about 52 percent of the respondents from the wet lowland and 62 percent from the dry lowland had perceived a change in climate (Table 3.1). This difference in perception of climate change between the two locations is statistically significant ($\chi2 = 6.636$ with $P<0.001$).

Table 3.1 Perception of climate change in the Dabus sub-basin

Perception	Wet lowland		Dry lowland		Total		$\chi 2$ value	P-value
	N	%	N	%	N	%		
Not perceived	175	47.7	141	38.4	316	43.1		
Perceived	192	52.3	226	61.6	418	56.9	6.636***	0.006
Total	**367**	**100**	**367**	**100**	**734**	**100**		

*** Values are significant at $P < 0.001$.

The descriptive analysis also signified that more than 55 percent of the respondents perceived an increasing trend in temperature while 42 percent and 25 percent, respectively perceived a stable and decreasing temperature. Regarding precipitation, about 64 percent of the respondents indicated a decreasing trend while 34 percent of them testified an increasing trend. Parallel to this, those farmers who inferred an increasing trend in temperature and a decreasing trend in precipitation itemized the respective local indicators that make them deduce these trends (Table 3.2).

Table 3.2 Indicators of farmers' perception of change in temperature and precipitation

Indicators of temperature change	**N**	**Percent**
Longest months with high day time temperature	133	33.3
Frequent occurrence of heat induced crop disease	119	29.3
Switch to heat tolerant crop types/varieties (not previously adapted to the area)	110	27.1
Frequent occurrence of heat induced livestock disease	107	26.4
Frequent occurrence of heat induced human disease	103	25.4
Emergence of new plant species/invasive species in the form of weed	82	20.2
Quick disappearance of water sources/points due to high evaporation	80	19.7
Indicators of precipitation change	**N**	**Percent**
Shortened length of rainy season	136	28.9
Change in planting time/date to adjust to onset of rainfall	123	26.2
Early onset and early exit of rainy season	114	24.3
Erratic nature of rainfall/Increased volume of rainfall at a time	100	21.3
Late onset of rainy season	99	21.1
Crop failure due to water shortage	98	20.9
Switch to drought tolerant crop types/varieties (not previously adapted to the area)	64	13.6

3.3.2 Farmers' adaptive responses

In the wet lowland condition, 62 percent of the respondents indicated that they know climate change adaptation measure and have implemented at least one in the past. In the dry lowland, only 48 percent the respondents reported to have knowledge of adaptation options while 52 percent of them have no any past experience concerning the measures (Table 3.3). This difference in the exposure to adaptation measures is statistically significant ($\chi2$=14.659 with P<0.001), showing the existence of a verified difference between the two agro-climatic zones.

Table 3.3 Awareness of adaptation measures in the study area

Exposure to adaptation	Wet lowland		Dry lowland		Total		$\chi2$ value	P-value
	N	%	N	%	N	%		
No exposure	139	38	191	52	330	45		
Have exposure	228	62	176	48	404	55	14.659***	0.000
Total	**367**	**100**	**367**	**100**	**734**	**100**		

*** Values are significant at P < 0.001.

The respondents from the wet and dry lowland were also compared in terms of the use of different adaptation strategies in their agricultural practices without considering their perception of climate change. The most used adaptation measures include soil and water conservation and agronomic practices such as crop rotation, conservation tillage, intercropping, adjusting planting dates, diversifying crop types, use of fertilize, use of improved crop varieties, application of manure, and irrigation practices. Accordingly, about 48 percent of the respondents in the wet lowland and 44 percent in the dry lowland have used soil and water conservation practices (Table 3.4). However, the use of this practice is not statistically different between the two agro-climatic zones implying that the role of soil and water conservation in copping the hazards of climate change is evenly recognized in both areas.

Table 3.4 Adaptation through soil and water conservation measures

Use of soil and water conservation practices	Wet lowland		Dry lowland		Total		$\chi2$ value	P-value
	N	%	N	%	N	%		
Non users of the practices	191	52	206	56	397	54		
Users of the practice	176	48	161	44	337	46	0.714	0.415
Total	**367**	**100**	**367**	**100**	**734**	**100**		

Congruently, about 60 percent of the respondents from the wet lowland and 49 percent from the dry lowland have implemented agronomic practices as adaptation strategy (Table 3.5) without considering their perception of climate change. The difference between the two agro-climatic zones in terms of use of agronomic practices is statistically significant ($\chi2$=8.497 with P<0.01). More use of the agronomic measures in the wet lowland condition might be attributed to farmers' longer years of crop cultivation experience and better exposure to the practices compared to the farmers in the dry lowland.

The proportion of respondents that have not used any of the adaptation practices is higher in the dry lowland. The non-users have pinpointed the constraints for not responding to climate change through adaptation, lack of climate change perception being the major deterrent. Moreover, respondents who failed to respond through the adaptation measures indicated lack of awareness about the adaptation measures, liquidity constraint, and lack of access to the adaptation measures as critical barriers.

Table 3.5 Adaptation through agronomic practices

Use of agronomic practices	Wet lowland		Dry lowland		Total		χ^2 value	P-value
	N	%	N	%	N	%		
Non users of the practices	147	40	187	51	334	46		
Users of the practice	220	60	180	49	400	54	8.497**	0.004
Total	**367**	**100**	**367**	**100**	**734**	**100**		

*** Values are significant at $P < 0.01$.

3.4 Determinants of Perception and Adaptation to Climate Change

Tables 3.6 and 3.7 portray summary of explanatory variables used in the Heckman probit selection and outcome models, respectively. As indicated in the Tables, about 52 percent of the respondents in the wet lowland and 62 percent in the dry lowland perceived a change in climate. Conditioned on this perception level of climate change in the two agro-climatic zones, about 52 percent of the respondents in the wet lowland and 49 percent in the dry lowland have implemented at least one adaptation options available to them.

The Heckman probit model was first tested for its suitability and explanatory power over the standard probit model. The test results indicated the presence of sample selection problem (dependence of the error terms from the outcome and selection models) justify the use of the model with rho significantly different from zero (Wald $\chi2=10\cdot77$ with $P=0\cdot001$). Moreover, the likelihood function of the Heckman probit model was significant (Wald $\chi2=84.36$ with $P<0\cdot001$), showing its strong explanatory power.

Table 3.6 Summary of model variables for the Heckman probit selection model

Dependent variable description	Farmers' perception status to climate change			
	Wet lowland		Dry lowland	
	Perceived (%)	Not perceived (%)	Perceived (%)	Not perceived (%)
Perception (Perceived=1)	52	48	62	38
Independent variables	Mean	SD	Mean	SD
Education level of HH head (years)	5.25	2.98	3.98	1.86
HH head age (years)	43.99	13.12	43.61	11.72
Climate change information (yes=1)	0.6	0.5	0.4	0.5
Frequency of drought (last 20 years)	2.30	1.43	2.81	1.48
Frequency of drought (last 10 years)	2.37	2.16	2.23	1.11
Number of crop failures (last 10 years)	2.33	1.22	2.09	1.26
Duration of food shortage (months)	2.91	1.50	2.37	1.66
Temperature (increasing=1)	0.7	0.3	0.65	0.3
Precipitation (increasing=1)	0.3	0.7	0.4	0.6

Table 3.7 Summary of model variables for the Heckman probit outcome model

Dependent variable description	Farmers' adaptation status to climate change			
	Wet lowland		Dry lowland	
	Adapted (%)	Not adapt (%)	Adapted (%)	Not adapted (%)
Adaptation (adapted=1)	52	48	49	51
Independent variables	**Mean**	**SD**	**Mean**	**SD**
Education of HH head (years)	5.25	2.98	3.98	1.86
Household size (number)	6.08	2.44	5.92	2.31
HH head sex (male = 1)	0.89	0.22	0.9	0.21
Farming experience (years)	22.68	11.47	14.71	7.27
HH head age (years)	43.99	13.12	43.61	11.72
Crop cash income (Ethiopian currency)	3352.23	3005.44	1332.64	952.61
Livestock cash income (Ethiopian currency)	3927.65	4916.84	3927.65	4916.84
Non-farm income (Ethiopian currency)	3393.89	3726.03	2566.24	1899.33
Extension advice (yes=1))	0.7	0.3	0.4	0.3
Climate change information (yes=1)	0.6	0.5	0.4	0.5
Cultivated land size (hectares)	2.23	1.69	3.85	1.08
Plots with steep slope (%)	0.5	0.5	0.2	0.11
Plots with mixed slope (%)	0.5	0.5	0.8	0.11
Semi-fertile plots (%)	0.4	0.3	0.4	0.33
Non-fertile plots (%)	0.5	0.5	0.4	0.4
Shared out land (ha)	0.64	0.46	1.15	0.73
Farm-home distance (km)	1.91	1.12	2.36	1.32
Number of parcels	2.08	0.93	1.85	0.85
Past knowledge of adaptation (yes=1)	0.62	1.34	0.48	1.62

Results of the selection and outcome models are presented in Tables 3.8 and 3.9, for the wet and the dry lowland agro-climatic zones, respectively. In both models, most of the explanatory variables and their respective marginal values are statistically significant in determining perception and adaptation in the directions that would be expected. The calculated marginal effects measure the expected changes in the probability of perception and adaptation with respect to a unit change in an explanatory variable.

Table 3.8 Results of the Heckman probit selection model for the wet lowland

Explanatory variables	**Outcome model**				**Selection model**			
	Regression		Marginal effect		Regression		Marginal effect	
	Coefficients	P-values	Coefficients	P-values	Coefficients	P-values	Coefficients	P-values
Education of HH head	0·082**	0·022	0·016**	0·012	0·033***	0·003	0·013***	0·002
Household size	0·044**	0·012	0·014 **	0·043				
HH head sex	0·580**	0·010	0·177**	0·012				
Farming experience	0.072	0.133	0.023	0.131				
HH head age	0.138**	0.012	0.012**	0.031	0·015***	0·000	0·008***	0·000
Crop income	0.001	0.142	0.031	0.531				
Livestock income	0.829***	0.000	0.145***	0.000				
Non-farm income	0·126**	0·023	0·021**	0·044				
Extension advice	1·024***	0·000	0·303***	0·000				
Cultivated land size	−0·565**	0.034	−0·009**	0·024				
Climate information	0·255**	0·021	0·074**	0·023	0.034	0.131	0.031	0.113
Temperature					0.168***	0.000	0.044***	0.000
Precipitation					-0.013***	0.000	-0.03***	0.000
Plots with steep slope	2.62*	0.054	0.263*	0.041				
Plots with mixed slope	2.62*	0.054	0.263*	0.043				
Semi-fertile plots	0.056	0.113	0.012	0.110				
Non-fertile plots	1.21**	0.022	0.066**	0.011				
Shared out land	-0·025	0·310	-0·012	0·310				
Farm-home distance	-0·122**	0·011	-0·033**	0·011				
Number of parcels	−0·013**	0.021	−0·011	0·012				
Number of crop failures					1.418***	0·000	0.278***	0·000
Frequency of drought in 20 years					0·255**	0·021	0·074**	0·023
Frequency of drought in 10 years					0·83***	0·001	0·212	0·000
Duration of food shortage					0.011**	0.028	0.003**	0.035
Past knowledge of adaptation	0.476***	0.002	0.132***	0.001				
Constant	-5·945***	0·003			-1.245***	0·000		
Total observations	367							
Censored	73							
Uncensored	294							
Wald Chi square (Zero slopes)	86·84, (P<0·001)							
Wald Chi square (independent equations)	10·29 (P<0·001)							

***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

Results of the selection model for the wet lowland (Table 3.8) indicate that education level of the household head, age of the household head, changes in temperature and precipitation, number of crop failures in the past, and frequency of drought in the past significantly increase the likelihood of farmers' perception of climate change (*P*<0.01). Likewise, duration of food shortage faced in the past is statistically significant in enhancing farmer's perception of climate change (*P*<0.05).

Table 3.9 Results of the Heckman probit selection model for the dry lowland

Explanatory variables	Outcome model				Selection model			
	Regression		Marginal effect		Regression		Marginal effect	
	Coefficients	P-values	Coefficients	P-values	Coefficients	P-values	Coefficients	P-values
Education of HH head	0.505***	0.000	0.144***	0.000	0.272**	0.014	0.070*	0.049
Household size	0.056***	0.000	0.023***	0.000				
HH head sex	0.016***	0.000	0.002***	0.000				
Farming experience	0.580**	0.010	0.165**	0.012	0.061**	0.017	0.019**	0.017
HH head age	0.058*	0.054	0.028*	0.043				
Crop income	1.022***	0.003	0.319***	0.003				
Livestock income	-0.140**	0.011	-0.042*	0.013				
Non-farm income	-0.565**	0.034	-0.019*	0.042				
Extension advice	0.015	0.143	0.045	0.141				
Cultivated land size	-2.70**	0.037	0.044*	0.041				
Climate information	0·203**	0·011	0·057**	0·023	0.155***	0.001	0.131***	0.002
Temperature					0.077	0.416	0.017	0.103
Precipitation					-1.121**	0.031	-0.123**	0.022
Plots with steep slope	0.543*	0.050	0.021*	0.056				
Plots with mixed slope	0.956	0.419	0.026	0.337				
Semi-fertile plots	0.139	0.124	0.003	0.124				
Non-fertile plots	-1.50	0.204	-0.127	0.342				
Shared out land	-0.54*	0.071	-0.149*	0.056				
Farm-home distance	-2.626*	0.046	-0.263*	0.051				
Number of parcels	-0.053	0.310	-0.016	0.310				
Number of crop failures					4.414**	0.017	0.278**	0.021
Frequency of drought in 20 years					0.238**	0.014	0.227**	0·034
Frequency of drought in 10 years					0·323**	0·032	0·044**	0·013
Duration of food shortage					2.634***	0·000	0·212***	0·001
Past knowledge of adaptation	2.662**	0.000	0.289***	0.000				
Constant	-5·032***	0·001			-1.133***	0·000		
Total observations	367							
Censored	79							
Uncensored	288							
Wald Chi square (Zero slopes)	88·43, (P<0·001)							
Wald Chi square (independent equations)	10·86 (P<0·001)							

***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

Results of the outcome model for the wet lowland condition are also portrayed in Table 3.8. Accordingly, income from livestock, the gender of the household head, extension advice and knowledge of adaptation measures strongly influenced farmers' adaptation decision (*P*<0.001).

Moreover, education level of the household head, household size, age of the household head, non-farm income, land size, climate information, the proportion of non-fertile land and farm-home distance are significant in determining farmers' adaptation decision (*P*<0.05).

Unlike the wet lowland condition, change in temperature and precipitation are less important in influencing farmers' perception of climate in the dry lowland. However, farming experience, climate information, duration of food shortage, number of crop failures experienced in the past, and frequency of drought are statistically significant in determining farmers' perception of climate change (Table 3.9).

The outcome model result for the dry lowland condition (Table 3.9) revealed that education level of the household head, household size, the gender of the household head, farming experience, age, income from crop enterprise, climate information, slope of a plot, and knowledge of adaptation options are positively and significantly related to farmers' adaptation decision. Income from livestock and non-farm activities negatively affected adaptation decision showing that income from these sources may not be invested for adaptation in the crop sector. Similarly, land size, size of shared-out land, and farm-home distance negatively influenced adaptation decision of smallholder farmers in the dry lowland.

Based on the model results, the marginal effects of the significant explanatory variables are compared between the two agro-climatic zones. The computed marginal effect for education variable showed that one additional year in educational status of the household head increases the probability of adaptation by 14.4 percent in the dry lowland compared to 1.6 percent in the wet lowland. The probability of adaptation increases by 16.5 percent for each additional year of farming experience in the dry lowland while the marginal effect of farming experience on adaptation is negligible in the wet lowland. Likewise, the probability of adaptation increases by 31.9 percent as income from crop enterprise increases by one unit in the dry lowland.

One unit additional income from livestock enterprise has increased the probability of adaptation by 14.5 percent for farmers in the wet lowland. However, additional income from livestock has decreased probability of adaptation by 4.2 percent in the dry lowland implying that income from this source may not be invested for adaptation in the crop sector. Likewise, one unit additional income from non-farm activities has increased the probability of adaptation by 2.1 percent in the wet lowland perhaps because it induces more investment in adaptation options. Nevertheless, non-farm income reduces the probability of adaptation by about 2 percent in the dry lowland showing that households who engaged in non-farm activities are less dependent on crop farming and hence less motivated to invest for adaptation in the crop sector.

Owning farm plots with steep-slope increases the probability of adaptation to climate change by 26.3 percent in the wet lowland implying that farmers are more likely to invest on adaptation measures if their farm plots are steeper. Likewise, as the proportion of non-fertile land increases by one hectare, probability of adaptation increases by 6.6 percent in the wet lowland. However, in the dry lowland, the probability of adaptation decreases by 12.7 percent as the size of non-fertile land increases showing that farmers may abandon a given farm plot if its fertility status significantly declines. This could be attributed to a relatively higher per capita landholding in the dry lowland which can possibly offset a decline in crop yield.

As the size of shared-out land increases by one-hectare, probability of adaptation decreases by 1.2 percent in the wet lowland and by 14.9 percent in the dry lowland. Increase in the farm-home distance by one kilometer decreases the probability of adaptation by 26.3 percent in the dry low land and by 3.3 percent in the wet low land. This is because farm size is relatively large in the dry lowland compared to the wet lowland and hence less attention is given to farm plots far away from doweling areas. Extension advice increased the probability of adaptation by 3 percent in wet lowland suggesting that extension service is instrumental for adaptation decision. Similarly, availability of climate information increases the probability of adaptation by 7.4 percent in the wet lowland and by 5.7 percent in the dry lowland.

The other variable of interest which affects the probability of farmers' adaptation decision is past knowledge of adaptation options (a proxy variable for awareness). The calculated marginal effect for this variable shows that the probability adaptation increases by 13.2 percent in the wet lowland and by 28.9 percent in the dry lowland showing that farmers’ desire to try the adaptation practices at own cost increases when they have prior exposure to the practices. This implies that the more a farmer is exposed to adaptation technologies, the more will be the willingness and trust to implement the techniques sustainably.

3.4.2 Discussion

Climate change adaptation in smallholder agriculture is vital to reduce rural poverty and maintain ecosystem health. Besides, adaptation improves agricultural productivity and income of smallholder farmers (Deressa et al. 2011). As confirmed by the results of this study, adaptation to climate change is a two-step process which requires that farmers perceive climate change in the first step and respond to the changes in the second step through adaptation. In the study locations, smallholder farmers well perceived the problem of climate change and make adaptive responses to minimize the negative effects that compromised their farm productivity and food security. However, different socio-economic, environmental and institutional factors affect farmers' climate change perception and adaptive behavior.

The results of this study revealed that farmers living in the dry lowland area perceived more change in climate than farmers in the wet lowland. This could either be associated with the repeated drought events occurring in the area in recent years or could be linked to various environmental changes that cause reduced water availability and agricultural yield in the dry lowland areas (Deressa et al. 2011). With regard to adaptation, better awareness and use of adaptation measures is revealed in the wet lowland condition as compared to the dry lowland. This difference between the two agro-climatic zones may call for further heightening of intervention to facilitate the prospect for enhanced climate change perception and adaptation.

The relevance of different agronomic practices as adaptation measure is increasing over years in the study area to lessen the challenges of climate factors on smallholder agriculture. Some agronomic practices (such as adjusting planting date and early maturing crop varieties) are flattering in both agro-climatic zones of the study area in response to change in the time of onset of rainy season, the incidence of terminal moisture stress and early cease of rainfall. This is in line with the findings of Lobell et al. (2008) who signified adjusting planting date and use of early maturing varieties as key adaptive responses for climate change in areas where rainfall is erratic.

Diversifying crop types is another agronomic practice emerging as adaptation strategy in the study locations attributed to farmers' risk aversion behavior. Moreover, diversifying crop types into high-value crops (such as horticultural crops) is a related new development as adaptation option aiming at intensifying the use of scarce farm resources (water and land) and maximizing returns thereof. This strategy is also further driven by improved access to market and growing experience of irrigation practices in the area. This result confirms the findings of previous studies that reported crop diversification as a contemporary practice in response to climate change (Nkonya et al. 2011). However, it is contrary to Jones and Thornton (2010), who predicted that climate change would induce a shift from crop to livestock production.

Based on the results of this study, farmers are more likely to implement soil conservation measures as adaptation strategy on parts of their agricultural land that are more susceptible (steep slopes) to climate change risks. This finding corroborates with the findings of Kassie et al. (2009) and Wossen et al. (2015). The same studies implied that farmers invest in adaptation measures in plots where they expect more risk from climate hazards.

The study showed a significant positive role of access to training, extension service and climate information in promoting farmers' investment on adaptation measures. Providing agricultural extension services helps to increase implementation of the adaptation measures since farmers can able to acquire new skills and hence ensures sustainable use of the techniques. The knowledge gained through training can also capacitate farmers with the technical know-how required for implementing adaptation measures in their agricultural production system and make them far-sighted to look for long-term benefits rather than immediate gains obtained at the expense of land degradation. This is in agreement with the finding of Guteta and Abegaz (2015), Ketema and Bauer (2012) and Beshir et al. (2012) who reported that access to extension and training is instrumental for in promoting sustainable use of land-based climate change adaptation measures.

As expected education is positively associated with farmers' climate change perception and adaptation decision suggesting that educated farmers tend to better recognize the risks associated with climate change. Education is also more likely enhances the cognitive proficiency and awareness of farmers about new technologies and hence induces them to adopt. This is in the same line with the findings of Deressa et al. (2009) and Asrat et al. (2004).

Gender of the household head is positively and significantly related to farmers' adaptation decision in the study area showing that male-headed households better adapt to climate change. This can be associated with the fact that in rural Ethiopia, women-headed-households are usually constrained by family labor because those women are responsible for both farming and domestic activities. Moreover, female-headed households have less access to resources, information and other socio-economic opportunities, and bear more burdens of family responsibilities than males. This finding concurs with other empirical findings (Guteta and Abegaz 2015; Deressa et al. 2011; Buyinza and Wambede 2008) who reported that male-headed households often have a higher probability of adopting new agricultural technologies.

Family members are important source of labor for any farm operation in smallholder agriculture. In line with this, household size increases the likelihood of farmers' climate change adaptation in the study area, for large family size is normally associated with a better labor endowment. The result also suggests households that are endowed with labor tend to use labor-intensive adaptation measures. This result is in harmony with the findings of Kassie et al. (2009) who stated the presence of more economically active household members favored adoption of labor-demanding agricultural technologies.

In the study area, the incidence of adaptation to climate change decreases with cultivated land size. This may reveal that adaptation is plot-specific and it is the specific characteristics of a plot that dictates the need for a specific adaptation rather than the size. Previous studies (Deressa et al. 2011; Kurukulasuriya and Mendelsohn 2006) also reported similar findings.

Income from livestock and non-agricultural sources is positively and significantly associated with adaptation in the wet lowland agro-climatic zone. This could be attributed to the fact that the income from these sources may provide farmers with additional capacity to finance adaptation measures. However, in the dry lowland, income from the livestock enterprise and non-farm sources decreases the likelihood of adaptation. This may imply that as households engage more in livestock and non-farm activities, they become less dependent on crop cultivation as a livelihood source and less motivated to invest for adaptation in the crop sector. This is in agreement with the findings of Simane et al. (2016) who reported a similar result for livestock-based farming systems in the northern highlands of Ethiopia.

Size of non-fertile land is negatively and significantly associated with the likelihood of adaptation in the dry lowland showing that farmers may abandon a given farm plot if its fertility status significantly declines. This could be attributed to a relatively larger per capita land holding in the dry lowland, which can possibly offset a decline in yield through extensification. In the same line, distant farmlands receive less adaptation measures in the dry lowland for the same reason of a relatively larger per capita land holding that may reduce the attention given to farm plots far away from doweling areas. This result corroborates with the findings of Ketema and Bauer (2012) and Beshir et al. (2012).

Farmers' previous knowledge of climate change adaptation measures increases their adaptation decision in both the wet and dry lowland agro-climatic zones. This shows that farmers' desire to implement adaptation measures at own cost increases when they have a prior exposure to the practices. The more a farmer is exposed to the technologies of adaptation the more will be the willingness and trust to implement the techniques sustainably. This is in agreement with previous empirical studies (Simane et al. 2016; Asrat et al. 2004).

3.5 Conclusion and Recommendation

Adaptation to climate change is a two-step process, which requires that farmers first perceive the climate change and then respond to the changes in the second step. This study employed the Heckman sample selection model to explore determinants of perception and adaptation to climate change in the Dabus sub-basin, focusing on the two agro-climatic zones (wet lowland and dry lowland). It is evidenced by the results that farmers in the area perceived the change in climate and have devised a means to survive through implementing different adaptation strategies. In this regard, farmers in the two agro-climatic zones are found to be similar with respect some variables that affected perception and adaptation to climate change. They have also considerable divergence in terms of the direction and effect of some other explanatory variables that affect perception and adaptation.

Education of the household strongly and positively affected both perception and adaptation in the wet lowland. It also strongly affected adaptation decision in the dry lowland area. Farming experience has a strong and positive effect on adaptation in the dry lowland, while it has no effect in the wet lowland. Similarly, income from crop enterprise positively and strongly affected adaptation decision in the dry lowland but it has shown no effect in the wet lowland condition.

Income from livestock enterprise positively and strongly affected farmers' adaptation decision in the wet lowland, while its effect is negative in the dry lowland. Likewise, income from off-farm activities has a positive influence on adaptation in the wet lowland area, while its effect is negative in the dry lowland. In the wet lowland condition, temperature change is statistically significant in affecting perception to climate change while its effect is insignificant in the dry lowland. Slope and fertility status of farm plots positively and significantly affected adaptation decision in the wet lowland while these variables have no effect on adaptation in the dry lowland.

The study result generally reveals that farmers' climate change perception and adaptation in both agro-climatic zones are commonly affected by some similar exogenous variables, which necessitate a joint policy intervention with regard to these variables. On the other hand, the two agro-climatic zones are considerably different in terms of the direction and effect of some other exogenous variables. This difference dictates the need to have location-specific intervention to enhance smallholder farmers' perception and adaptation to climate change. Comparison of the two agro-climatic zones also revealed better awareness and use of the adaptation measures in the wet lowland condition as compared to the dry lowland. However, further heightening of awareness in both parts of the study area may facilitate the prospect for enhanced adaptation.

Most of the factors affecting farmers' perception and adaptation to climate change in the study areas are directly related to institutions, infrastructure, and technologies. Hence, there is a need for policy intervention aiming at enhancing institutional services, infrastructural facilities and delivering effective adaptation technologies. It is evident from the results that lack of experience, lack of access to information on climate change and lack of education limit perception and adaptation decision of smallholder farmers. Hence, facilitating effective and reliable access to information and improving farmers' awareness of potential benefits of adaptation are important policy intervention measures.

In line with the findings of this study, there is a need for agro-ecology-specific readily available adaptation technologies that could help to reduce negative effects of climate change on the already weak agriculture and on the livelihood of smallholder farmers. Policies must also aim at promoting farm-level autonomous adaptation through effective participation of farmers in developing and implementing relevant adaptation measures. Parallel to this, any intervention that promotes the implementation of climate change adaptation techniques should take in to account specific factors relevant to the nature of the practices. Since adaptation process is knowledge and resource intensive, it may not be implemented easily given the limited awareness and resource endowment of smallholder farmers. Therefore, enhancing perception and scaling up of climate change adaptation technologies require a shared vision of all potential stakeholders and public-private partnership.

Chapter Four

4. Adapting Smallholder Agriculture to Climate Change through Climate-Smart Land Management Practices: Empirical Evidence from the Dabus Sub-basin, Blue Nile River

Abstract

The objective of this paper is to determine the factors that influence farmers' decision to use two categories of climate-smart land management practices as adaptation strategy to climate change in the Dabus sub-basin. It is based on analysis of data collected from 734 farm household heads and employed probit regression model to analyze the determinants of adaptation to climate change through climate-smart land management measures. Based on the model result, factors like perception of climate change, exposure to adaptation techniques, education, perception of land degradation, slope, land prone to degradation; number of parcels, crop enterprise income, land size, farm distance, economically active family size, and agro-ecology are found to be important in determining farmers' decision to use structural land management practices. Likewise, perception of climate change, exposure to adaptation, farming experience, slope, crop enterprise income, land prone to degradation and agro-ecology are found important in affecting farmers' decision to use non-structural land management practices as adaptation measure. Therefore, in line with the findings of the analysis, any intervention that promotes use of climate-smart land management practices as adaptation strategy should take in to account agro-ecology specific factors that are relevant to the nature of the land management practices. Moreover, since scaling up of the climate-smart practices is resource intensive, it requires both public and non-public investment for providing technological support and raising awareness. Failure to do so would adversely affect crop productivity and exacerbate food insecurity problems at farm household level.

Keywords: *climate change, adaptation, land management, structural/physical, non-structural*

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4.1 Introduction

The impact of climate change is detrimental in low income Tropical African countries including Ethiopia that depend on agriculture as a main livelihood. The combination of the already fragile environment, dominance of the climate-sensitive sector in the economy, and low autonomous adaptive capacity in these regions aggravates the harmful effects of climate change and variability on agricultural production, food security, and ecosystems (IPCC 2007b). However, the effects of climate change vary across countries and adaptation capabilities are influenced by geographical, economic, cultural and political factors, which require that adaptation programs must take into account country-specific circumstances (IPCC 2007b; Adger et al. 2005; Stern 2007; World Bank 2010).

Ethiopia is heavily dependent on a rain-fed agriculture, and its geographical location and topography in combination with low adaptive capacity entail a high vulnerability to adverse impacts of climate change (Yirga 2007). The country has been suffering from such disasters which manifest in the form of drought, flood, heavy rains, high temperature and frost with seemingly increasing trend from year to year (Abate 2013; Tadege 2007). Although Ethiopia has a long history of drought in the past with recurrence of the event in an interval of a decade, recently the frequency and extent appear to be growing. For example the country has experienced eight drought events since 1990 in less than two decades. Similarly six serious flood attacks occurred since 1988. During the two recent drought events, GDP declined by around 3-10 percent and flooding in turn causes significant damage to settlements and infrastructure, and undermines agriculture by delaying planting, reducing yields, and compromising the quality of crops (Nkonya 2011; Tadege 2007).

Following such recurrence of extreme events and the catastrophic effects, climate researchers believe Ethiopia as one of the victims of climate change (Philander 2008). Studies on the trend of climate in Ethiopia show that temperature has been increasing throughout the century with a mixed trend of precipitation. Average annual maximum temperature and average annual minimum temperature over the century have increased by 0.1^0C and 0.25^0C per decade, respectively (NMSA 2001). Historical trend also shows that mean temperature increased by 1.3^0C from 1996-2006 with more hot days and nights and fewer cold days and nights. The rainfall is highly variable from year to year, season to season, and decade to decade with no regular trend. As a result, Ethiopia is experiencing the effects of climate change and this can holdback economic progress in the range of 0.5-2.5 percent each year (Nkonya 2011; Camberlin 2009).

With regard to the future, GCM (General Circulation Models) predictions show an increasing trend of temperature with moderate inter-model differences (Camberlin 2009). Considering different emission scenarios, mean annual temperature will increase in the range of 0.9 and 1.1 ^{0}C by the year 2030 and in between 1.7 to 2.1 ^{0}C by the year 2050 from the average of 1961-1990 (IGAD-ICPAC 2007). Whereas, the corresponding result for annual precipitation show a change between 0.6 and 4.9 percent for 2030 and between 1.1 and 18.2 percent for 2050. Following this, the crop simulation models as well as econometric studies of climate change impacts suggest a negative impact on crop productivity in Ethiopia on the order of 5 to 10 percent by 2030 due to changes in the mean seasonal temperature and precipitation with more severe impacts towards the end of the century (IGAD-ICPAC 2007).

Agriculture's heavy dependence on rainfall signifies that the main source of the economy is rooted on climate sensitive sector, and hence an episode of a single climate event could retard or even reverse whatever economic growth achieved in the past. In line with this, a study on consumption in rural Ethiopia (Dercon 2004) shows that a rainfall shock in a single year has a lingering effect on household's welfare for many years to come. The same study showed that a 10 percent rainfall decrease in one year has an impact of 1 percent decrease on the growth rates of agricultural output for 4 to 5 years to come. These impacts of climate on agriculture are first-order effects that trigger direct and indirect economic impacts, which necessitate the need for an economy-wide framework to cope up with climate change shocks. Overall, climate impacts in Ethiopia are significant, but variable over regions and economic sectors. Thus, given the agro-ecological diversity of the country, understanding location specific climate pattern, its impacts on agricultural production and possible resilience options seems to be critical (Simane et al. 2016; Mertz et al. 2009).

Studies indicated that smallholder farmers perceive climate change and also adapt to reduce the negative impacts (Deressa et al. 2011; Mertz et al. 2009). In this regard, climate-smart land management practices have been shown to be effective for adaptation in moisture stress areas. Empirical evidence has also shown that synergistic relationships exist among different land management practices (Nkonya 2011). That is, holding all else constant, a household that uses more than one practice is likely to have better adaptation than a household using a single practice.

Soil and water conservation practices and agronomic practices that include improved crop varieties, soil fertility management practices, crop rotation, intercropping, conservation tillage, and agro-forestry practices enhance adaptation to climate change, reduce crop production risk and increases crop productivity (Nkonya 2011; Lobell 2008). However, previous studies in Ethiopia failed to explicitly address land management based adaptation methods that farmers employ at local level given the diverse agro-ecological setting of the country. Existing studies are also highly aggregated and are of little help in addressing agro-ecology specific adaptations to climate change. They have paid little attention to the analysis of climate-smart land management practices as adaptation strategy and the factors influencing farmers' decision to use the practices. Since adaptation is a local response to climate stimuli, addressing agro-ecology specific adaptation decisions is an important research gap that needs to be addressed. Therefore, the present study is aimed at filling these knowledge gaps.

Past studies showed that there are plausible methodological similarities among agricultural technology adoption and climate change adaptation methods as both involve decisions on whether or not to adopt a given course of action (Pryanishnikov 2003; Ervin and Ervin 1982). On these premises, probit regression model is selected to analyze the determinants of using two sets of land management practices (structural/physical and non-structural measures) as an adaptation strategy in the Dabus sub-basin. The structural/physical land management techniques refer to the use of physical soil and water conservation measures whereas the non-structural measures refer to agronomic practices such as the use of improved crop varieties, use of soil fertility management techniques, crop diversification, intercropping, crop rotation, conservation tillage, and changing planting date. The major focus of this paper is, therefore, to explore how physical, human, natural, and socio-economic factors influence farmer's decision to use these two sets of climate-smart land management practices as adaptation strategy considering two major agro-ecologies in the Dabus sub-basin of the Blue Nile River.

4.2 Methodology

4.2.1 Data source and type

The paper is based on a cross-sectional household survey data of 734 mixed farmers enumerated during November and December 2016 from the Dabus sub-basin of the Blue Nile River in the North-west part of Ethiopia. The primary data majorly include demographic, socioeconomic, institutional, and biophysical attributes of the respondents. The data also include information on the types of land management practices being implemented by smallholder farmers, factors affecting the practices and the constraints in implementing the practices. Survey questionnaires, FGD, and field observation were the data collection methods employed. Household-level data were collected through an open and close-ended survey questionnaire. FGD were also carried out to complement the responses acquired through the survey questionnaire. The primary data were substantiated by the data obtained from secondary sources.

4.2.2 Data analysis

The study used descriptive and econometric methods to analyze the collected data. Descriptive method was employed to reveal differences and similarities between the two agro-climatic zones of the study area as well differences and similarities between users and non-users of the land management practices in terms of socio-economic and environmental variables. With regard to the econometric method, the study employed the probit regression model to analyze the determinants of using the two sets of climate-smart land management practices as adaptation strategy to climate change.

4.2.2.1 Specification of the probit model

There are plausible methodological similarities among agricultural technology adoption and climate change adaptation methods as both involve decisions on whether or not to adopt a given course of action (Deressa et al. 2011). The models are based on farmers' utility or profit-maximizing behavior (Greene 2000) and the assumption here is that farmers adopt a technology/practice only when the perceived utility or profit from using the new technology is greater than the traditional or the old technology. It is on these premises that probit regression model is selected for the analysis of the determinants of farmers decision to use the land management practices as adaptation strategy.

It is assumed that subsistence farmers use adaptation methods only when the perceived utility or net benefit from using such a method is significantly greater than the case without it. Although utility is not directly observed, the actions of economic agents are observed through the choices they make. Suppose that Y_j and Y_k represent a household's utility for the two choices, which are denoted by U_j and U_k , respectively. The linear random utility model could then be specified as:

$$U_j = \beta_j X_i + \varepsilon_j \quad \text{And} \quad U_k = \beta_k X_i + \varepsilon_k \text{ --- (4.1)}$$

where $U\,j$ and $U\,k$ are perceived utilities of adaptation methods j and k, respectively, X_i is the vector of explanatory variables that influence the perceived desirability of the methods, B_j and B_k are parameters to be estimated, and ε_j and ε_k are error terms assumed to be independently and identically distributed (Green 2000) and Ervin (1982). In the case of climate change adaptation methods, if a household decides to use option j, it follows that the perceived utility or benefit from option j is greater than the utility from the other options (say k) depicted as:

$$U_{ij}\left(\beta_j X_i + \varepsilon_j\right) > U_{ik}\left(\beta_k X_i + \varepsilon_k\right), k \neq j \text{ --- (4.2)}$$

The probability that a household will use method j among the set of climate change adaptation options could then be defined as:

$$P(Y = 1|X) = P(U_{ij} > U_{ik}) \text{--- (4.3)}$$

$$P(\beta_j X_i + \varepsilon_j - \beta_k X_i - \varepsilon_k > 0|X)$$

$$P(\beta_j X_i - \beta_k X_i + \varepsilon_j - \varepsilon_k > 0|X)$$

$$P(X^* X_i + \varepsilon^* > 0|X = F(\beta^* X_i)$$

where P is a probability function, Uij, Uik,, and Xi are as defined above, $\varepsilon^* = \varepsilon j - \varepsilon k$ is a random disturbance term, $\beta^*=(\beta_i-\beta_j)$ is a vector of unknown parameters that can be interpreted as a net influence of the vector of independent variables influencing adaptation, and $F(\beta^* X_i)$ is a cumulative distribution function of ε^* evaluated at $\beta^* X_i$. The exact distribution of F depends on the distribution of the random disturbance term, ε^* and depending on the assumed distribution that the random disturbance term follows, several qualitative choice models can be estimated (Green 2000).

As it is already mentioned, the purpose of this study is to analyze which of the hypothesized independent variables are related to the adaptive responses of farmers to climate-change worsened land degradation problems. The dependent variables (adaptation 1 and adaptation 2) are dummy (binary), which take a value zero or one depending on whether or not a farmer is applying any of the structural/physical or non-structural land management practices as adaptive response to climate change aggravated land degradation. On the other hand, the explanatory variables are either continuous or binary/categorical. Based on this, the probit model is specified as:

$$I_j^* = \beta X_j + \varepsilon_j \qquad (4.4)$$

Where; β is vector of parameters of the model, Xj is vector of explanatory variables and εj is the error term assumed to have random normal distribution with mean zero and common variance δ^2 (Green 2000).

Ij= Unobservable households' actual decision to use a structural/physical and non-structural land management practice (which is also named to be a latent variable) and what we observe is a dummy variable (use of land management measures) which is defined as: 1 if $I_j^*>0$ and 0 otherwise

$$pro(adoption = 1) = \phi(\beta X_j) \qquad (4.5)$$

$$pro(adoption = 0) = 1 - \phi(\beta X_j) \qquad (4.6)$$

4.2.2.3 Definition of explanatory variables and working hypotheses

Dependent variable: The first dependent variable for the probit analysis (**adaptation1**) has a dichotomous nature measuring the decision of the farmer to use structural/physical land management practices as an adaptive response to climate change/variability. It is represented in the model by 1 for a user farmer and by 0 for a non-user farmer. Similarly, the second dependent variable (**Adaptation2**) has also a dichotomous nature measuring the decision of the farmer to use non-structural land management practices as an adaptive response to climate change/variability. It is represented in the model by 1 for a user farmer and by 0 for a non-user farmer.

The independent variables: It is hypothesized that the decision to make adaptive responses is influenced by a set of explanatory variables. Based on theories, the findings of past studies (Deressa et al. 2011, Nkonya 2011; Mertz et al. 2009; Deressa et al. 2009; Lobell 2008; Asrat et al. 2004), and observation made in the study area, the variables presented in Table 4.1 are hypothesized to determine farmers' decision to use climate-smart land management practices as adaptation strategy to climate change/variability.

Table 4.1 Hypothesized explanatory variables and their direction of effect

Explanatory variable	Type of variable	Hypothesized effect
Perception	Dummy	+
Education	Categorical	+
Farmexperiance	Continuous	+/-
Activelabor	Continuous	+
Exposureadpt	Dummy	+
Cultivatedland	Continious	+
Slope	Categorical	+
Cropincome	Continuous	+
Noparcel	Integer	-
Exposurepercep	Categorical	+
Pronefarmland	Dummy	+
Farmdistance	Continuous	-
Agro-ecology	Dummy	+

4.3 Results and Discussion

4.3.1 Comparison of agro-climatic zones

Comparison of perception of climate change between the two agro-climatic zones indicated that 52 per cent of the respondents from the wet lowland and 62 per cent from the dry lowland had perceived change in climate (Table 4.2). This difference in perception between the two agro-climatic zones is statistically significant ($\chi2$ = 6.636 with P<0.01). More perception in the dry lowland is attributed to the occurrence of a repeated drought and various environmental changes in recent years that caused crop failure. The majority of the respondents in the wet lowland (62 per cent) have exposure to adaptation measures to climate change as compared to 48 percent in the dry lowland showing existence of statistically verified difference between the two agro-climatic zones ($\chi2$=14.659 with P<0.001) in terms of exposure to adaptation measures. With respect to use of non-structural practices, about 60 percent and 49 percent of the users are fond in the wet lowland and dry lowland, respectively (Table 4.2) and the difference in the use of these practices between the two agro-climatic zones is statistically significant at 1 percent probability level ($\chi 2$=8.497). However, the two agro-climatic zones are not statistically different in the use of physical land management measures.

The average cultivated land per household in the wet lowland is 1.68 hectare compared to 1 hectare in the dry lowland and the mean difference is significant at 1 percent probability level (t =-9.6467). In terms of total land owned, the average is 6.6 hectares in the wet lowland as compared to 5.8 hectares in the dry lowland (t =-3.2930; P<0.001). With respect to farming experience, the average is 17.9 for the wet lowland as compared to 13 years for the dry lowland (Table 4.2).

Table 4.2 Comparison of agro-climatic zones in terms of socio-economic variables

Comparison variable		Agro-climatic zones						χ^2 value
		Wet lowland		Dry lowland		Total		
		No.	%	No.	%	No.	%	
Perception of climate change	Not perceived	177	47.7	139	38.3	316	43.1	6.636^{***}
	Perceived	194	52.3	224	61.7	418	56.9	
Exposure to adaptation measures	No exposure	141	38.0	189	52.1	330	45.0	14.659^{***}
	Have exposure	230	62.0	174	47.9	404	55.0	
Adaptation through physical measures	Non-users	191	52	206	56	397	54	0.714
	Users	176	48	161	44	337	46	
Adaptation through non-physical measures	Non-users	147	40	187	51	334	46	8.497***
	Users	220	60	180	49	400	54	
		Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	***t* value**
Cultivated land (ha)		1.68	0.94	1.00	0.58	1.34	0.85	-9.6467^{***}
Total land (ha)		6.60	2.98	5.81	2.17	6.21	2.63	3.2930^{***}
Farm experience (years)		17.87	8.05	13.01	6.6.2	15.44	7.76	-7.3685^{***}

*** Values are significantly different at $P < 0.01$.

4.3.2 Determinants of climate-smart land management practices

Thirteen explanatory variables were included in the binary probit regression model as determinant factors affecting the use of land management measures as adaptation strategy. Prior to running the probit model, the explanatory variables were checked for existence of multicollinearity problem using the Variance Inflation Factor (VIF). Based on the VIF(X_i), the data has no problem of multicollinearity with a mean VIF value of 1.21 and for each explanatory variable, the value of VIF is less than 10 (Table 4.3). Hence, all the explanatory variables are included in the model. Finally, maximum likelihood estimation method was used to elicit the parameter estimates of the probit model.

Table 4.3 Variance Inflation Factor (VIF) for explanatory variables

Variable	**VIF**	**1/VIF**
Agroecology	1.5	0.665541
cultivated~d	1.34	0.748889
Slope	1.27	0.784632
pronefarml~d	1.26	0.794141
Exposureadpt	1.21	0.82679
Perception	1.21	0.828529
farmexperi~e	1.2	0.834582
exposurepe~p	1.17	0.853042
Cropincome	1.16	0.86443
Noparcel	1.15	0.871594
Educ	1.14	0.874496
Activelabor	1.08	0.921693
Farmdistance	1.08	0.922661
Mean VIF	**1.21**	

Tables 4.4 and 4.5 depict the mean values of the explanatory variables included in the model revealing statistically significant difference between users and non-users of the practices.

Table 4.4 Descriptive summary of explanatory variables (adaptation 1)

Dependent variable	Adaptation to climate change using structural/physical land management measures (adaptation 1)						
Independent variables	Famers who adapt (N=316)		Farmers who do not adapt (N=418)		Total		t value
	Mean	SD	Mean	SD	Mean	SD	
Slope	2.897196	0.649081	2.153846	0.877058	2.472	0.868749	-10.8913***
Cropincome	12131.523	1299.587	11199.157	924.9919	1598.21	1192.831	-8.9371***
Exposureadpt	0.696262	0.460949	0.332168	0.471816	0.488	0.500357	-8.6512***
Exposurepercep	2.084112	0.70706	1.475524	0.613671	1.736	0.720654	-10.0694***
Pronefarmland	0.691589	0.46292	0.479021	0.500435	0.57	0.495572	-4.9064***
Noparcel	1.82243	0.735589	2.164912	1.016153	2.018036	0.921451	4.3666***
Cultivatedland	1.611784	0.879643	1.141653	0.770244	1.342733	0.850461	-6.2192***
Farmdistance	1.761519	1.044059	2.243951	1.254578	2.03747	1.192203	4.6864***
Activelabor	2.485981	1.17377	2.122378	0.985361	2.278	1.084005	-3.6668***
Perception	0.78972	0.408463	0.398601	0.490469	0.566	0.496121	-9.7152***
Farmexperiance	17.00467	9.251569	14.26573	6.179708	15.438	7.757998	-3.7499***
Agroecology	0.61215	0.488403	0.416084	0.493772	0.5	0.500501	-4.4206***
Educ	1.280374	1.032745	0.451049	0.805278	0.806	0.997172	-9.7390***

*** Values are significantly different at $P < 0.01$.

Table 4.5 Descriptive summary of explanatory variables (Adaptation2)

Dependent variable	Adaptation to climate change using non-structural land management measures (Adaptation2)						
Independent variables	Famers who adapt (N=440)		Farmers who do not adapt (N=294)		Total (N=734)		t value
	Mean	SD	Mean	SD	Mean	SD	
Slope	2.67893	0.779729	2.164179	0.904384	2.472	0.868749	t = -6.5893***
Cropincome	11601.662	1173.684	11593.075	1223.696	1598.21	1192.831	t = -0.0782
Exposureadpt	0.6	0.4961073	0.4	0.4835091	0.5	0.5003566	t = -4.4966***
Exposurepercep	1.856187	0.70667	1.557214	0.705663	1.736	0.720654	t = -4.6423***
Pronefarmland	0.6856187	0.465047	0.39801	0.49071	0.57	0.495572	t = -6.5615***
Noparcel	1.97651	0.814092	2.079602	1.060015	2.018036	0.921451	t = 1.1662
Cultivatedland	1.439354	0.838267	1.199965	0.850312	1.342733	0.850461	t = -3.1000***
Farmdistance	1.967525	1.176693	2.141517	1.210374	2.03747	1.192203	t = 1.5937
Activelabor	2.294314	1.033175	2.253731	1.157713	2.278	1.084005	t = -0.4011
Perception	0.6889632	0.463694	0.3830846	0.487353	0.566	0.496121	t = -7.0159
Farmexperiance	15.57525	7.812625	15.23383	7.690907	15.438	7.757998	t = -0.4836
Agroecology	0.6287625	0.483946	0.3084577	0.46301	0.5	0.500501	t = -7.4472***
Educ	0.9331104	1.01443	0.6169154	0.942079	0.806	0.997172	t = -3.5672***

*** Values are significantly different at $P < 0.01$.

For structural/ physical land management practices (adaptation 1), out of the thirteen explanatory variables hypothesized to explain farmers' decision of use of the practice, eleven were affirmed to be significant, while two were less powerful in explaining the variation in the dependent variable (Table 4.6). The chi-square test confirms the overall goodness of fit of the model at less than 1% probability level. Table 4.6 also portrays the calculated marginal effects after probit, which measure the expected changes in the probability of adaptation with respect to a unit change in an independent variable. For use of non-structural measures (adaptation 2) 8 explanatory variables and their marginal values are statistically significant in explaining farmers' decision to use the practices and are generally in the directions that would be expected (Table 4.7).

Slope category of cultivated land (slope): For the structural measures (adaptation 1), this variable took the expected positive sign and its coefficient is significant at less than 1 percent probability level. All other things held constant, the probability of adaptation through structural land management techniques increases by an average of 23.5% as the slope category of the farm land changes from flat to higher slope categories. Similarly, this variable positively and significantly influenced the adaptive responses through non-structural land management measures (adaptation 2) practices (P<1%). On the average, probability of adaptation increases by 9.4 percent as the slope category of a farm land changes from flat to steep and very steep. This finding is in line with the results of past studies that showed a positive relationship between slope category of a parcel and land management decisions (Simane et al. 2016; Deressa et al. 2011; Asrat et al. 2004; Gould 1989).

Table 4.6 Parameter estimates of the prbit regression model with marginal effects (adaptation 1)

adaptation1	**Coef.**	**Robust Std. Err.**	**Z**	**P>z**	**dy/dx**
slope: 2(gentle)	0.859651	0.535813	1.6	0.109	0.235232***
3 (steep)	2.388772***	0.517087	4.62	0.000	
4 (very steep)	2.759203***	0.709283	3.89	0.000	
Cropincome	0.000969***	0.000166	5.84	0.000	0 .0001937***
Exposureadpt	1.434466***	0.315493	4.55	0.000	0.2892063***
Exposurepercep					0 .2672321***
2 (medium exposure)	1.283574***	0.356038	3.61	0.000	
3 (high exposure)	2.394583***	0.44346	5.4	0.000	
Pronefarmland	0.523634	0.351561	1.49	0.136	0.1018843
Noparcel	-0.8361***	0.223834	-3.74	0.000	-0.1697717***
Cultivatedland	0.71687***	0.221225	3.24	0.001	0.1608822****
Farmdistance	-0.38728***	0.129279	-3	0.003	-0.0822392***
Activelabor	0.461275***	0.167923	2.75	0.006	0.0961324***
Perception	1.658744***	0.332317	4.99	0.000	0.3268772***
Farmexperiance	0.04125*	0.02502	1.65	0.099	0.0068929
Agro-climatic zone	1.38613***	0.379753	3.65	0.000	0.2573748***
Educ					0.2138982***
1(Basic education)	1.73804***	0.514294	3.38	0.001	
2 (primary education)	2.075244***	0.407237	5.1	0.000	
3 (secondary education)	2.723195***	0.571008	4.77	0.000	
_cons	-6.94869***	1.063771	-6.53	0.000	
Number of obs	734				
Wald chi2(18)	131.87				
Prob > chi2	0.0000				

*** Values are significantly different at $P < 0.01$.

Income from crop enterprise (*cropincome):*** The sign of this explanatory variable is consistent with the a *priori* expectation and it is positively and significantly associated to farmers' decision to use structural measures at 1 percent probability level. The calculated marginal effect shows that the probability of using structural land management techniques increases by 0.02 percent as income from crop enterprise increases by one birr implying that more income may ease the constraint on the liquidity needed for the investment in the land management practices. Likewise, this variable is positively associated with using the non-structural land management practices as adaptation measure (P<1%). The calculated marginal effect shows that the probability of adaptation through non-physical techniques increases by 0.007 per cent as income from crop enterprise increases by birr 1.

Exposure to adaptation practices (*exposureadpt****):*** This variable had positive and significant effect on farmers' decision to use structural land management measures (P<1%). The calculated marginal effect shows that the probability to adopt the techniques increases by 28.9 percent for farmers who have past knowledge of adaptation measures. This variable is also positively and significantly associated with using non-structural land management practices (P<1%) with a calculated marginal effect of 10 percent. The finding is in line with previous studies (Simane et al. 2016; Asrat et al. 2004; Bekele and Holden 1998) that revealed the positive role of previous exposure on the current adaptive responses of the smallholder farmers.

Table 4.7 Parameter estimates of the probit regression model with marginal effects (Adaptation2)

Adaptation2	**Coef.**	**Robust Std. Err.**	**Z**	**P>z**	**dy/dx**
slope					.0941255***
2(gentle)	0.282189	0.207788	1.36	0.174	
3 (steep)	0.612079***	0.197267	3.1	0.002	
4 (very steep)	0.531583*	0.307448	1.73	0.084	
Cropincome	0.00019***	5.34E-05	-3.48	0.000	.0000697***
Exposureadpt	0.277658**	0.139614	1.99	0.047	.1007365*
Exposurepercep					.0655957*
2 (medium exposure)	0.450258***	0.144868	3.11	0.002	
3 (high exposure)	0.157895	0.197197	0.8	0.423	
Pronefarmland	0.318202*	0.137312	2.32	0.02	.1268056*
Noparcel	-0.06158	0.073625	-0.84	0.403	-.0240607
Cultivatedland	0.058839	0.085434	0.69	0.491	.0237616
Farmdistance	0.054931	0.054455	1.01	0.313	.0154823
Activelabor	-0.01193	0.055596	-0.21	0.83	.0006254
Perception	0.615679***	0.138079	4.46	0.000	.234494***
Farmexperiance	0.02128**	0.009264	-2.3	0.022	.0078245**
Agro-climatic zone	0.869699***	0.163101	5.33	0.000	.3014664***
Educ					.027255
1(Basic education)	0.244881	0.210366	1.16	0.244	
2 (primary education)	0.251007	0.15634	1.61	0.108	
3 (secondary education)	-0.08917	0.291392	-0.31	0.76	
_cons	-0.89408	0.335098	-2.67	0.008	
Number of obs	497				
Wald chi2(18)	117.88				
Prob > chi2	0.0000				

***, ** and * Indicate significance levels at $P < 0.01$ and $P < 0.05$, and $p<0.1$, respectively.

Perceived risk level of farm land (Exposurepercep)*:* This variable is positively and significantly related to the dependent variable (adaptation 1) at 1 percent probability level. The probability of using structural land management techniques increases on average by 26.7 percent as the perceived risk level of farm land's exposure to land degradation changes from low/no risk to medium and high risk level. However, this variable is not significant in affecting farmers' decision to use non-structural land management measures as adaptation strategy.

Number of parcels (noparcel): This variable negatively and significantly influenced farmers' adaptation decision through structural land management measures and the finding is consistent with previous studies (Deressa et al. 2009; Asrat et al. 2004; Bekele and Holden 1998; Vieth et al. 2001). The marginal effect shows the probability of using the practices decreases by 17 percent as the number of parcels owned increase by one. This justifies that installing physical structures in small and fragmented plots creates difficulty on farming as it squeeze farm operations between the structures and also induces further stress on the scanty resources available at disposal of the smallholder farmers. However, this variable is less important in determining farmers' decision to use non-structural land management practices as adaptation strategy.

Size of cultivated land (cultivatedland): This variable is positively and significantly related to the use of structural land management practices (P<1%) and the finding is in line with the prior hypothesis and past studies (Simane et al. 2016; Bekele and Holden 1998; Vieth et al. 2001). The probability of using the practice increases by 16.1 percent as the size of cultivated land increases by one hectare justifying that structural land management measures are non-scale neutral and cannot be equally applied to all land sizes. However, this variables doesn't affect the use of non-structural measures as these practices are scale-neutral and can be equally applied both to small and large land sizes.

Farm-home distance (*farmdistance****):*** This variable influenced farmers' use of structural land management techniques negatively and significantly (P<1%). The probability of using the measures decreases by 8.2 percent as the farm-home distance increases by 1 kilometer. This imply that the further the location of the farm, the higher would be the opportunity cost of labor and other resources used for the practice and hence farmers may refrain from allocating resources. However, this variable is not important in affecting the use of non-structural measures since the practices are comparatively less labor intensive.

Economically active household size (*Activelabor****):*** Farmers' decision to use structural land management practices is positively and significantly associated with the size of economically active family (P<1%). The probability of using the practice increases by 9.6 percent as the number of economically active family members increases by 1 implying that more active members in a family may provide the labor that might be required by the practices. However, this variable has no significant effect on the use of non-structural land management measures as the practices are less labor intensive as compared to the structural measures.

Farmer's perception of climate-change (*perception****):*** Consistent with a *priori* expectation and past research findings (Deressa et al. 2011; Bekele and Holden 1998; Vieth et al. 2001), this variable is positively and strongly related with the use of structural land management measures (P<1%) showing that perceiving climate change as a risk induces adaptive response. The calculated marginal effect shows that the probability of the practice will increase by 32.7 percent for farmers who perceived climate change as a risk. Likewise, perception of climate change positively and strongly induces the use of non-structural measures (P<1%). The marginal effect indicates that the probability of using these techniques increases by 23.4% for those farmers who perceive climate change.

Cultivated land prone to land degradation (*pronefarmland):* This variable is significantly and positively associated with the use of non-structural land management practices (P<5%). The calculated marginal effect shows that as the cultivated land's exposure risk increases, the probability of adaptation through non-structural land management measures increases by 12.7%. However, the role of this variable in affecting the use of structural land management measures is statistically insignificant.

Farm experience (farmexperiance): This variable is positively associated with the use of non-structural land management practices at 5% significance level implying that farmers with long farming experience are well aware of the risk of climate change and opt to adapt to the challenges. The marginal effect shows that the probability of using non-structural land management practices increases by 0.7% for each additional year of farming experience. However, farm experience is not statistically significant in affecting the use of structural land management techniques.

Education level of the respondent (*educ****):*** Education is positively and significantly related with using structural land management techniques at 1 percent probability level. The calculated marginal effect shows that the probability of practicing the techniques increases by 21.3 percent as the level of education increases. This finding is in agreement with past research (Deressa et al.

2009; Tegene 1999; Pender 1996), which justified the role of education in inducing famers' decision to adopt agricultural technologies. Nevertheless, the role of education in affecting the use of non-structural land management practices is not statistically significant.

Agro-climatic zone (**agroecology**): Dwelling and farming in the wet lowland agro-climatic zone is positively and significantly associated with farmers' use of structural land management measure and the probability of using the practices will increase by 25.7 percent for farmers in the wet lowland. Likewise, the probability of using non-physical land management measures increases by 30 percent for farmers in the wet lowland. This finding is alike with the prior expectation and past research findings (Deressa 2011; Asrat et al. 2004) showing that farmers living in the wet lowland are more experienced, better exposed to adaptation measures and have better access to climate specific extension advises compared to farmers in the dry lowland.

4.3.3 Relative importance of significant explanatory variables

Four explanatory variables (number of parcels, land size, farm-home distance and economically active family), which are strongly decisive in determining farmers decision to practice structural land management techniques were found to be less important in affecting the decision to use non-structural land management practices. Besides, the strength of some of the significant explanatory variables varies between the two land management categories as can be depicted from the respective significance levels (Table 4.8).

For all the significant explanatory variables, the calculated marginal effects after probit are higher for structural land management techniques compared to the non-structural measures. Apart from these, two explanatory variables (farm experience and farm land prone to land degradation), which are not important in explaining the use of structural land management techniques are turned out to be significant in determining farmers use of non-structural land management techniques. The comparison of the marginal effects from the probit regression decrees that any intervention that promotes the use of climate-smart land management practices as adaptation strategy should take in to account the specific factors that are relevant to the nature of the practices.

Table 4.8 Comparison of marginal effects after probit for the two sets of land management practices

Explanatory variables	Adaptation 1(structural measures)		Adaptation2 (non-structural measures)	
	dy/dx	**P>z**	**dy/dx**	**P>z**
slope	0.235232***	0.000	.0941255***	0.003
Cropincome	0 .0001937***	0.000	.0000697***	0.000
Exposureadpt	0.2892063***	0.000	.1007365*	0.051
Exposurepercep	0 .2672321***	0.000	.0655957*	0.081
Pronefarmland	0.1018843	0.147	.1268056*	0.014
Noparcel	-0.1697717***	0.000	-.0240607	0.375
Cultivatedland	0.1608822****	0.000	.0237616	0.47
Farmdistance	-0.0822392***	0.002	.0154823	0.45
Activelabor	0.0961324***	0.004	.0006254	0.976
Perception	0.3268772***	0.000	.234494***	0.000
Farmexperiance	0.0068929	0.162	.0078245*	0.022
Agroecology	0.2573748***	0.000	.3014664***	0.000
Educ	0.2138982***	0.000	.027255	0.293

***, ** and * Indicate significance levels at $P < 0.01$ and $P < 0.05$, and $p<0.1$, respectively.

4.4 Conclusion and Recommendation

In this study, descriptive statistic is employed to compare the two agro-climatic zones and users and non-users of climate-smart land management practices as adaptive response to climate change. The study also employed binary probit regression model to analyze the determinants of climate-smart land management practices as adaptation strategy. The model result indicates that slope, exposure to adaptation, perceived level of land degradation, number of parcels, income from crop enterprise, size of cultivated land, farm-home distance, size of economically active family, perception of climate change, agro-ecology and education are important in determining farmers' decision to use the land management practices as adaptation strategy.

Four explanatory variables, which are strongly decisive in determining farmers' decision to use structural land management measures, were found to be less important in determining the decision to use non-structural practices. Moreover, two explanatory variables, which are not important in explaining farmer's decision to use the structural land management techniques, are turned out to be important in determining the decision to use the non-structural techniques.

The findings of this study verbalize that any intervention that promotes the use of climate-smart land management practices as adaptation strategy should take in to account specific factors that are relevant to the nature of the practices. The results also reveal that agro-climatic differences determine adaptation decision and hence location specific intervention is required to enhance smallholder farmers' adaptation to climate change. Besides, climate-smart land management practices are knowledge and resource intensive and may not be easily implemented given the limited awareness and resource constraints of the smallholder farmers. Therefore, scaling up of the practices as adaptation strategy should be backed by both public and non-public investments to raise awareness and to provide technological support. Failure to do so would adversely affect crop productivity and sustainability of land use systems in subsistence agriculture.

Chapter Five

5. Exploring Causality among Climate-Smart Agricultural Practices in the Dabus Sub-basin, Blue Nile River, Ethiopia

Abstract

‘No regret” actions are the best way for smallholder farmers to increase income while at the same time adapting to the risks of climate change. However, the use of these practices is not to the adequate level in Ethiopia in general and in the Dabus sub-basin in particular. This study used household and plot level data to assess the relationships among short-term climate-smart agricultural practices. It employed a two-stage probit (TSP) model to investigate causality between the uses of external agricultural inputs. On the other hand, a bivariate probit (BP) model was employed to determine the interrelationships between modified farming practices and the factors affecting the uses of these practices. The result from TSP model revealed a negative reciprocal causation between fertilizer and manure application justifying that these inputs are substitutes to one another in the context of the study area. Beyond the reciprocal relationship, the use these two inputs was affected by labor endowment of the farm household, plot characteristics, and farm distance in different magnitude and direction. The BP model estimates revealed that parcel size, extension services, farm-home distance, permanent crops, land size and agro-climatic zone significantly affected intercropping practices. Similarly, slope, physical soil conservation measures, training, extension service, education, and agro-climatic factors significantly affected conservation tillage practices. The results imply that there is a reciprocal causation between the uses of fertilizer and manure. Further, the short-term climate-smart agricultural practices have complementary relationships with long-term land management measures. The significance of parcel size across the climate-smart agricultural practices may call for a decision towards farm consolidation. There is also a need to give due attention to other variables that are significant across the four types of climate-smart agricultural practices to enhance the role of the practices as an adaptation strategy. Moreover, there is a need to find out a sensible blend of the climate-smart agricultural practices to realize their synergetic effect on agricultural productivity and climate change adaptation.

Keywords: No regret, adaptation, climate-smart, TSP, BP, reciprocal causation

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5.1 Introduction

Due to its significant reliance on weather patterns, as well as other environmental factors, agricultural production is vulnerable to climate variability and change (Khanal 2009; IPCC 2007d). While the need for agricultural expansion partly attributed to growing agricultural population, most part is attributed to the declining soil fertility and low technology adoption (FAO 2014). The decline in soil fertility, being aggravated by climate variability and change, usually induces smallholder farmers to abandon unproductive farmland and mine previously uncultivated soils. In the face of changing climate and variability, smallholder farmers' use of climate-smart agricultural practices can provide adaptation and mitigation co-benefits through reducing climate risks on agriculture and contributing to reduced GHG (greenhouse gas) emission efforts (mitigation). Increased productivity and income from climate-smart agricultural practices can ensure farmers sustainable investment in adaptation and mitigation technologies (Khanal 2009; IPCC 2007c).

In this regard, there is substantial need to promote smallholder farmers sustainable use of "no regrets" adaptation interventions that have positive returns on productivity, profitability, environment, biodiversity, and production risk reduction regardless of future climate change (Rizvi 2014). No regret actions include measures taken by communities and/or facilitated by policy makers/development actors which do not worsen vulnerabilities to climate change or which increase adaptive capacities and measures that will always have a positive impact on livelihoods and ecosystems regardless of how the climate changes. The no regret actions are also packages of climate-smart agricultural practices that increase productivity on a sustainable basis by improving soil composition, reducing soil loss, razing soil fertility and water holding capacity, and creating a balanced ecology of micro flora and fauna within the soil and the crop environment. The actions are the best way for smallholder farmers to increase agricultural income while at the same time adapting to the risks associated with climate change (FAO 2010b).

Promoting farmers' use of climate-smart agricultural practices induces increased income through enhanced productivity, reduced cost and higher gross margins and becomes the primary conduit for food security and reduced poverty (FAO 2010a). While adaptation/income generation may be the foremost reason for adopting the practices, a substantial socio-environmental mitigation co-benefits in terms of reducing GHG emissions could also be realized. Climate-smart agricultural practices take the best aspect of traditional agriculture such as crop rotation, conservation tillage, intercropping, recycling organic plant and manure supplemented by the precision use of inorganic fertilizer, safe use of farm chemicals and the introduction of small-scale irrigation systems that minimize water use (Boto 2012). Farmer's decision to use these practices in a given year is associated with the resource endowments at the beginning of the year, income and expected risk in the present and the future.

Based on the regional climate change adaptation plan of action (BGNRS 2013), the human induced process such as climate change and pressure on the available agricultural land is accelerating land degradation problems in the Dabus sub-basin (study area). The degradation problems on agricultural land are manifested in the form of soil loss and nutrient depletion and the effects are revealed in the form of reduced crop production potential, which ultimately jeopardizes the livelihood and adaptive capacity of the smallholder farmers. The farmers in the area have been adopting different forms of climate-smart agricultural practices in an effort to curtail the consequences of land degradation problems on agricultural productivity. In view of this, there are some noteworthy fertility maintenance techniques such as the use of manure, chemical fertilizers, inter-cropping, conservation tillage, crop rotation, crop residue incorporation, fallowing, grass strip, tree planting and agroforestry practices (BARD 2016; BoLA 2016; BGNRS 2013).

However, climate-smart agricultural practices are not in the general use to the adequate level in the area due to various factors. For instance, most of the framers do not leave crop residue on the farm since the alternative uses of this residue for livestock feed, sales, fuel, and construction purposes overshadow their soil fertility maintaining function in most part of the study area. The shortfall in the use of these practices is also associated to lack of awareness, lack of climatic specific extension advice and the general in effectiveness of the existing system (BoARD 2016; BGNRS 2013).

Studies on land management related issues have sought to identify determinants and extents of land degradation and factors affecting adoption of physical soil conservation measures (Pender and Kerr 2008; Pender and Gebremedhin 2008; Asrat et al. 2004; Bekele and Holden 1998). Yet, empirical literature that systematically addressed causality between the land management decisions are critically lacking and hence solid empirical analysis in this regard is very scarce. Previous studies have also limitations in terms of the composition and the range of the land management practices they addressed and overlooked the possible complementarity and competition among the land management decisions. Particularly, past studies did not consider how the use of one strategy may hinder or foster the use of the other strategy. This study, therefore, responded to the paucity of empirical information regarding the indicated gaps of knowledge using household and plot level data given the smallholder farmers' labor and capital endowments and considering environmental and institutional factors prevailing in the study area.

Thus, this study explored the complementarity and competition between different climate-smart agricultural practices and how the use of a specific type of climate-smart agricultural practices hiders or fosters the use of the other (reciprocal causation) given a set of factors affecting both at a time considering four types of practices which are relatively in wider use in the study area: namely inorganic fertilizer, manure, intercropping and conservation tillage.

5.2 Methodology

5.2.1 Data types and source

The study is based on a cross-sectional household survey data of 734 farm households enumerated during November and December 2016 substantiated with FGD, field observations, and secondary data. The collected data were generally at three levels: community-level, household-level, and plot-level. Community-level data were collected through FGD supplemented with data from secondary sources. The community-level variables included information about institutions in the area, market access, and land management/land conservation activities. The sources for household level and plot level data were household survey administered using a structured and semi-structured questionnaire. Observations were also made to cross check the data collected through questionnaire. The household-level data included variables like income, extension, credit access, training, size of holding, livestock holding, number of parcels, crop types grown, proportion of perennial crops, family size, dependency ratio, age, sex, education of the household head, involvement in off farm activities and other relevant variables. The plot-level variables included plot level production data, input utilization data, land management and conservation activities at plot level, physical characteristics of farm plots that include slope, fertility status, and other relevant variables.

5.2.2 Data analysis

The short-term climate-smart agricultural strategies considered are manure application, use of chemical fertilizer, intercropping and conservation tillage (minimum and/or contour tillage). The set-up of the analytical framework for these practices is categorized into two major parts: manure application and the use of inorganic fertilizer (external inputs) under one group; while the practices of intercropping and conservation tillage (modification of farm practices) in the other group. Since the smallholder farmers' decision to use the practices is related to the characteristics of the specific plots, the analysis is made at plot level instead of household level.

5.2.2.1 A two-stage probit (TSP) model application for the use of external inputs

The main purpose here is to assess how the uses of external inputs (chemical fertilizer and manure) affect one another and how they are affected by other variables. Use of manure on a given plot is measured as a dummy variable of using and not using. This measurement is used because collecting data on the amount of manure applied on a given plot using a single-shot survey may result in unreliable information. In the case of fertilizer also, discrete measurement (using or not using) is used since most of the respondents are non-users and the use levels were very small for users. Therefore, the nature of the data calls for the application of the choice models derived from random utility theory.

Let's define a given climate-smart land management strategy by Y and factors assumed to affect the decision to use this strategy by X, then the underlying utility function U which ranks the preference of the ith farmer is assumed to be a function of X. Thus, the utility function for using a given strategy (Ui1) and for not using it (Ui0) can be specified as:

$$\{U_{i1}(X) = \beta_1 X_i + \varepsilon_{i1} \quad (5.1)$$
$$\{U_{i0}(X) = \beta_0 X_i + \varepsilon_{io} \quad (5.2)$$

Following the random utility assumption, the i^{th} farmer will use a given climate-smart land management strategy if the utility derived from using it is greater than the utility without it ($U_{i1}>U_{i0}$). This means the probability of the i^{th} farmer to use a given strategy is:

$P(1) = P(U_{i1} > U_{i0})$ ....(5.3)

Then, substituting in the above equations (5.1 & 5.2) gives:

$P(1) = P(\beta_1 X_i + \varepsilon_{i1} > \beta_0 X_i + \varepsilon_{io})$ ....(5.4)

After rearranging, we have

$P(1) = P(\varepsilon_{i0} - \varepsilon_{i1} < \beta_1 X_i - \beta_0 X_i)$ ....(5.5)

Let $\varepsilon_{i0} - \varepsilon_{i1} = \varepsilon_i$ and $\beta_1 X_i - \beta_0 X_i = \beta X_i$, then

$P(1) = P(\varepsilon_i < \beta X_i)$ ....(5.6)

$P(1) = \phi(\beta X_i)$ ....(5.7)

Where ϕ is the cumulative distribution function for ε_i. The functional form for ϕ depends on the assumption made about ε_i. Based on Meddala (1983), if it is assumed to follow a logistic distribution function logit model is appropriate; and if it is assumed to follow a normal distribution function probit model is appropriate. For the purpose of this study, ε_i is assumed to be normally distributed and hence ϕ takes a probit functional form. If we denote one climate-smart practice (fertilizer application) by Y_1 and the other (manure application) by $Y_{2,}$ the probability of using the two inputs, respectively, is given by:

$$\phi_{y_1}(\beta X) = \int_{-\infty}^{\beta X} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right) dz \qquad (5.8)$$

$$\phi_{y_2}(\beta X) = \int_{-\infty}^{\beta X} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right) dz \qquad (5.9)$$

Where: Z is the standard normal variable, i.e. $Z \sim N(0, \delta^2)$

In order to select the appropriate type of probit model that takes into account the interrelationship between fertilizer use and manure application, it is necessary to start with basic assumptions based on past empirical studies (dependence of the decision to use one input on the decision of using the other and vise versa). This means that there is a reciprocal causation between the use of the two inputs and are also affected by other factors (such as farm characteristics, household characteristics, institutional factors, etc.). The direction of the relationship between the two inputs shows whether there is substitutability or complementarity.

The two-stage probit (TSP) model that is used in (Heckman, 1978; Lyons and Yilmazer 2005; Mengistu 2010) for technology adoption decision is customized and used to determine the reciprocal causation and interdependence between climate-smart agricultural practices in the present study. Where there is a reciprocal relationship of such type, TSP is applied, for it can control for the dual endogeneity between the two factors. Let X_1 and X_2 respectively (suppressed for the sake of simplification) be the vectors of exogenous explanatory variables that are expected to affect the decision to use two external inputs Y_1 and Y_2, then

$$Y_1^* = \gamma_1 Y_2^* + \beta_1 X_1 + \varepsilon_1 \quad \text{.......(5.10)}$$

Where $Y_1=1$ if $Y_1^* > 0$ and $Y_1=0$ if $Y_1^* \leq 0$

$$Y_2^* = \gamma_2 Y_2^* + \beta_2 X_2 + \varepsilon_2 \quad \text{.......(5.11)}$$

Where $Y_2=1$ if $Y_2^* > 0$ and $Y_2=0$ if $Y_2^* \leq 0$

Y_1^* and Y_2^* are latent variables which are not observable and Y_1 and Y_2 are there observable counterparts as defined above. Y_1 is 1 if the input under consideration is applied (fertilizer) by a farmer and zero otherwise. Similarly, Y_2 is 1 if the other input (manure) is applied by a farmer and zero otherwise. The factors that determine the use of the first input (fertilizer) Y_1^* include the endogenous regressor Y_2^* and vector of exogenous variables, X_1. The factors that determine the use of the second input (manure) Y_2^* on the other hand include the endogenous regressor Y_1^* and vector of exogenous variables X_2.

Following Lyons and Yilmazer (2005) and Mengistu (2010), it is necessary to include certain variables to the first input equation (fertilizer) and exclude from the second input (manure) equation and vice versa so as to ensure that each coefficient in the system of equation is identified. To be included in X_1 but not in X_2 (example market distance and off-farm income directly affect the use of fertilizer but not directly affect manure application). On the other hand variables like adult equivalent, female to male ratio, etc. may affect the application of manure directly but less relevant in the case of fertilizer hence will be included in X_2 and not in X_1. To estimate the above equations (5.10 and 5.11), a two-stage approach is used to account for the endogenous regressors Y_1^* and Y_2^*. The error terms ε_1 and ε_2 are assumed to be distributed normally (standard) with zero mean and variances δ_1^2 and δ_2^2 both equal to one. In the first stage, a binary probit model is used to estimate the following reduced form equations.

$$Y_1^* = \alpha_1 X + u_{.1} \qquad (5.12)$$

$$Y_2^* = \alpha_2 X + u_2 \qquad (5.13)$$

Therefore, X includes all of the exogenous variables in the previous equation. The first stage regression is used to estimate the likely correlation between the endogenous explanatory variables and the stochastic disturbance terms in each equation. The reduced form estimates from the above equations are used to obtain predicted values $\hat{Y}_1^*$ and $\hat{Y}_2^*$. Then the predicted values are substituted into the right-hand side of the equation (previous above) such that:

$$Y_1^* = \gamma_1 \hat{Y}_1^* + \beta_1 X_1 + \varepsilon_{1.} \qquad (5.14)$$

$$Y_2^* = \gamma_2 \hat{Y}_2^* + \beta_2 X_2 + \varepsilon_2 \qquad (5.15)$$

In the second and final stage, the probit method is again applied to estimate the above equations, which results in final parameter estimates from two-stage probit models.

5.2.2.2 A bivariate probit (BP) model application for modification of agricultural practices

Intercropping and conservation tillage (plowing along the contour/minimum tillage) are modification of the existing cropping and tillage practices in the study area. These are considered as modification because the existing agricultural practices in the study area are dominated by sole cropping and conservation tillage practices have been less common. Therefore, the purpose here is to assess the factors that determine smallholder farmers' decision to implement the modified farming activities. The assumption is that the decisions to practice the intercropping and conservation tillage practices are functions of the same regressors (X) but are not directly affect one another. Since farmers decide based on the same farm resources at their disposal, implementing these practices cannot be totally independent. Letting Y_1 and Y_2 be observed values of conservation tillage and intercropping practices, respectively (taking a value of 1 for using and 0 for not using), and Y_1^* Y_2^* be the respective latent variables which are not observable, then the binary probit for the two choice models can be specified as:

$$Y_1^* = \beta_1 X + U_1 \qquad (5.16)$$

Where Y_1=1 if $Y_1^* > 0$ and Y_1=0 if $Y_1^* \leq 0$

$$Y_2^* = \beta_1 X + U_2 \qquad (5.17)$$

Where: Y_2=1 if $Y_2^* > 0$ and Y_2=0 if $Y_2^* \leq 0$

Statistically, the above two equations can be consistently estimated by a single-equation probit or logit models. However, based on Green (2003) and Maddala (1992), use of single-equation probit is inefficient because of the possibility of the correlation between the two disturbance terms u_1 and u_2. This problem follows a seemingly unrelated regressors (SUR) model with identical regressors. It is seemingly unrelated because the regressors do not include endogenous variables and but the errors terms may be related. In this situation where the disturbance terms of the two models are correlated, the bivariate probit model is employed to evade the inadequacies of the single probit or logit models. The bivariate probit model is based on the joint distribution of the two normally distributed variables.

Hence, the decision to practice the climate-smart agricultural practices (intercropping and conservation tillage) is analysed customizing the bivariate probit model that had been commonly applied to study technology adoption decision in (Mengistu 2010; Amsalu and De Graaff 2007; Christofides et al. 1997; Nkamleu and Adesina 2000). Under bivariate probit model, it is necessary to make a test of the interdependence (a test whether the two disturbance terms are correlated or not) of the error terms of the two equations using likelihood ratio test of the covariance of the error terms (ρ). This test result justifies whether the two models can be treated as a system of equations or as a single equation model.

In running the bivariate probit model, it is indispensable to calculate marginal effects, which are the sum of the direct and indirect effects (through the residuals of the two models) of the independent variables on the dependent. The total marginal effects show the effect of a given change in the independent variable on the dependent variable keeping all other continuous variables at their mean levels and categorical variables at their mode values (Davidson and Mackinnon 2004).

5.3. Results and Discussion

Use of manure has been the most widely practiced soil nutrient replenishment technique in the study area. The use of this technique is labor intensive as it engages the collection of farmyard manure, green manure, compost and transporting and applying it to the farm. On the other hand, the use of chemical fertilizer is a recent practice in the study area and its application rate is by far less than the recommended level. This is associated with lack of awareness, high cost, and less availability. However, for the purpose of this study, the effect of price on fertilizer application is not assessed, for the study is based on cross-sectional data and hence fertilizer prices are assumed to be the same across all the respondents.

Similarly, agronomic practices such as tillage and intercropping are also exercised by the smallholder farmers in order to curb soil degradation problems. Intercropping of sorghum and maize with legumes like haricot beans is a common practice. Practices like plowing along the contour and minimizing the number of tillage are conservation tillage practices commonly used by farmers in the study area. However, there are also farmers who did not use some or all of these techniques either because of lack of awareness about the land degradation problem and its damaging consequences or because they are trapped in various constraints impeding the use of the available techniques.

5.3.1 Determinants of the external input application

In order to assess the interrelationship between the uses of the two external inputs (manure and fertilizer), the TSP estimation is applied since it can correct for simultaneity problem. The models in each stage consist of an equation for the probability of using chemical fertilizer and another one for the probability of using manure. In the two stages estimations, the first stage equations are for manure use and fertilizer use by including all of the exogenous variables. Then, predicted probabilities in the first stage are used as independent variables in the second stage. Table 5.1 depicts parameter estimates of the TSP model for determinants of manure and fertilizer applications that results from the second stage estimation.

As presented in Table 5.1, the estimated coefficient for predicted manure application in fertilizer application model (-0.188) and for predicted fertilizer use in manure application model (-0.191) are both negative and significant indicating a negative reciprocal causation in the use of the two external inputs. The negative coefficients imply that the two inputs are substitutes to one another, and hence more use of one input renders less of the other and vice versa. Farmers who can afford to buy fertilizers may not opt for labor-intensive manure and conversely, farmers who are endowed with sufficient labor to apply manure may not opt for using expensive fertilizers. This finding is contrary to Waithaka et al. (2007) who indicate a positive relationship but in line with Mengistu (2010) who reveals a negative reciprocal relationship between the two inputs.

Table 5.1 Two-stage probit model estimates for manure and fertilizer application

Variables	Manure application		Fertilizer application	
	Coefficient	Robust S.E	Coefficient	Robust S.E
Predicted probability (fertilizer)	-0.188**	0.073		
Predicted probability (manure)			-0.191**	0.073
Age (years)	0.153*	0.120	0.012	0.101
Sex (dummy)	0.110	0.211	-0.212	0.132
Adult equivalent ratio	0.321*	0.144	0.001	0.110
Proportion of female	0.397*	0.168	-0.001	0.042
Educational attainment (cf. no formal education)				
Primary	0.022	0.233	0.013	0.440
Secondary	0.111	0.211	0.123	0.022
Size of land holding (ha)	-0.651***	0.143	-0.153	0.221
Parcel size(ha)	1.910***	0.531	1.740***	0.631
Land fragmentation (simpson index)	-0.066	0.324	0.033	0.327
Farm distance (km)	-0.134*	0.121	0.011	0.022
Fertility level (control factor: poor)				
Good	-0.102	0.124	-0.022	0.152
Medium	-0.673***	0.169	-0.027	0.184
Slope (cf. flat)				
Gentle	-0.313**	0.127	-0.065	0.141
Steep	-0.328*	0.198	-0.101	0.112
Very steep	-0.312	0.333	-0.063	0.144
Physical soil conservation (dummy)	0.588**	0.153	-0.101	0.184
Proportion of fruits	-0.222	0.121	0.632***	0.371
Livestock holding (TLU)	0.021	0.101	0.142**	0.054
Off-farm/non-farm activities (dummy)	-0.021	0.142	0.031	0.053
Extension (dummy)	0.001	0.214	0.322*	0.227
Credit (dummy)	0.003	0.132	0.288*	0.186
Membership to local institution (dummy)	0.111	0.161	0.232**	0.132
Market distance (km)	-	-	-0.044	0.133
Wet lowland agro-climatic zone (dummy)	0.814***	0.291	1.021***	0.221
Dry lowland agro-climatic zone (dummy)	-0.135	0.227	-1.310***	0.218
Constant	-0.106	0.786	-0.413	0.323
Log likelihood (Wald Chi2)	-278.466 (95.87***)		-204.244 (116.26***)	

***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

Beyond the reciprocal relationship, application of these two external inputs is affected by other factors such as labor endowments, plot characteristics, and farm distance. The TSP model result reveals that the likelihood of applying fertilizer and manure increases with an increase in parcel size. This finding is in agreement with Clay et al. (1998) and Mengistu (2010) that reported a positive effect of parcel size on the decision to use the two external inputs. The result from the

TSP model also reveals a negative effect of the steepness of a slope and fertility level of a parcel on the likelihood of using manure. This is in line with Clay et al. (1998) and implies that farmers tend to use manure on flat plots in a fear of runoff problem and on less fertile plots as compared to plots with relatively good fertility status.

The TSP model result also shows that manure application decreases with an increase in dwelling-farm distance due to the labor intensiveness of transporting manure from homestead to farm plots. As also reported in Nkonya et al. (2005), this can also be associated with the fact that distant farms are relatively fertile as they are less intensively utilized as compared to nearby farms. For the same reason of high labor demand, manure use is negatively associated with farm size.

Based on the results of the TSP model, the proportion of female members in a household has a positive and significant effect on the likelihood of manure use. This is probably related to the fact that male members of the household are more engaged in other agricultural activities and manure application is assigned to female household members in the study area. Moreover, manure use is proved to increases with labor endowment of the farm household expressed in terms of adult equivalent.

The likelihood of using manure increases in farm plots where physical soil conservation measures are already installed. This may imply that a prior investment in long-term land management practices induces current decision on the use of short-term climate-smart agricultural practices conveying the message that there is complementarity between long-term and short-term land management techniques. Age, which is a proxy variable for farm experience, is positively associated with the use of manure implying that farm experience enhances soil fertility maintenance decisions as also implied by Asrta et al. (2004).

Unlike prior expectation and contrary to the findings of Somda et al. (2002) and Sserunkuuma (2005), livestock ownership does not affect the likelihood of using manure. This probably indicates that manure availability is not considerably different among the farm households and hence availability is not a crucial factor in determining its application in the study area.

Some variables which are proved less important in affecting the likelihood of manure application are found to strongly influence farmers' decision to use chemical fertilizer. These variables are related to the financial capacity of smallholder farmers, technical know-how and prior exposure to the technology. In contrast to manure use, farmers who own more livestock are more likely to use fertilizer as livestock holding can relax the financial constraint that hider fertilizer application. These findings are in line with Marenya and Barett (2007), and Pender and Gebremedhin (2008). Consistent with the finding of Pender and Gebremedhin (2008) access to credit positively and significantly influenced the use of chemical fertilizer through smoothing cash requirement for the purchase of the input on cash basis. As expected, access to agricultural extension increases the likelihood that a farmer uses chemical fertilizer.

The result from TSP model also shows that farmers in the wet lowland agro-climatic zone are more likely to use both manure and chemical fertilizers as compared to those in the dry lowland. The justification for this finding is that farmers in the wet lowland have a relatively more years of experience in crop farming and have also better access to agricultural extension services, market, and input supply, which are instrumental in determining the investment decision on productivity-enhancing technologies. In this study, education is not significant in affecting the decision of farmers to use both external inputs. This is probably attributed to low level of educational attainment and low variability of educational status among the smallholder farmers in the in the study area.

5.3.2 Factors affecting modification of conventional tillage and cropping practices

Intercropping and conservation tillage (plowing along the contour and conservation tillage) are the two key climate-smart agricultural practices that are modifications to conventional practices (sole cropping and intensive tillage) in the study area. Intercropping is a multiple cropping system involving simultaneous cultivation of two or more crops in space and time on the same land. The practice involves the use of land and labor more efficiently (Mengistu 2010) and hence thought to offer higher benefit to smallholder farmers’ productivity coupled with enhancing the soil fertility status and lowering climate related production risks as compared to sole cropping. In the study area, the practice is particularly characterized by typical cereal-legume intercropping (one annual crop intercropped with another annual crop). Maize and sorghum are dominant cereals whereas haricot bean, potato, groundnut, and sweet potato are the associated crops in the intercropping system.

Conventional intensive tillage practices have been the most important factors contributing to soil erosion problem, particularly when soil losses are in excess of the natural replacement rates. This has led to the development of alternative tillage practices generally referred to as conservation tillage (Fowler and Rockstorm 2001). Therefore, conservation tillage is a modification of the existing agricultural practice aiming at reducing the adverse effect of soil loss due to climate factors. This practice aims to conserve land resources with the minimal use of external inputs, sometimes synonymously used with conservational farming and conservation agriculture (SSSA 2008; Fowler and Rockstorm 2001) aimed at minimizing soil and water loss. In line with this, minimum tillage (minimum plowing frequency) and contour plowing (plowing perpendicular to the slope) are emerging practices in the study area, with a critical component of minimizing soil disturbance. Minimum tillage generally uses minimum disturbance to prepare the seedbed for planting leaving some crop residue on the farm. Contour plowing, on the other hand, dissuade soil and water loss down the slope.

Table 5.2 portrays the results from maximum likelihood bivariate probit model with marginal effects explaining the probabilities of farmers' decision to use intercropping and conservation tillage practices. The likelihood ratio test of the covariance of the error terms (ρ= -0.411; $P<0.000$) that maximized the bivariate probit likelihood is used to make a test of the interdependence of the error terms of the equations in the bivariate system of equations. The significance of rho (ρ) suggests that the random disturbances in the two decisions (intercropping and conservation tillage) are affected by random shocks (in opposite direction) and that the two decisions are statistically independent. This indicates that the error terms of the two equations are interdependent and hence treating the two equations as bivariate probit model, rather than two univariate probits, is more appropriate (Hausman 1978). The bivariate probit model fits the data well ($\chi2$=1434.13; $P<0.000$), implying that the explanatory variables altogether influence both intercropping and conservation tillage decisions.

Table 5.2 Parameter estimates of a bivariate probit model for intercropping and conservation tillage

Variables	Intercropping			Conservation tillage		
	Coefficient	Robust S.E	Marginal probabilities	Coefficient	Robust S.E	Marginal probabilities
Age (years)	0.003	0.020	0.004	-0.014	0.001	-0.003
Sex (dummy)	-0.210	0.200	-0.003	-0.201	0.032	-0.021
Adult equivalent	0.201	0.105	0.011	0.001	0.010	0.001
Dependency ratio	0.287*	0.108	0.110	-0.001	0.032	-0.034
Education (cf. no formal education)						
Primary	0.122	0.123	0.012	0.513***	0.210	0.241
Secondary	0.121	0.011	0.022	0.924***	0.322	0.276
Extension (dummy)	0.444**	0.242	0.130	0.442*	0.242	0.141
Training (dummy)	0.045	0.153	0.033	0.620***	0.167	0.210
Size of land holding (ha)	-0.501***	0.144	-0.170	-0.113	0.201	-0.033
Parcel size(ha)	2.911***	0.511	0.634	0.540	0.331	0.043
Land fragmentation (simpson index)	-0.222	0.024	-0.112	0.063	0.325	0.022
Farm distance (km)	0.504*	0.101	0.101	-0.021	0.002	-0.011
Fertility level (cf. poor)						
Good	0.412**	0.224	0.151	0.032	0.352	0.002
Medium	0.601***	0.168	0.191	-0.023	0.111	-0.033
Slope (cf. flat)						
Gentle	0.213	0.157	0.044	0.765***	0.141	0.121
Steep	0.321	0.198	0.021	0.401**	0.212	0.142
Very steep	0.112	0.123	0.001	0.563**	0.344	0.165
Physical soil conservation (dummy)	-0.101	0.103	-0.021	0.401**	0.224	0.141
Proportion of fruits/trees	-0.622**	0.221	-0.194	-0.134	0.071	-0.033
Livestock holding (TLU)	0.121	0.103	-0.001	0.102	0.066	-0.032
Market distance (km)	-0.110	0.022	-0.004	-0.014	0.123	-0.021
Wet lowland agro-climatic zone (dummy)	1.204***	0.221	0.243	1.070***	0.233	0.212
Dry lowland agro-climatic zone (dummy)	0.144	0.044	0.023	0.121	0.011	0.071
Constant	-1.106**	0.826		2.213**	0.553	
Rho (p)						-0.411***
Log likelihood function						-822.044
Wald x2 (significance)						1434.13 (P<0.000)
Number of observations						1101

***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

5.3.2.1 Determinants of intercropping

The bivariate probit model estimates revealed that parcel size has positively and significantly affected farmers' decision to use intercropping. The calculated marginal effect indicated that for a unit (1ha) increase in parcel size, the probability of intercropping practice increases by 63.4 percent, holding all other variables constant at their reference points (mean level for continuous variables and modal level for dummies). This high marginal effect implies that as farm plots are more fragmented the probability of intercropping practice decreases. The model estimate also shows the probability of intercropping is higher on fertile plots compared to less fertile ones, implying that intercropping is aimed at maintaining the available fertility than adding fertility to less fertile plots. This finding is also verified by results from the FGD discussions, which indicated that less fertile plots cannot provide adequate nutrients that can support two or more crops and hence crop intensification may not be paying on such plots.

Based on the model result, access to extension services increases the probability to practice intercropping by 13 percent implying that information provided through the extension system helps in enhancing implementation of the intercropping practices. The probability to practice intercropping also increases as farm-home distance increases since farmers opt for less labor intensive alternatives on the distant farm plots. As the proportion of fruits/trees in a given farm plot increases the likelihood of practicing intercropping decreases by 19.4 percent implying that soil fertility maintenance role of intercropping can be substituted by agroforestry practices. Moreover, the canopy of the fruit/tree may not allow two or more annual crops to be efficiently intercropped. In addition, fruits are important cash sources for considerable number of farm households in the study area and hence proceeds from the fruits may enable farmers to afford other cash demanding types of soil fertility maintenance techniques such as organic fertilizer.

Size of land holding is negatively related to intercropping practices depicting that farmers are more curious on soil fertility problem when they are constrained by land shortage as large holding may relax such a constraint imposed on productivity. In terms of agro-climatic zone, farmers in the wet lowland are more likely to practice intercropping. The calculated marginal effect revealed that dwelling and farming in the wet lowland agro-climatic zone increase the probability of intercropping practice by 24.3 percent. This can be justified by the fact that farmers in the wet lowland are more experienced in farming, have better access to agricultural extension service, and more dependent on crop enterprise than other sources of livelihood such as livestock rearing and off-farm/non-farm economic engagements. On the other hand being in the dry lowland has no statistically significant effect on intercropping practice.

5.3.2.2 Determinants of conservation tillage

The results of the bivariate probit model indicated the slope of a plot is positively related to conservation tillage practices possibly because soil degradation problems are more prevalent on steep slope plots as compared to the levelled fields. Furthermore, plowing techniques are more suitable soil fertility maintenance techniques on steeper slopes than other measures like fertilizer and manure because the latter is more likely to be washed away when applied on steeper farm plots. Prior implementation of physical soil conservation techniques (long-term) affects conservation tillage positively and significantly. The physical soil conservation measures that are already implemented on a plot increase the probability of applying the conservation tillage by 22.4 percent justifying the complementarity between short term and long term land management strategies.

The bivariate probit model result also shows that the likelihood of implementing conservation tillage increases with involvement in training, access to extension service and educational attainment of the household head as also implied in the findings of Mengistu (2010) and Jansen et al. (2006). This finding justifies the need for technical know-how in implementing climate-smart agricultural practices. The agro-climatic variable shows that the probability of implementing conservation tillage increases by 21.2 percent for the farmers dwelling and farming in the wet lowland. This is attributed to the fact that farmers in this agro-climatic zone have longer years of farming experience and have well understood the consequences of soil disturbance on soil nutrient loss through climate change intensified land degradation problems. Therefore, it is more likely that they opt for minimum tillage practices to reduce the risks. This decision of farmers in the wet lowland may also be related to their better exposure to the extension services and training opportunities that help them recognize the advantage of the conservation measure.

5.4. Summary and Policy Recommendation

This chapter explored the farmers' decisions to use short-term climate-smart agricultural practices, their interdependence, and factors affecting the decision to implement the practices. The findings generally show that there are opportunities to apply the practices although the use level is not to the adequate level in the study area owing to various impeding factors. Two models are employed to determine factors affecting farmers' decision to use the two categories of the short-term climate-smart agricultural practices that involve the application of external inputs (fertilizer and manure) and modification of existing crop cultivation practices (intercropping and conservation tillage).

The result from the TSP model revealed that manure use and fertilizer application have a negative reciprocal influence on one another demonstrating the substitutability of these two practices. The probability to apply manure is positively and significantly associated with parcel size, availability of physical soil conservation structures on a plot, age of the household head, adult equivalent ratio, and the proportion of female members of the household. Besides, slope of a parcel, fertility status of the soil, farm-home distance, and land size affect the likelihood of manure application negatively. The model result also demonstrated that parcel size, livestock holding size, the proportion of fruits/trees on a plot, access to extension service and access to credit affected fertilizer use positively and significantly.

The decisions to practice intercropping and conservation tillage are not independent, for both are affected by the same regressors in the same or in a different direction. Intercropping is positively and significantly affected by parcel size, fertility level of the soil, farm distance, and access to extension service. Based on the results, being in the wet lowland agro-climatic zone increases the probability of intercropping practice. Variables like land size and proportion of land allocated to fruits affected intercropping practice in a negative direction. On the other hand, the probability to practice conservation tillage is positively and significantly affected by slope, prior implementation of physical soil conservation measures, extension contact, training, and educational attainment. Dwelling/farming in the wet lowland is also positively associated with conservation tillage practice.

Therefore, given the magnitude and direction of effect of these variables, careful decisions are required to enhance adoption and use levels of the climate-smart agricultural practices to maintain fertility status of the soil in the face of changing climate. The most important implication of the findings is that the practices have supplementary and complementary relationships with long-term land management investments that are aimed at reducing the risks from land degradation problems. Moreover, parcel size is found to be very important variable across manure application, fertilizer use and intercropping, which may call for a decision towards farm consolidation. There is also a need to give due attention to the significant variables across the four types of the climate-smart agricultural practices so as to enhance the role of the practices as an adaptation strategy to climate change intensified land degradation problems. In line with this, there is a need to find out a sensible blend of external inputs (fertilizer and manure) with the modification agricultural practices (intercropping and conservation tillage).

Chapter Six

6. Climate-Smart Agricultural Practices, Crop Yield Variability and Productivity: Exploring the Link in Dabus sub-basin, Blue Nile River

Abstract

Climate-smart agricultural practice can increase productivity through offsetting crop yield variability at farm level. However, the use of these practices remains low in Ethiopia in general and in the Dabus sub-basin in particular. This study was designed to quantify the effect of climate-smart agricultural practices on crop yield variability and productivity using household and plot level data. The study employed the mean variance method to assess the effect of climate-smart agricultural practices on crop yield variability. Moreover, the Instrumental Variable (IV) estimation method was employed to assess the relationship between climate smart agricultural practices and crop productivity. The result revealed that climate-smart agricultural practices helped smallholder farmers in counteracting crop yield variability as implied by the calculated negative variances. Most of the practices are also positively and significantly correlated to crop productivity. The implication is that climate related risks that lead to yield variability are significantly reduced through the use of the climate smart agricultural practices. Based on the IV estimation result, climate-smart agricultural practices that include manure application, intercropping, conservation tillage, physical soil conservation measures and crop diversification are positively and significantly related to crop productivity. Moreover, household and plot characteristics such as labor input, parcel size, soil fertility level, livestock holding, crop diversification, and access to credit are indirectly related to crop productivity through the climate-smart agricultural practices with a positive and significant effect. Conversely, slope, land fragmentation, and off-farm activities negatively and significantly affect crop productivity indirectly through the climate-smart agricultural practices. Based on the results, there is a need to introduce and scale up alternative set of climate-smart agricultural practices that suit to a local context. There is also a need for policy attention towards land consolidation so that smallholder farmers could benefit from the advantages of economies of scale in the use of different climate-smart agricultural practices. Parallel to the promotion and scaling up of the practices, future research should gear towards investigating the synergetic effect and possible complementarities among the climate-smart agricultural practices.

Keywords: climate-smart, mean variance, variability, productivity, instrumental variable

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6.1 Introduction

Agricultural is expected to supply food for the global population that will amount to 9.1 billion in 2050 and over 10 billion by the end of the century (UNFPA 2011). To secure and maintain food security for such a population, agricultural systems need to be transformed in terms of productive capacity and stability. However, there is a question of which technologies and practices are most appropriate to reach this objective. In the past, agricultural intensification through increased use of the capital intensive inputs such as fertilizer and pesticide has been dominant but remained to be inadequate and economically in feasible (Tillman et al. 2002) along with the generation of unacceptable levels of environmental damage. Thus, greater attention is being given to alternative means of agricultural intensification, particularly the adoption of climate smart agricultural practices (FAO 2010a; IAASTD 2009).

The key benefits of climate smart agricultural technologies include increasing food production without further depleting soil and water resources (FAO 2010a), restoring soil fertility, increasing the resilience of the farming systems to climatic risk, and improving the soil's capacity to sequester carbon and mitigate climate change (FAO 2010b). The practices can generate both private and public benefits and thus constitute a potentially important means of generating "win-win" solutions to addressing poverty, food insecurity, and environmental problems. The widespread use of these practices can generate significant public environmental goods such as improved watershed functioning, biodiversity conservation, and climate change mitigation while ensuring private benefits in the form of increased productivity and stability of production through reduced production risk (Cooper and Coe 2011; Conant 2009; Woodfine 2008).

Empirical evidence has shown that climate-smart agricultural practices can reduce crop production risk (Cooper and Coe 2011) through offsetting the negative effects of climate change at a plot/ farm or landscape level. These practices help to enhance moisture holding capacity and improve biological activity, increase the length of the growing period thereby reducing climate-change induced yield variability. Moreover, practices like adjusting plating time, fertilizer application, manure application, intercropping, conservation tillage, and crop rotation can reduce yield variability and increases crop productivity through adjustments to the new climatic patterns (Lobell et al. 2011b; Nkonya et al. 2011).

Hine and Pretty (2008) showed that combined use of climate friendly agricultural practices in the western regions of Kenya increased maize and bean yields by 71% and 158%, respectively. The International Centre for Tropical Agriculture (CIAT) showed that the average yield of maize and sorghum increased by 198% due to the introduction of organic fertilization and composting in Brazil, Guatemala and Honduras (CIAT 2008). A study by WOCAT (2011) showed the role of agroforestry (woody perennials integrated with agricultural crops) practices in improving land productivity through providing a favorable micro-climate, permanent cover, improved soil structure and organic carbon content, increased infiltration, enhanced fertility and reducing the need for mineral fertilizers.

Other studies (Tittonell et al. 2008; Vanlauwe and Giller 2006) have shown synergistic relationships among different climate-smart agricultural practices. Holding all else constant, a farmer that uses more than one climate-smart agricultural practice is likely to have less crop production risk and better productivity than a farmers using only one practice. The same studies also showed that plots receiving crop residues, fertilizer, and manure registered higher yield compared to plots receiving only recommended inorganic fertilizer doses.

Despite the public-private co-benefits, the use of climate-smart agricultural practices has been relatively low at global level (FAO 2010a). Given the limited prospect for extensification (increasing cultivated area) and the ever increasing climate challenges on agriculture, the potential to increase agricultural output is supposed to be achieved through increased productivity. This improvement in productivity, therefore, calls for a policy attention and it should be a vital goal of rural development policies (FAO 2010a).

In this regard, there is a considerable interest in understanding the barriers in the wider adoption of the climate smart agricultural practices and how they influence agricultural production risk and productivity. In Ethiopia, studies that focus on the analysis of factors that influence farmers use of the climate-smart agricultural practices is very scant. There are also no studies that address the likelihood impact of the practices on crop yield variability and productivity. The purpose of the present study is, therefore, to determine how these practices affect private benefits such as reduced crop yield variability and augmented productivity. The study assessed the effect of selected climate-smart agricultural practices on the crop yield variability and productivity of crops considering a set of practices as indicated in FAO (2010a) and IPCC 2007c): (i) agronomic practices, (ii) soil and water conservation practices (ii) tillage practices and (iii) agroforestry. For this purpose, the study employed the mean-variance method of Just and Pope (1979) to assess the yield variability offsetting effect of the climate-smart agricultural practices. Besides, the Instrumental Variable (IV) technique is used to determine the effect of different climate-smart agricultural practices on value production at plot level.

6.2 Methodology

6.2.1 Data source and data types

The study is based on a cross-sectional household survey data of 734 mixed farmers enumerated during November and December 2016 substantiated with Focus Group Discussions and field observations. The household and plot level survey employed a structured questionnaire that addressed household characteristics, farmers' use of climate-smart agricultural practices, and factors affecting the use of the practices. The plot level data included biophysical characteristics of a plot, crop production level per plot, and the types of climate-smart agricultural practices applied to each plot. These data were mainly used to determine how climate smart agricultural practices affect crop yield variability and productivity at plot level. Focus group discussions were also carried out to substantiate the responses acquired through the questionnaire. The primary data were also supplemented by a data from secondary sources.

6.2.2 Data analysis

The mean-variance method of Just and Pope (1979) for cross-sectional data is used to estimate the crop yield variability at plot level. In order to estimate the effect of a particular climate smart agricultural practice on crop yield variability, we divided the sample into those with and without the practice. The mean productivity for the subsample was calculated and then for each observation a deviation about the mean or variance was identified. The hypothesis tested was that the climate-smart agricultural practices would help to reduce the variance of production among those who had adopted the practices. Moreover, the Instrumental Variable (IV) estimation method is employed to determine the relationship between the climate smart agricultural practices and crop productivity.

6.2.2.1 Instrumental variable estimation

This study used both household and plot level data to assess how different climate smart agricultural practices are related to crop productivity. Crop productivity is assessed at plot level because there is a possibility to have multiple types of crops produced on a given plot. Moreover, since it is difficult to compare productivity using quantity units, aggregation is made using monetary units (value of crops) so as to have a common denominator for comparison. For this purpose, the total value of crops produced from a given plot was aggregated by the regional price levels of the respective crops and then converted into per hectare basis. Following this, the relationship between productivity and climate smart agricultural practices is assessed employing the instrumental variable (IV) estimation as analytical framework.

Crop productivity (value of crop production per hectares) is a function of various plot level and household level variables. In this case applying ordinary least squares (OLS) regression may lead to a bias due to potentially available endogenous choices that involve climate smart agricultural practices and the use of the basic inputs included in the explanatory variables. It may result in some correlation between these potential endogenous variables and the error terms of the equation. Based on Bascle (2008) and Wooldridge (2006), there are three sources of violating edogeneity conditions in OLS, which include errors in variables (due to measurement error), omitted variables (due to omission of explanatory variables), and simultaneous causality (resulted when causality runs in both direction from the regressors to the dependent variable and vise versa). When simultaneous causality occurs, the OLS leads to biased and inconsistent estimators. Therefore, to adequately address these sources of endogeneity, the IV estimation is proved to be suitable option (Baum et al. 2003). The IV is also called two-stage least square (2SLS) reflecting the fact that the estimators are calculated in a two-step procedure (Meddala 1992). Following Wooldridge (2002) and Maddala, (1992) and considering variables of interest in this study, the IV estimation can be specified as follows:

$$Y_1 = \beta_0 + \beta_1 Y_2 + \beta_2 X + U \quad (6.1)$$

Where, Y_1 is value of crop yield per hectare; Y_2 is a vector of endogenous variables that include the climate smart agricultural practices and the use of basic inputs; X is a vector of exogenous variables that are assumed to affect crop yield; and U is the error term of the model. Equation (6.1) is called a structural equation. Endogeneity of Y_2 means that it is correlated with the error term U, and hence violates an important assumption under OLS. In order to obtain consistent estimators in this case, we need some additional information. The information come by way of new variables called instruments (Bascle 2008).

Let Z denotes a vector of such instruments satisfying two major properties: uncorrelated with U, also called orthogonal the error process (exogeneity condition i.e. $Cov(Z,U) = 0$) and correlated with the endogenous variable Y_2 (relevance condition i.e. $Cov(Y_2, Z) \neq 0$) (Baum et al., 2003; Wooldridge, 2002). This means Z is a variable directly affecting the endogenous variable and may not directly related to the dependent variable Y_1. This requires potential exogenous variables that are hypothesised to have an influence on the climate smart agricultural practices and the basic inputs but with no hypothesised direct effect on value of crop yield.

Hence, Z includes variable categories like human capital and (family size, dependency ratio, age, sex, and level of education) and village level factors (like market distance) which are assumed to affect crop yield through an indirect way by affecting the climate smart agricultural practices and the other potential endogenous variables. The predicted probabilities of the dummy endogenous variables can also be used as instruments of their actual values. It is also possible to exclude those explanatory variables that are jointly statistically insignificant from regression and use them as instruments in the less restricted version of the model (Jansen et al. 2006; Nkonya et al. 2004; Pender et al. 2004).

In the IV estimation, we estimate the value of crop yield by a two stage procedure in which the potentially endogenous variables are predicated from the first stage by regressing on the other exogenous variables and used in the second stage estimation as independent variables. It follows by first fitting the regressors as follows:

$$Y_2 = \alpha_0 + \alpha_1 X + \alpha_2 Z + \varepsilon \qquad (6.2)$$

Equation (6.2) is first stage regression in the IV method (also called reduced form for the endogenous variable equation) where the endogenous regressor, Y_2, is expressed as a function of a vector of exogenous variables X, and a vector of excluded instruments Z. The key idea is that this stage isolates the variation in Y_2 that is not correlated with the error term U in the structural equation. Here both X and Z are called instruments, included and excluded respectively. For identification of the above equation, there must be at least as many excluded instruments as there are endogenous regressors and the process is called order condition for identification. For obtaining a vector of predicated values in the $\hat{Y}_2$ equation (6.3), the two stages least square method requires estimation of the second stage by replacing the right hand vector of endogenous variable by $\hat{Y}_2$ in equation (6.3). Then we will have the following equation

$$Y_1 = \beta_0 + \beta_1 \hat{Y}_2 + \beta_2 X + U \qquad (6.3)$$

However, the estimated standard errors from the second stage are wrong ones, as it is computed by using $\hat{Y}_2$ instead of Y_2. This has to be corrected using the appropriate technique as indicated in Meddala (1992). In STATA, the 'iverge2' command with the option 'ffirst' automatically reports these values based on the command created by Baum et al. (2003).

The IV coefficients are consistent, provided that a unique solution to the estimation problem exists and the instruments are uncorrelated with error term in the model (Davidson and Mackinnon 2004; Nkonya et al. 2008). However, in finite samples, IV estimators are generally biased, and they can be more biased than OLS estimates if the instruments are weak predictors of the endogenous explanatory variables (Davidson and Mackinnon 2004). In the IV estimation, it is necessary to have at least as many restriction as endogenous explanatory variables to be able to identify the model (order condition model), and additional restrictions (over identifying restrictions) that can help to increase the efficiency of the model, provided that these restrictions are significant predictors of the exogenous explanatory variables.

Therefore, it is vital to make different tests in the IV estimations. First, it is necessary to test whether the excluded instruments are significant predictors of the exogenous variables (test of relevance of instruments). This is a test of whether these instruments are correlated with the endogenous variables. When the correlation is strong (weak), the instrument is strong (weak). When there is no correlation, the instrument is said to be irrelevant. In this study, relevance of the instruments is tested using Shea's partial R^2 and the standard partial R^2 obtained from the first stage regression. As a rule of thumb, if partial R^2 is large and Sheas's partial R^2 is small, one may conclude that the instruments lack sufficient relevance to explain all the endogenous regressors.

Another important test made in IV estimation is test of exogeneity condition (also called orthogonality condition) of instruments. It is a test whether the instruments are not correlated with the error term of the structural equation (i.e. whether they do not add additional explanatory power to the regression after controlling for the endogenous variables). This is also called test of overidentifying restrictions. This test can be performed only if there are more instruments than the endogenous variables and assumes that at least one instrument is exogenous.

In this study, overidentfying restrictions are tested using Hansen's J test which is robust to heterodcedasticity (Baum et al., 2003). A failure to reject Hansen's J statistic mean, that the instruments can be considered as exogenous. Generally, when instruments are valid (i.e. relevant and exogenous), the resulting IV estimator of the structural model is consistent estimator of the true population parameter.

The IV estimators are less efficient than OLS when the explanatory variables are all exogenous. Therefore, it is also essential to have a test for endogeneity on the suspected explanatory variables, a test to know whether IV method is even necessary (Wooldridge 2002). Endogenety bias, potentially resulting from the actual values of the endogenous explanatory variables (OLS method) rather than their predicted values (IV method) can be tested by using Hausman test (Green 2003; Hausman 1978). However, this test can possibly result in a negative statistic, and furthermore the Hausman command will report the correct statistic but with a wrong degree of freedom. To overcome this problem in the present study, the endogeneity of the potentially endogenous variables are tested using the C-statistic test (Baum et al., 2003). The test is perhaps best interpreted not as a test for endogenitey or exogeneiety of regrossors per se, rather as a test of consequence of employing different estimation methods (in this case, OLS and IV) on the same equation.

The other estimation and data issues considered included hetertoskedasticity, multicolinearity and outliers. For these, appropriate logarithmic transformation of the continuous uncensored variables toward normality was made. This gives an empirical merit of improving the model specification. The merits are reducing problem of non-linearity, outliers and heterosckedasticity (Mukherjee et al. 1998) and simplifying interpretation of results (Nkonya et al. 2008). Hence, in estimating the IV model, a logarithmic Cobb-Douglass type specification was used. That means both the dependent and the continuous uncensored right hand side variables under this model are transformed in to logarithmic forms. The Huber-White robust standard errors is also used in all cases to address heteroskedasticity, while multicolinearity was tested using Variance Inflation Factor (VIF).

6.3. Results and Discussion

6.3.1 Farmers' use of climate smart agricultural practices

The most commonly practiced climate-smart agricultural practices in the study area are portrayed in Table 6.1 along with the proportion of farmers that use the respective practices. Although diversified types of climate-smart agricultural practices are identified in the study area, most of these have been used only by few farmers. Changing crop varieties and/or changing crop type are common practices across the wet lowland and dry lowland agro-climatic zones of the study area. In this regard, farmers shifted/diversified crop types from maize and sorghum into other crops such as beans and vegetables. In the wet lowland condition, the new crops being used widely than before include *teff*, vegetables, and soybeans. In the dry lowland, crop diversification has been into groundnuts, sesame, and vegetables away from maize and sorghum.

Some of the new crop types/varieties are more drought-tolerant than the crops replaced, while others, notably vegetables, require more water, contrary to the expectation that farmers would move toward less water demanding crops. In both agro-climatic zones, however, the farmers switching to vegetables had some form of access to irrigation. As stated in Simane et al. (2016), the diversification in to vegetables is partly a reflection of the effect of better market access and a tendency to move to high-value crops as a strategy of intensifying the use of scarce resources such as land and labor.

Adjusting planting date is practiced towards addressing the late and/or early onset of rainfall by farmers in both parts of the study area with a varying degree of intensity. The largest share of the respondents that used this practice is from the wet lowland agro-climatic zone owing to better perception about the change in the onset of rainfall. However, respondents from the dry lowland felt that planting dates are less flexible due to the relatively shorter growing period. As indicated in Table 6.1, the use of different soil and water conservation measures is a common practice in the study area. In the wet lowland condition, the use rate of physical soil conservation measures is higher compared to the dry lowland implying that farmers in the wet lowland are more aware of the techniques and respond to climate change and variability through these measures.

Table 6.1 Commonly used climate-smart agricultural practices in the study area

Adaptation strategy	Percent of user farmers by Agro-climatic zones		Total
	Wet lowland	Dry lowland	
Improved crop variety	55	34	45
Change the crop type	34	28	31
Adjust planting dates	58	22	40
Crop rotation	60	48	55
Intercropping	44	32	38
Animal manure	61	43	52
Fertilizer	65	28	46
Conservation tillage	42	22	32
Grass strips	42	28	35
Agro-forestry	38	30	34
Soil bunds	58	41	50
Check dams	34	22	28
Insitu water harvesting	39	24	32
Irrigation	17	8	13
Number of plots	558	337	915

6.3.2 Effect of climate-smart agricultural practices on yield variability and productivity

This section presents the effect of the climate smart agricultural practices on crop yield variability (derivation from conditional mean yield) and prductivity. The plot level cross-sectional data is used to compare the two agro-climatic zones of the study area in terms of estimated effect of the climate-smart agricultural practices on crop yield variability and productivity.

As revealed in Table 6.2, the climate-smart agricultural practices helped to reduce crop yield variability in both agro-climatic zones. Of the 14 coefficients that correspond to the different climate-smart agricultural practices, 11 are negative and statistically significant indicating that the practices helped to reduce crop yield variance. The results are consistent with other studies (Branca 2010; Bationo et al. 2007), who have shown that soil fertility management practices and water conservation measures increase moisture storage capacity, which in turn reduces yield variability that attributes to productivity stressing climate factors. It is expected that the synergetic effect of the climate smart agricultural practices could be higher in reducing the crop yield variability and hence future research should investigate the synergistic effect and possible complementarities among the practices.

Table 6.2 Effect of climate-smart agricultural practices on crop yield variability and productivity

Climate-smart agricultural practice	Log (variance of productivity/ha)		Log (value of crop produced/ha)	
	Wet lowland	Dry lowland	Wet lowland	Dry lowland
Manure	-2.071*	-2.308*	1.512**	0.412*
Crop residue	-0.115**	-0.102**	0.272	0.102
Inorganic Fertilizer	1.04	0.423	0.641	0.053
Crop rotation	-0.404**	-0.601*	0.703**	0.354*
Intercropping	-0.738**	-0.313	0.403**	0.344**
Conservation tillage	-2.218**	0.149	0.224*	0.186*
Water harvesting (insitu)	-0.464*	-0.881*	0.566**	0.233*
Irrigation	-0.394*	-3.23**	0.826**	0.44*
Agroforestry	-0.097	-0.076	0.806**	0.576*
Soil/stone bunds	-2.024**	-1.043*	2.342**	1.423*
Grass strips	-0.442*	-0.756*	0.542**	0.408*
Improved seed	-0.004	-0.027	1.78**	0.712*
Check dam	-0.323*	-0.412*	0.246	0.137
Conservation tillage	-0.343*	0.422*	0.224*	0.186*
Number of plots	558	337	558	337

**, and * indicate significance at 5%, and 10% levels, respectively

Table 6.2 also shows the effect of the climate-smart agricultural practices on crop productivity expressed in term of value of crops produced per hectare. Application of inorganic fertilizer had no significant effect on crop productivity in both the wet and dry lowland agro-climatic zones. The insignificant effect of fertilizer on crop productivity in both parts of the study area could be attributed to the low rate of application, poor fertility status of the soil and other biophysical characteristics of the plots receiving fertilizer. The results from FGD conducted in the two parts of the study area also revealed that farmers are applying inorganic fertilizer with a very low rate and without taking into account the fertility status of a plot, which may resulted in a low productivity response.

Agro-forestry practices have shown a positive effect on crop productivity in both agro-climatic zones. As expected, water harvesting and irrigation had a significant positive influence on crop productivity revealing the importance of the practices in offsetting the possible risk of moisture stress. Similarly, crop rotation, intercropping, use of improved seed, use of physical soil conservation measures, conservation tillage, and manure application positively and significantly contributed to crop productivity in both agro-climatic zones.

6.3.3 Determinants of productivity: Results of the instrumental variable regression

Where the scope for extensification (expansion of arable land) is very limited, the option to increase agricultural output is through intensification (increasing productivity per unit area). Nevertheless, several factors may affect the scope of increasing productivity. Table 6.3 presents the description of variables used in the IV estimation as determinants of productivity.

Table 6.3 Description and summary statistics of variables used in the IV estimation

Variables	Description	Obs	Mean	SD
Value of output	Value of total output per ha	915	33496	11104.1
Labor	Pre-harvest labor use (man-days)	915	211.44	112.14
Sex	1 if the household is male headed	734	0.83	0.234
Manure	1 if manure is applied, 0 otherwise	915	0.522	0.475
Fertilizer	1 if fertilizer is applied, 0 otherwise	915	0.422	0.443
Intercropping	1 if intercropping is practiced, 0 otherwise	915	0.382	0.441
Conservation tillage	1 if intercropping is practiced, 0 otherwise	915	0.321	0.612
Physical soil conservation measures	1 if conservation is practiced, 0 otherwise	915	0.431	0.427
Crop rotation	1 if crop rotation is practiced, 0 otherwise	915	0.631	0.337
Improved crop variety	1 if improved crop variety is used, 0 otherwise	915	0.461	0.342
Irrigation (dummy)	1 if irrigation is practiced, 0 otherwise	915	0.251	0.652
Oxen-pair	Draft power used (oxen-pair/ha)	915	10.22.	5.76
Parcel size	Parcel size (ha)	915	0.68	0.257
Slope : flat	1 for flat slope, 0 otherwise	915	0.355	0.544
Slope: gentle	1 for gentle slope, 0 otherwise	915	0.441	0.403
Slope: steep	1 for steep slope, 0 otherwise	915	0.201	0.406
Slope: very steep	1 for very steep slope, 0 otherwise	915	0.003	0.243
Fertility: poor	1 for poor soil fertility, 0 otherwise	915	0.321	0.423
Fertility: good	1 for medium soil fertility, 0 otherwise	915	0.278	0.386
Fertility: medium	1 for good soil fertility, 0 otherwise	915	0.401	0.446
Farm distance	Farm-home distance (kilometers)	915	2.037	1.192
Size of holding	Total size of holding (ha)	734	6.210	2.630
Livestock (TLU)	Livestock size (TLU0	734	8.52	3.48
SI index)	Land fragmentation in simpson index (SI)	912	0.34	0.102
Proportion of fruits	Proportion of earning from fruits (Br)	351	0.18	0.221
Number of crops	Number of annual crop types grown	734	3.10	2.01
Credit	1 if credit is received, 0 otherwise	734	0.231	0.388
Education	1 if no formal education	734	0.45	0.334
Adult equivalent	Family size in adult equivalent	734	4.42	1.62
Dependency ratio	Ratio of dependents to active labor	734	1.33	0.58
Female proportion	Proportion of female members in the family	734	0.44	0.131
Market distance	Distance of the nearest market (km)	734	4.47	3.121
Off-farm/non-farm activities	1 if involved in off-farm activities, 0 otherwise	734	0.411	0.213
Ago-climatic zone: wet lowland	1 if wet lowland, 0 otherwise	734	0.5	0.5
Agro-climatic zone: dry lowland	1 if wet lowland, 0 otherwise	734	0.5	0.5

In this study, the IV estimation result revealed the effects of climate-smart agricultural practices and other factors on crop productivity. In the IV estimation, pre-harvest labor, plowing techniques, intercropping, manure application, and fertilizer application are assumed to be endogenous variables. The instrument variables used for this analysis include household characteristics (sex of the household head, level of education, adult equivalent, dependency ratio, and proportion of female members in a household labor) and location characteristics (market distance) and location (agro-climatic zone) dummies (Table 6.3).

Table 6.4 depicts the results of the IV estimation. Different test were made in order to evaluate whether IV model properly fits to the data set. The relevance test (based on Sheas's partial R2 and the standard partial R2 obtained from the first stage regression) indicate that the instruments are significant predicators of the indicated endogenous variables. The test of overidentifying restriction of the instruments (based on Hansen's J statistic) indicates that the instruments are orthogonal (not correlated with the error term of the structural model). Based on the two tests, the instruments are valid in the IV model being used. Moreover, the Hausman and C-statistics for testing the erogeneity of potentially endogenous variables (whether OLS is preferable) indicates that the variables are endogenous. The overall test results generally confirm that the IV method is preferred over the OLS method for the present data set. Hence, only the IV estimates are presented and discussed here while OLS results could be used only for comparison purpose.

The existence of causality and endogeneity may lead to a direct or/and indirect effect of some variables on the dependent variable. In other words, a variable that may not have a direct significant effect may have an indirect effect via endogenous variables. Further, a variable which does not appear in the structural model may also have an indirect effect on the dependent variable via endogenous variable. In this paper, however, only the direct effects are explained and the indirect effects can be inferred from explanations made in recent empirical studies on the determinants of soil fertility management practices (Mihretu and Yimer 2017; Belay et al. 2016; Branca 2010; Mengistu 2010; Asrat et al. 2004).

Table 6.4 Parameter estimates of IV regression model for land productivity analysis

Explanatory variables	**Coefficient**	**S.E**
Ln(labor)	1.134**	0.376
Manure (dummy)	0.477***	0.301
Fertilizer (dummy)	0.089	0.191
Intercropping (dummy)	0.344***	0.132
Conservation tillage (dummy)	0.342***	0.134
Physical soil and water cons. measures (dummy)	0.212**	0.207
Crop rotation (dummy)	0.101	0.122
Improved crop variety (dummy)	0.221*	0.236
Irrigation (dummy)	0.311**	0.321
ln(oxen-pair)	0.110	0.121
ln(parcel size)	0.231*	0.101
Slope (cf. flat)		
Gentle	0.033	0.210
Steep	-0.155*	0.131
Very steep	-0.312	0.222
Fertility level (cf. poor)		
Good	0.012	0.111
Medium	0.228*	0.149
ln(farm distance)	0.121	0.043
ln(size of land holding)	0.041	0.150
ln(TLU)	0.241*	0.117
Land fragmentation (simpson index)	-0.588*	0.242
Proportion of fruits	0.211	0.202
Ln(number of crops)	0.982**	0.243
Credit (dummy)	0.321*	0.434
Off-farm/non-farm activities (dummy)	-0.156*	0.178
Wet lowland (dummy)	0.443*	0.240
Dry lowland (dummy)	-0.132	0.041
Relevance test of excluded variables (p-value)[ф]		
Ln(labor)	0.000	
Conservation tillage	0.000	
Intercropping	0.000	
Fertilizer use	0.000	
Manure application	0.000	
Hansen's J-test of overid. restrictions (p-value) [φ]	0.7465	
Endogeneity test based on C-statistic (p-value)	0.0302	

Notes: Productivity (dependent variable) is expressed as a natural logarithm of the value of crop output per hectare; [ф] Based on Shea's R^2 and standard partial R^2 for the indicated endogenous variables; [φ] Subset of instruments have also passed overidentifying restrictions based on C-statistic test; ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

The IV estimation result presented in Table 6.4 shows that different climate-smart agricultural practices are found to be significant and positively affecting crop productivity. Manure application positively and significantly influenced crop productivity justifying the crop-livestock complementarity in the smallholder agriculture system. Likewise, intercropping practices positively and significantly affected crop productivity implying the possibility that the practice could help improve crop productivity in the smallholder farming system where access to external inputs and the use level is very limited. Conservation tillage also had a positive and significant effect on crop productivity signifying the role of the practice in sustaining crop productivity through conserving water and soil moisture. The findings generally infer that the promotion of climate-smart agricultural practices is vital to boost and sustain crop productivity in the face of changing climate and unreliable access to the modern agricultural inputs. The role of labor input is also found significant and positive in affecting crop productivity implying the labor intensiveness of the smallholder agricultural production systems.

The IV estimation result shows that application of inorganic fertilizer (one of the endogenous variables) has no significant effect on crop productivity, controlling for other factors that affect productivity. This can be associated to the fact that fertilizer application in the study area is generally low owing to lack of access, limited supply and high price. This finding is in line with Mengistu (2010), who reported fertilizer to be among the most expensive farm inputs in Ethiopia and known to have inefficient delivery system. However, all the endogenous variables (manure, intercropping, conservation tillage and fertilizer use) taken together are jointly significant in affecting crop productivity based on Aderson-Rubin Wald test of joint significance. The joint significance may imply that there is an opportunity to increase crop productivity through the climate smart agricultural practices that include manure application, intercropping, conservation tillage and physical soil conservation measures while at the same time inducing low-external input investment.

Factors like parcel size, soil fertility status, livestock units, number of crops grown (diversification), and households' access to credit positively and significantly affect crop productivity. On the other hand the slope category of a plot, land fragmentation, and involvement in off/non-farm activities have negative and significant effect on crop productivity.

The positive effect of parcel size on crop productivity is associated with economies of scale. There is a possibility for economies of scale from an increase in a plot size particularly when the size of the plot is below minim operational level. This finding is in agreement with several studies (Mengitu 2010; Nkonya et al. 2005; Nkonya et al. 2008; Pender et al. 2008). On the contrary, the negative effect of land fragmentation on productivity suggests that it reduces the ability to achieve economies of scale, for it makes a plot of land below the minimum operational level. The implication from the effect of these two variables is that policy measures towards land consolidation may enhance productivity in the study area as well as other locations in the country with similar socioeconomic and environmental physiognomies.

Crop diversification has a positive and significant effect on productivity confirming that increasing the number of crops grown reduces the farmers' exposure to production and price risks as opposed to the specialization on a single crop. However, since diversification in the study area is mostly at the expense of high value crops (based on the FGD results and key informants), it may result in less risk and more production but less income, which is a typical feature of a subsistence agricultural systems. Hence, this may call for alternative risk minimizing options such as small-scale irrigation, drought tolerant crop varieties, and crop insurance aligned to the major crop production risk factors (moisture stress, pest and diseases). There is also a need to look for possible market linkages for the currently less marketable crops.

Based on the IV model result, institutional arrangements such as creating access to rural credit is found to be important in boosting crop productivity. Credit availability in the form of basic agricultural inputs could help farmers to relax their financial constraints for the purchase of the farm inputs. Similarly, implementation of long term soil conservation measures (physical structures) on farm plots may complement the short run measures and the synergy may boost crop productivity in the study area.

Livestock ownership is positively and significantly related to crop productivity justifying the complementarity between livestock and crop enterprises in the context of the smallholder agriculture. The role of livestock in crop production is also evident in that it serves as a source of manure (which is also significant in affecting productivity as indicated earlier), source of draft power, and transportation all of which are augmenting crop production activity. This finding is consistent with other researchers (Nkonya et al. 2005; Asat et al. 2004; Pender et al. 2004).

An increase in a slope of a plot has a negative effect on crop productivity. On steep slopes, the hazards of soil loss through erosion increases and may call for increased use of expensive external inputs and conservation measures so as to sustain crop productivity. The negative effect of off-farm/non-farm activities on productivity implies that these activities may compete for the family labor, which is critically important for the farm operations. This finding is in line with Mengistu (2010) who reported a negative effect of non-farm activities but in contrast with Nkonya, et al. (2004; 2006) who found a positive effect of the off-farm activities on crop productivity.

The total land holding size turns out to be statistically insignificant implying that it has no direct effect on crop productivity. Hence, there is no adequate statistical evidence to argue either against or in favour of the inverse farm size productivity relationship. However, some variables which have no direct significant effect may influence crop productivity indirectly through influencing the variables which are treated as endogenous. In the IV estimation, absence of a variable or its insignificance may not necessarily imply that the variable is not influencing crop productivity. This means the variable may exert either positive or negative indirect effect on crop productivity through affecting the endogenous determinants of productivity. .

6.4 Conclusion and Recommendation

This study used household and plot-level cross sectional data to assess the effect of climate smart agricultural practices on crop yield variability and productivity. The analysis indicated that the practices helped to reduce climate-change-induced yield variability. Likewise, most of the practices positively and significantly affected crop productivity. It is apparent that the IV regression is an appropriate model for the data set used as compared to the conventional OLS regression as verified by different tests. The IV estimation result shows application of manure, intercropping, conservation tillage, physical soil conservation practices, pre harvest labor input, parcel size, soil fertility status, livestock holding, number of crops grown, and access to credit positively and significantly affect crop productivity. On the other hand, the slope variable, land fragmentation, and the involvement in off-/non-farm activities are negatively and significantly related to crop productivity.

The results generally revealed a ‘win-win’ outcome of increasing agricultural productivity and reducing climate-change worsened land degradation can be achieved by improving soil fertility through the use of climate-smart agricultural practices, while at the same time increasing parcel size and reducing fragmentation. Hence, promotion of climate-smart agricultural practices is vital to boost and sustain crop productivity in the face of changing climate and unreliable access to the modern agricultural inputs. Further, there is an opportunity to increase crop productivity through these practices while at the same time inducing low-external input investment.

Farmers in the study area use crop diversification as a strategy against production and price risks. However, the decision on diversification is mostly at the expense of high value crops and hence may induce less farm income. Therefore, there is a need either to introduce alternative risk minimizing alternatives or to create market linkage for the crops which are less marketable but being used in the diversification. This study also indicated the need for policy attention towards land consolidation that may enhance productivity in the study area as well as other locations in the country with similar socioeconomic and environmental features. Based on the results it is evident that the synergetic effect of the climate smart agricultural practices could be higher in reducing crop yield variability and in enhancing productivity. Therefore, future research should further gear to investigating and modeling the synergetic effect and possible complementarities among the climate-smart agricultural practices.

Chapter Seven

7. Household and Plot Level Impacts of Climate-Smart Land Management Practices in the Face of Climate Variability and Change: Empirical Evidence from Dabus Sub-basin, Blue Nile River, Ethiopia

Abstract

Smallholder farmers can adapt to climate variability and change through climate-smart land management practices that help to offset the negative impacts at farm level. However, use of these practices as adaptation strategy remains low in Ethiopia in general and the study sites in particular. This study is aimed at examining the factors that determine farmers' decision to use physical land management measures and quantifying the impact of the practices on crop productivity at household and plot level. The study is based on household and plot level primary data and employed the nearest-neighbor matching technique to quantify the impact of using the climate-smart land management practices on the value of production at household level and plot level. The results revealed that households that implemented the physical land management practices within the period (2004-2009) experienced a 24.1 percent higher value of production in 2016 over the non-users. Similarly, plots that received the climate-smart land management measures within the period (2004-2009) experienced a 28.6 percent increase in value of production in 2016. The study also made further analysis at plot level using the continuous treatment effects in order to take into account the number of years a plot has been under the practice. The result showed plots with the physical land management structure that are maintained for at least 6 years have a positive increase in value of production at the end of the 6th year, while those that received the practices recently or those that lacked continuous maintenance did not experience a statistically significant increase in value of production. The result also showed the marginal benefit of sustaining the land management practices increases over time at an increasing rate. The implication is that maintenance of the land management structures is crucial to reap significant benefits from the practices. Although the value of production increases given the land management practices, their implementation is labor and time intensive and there is always a trade-off with other agricultural activities. Therefore, policy measures are required to incentivize the implementation and longer maintenance of the land management structures by smallholder farmers.

Keywords: climate-smart land management, climate change, adaptation, matching, treatment effect, impact

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7.1 Introduction

In primarily agricultural based economies, the immediate trade-off between short-term welfare and long-term development represents major challenges. In this type of economies, land degradation pose a critical development challenge contributing to high production risk, reduced output, lower economic growth and increased poverty (Olarinde et al. 2011; Zeleke and Hurni 2001). In recent years, this challenge is more aggravated in the face of changing climate and variability. More particularly, heavy dependence on rain-fed agriculture makes the sector most vulnerable to climatic change risks and led productivity to unsustainable level (Barnichon and Peiris 2008).

Ethiopia's biophysical potential for sustainable agricultural development opportunities has been continuously challenged by land degradation and poverty (Sonneveld 2002; Tefera et al. 2002; Shiferaw and Holden 2001). The problem is further aggravated by climate variability and change, population pressure, limited use of land management practices, deforestation, rugged terrain characteristics, erratic rainfall, vulnerable soil and heavy dependence on rain-fed agriculture (Kassie et al. 2008; Okumu et al. 2002). The on-site cost due to erosion of top soil is estimated to be 2 to 6.8% of the Ethiopia's agricultural GDP per annum (FAO 2014; Yesuf et al. 2005; Asrat et al. 2004). Ethiopia could also experience negative and positive off-site productivity effects on downstream plots in terms of eroded soil that is washed out (Bojö and Cassells 1995; Hurni 1988).

The onsite and offsite cost of soil erosion are also critical challenges in the Dabus sub-basin of the Blue Nile River being intensified by the prevailing unsustainable land use system, watershed degradation, erratic rainfall, and severe deforestation (BGNRS 2013). Based on the same source, agricultural practices in the area are dominated by cereal crops cultivation, which necessitates frequent plowing that leads to little ground cover during the rainy season, which in turn renders the soil to be more susceptible to erosion. Therefore, there is an urgent need for efficient mechanisms that helps to reduce soil loss and improve agricultural output in the sub-basin.

Previous studies on productivity impacts of soil conservation measures revealed diverse results. A study by Pender and Gebremedhin (2006) in the Northern Ethiopia suggests that plots with stone terraces experience higher crop yields. A study by Zeleke and Hurni (2001) estimated that users of soil and water conservation measures achieved 17–24 percent higher value of production compared to non-users. Similarly, a soil and water conservation program evaluation study in Honduras by Bravo-Ureta (2010) revealed a positive effect on the value of production. Conversely, Kassie et al. (2008), using matching methods and switching regression analysis at farm-level data from high rainfall areas in the Northern Ethiopia revealed that plots with soil bunds resulted in a lower yields compared to non-conserved plots.

A study by Yesuf et al. (2008) indicated that only 31 percent of smallholder farmers in Ethiopia adopted physical soil and water management practices to address perceived changes in rainfall and only 4 percent adopted water harvesting technologies. The study results by Benhin (2006) and Kabubo-Mariara Karanja (2006) also found similar results in South Africa and Kenya. However, there is inadequate evidence to what extent that smallholder farmers have used climate-smart land management practices for climate risk management in Sub-Saharan Africa in general and in Ethiopia in particular. The results of the previous studies are highly aggregated and are of little help in addressing local conditions in relation to adaptations to climate change. The studies have also paid little attention to the analysis of local factors that influence smallholder farmers' use of the physical land management practices as adaptation strategy. Moreover, the studies overlooked the likelihood impact of climate-smart land management practices on crop productivity both at farm and plot level.

Since adaptation is a local response to climate stimuli, location specific factors that affect famers' decisions to use the land management practices and measuring the impact of the practices on rural livelihood is an important research gap that needs to be addressed. Hence, the present study aims to contribute to a formulation of location specific climate change adaptation strategy through identifying household and plot level factors that determine the use of climate-smart land management practices and the crop productivity impact both at household and plot level. For this purpose, the study employed the nearest-neighbor matching technique to measure the household and plot level impacts of adopting the physical land management measures on value of agricultural production. The study also aims to understand the timing of benefits and then to calculate marginal benefits of each additional year of maintenance of the land management measures. For this purpose, the study employed a continuous treatment effect estimation method and measured the length of time a plot of land must be maintained under the physical land management measures in order to experience a benefit.

7.2 Methodology

7.2.1 Data sources and types

A household survey conducted in November and December 2016 enumerated 734 farm households, which are spatially distributed in the wet and dry lowland agro-climatic zones of the Dabus sub-basin. The household survey employed a structured questionnaire that addressed household characteristics, farmers' use of physical land management measures, factors that affect use of the measures, agricultural inputs and outputs, and crop enterprise income. The plot level data included biophysical characteristics of a plot, crop production level per plot, and the types of physical land management measures applied to each plot. These data were mainly used to determine how climate-smart land management measures affect crop productivity at plot level. In addition, Focus Group Discussions were conducted at village level to substantiate the data from the household survey. Data on grain prices is obtained from the respective woreda level agricultural offices and CSA (2004-2016).

7.2.2 Data analysis

The study used both descriptive and econometric methods to analyze the data. Descriptive method was employed to compare the two agro-climatic zones of the study area and to describe users and non-users of the land management measures. Productivity was measured using gross value of output per hectare. Monetary value was used to measure output performances as households cultivate more than one crop and there need to be some basis for aggregation.

The econometric models are used to address two primary questions. First, we calculated the impact that the physical land management measures have on value of production for the users compared to the non-users and at plot level, for plots that received the land management practices versus those that did not. In doing so, we used the probit regression model to have insight on which type of household or plot is more likely to use and maintain the land management structures. Second, we estimated the impact of the land management practices, the marginal benefit of maintaining the land management structure from year to year and how long farmers must maintain the structures in order to experience a benefit.

7.2.2.1 Specification of the probit model

Technology adoption models are based on farmers' utility or profit-maximizing behavior (Pryanishnikov and Katarina 2003). The assumption is that farmers adopt a technology/practice only when the perceived utility or profit from using a new technology is greater than the traditional or the old technology. On this assumption, probit regression model is selected to analyze the determinants of farmers' decision to use physical land management practices as adaptation strategy. Suppose that Y_j and Y_k represent a household's utility for two choices, which are denoted by U_j and U_k , respectively. The linear random utility model could then be specified as:

$$U_j = \beta_j X_i + \varepsilon_j \quad \text{And} \quad U_k = \beta_k X_i + \varepsilon_k \text{ -- (7.1)}$$

where U_j and U_k are the perceived utilities of adaptation methods *j* and *k*, respectively, X_i is the vector of explanatory variables that influence the perceived desirability of the methods, B_j and B_k are parameters to be estimated, and ε_j and ε_k are error terms assumed to be independently and identically distributed (Greene 2000). Therefore, if a household decides to use option *j*, it follows that the perceived utility from option *j* is greater than the utility from the other options (say *k*) depicted as:

$$U_{ij}\left(\beta_j X_i + \varepsilon_j\right) > U_{ik}\left(\beta_k X_i + \varepsilon_k\right), k \neq j \text{ -- (7.2)}$$

The probability that a household will use method *j* among the set of options could then be defined as:

$$P\left(Y = 1 \middle| X\right) = P\left(U_{ij} > U_{ik}\right) \text{--- (7.3)}$$

$$P\left(\beta_j X_i + \varepsilon_j - \beta_k X_i - \varepsilon_k > 0 \middle| X\right)$$

$$P\left(\beta_j X_i - \beta_k X_i + \varepsilon_j - \varepsilon_k > 0 \middle| X\right)$$

$$P\left(X^* X_i + \varepsilon^* > 0 \middle| X = F\left(\beta^* X_i\right)\right.$$

where *P* is a probability function, *Uij, Uik,,* and *Xi* are as defined above, $\varepsilon^* = \varepsilon j - \varepsilon k$ is a random disturbance term, $\beta^* = (\beta_i - \beta_j)$ is a vector of unknown parameters that can be interpreted as a net influence of the vector of independent variables influencing the decision to use climate-smart land management practices, and $F(\beta^* X_i)$ is a cumulative distribution function of ε^* evaluated at $\beta^* X_i$. The dependent variable is dummy (binary), which takes a value zero or one depending on whether or not a farmer is using any of the land management practices as adaptive response to climate variability and change. Contrariwise, the explanatory variables are either continuous or binary/categorical. Then, the probit model is specified as:

$$I_j^* = \beta X_j + \varepsilon_j \quad (7.4)$$

Where β is vector of parameters of the model, Xj is vector of explanatory variables and *εj* is the error term assumed to have random normal distribution with mean zero and common variance δ^2 [2]. Ij is unobservable (latent variable) household's actual decision to use the land management practice and what we observe is a dummy variable (use of land management measures) which is defined as: 1 if $I_j^*>0$ and 0 otherwise

$$pro(adoption = 1) = \phi(\beta X_j) \quad (7.5)$$

$$pro(adoption = 0) = 1 - \phi(\beta X_j) \quad (7.6)$$

7.2.2.2 Nearest- neighbor matching

Given that a variety of differences exist between users and non-users of the physical land management practices, it is important to control for these potential underlying effects in order to ensure reliable impact estimates. Thus, the nearest neighbor matching approach was used as it allows matching the users to non-users at household and plot level. In addition, a continuous treatment effect estimation technique developed by Hirano and Imbens (2004) has been adopted to quantify the differences in value of production.

In order to control for causal effect that arises due to self-selection bias or methodical assignment of treatment groups, we estimated the average treatment effect on the treated (ATT), using the nearest-neighbor matching method (NNM). This method matches users and non-users/control households based on observable characteristics and calculate the mean difference in outcomes between the two groups (Quisumbing et al. 2011). Thus, the control group is matched on the probability (propensity score) of adopting the land management practices given a set of observable characteristics from the probit regression model. When matching users with non-users, we used the following definitions for user households: (1) the household implemented and continues to maintain stone/ soil bunds or grass strips on their cultivated land and (2) the household implemented the structures at least on 1/4 of the total cultivated land.

The user households are paired with the non-users when their respective observable characteristics are similar, as determined by a weighted average of the distance between the values of the observed characteristics. The comparison households with propensity scores that are nearest to user households receive the highest weights and are matched accordingly. We trimmed five percent of the sample from the top and bottom of the non-participant distribution in terms of propensity scores to ensure comparisons over the same propensity score range. Then we compare average outcomes of the user households with the matched non-user/comparison households. Once a balanced sample is realized, NNM technique was applied to estimate the average treatment effect of using the physical land management practices.

Each user household is matched to a non-user household with its closest propensity score allowing for five nearest neighbors in terms of absolute difference in propensity scores. Thus, for each household i, there are two potential outcomes: using the physical land management practice or not using. We denote users as $A_{i(1)}$ and non-users as $A_{i(0)}$, whereby the impact of using the practice is the difference in outcome between users and non-users ($\Delta = A_1 - A_0$). Thus, D is an indicator variable equal to 1 if the household uses the practice and 0 otherwise. Then we find the average impact of the treatment on the treated (ATT) as follows when X is a vector of control variables:

$$ATT = E(\Delta | X, D=1) = E(A_1 - A_0 | X, D=1) = E(A_1 | X, D=1) - E(A_0 | X, D=1) \ldots\ldots\ldots\ldots\ldots \text{(7.7)}$$

There are two key results from this analysis. The first result is obtained from estimating the probit model which predicts the probability of each household using the land management practice. This result allows us to identify specific household level determinants of using the physical land management practices, controlling for initial characteristics. The probit model is also integral to obtaining a balanced sample of user and non-user observations that help us to estimate impact. The second result estimates the average impact of climate-smart land management practices through measuring the difference in total value of production between users and non-users.

7.2.2.3 Continuous treatment effect estimation

We followed Hirano and Imbens (2004) to estimate the continuous treatment effect. For this purpose, farm plots were indexed by I where i=1, 2… N and letting t=T where t is the level of treatment defined as the number of years a household has been implementing the selected climate-smart land management practices on a specific plot. Accordingly, there is a certain level of potential outcome, $Y_i(t)$ capturing a response to a level of treatment. A continuous treatment is considered where the treatment level lies in the interval $[t_{0,} t_1]$ and defines the potential outcome as value of production per hectare. For each plot, observation is made on the treatment level, vector of covariates X_i, and potential outcome corresponding to the received level of treatment with the interest of calculating the average dose response function defined as $\mu(t) = E[Y_i(t)]$.

Un-confoundedness for binary treatments given a set of covariates explaining adoption and non-adoption is generalized by Hirano Imbens (2004). Following this, in a continuous treatment case conditional on a set of covariate Xs, the extent of treatment is also random. The assumption is that the number of years of maintaining the land management structures is random conditional on a set of plot and household characteristics. Since the length of time for maintenance also depends on unobservable characteristics of the farmers, we proxy the decision to invest labor/and or finance by including a binary variable that denotes manure and fertilizer application. Thus we assume that farmers that decide to invest on agricultural inputs such as manure and fertilizer may have other non-observable traits that can be linked to investment decisions on agricultural technologies. Thus, we captured some of the non-observable characteristics by including these covariates.

We define the generalized propensity score (GPS) following Hirano Imbens (2004). Let $r(t, x) = f_{r/x}(t, x)$ be the conditional density of the treatment given the covariates, and then the GPS is $R = r(T, X)$. As in the case of binary propensity score, GPS has a balancing property that ensures within each given strata (where the conditional density holds the same value), the probability that T=t does not depend on the covariates X. The estimation of the dose-response function requires that we first compute the conditional expectation of outcomes as a function of the treatment level t and the GPS score R. Then the dose response at a particular t level of treatment is the conditional expectation over the GPS and given by:

$$\mu(t) = E[\beta(t, r(d, X))] = E[Y(t)] \text{ where } \beta(t, r) = E[Y / T = t, R = r] \quad \ldots\ldots(7.8)$$

In order to implement the above estimation, the first stage estimates the treatment level given the covariates: $T_i / X_i \sim N\left(\beta_0 + \beta_1' X_{i,} \sigma^2\right)$. In the simple normal model β_0, β_1, σ can be estimated by maximum likelihood. The GPS is thus estimated as:

$$\hat{R}_i = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} \exp\left(-\frac{1}{2\sigma^2}\left(T_i - \hat{\beta}_0 - \hat{\beta}_1 X_i\right)^2\right) \text{...(7.9)}$$

In the second stage, the conditional expectation of Y_i given T_i and R_i is estimated using a quadratic approximation as suggested by Hirano Imbens (2004).

$$E[Y_i, R_i] = \alpha_0 + \alpha_1 T_i^2 + \alpha_2 T_i^2 + \alpha_3 R_i + \alpha_4 R_i^2 + \alpha_5 T_i R_i \text{ ………………………………….…….. (7.10)}$$

The parameters $(\alpha_0, \alpha_1 .... \alpha_5)$ are estimated using the calculated GPS R_i by ordinary least squares. Given the second stage estimated parameters, the average potential outcome at the treatment level t is estimated to obtain the entire dose response function. We used bootstrap methods to calculate more robust estimates, standard errors and confidence intervals. The results and discussion section presents results for both binary treatment at household and plot level as well as the continuous treatment effects at plot level.

7.3. Results and Discussions

7.3.1 Description of users and non-users of climate-smart land management measures

Responses to climate shock through use of different land management measures are common in both agro-climatic zones though intensity of use shows some degree of variation. Soil and water conservation measures and agronomic practices are common among the smallholder farmers in the study area. The relevance of these measures is reported to be increasing from time to time to adapt agricultural practices to the challenges of declining productivity attributed to climate factors (Yesuf et al. 2008). The crux of this paper is to assess responses to climate variability and change through long term land management practices including soil bunds, stone bunds, grass strips and to measure the impact of these practices at household and plot level.

Unlike short term land management technologies that reap increased yields within a season or a year, benefits from long term measures may accrue over longer time horizons. Given this lag, the household survey for this study was designed to take into account previous land management intervention that farmers have implemented and the length of time that the practices have been maintained. Here, only three types of climate-smart land management practices namely soil bund, stone bund, and grass strip were identified as the most common long term practices in the area. Accordingly, households that constructed and maintained any of these practices on at least on 1/4 of their cultivated land since 2004 and onwards and maintain the structures until the date of the survey in 2016 are considered users/adopters. With this criterion, 41 per cent of the responds are found to be users of the practice.

Comparison is made between the users and non-users of the land management measures in terms of socio-economic and environmental variables. The results revealed that households with farmland that is poor in fertility and steeper slope have adopted the land management practices than those households with fertile plot and plain field. Moreover, significant percentage of the users have applied fertilizer and manure and received extension advice on soil conservation measures. The comparison also revealed significant differences between users and non-users in terms of frequency of challenges faced from extreme climate events, time spent in non-farm activities, cultivated land size, literacy level and other household characteristics (Table 7.1).

Table 7.1 Comparison of users and non-users of the selected land management practices

Variable	Non-users	Users	Mean difference (p value)
HH head age (years)	46.4	43.7	0.00
HH head sex (male=1)	0.9	0.8	0.87
Education (literate=1)	0.4	0.5	0.03
Household size (number)	5.9	5.8	0.61
Time spent on non-farm activity (months)	3.5	4.3	0.00
Land size in hectares	4.3	5.4	0.45
Household experienced erosion (yes=1)	0.2	0.3	0.05
Household experienced drought (yes=1)	0.4	0.6	0.03
Adult equivalent ratio	3.3	4.3	0.72
Steep slope (proportion)	0.1	0.3	0.00
Mixed slope (proportion)	0.05	0.1	0.21
Manure use (proportion of farmers)	0.4	0.6	0.04
Fertilizer use (proportion of farmers)	0.3	0.6	0.05
Received credit (yes=1)	0.3	0.3	0.24
Semi-fertile plots (proportion)	0.3	0.4	0.13
Non-fertile plots (proportion)	0.2	0.4	0.00
Extension advice (yes=1)	0.4	0.8	0.00
Distance from market (km)	5	4.6	0.22
Wet lowland (1=yes)	0.2	0.3	0.00
Dry lowland (1=yes)	0.3	0.2	0.00

Following the comparison, the overall effect of the climate-smart land management practices is assessed through matching all user households with non-use households. In doing so first we made a probit model estimation to identify determinants of the use of the practices and then evaluate if any impact exists due to the practice at household and plot level. To account for the hypothesized time lag for benefit realization, we split the user sample by the reported date that the land management measures were first installed on the plots. Then, we separately evaluate users that installed the structure during the initial period (2004–2009) and in the recent period (2010–2016). The analysis started since 2004 because only 6 percent of the total users implemented the practices in any given year prior to 2004. For each of these periods, a separate NNM estimation was undertaken, maintaining the same variables for each analysis with a balanced sample.

7.3.2 Determinants of climate-smart land management practices

Given that a variety of differences exist between users and non-users of the land management practices, it is important to control for these potential underlying effects in order to ensure reliable impact estimates. The Probit model is used to match user and non-user households and to provide information on the household's probability of using the land management practices on cultivated land. The probit regression results for household-level and plot-level determinants of the land management practices are presented in Table 7.2 and Table 7.3, respectively.

The results from the probit model estimation indicate that biophysical factors such as share of non-fertile lands and slope category of a plot are significantly different between users and non-users suggesting that these factors are correlated with land management decisions. On the average, probability of using climate-smart land management practices increases by 21.1 percent as the proportion of plots with steep slope increases by 1 percent. This finding is in line with Lobell et al. (2008) who reported a positive relationship between slope category of a plot and land management decisions.

Respondents that have past experience of soil erosion problems are more responsive through climate-smart land management measures to combat similar future incidents. The probability of implementing the practices increases on average by 2.3 percent for households that have past experience of erosion risk. Users of the land management practices have also past experience of crop failure due to terminal moisture stress and depletion of soil fertility as compared to the non-users. In this regard, the probability of adopting the practices increases by 1.1 percent for households that have experience of crop failure due to drought. Likewise, probability of using the practices increases in a range of 3.9 percent to 7.1 percent as the proportion of infertile and semi fertile plots increases by 1 percent. Similarly, the probability of implementing climate-smart land management practices increases by 42.1 percent as the proportion of non-fertile plots increases by 1 percent.

Table 7.2 Probit results for household-level determinants of land management practices (2004-2016)

Variable	**dy/dx**	**Std. Err.**
HH head age (years)	0.035	(0.021)
HH head sex (male=1)	0.003	(0.021)
Land size in hectares	0.024 **	(0.011)
Household experienced erosion (yes=1)	0.023 *	(0.041)
Household experienced drought (yes=1)	0.011 **	(0.025)
Household size (number)	0.021	(0.003)
Adult equivalent ratio	0.013	(0.011)
Non-farm employment (months)	0.001	(0.011)
Steep slope plots (proportion)	0.211 ***	(0.032)
Mixed slope plots (proportion)	0.018	(0.028)
Manure/fertilizer use (yes=1)	0.053***	(0.061)
Education of HH head (literate=1)	0.031	(0.017)
Semi-fertile plots (proportion)	0.071**	(0.037)
Non-fertile plots (proportion)	0.039 **	(0.062)
Extension advice (yes=1)	0.053	(0.024)
Distance from market (Km)	-0.031 **	(0.011)
Wet Kola agro-ecology (1=yes)	0.241 ***	(0.028)
Dry Kola agro-ecology (1=yes)	0.067 **	(0.046)
Assosa Woreda	0.261***	(0.053)
Bambasi Woreda	0.217 ***	(0.101)
Sherkole Woreda	0.042 *	(0.006)
Mengie Woreda	0.135*	(0.015)
Number of observations=506		
Wald chi2(20) =218.21		
Prob > chi2 =0		
Pseudo R2 =0.3232		

Note: *, **, and *** are significance level at 10%, 5% and 1%; Dependent variable: household that used climate-smart land management practices (soil/stone bund, grass strips) on at least 1/4 of cultivated land (Yes=1)

Distance from market revealed significant negative correlation with probability of using the land management practices. The probability of implementing the practices decreases by 3.1 percent as distance from market increases by 1 kilometer. This finding may reveals that if farmers do not realize a market outlet for increased production, they may be less willing to implement the structures that could increase yields. Moreover, fertilizer/manure application is a matching binary variable used as a proxy to the willingness of a farmer to invest money/labor in technologies /innovations. The result shows that the decision to apply fertilizer/manure is positively related with the land management decision verifying the willingness of the users to invest in productivity enhancing technologies. The probability of practicing the land management measures increases by 5.3 percent for those households who are using fertilizer or manure on their cultivated land. The plot level analysis also revealed that the probability of implementing climate-smart land management practices increases by 14.3 percent for plots that received fertilizer or manure.

Table 7.3 Probit results on plot level determinants of land management practices (2004-2016)

Variable	dy/dx	Std. Err.
HH head age (years)	0.021	(0.018)
HH head sex (male=1)	0.023	(0.001)
Household experienced erosion (yes=1)	0.034 *	(0.032)
Household experienced drought (yes=1)	0.141 **	(0.025)
Plots with steep slope (proportion)	0.301 ***	(0.022)
Plots with mixed slope (proportion)	0.015	(0.006)
Percentage of plots received manure/fertilizer	0.143***	(0.001)
Education of HH head (literate=1)	0.044	(0.008)
Semi-fertile plots (proportion)	0.043**	(0.011)
Non-fertile plots (proportion)	0.421 **	(0.004)
Extension advice (yes=1)	0.048*	(0.001)
Plot size (hectare)	0.014*	(0.021)
Number of observations=506		
Wald chi2(12) =241.31		
Prob > chi2 =0.000		
Pseudo R2 =0.2412		

Note: *, **, and *** are significance level at 10%, 5% and 1%; Dependent variable: plots that received climate-smart land management practices (soil/stone bund, grass strips) (Yes=1)

It is important that the probit model results discussed above includes covariates that would not have changed after adopting the land management measures. For example, we included total landholding size, biophysical characteristics of the agricultural land such as soil fertility and slope, and a household head's characteristics, which are less likely to change over the study period. In order to control for endogeneity, we did not match user and non-user households based on assets which may have been affected by the successful or unsuccessful investment in the land management practices (e.g. variables that proxy income such as changes in livestock holdings).

7.3.3 Impacts of climate-smart land management practices on value of production

Propensity scores are estimated both for the treated and control households (Figure 19). The estimated propensity scores for the treated households vary between 0.069 and 0.964 with mean of 0.688. For the control households the estimated propensity scores vary between 0.005 and 0.928 with mean of 0.401. Therefore, the common support region lies between 0.069 and 0.928. Flowing Caliendo and Kopeinig (2008), to evaluate the average treatment (ATT) effect on the treated, it is important to ensure that for each treated household a close non-treated is found. To ensure this, the households whose estimated propensity scores less than 0.005 and larger than 0.928 are not considered for the matching exercise and hence a total of 10 observations have been dropped.

It is assumed that most land management practices require a longer time horizon to generate significant benefits to the user households. In this regard, the impact of the practices is analyzed in two ways. First the impact on the value of production is analyzed using the entire sample considering the households that implemented the practices between 2004 and 2016. Then, in order to take into account the time lag in the land management benefit, the sample is splinted between early users (2004-2009) and late users (2010-2016).

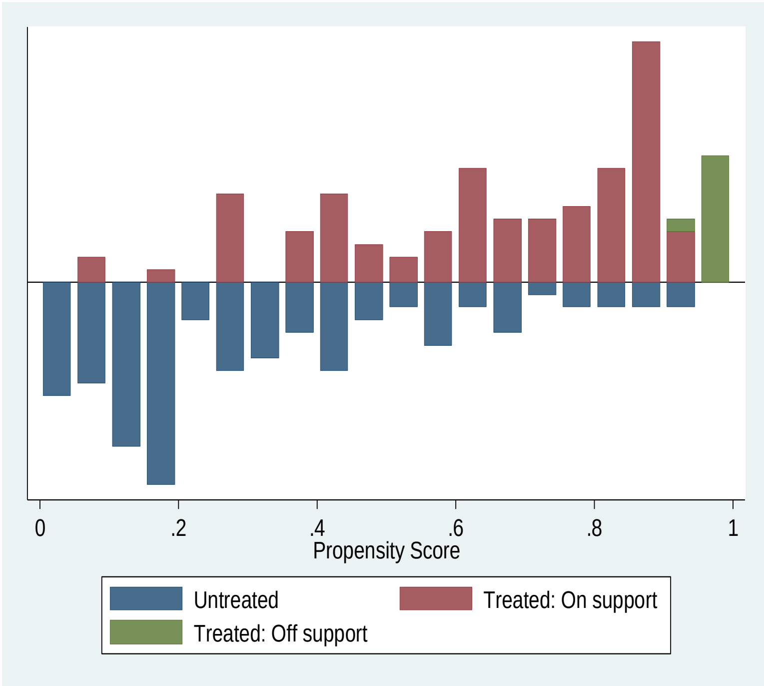

Figure 19 Common support of the propensity scores

The result shows that households that implemented the climate-smart land management practices in the initial period (2004-2009) gained a 24.1 percent higher value of production (significant at $P<0.001$) in 2016 compared to the matched households that did not implement the practice (Table 7.4). However, the households that adopted the practices in the later years (2010-2016) did not realize a significant increase in value of production compared to the matched households that did not implement the practices. This could be attributed to the fact that the time is not sufficient to allow the late users realize the effects of the practice in terms of replenishing soil nutrients that could help increase agricultural production. The result also implied that the impact of using the land management measures is not significant when the entire sample (2004-2016) is used showing only a three per cent higher value of production over the non-users (Table 7.4). This is attributed to the fact that the late users have yet to experience increase in production and hence miscomprehend the gains by early users.

Table 7.4 Household and plot level impacts of climate-smart land management practices

Impact	**Outcome variable (**Value of production)	ATT	SE	Observations
Household level	2004-2009	0.241***	0.081	602
	2010-2016	0.013	0.044	614
	2004-2016	0.030	0.044	614
Plot level	2004-2009	0.286***	0.021	903
	2010-2016	0.015	0.041	915
	2004-2016	0.048	0.031	915

Note: ATT: Average Treatment Effect on the Treated; ***significant at ($P<0.001$)

The household level aggregation is based on the threshold that the users implemented the land management structures on at least 1/4 of their cultivated land. The plot-level disaggregated analysis allows a robustness check of the impact at the household level and across plots given the differences in soil fertility, slope, soil degradation prevalence, and application of external inputs such as manure and fertilizer. In this regard, the plot-level results are reflections of the household level analysis. Accordingly, plots that received the land management measures in the first period (2004-2009) experienced a 28.6 per cent increase in value of production (significant at $P<0.001$) compared to matched plots that did not receive the measures (Table 7.4). On the other hand plots that received the practice in recent period (2010-2016) had no significant increases in value of production compared to the matched plots. The plot level impact for the entire period (2004-2016) revealed a five per cent increase in the value of production over the matched plots, though the increase is not statistically significant.

7.3.4 Sensitivity analysis

Rosenbaum Bound sensitivity test for possible hidden bias is presented in Table 7.5. As depicted in the Table, the impact of climate-smart land management practices on the value of production is inferred with the critical level of gamma (eγ). The effect of practicing the land management (treatment effect) measures are found to be significant at P<0.001 showing that the inference for the effect of practicing the land management measures is not changing when the odds of being treated for both users and non-users is changed twice (eγ =3) in terms of unobserved covariates. The outcome variable which is estimated at various level of critical value of eγ is significant and this indicates that all the important covariates that affected the use of climate-smart land management practices are well addressed in the impact analysis.

Table 7.5 Rosenbaum Bound sensitivity analysis test for hidden bias

Gamma (e^{γ})	*p – critical*
$e^{\gamma}=1$	0
$e^{\gamma}=1.5$	0
$e^{\gamma}=2$	0
$e^{\gamma}=2.25$	2.80e-12
$e^{\gamma}=2.5$	4.70e-18
$e^{\gamma}=2.75$	5.80e-14
$e^{\gamma}=3$	6.60e-16

Based on the sensitivity analysis, the estimated ATT is not rejected at all critical values even when we set eγ at the largest value (eγ =3) compared to the value set in different literatures eγ =2 (100%). Therefore, the sensitivity analysis tends to show that the estimated impact (ATT) is mainly the effect of the climate-smart land management practices on value of production for both household and plot level cases. Hence, the estimated household and plot-level impact are insensitive to an unobserved selection bias.

7.3.5 Continuous treatment effect estimation results

The continuous treatment estimation procedure proposed by Hirano and Imbens (2004) is customized to evaluate the payoff period and marginal effects of the climate-smart land management measures on crop productivity expressed in terms of value production per hectare. Based on this approach, we estimated how the plot level value of production varies depending on the number of years that the land management measures are maintained. The Impact is evaluated at plot level since the households implement the land management structures on diverse plots in different years. The difference in impact is evaluated based on the length of time that the practices are maintained on a specific plot.

First, we estimate the conditional distribution of the number of years the land management measures are maintained given a set of covariates. The treatment level (defined by number of years) is estimated in order to obtain a GPS using the plot and household characteristics. Then the treatment distribution is divided by the treatment level whereby we define three time intervals in years: [1, 4], [5, 8] and [9, 12] and for each interval a group of observations are identified. Accordingly, there are 390, 259, and 266 observations in each group, respectively.

For each of the covariates in the first regression, we test that the mean of one group is similar to the other two groups combined, and thus we are able to satisfy the balancing property. Table 7.6 presents whether the GPS actually balances the set of variables in the different intervals of the treatment level. The first three columns presented the test whether the covariates have the same mean for observations within the same treatment intervals using the raw data. In this case, the raw data are unbalanced for most of the covariates as implied by significant mean differences. In contrast, the last three columns are mean differences after adjusting for the GPS to see whether the covariates are better balanced conditioned on the estimated GPS. When comparing the two sets of results, one can see that the covariates are better balanced after the GPS adjustment as implied by non-significant mean differences.

The test result in Table 7.6 reveals that adjusting for the GPS improves the balance of the covariates across the treatment intervals, and the next step is estimating the second stage model that generates OLS estimates on log of value of production. Based on Hirano and Imbens (2004), the parameters of the second-stage estimation do not have a direct meaning rather they are primarily used to test whether the covariates introduce any bias.

Following the bias test, we generate the derivative of the dose-response function, which reveals the marginal effect of an additional year of maintenance of the land management structure. The result suggests that maintenance of the structures is crucial to reap significant benefits from the resources invested on the practices. In this regard, users that maintain the practices for at least six years experienced a positive increase in value of production at the end of the 6^{th} year (Table 7.7).

Table 7.6 Test for equality of means between treatment groups

Variable	Raw data treatment terciles			Data adjusted by GPS		
	[1,4]	[5,8]	[9,12]	[1,4]	[5,8]	[9,12]
HH head age (years)	-0.32	0.88**	-0.08	-0.28	1.01	-0.18
HH head sex (male=1)	-0.01	-0.21	-0.01	0.00	0.00	0.01
Household experienced erosion (yes=1)	-0.43*	-0.10	0.26*	-0.23	0.00	0.16
Household experienced drought (yes=1)	-0.32*	-0.11	0.16	-0.11	0.01	0.11
Steep plot (yes=1)	0.01	-0.21*	0.00	0.01	-0.11	0.01
Manure/fertilizer (yes=1)	-0.12*	0.00	0.11*	-0.02	0.00	0.01
Education of HH head (literate=1)	0.00	0.01	0.01	0.01	0.01	0.00
Semi-fertile plot (yes=1)	0.21**	0.01	0.23**	0.0	0.00	0.01
Non-fertile plot (yes=1)	-0.12**	0.01	0.09**	-0.02	0.01	0.00
Plot size	-0.22*	0.01	-0.00	-0.02	0.01	-0.01

Note: GPS: Generalized propensity score; **and * are significance level at 5% and 10%, respectively

As shown in Table 7.7, users that have maintained the practices for less than six years do not experience a statistically significant impact on the value of production as implied by insignificant marginal effects during the initial six years of implementation. The negative marginal effects suggest that the climate-smart land management practices may require a longer time horizon to slow down soil loss and reach a point where nutrient replenishment and other biophysical improvements are realized to a full potential.

Table 7.7 Estimated marginal effect per additional year of maintenance

Years	**Marginal effects**
1	-0.1
2	-0.08
3	-0.05
4	-0.03
5	-0.01
6	0.04*
7	0.06*
8	0.08*
9	0.10*
10	0.12*
11	0.14*
12	0.16*

Note: *significant at 10% level

Beyond the sixth year, maintaining the land management structures results in positive marginal benefits that increase at an increasing rate. Thus, for each additional year one sustains the climate-smart land management practices, the higher the gains in value of production. As indicated in Table 7.7, if a household sustains the land management structures for 8 to 9 years, the value of production would increase by about 10 percent and if a household continues to maintain the structures for 11 to 12 years the expected value of production increases by 16 percent. In this regard, maintenance should continue as far as the increase in marginal benefit becomes statistically insignificant. However, since the number of observations is negligible for households that sustained the land management structures for more than 9 years, further enquiry is required to fully understand the impacts of long-term maintenance. Once the soil degradation problems are successfully controlled and the necessary soil components are replenished after long-term maintenance of the land management structures, one would expect diminishing returns to such practices. Therefore, further research over a longer time period may provide an estimated envelope of the benefits and marginal returns of the climate-smart land structures in the study area.

7.4 Conclusions and Policy Recommendations

This study explored the household and the plot level impacts of climate-smart land management practices (physical measures) on value of production among the users given the difference in length of time that the structures are maintained. The result revealed that households that implemented the physical land management practices during the period (2004–2009) experienced a 24.1 percent higher value of production in 2016 compared to the non-users. Conversely, households that implemented the practices in later years (2009–2016) have no significant increases in value of production. The plot-level analysis suggests similar impact; whereby the plots that received the physical land management measures in the first period have 28.6 percent higher value of production in 2016 compared to the matched-plots that did not receive the practices. The analysis also showed that long term maintenance of the land management structures is crucial and the users that maintain the structures for at least 6 years experienced a positive increase in value of production at the end of the 6^{th} year.

Climate-smart land management practices are knowledge, labor and time intensive and may not be implemented easily given the awareness level and resource endowments of the smallholder farmers. Therefore, scaling up of the practices requires interventions that provide technological and training support. Creating market access may also motivate farmers to decide on the land management investment and long-term maintenance, for it helps to boost agricultural surplus, lower transport costs and improve input distribution mechanisms. Longer maintenance of the climate-smart land management structures provides sustainable and greater payoffs overtime. Given the situation in the study area, significant benefits are experienced when the structures are maintained at least for six years. In line with this, further research could come up with a policy options that encourage farmers to accept longer time horizons. Besides, further research is required to provide an estimated envelope of long term benefit and marginal returns of the climate-smart land management practices. Likewise, modeling of the synergetic effects and complementarities among the different land management measures is an important gap the need to be addressed through future research.

Chapter Eight

8. Synthesis

Climate change intensified land degradation has become a major threat to those whose livelihood is strongly attached to the subsistence agriculture on degraded areas. Various studies have indicated that Sub-Saharan Africa is seriously threatened by land degradation (Woodfine, 2008) and Ethiopia is among the countries in sub-Saharan Africa that are reported to suffer severe land degradation problem, aggravated by current climate trends. The agricultural sector in Ethiopia is characterized by a volatile production as compared to most developing countries and in most cases unable to keep pace with the population growth. As a result food insecurity and pervasive poverty typify the country as this desolates the lives of the significant portion of the population.

Climate change intensified land degradation problem mainly occurring in the form of accelerated soil loss and nutrient depletion can be singled out as a formidable threat to agricultural production self-sufficiency goal of the country directly affecting the livelihood of the smallholder farmers and significantly costing the national economy (FAO 2014). Consequently, the objective of increasing production, reducing vulnerability of the subsistence farmers and using natural resources sustainably (termed as *'a critical triangle'* of development objectives) (Vosti and Readon 1997) is challenged by pervasive poverty, resource depletion and declining productivity which co-exist with some sort of spiral relationships (termed as the *down spiral of land degradation and vulnerability*)(Scherr 2000). The notion behind the downward spiral is that subsistence farmers are compelled to apply unsustainable farming practices that further erode the natural resource base, reduce crop yield, and in turn, promote vulnerability being aggravated by climate factors (Way, 2006).

The challenge is, therefore, how to reconcile the three objectives of increasing production, reducing vulnerability and using natural resources sustainability in the face of changing climate (McCarthy 2011). This requires carful assessment of the nature of the linkage among climate change intensified land degradation and productivity, which can also be translated into the linkage among climate-smart land management strategies, agricultural productivity and rural livelihoods (Pretty 2008). In recent years, much research related to land resources has been conducted in the country. Yet few studies have systematically addressed the linkage between climate-smart land management practices and productivity and its implication to the rural livelihood in the face of climate change and variability. More importantly, previous research efforts failed to adequately addresses how climate-smart land management strategies affect one another and how the practices are linked to crop yield variability and land productivity.

It is to be recalled that the objective of this research was to investigate autonomous climate-smart adaptation strategies and the impact of these strategies on crop yield variability, land productivity and rural livelihoods in the Dabus Sub-basin of the Blue Nile River. In the process, the research assessed vulnerability of smallholder farmers to climate change and variability; investigated farmers' two stages process of adaptation to climate change (perception then adaptation); identified factors affecting the use of different climate-smart land management practices as adaptation strategy; examined the causation among different climate-smart agricultural practices; identified the link among climate-smart land management decisions, crop yield variability, and crop productivity; and determined the impact of climate-smart land management strategies on crop productivity. This chapter presents the synthesis of the main findings and their implication for sustainable agricultural livelihood in the face of changing climate and variability.

The study customized the concept of the *critical triangle* of development objectives (Vosti and Readon 1997), to reconcile the three objectives of increasing production, reducing vulnerability of subsistence farmers and using natural resources sustainably in the face of changing climate. The findings in the study are in line with the core aspects of the notion of the *critical triangle* and proved that land degradation problems in the study area result in high crop yield variability and low productivity (*downward spiral of land degradation*), among other consequences, and in turn contributes to vulnerability of rural livelihoods to climate change induced hazards. If this remains unchecked, the vulnerability may further contribute to land degradation as subsistence farmers lack the ability or the incentive to invest in conserving and managing their land. This makes the land more impoverished, which further impoverishes the already vulnerable subsistence farmers. Thus, if the land degradation challenge in the subsistence livelihood system is to be addressed, there is a need to first tackle vulnerability of subsistence farmers to climate change and variability.

Social, institutional, natural and technological constraints resulted in lower farmers' perception and limited adaptive capacity to climate change intensified land degradation problem in the study area. This ultimately resulted in a circular/spiral relationship that the land degradation problem leads to further vulnerability as being sated in the notion of the *down spiral of land degradation and vulnerability* (Scherr 2000), which is the poverty-environment interaction side of the *critical triangle*. Thus, the subsistence and vulnerable farmers may be forced to degrade the land in response to climate induced hazards unless efforts are made to reduce their vulnerability through enhancing their subjective and objective adaptive capacity.

In the context of the study area, subsistence and vulnerable farmers have limited livelihood assets but exerted considerable effort in conserving their land. This is contrary to the notion of the *down spiral of land degradation and poverty/vulnerability* side of the *critical triangle* but in line with other empirical evidences (Nkonya 2008; Way 2006) that argued subsistence and vulnerable farmers are not always responsible for land degradation, but they have interest and capacity in managing their land either by mitigating the effects of climate change on their livelihoods or by rehabilitating the degraded land resources. Subsistence farmers' decision to adopt different climate-smart agricultural practices as a protective measure to climate-change persuaded land degradation is also contrary to the notion of the *down spiral of land degradation and poverty/vulnerability* but in agreement with the empirical arguments against this notion that include (Nkonya et al. 2011; Mengisu 2010; Forsyth et al. 1998).

Theoretical and empirical evidences generally revealed that there is striking heterogeneity regarding land resource management by subsistence farmers. In whatever direction, enhancing use of climate-smart land management practices is a critical aspect in addressing vulnerability of subsistence farmers in the study area as evidenced by the effect of the practices in reducing crop yield variability (production risk management impact) and augmenting productivity (productivity and livelihood impact). However, success of the subsistence farmers in implementing the practices is a function of endogenous factors (farmer related) and exogenous factors (policies, institutions, environment, and technologies) that influence the outcomes (livelihood impacts in terms of reduced crop yield variability and enhanced productivity) as clearly indicated by the conceptual framework of this study, which is customized from the notion of the *critical triangle* of development objectives.

8.1 Vulnerability to Climate Variability and Change

The Dabus sub-basin is characterized by diverse environmental, social, demographic and economic factors. In order to capture the diversity in the sub-basin, the vulnerability analysis is aggregated at agro-ecology level in reference to the moist lowland the dry lowland (**Chapter 2**). The dry lowland agro-climatic zone of the Dabus sub-basin is characterized by a higher exposure and sensitivity to climate stresses with a comparatively limited adaptive capacity as compared to the wet lowland. As a result, this agro-climatic zone is more vulnerable to climate change and variability than the wet lowland. The wet lowland exhibits intermediate vulnerability with a relatively lower perceived exposure and higher adaptive capacity (**Asrat and Simane 2017a**).

The vulnerability analysis revealed the prominent factors that induce exposure and sensitivity to climate risks as well as the barriers that stress adaptive capacity. Exposure to climate risk is induced by natural disaster and climatic variables in both agro-climatic zones, while lack of sustainable land use system is the major responsible factor for the sensitivity of smallholder farmers to climate risks in both agro-climatic zones. Agricultural technologies, infrastructure, and knowledge are detrimental to the adaptive capacity of smallholder farmers in both agro-climatic zones.

Given the exposure, sensitivity and the prevailing autonomous adaptive capacity of smallholder farmers in the Dabus sub-basin, the specific interventions that may call for policy attention include supporting alternative livelihood options based on available resources, water harvesting for supplementary irrigation, and early warning system on extreme events. Along with these, it is vital to enhance the skill and literacy level of the smallholder farmers through informal education programs (**Chapter 2; Asrat and Simane 2017a**).

8.2 Climate-Smart Adaptive Responses

Given the vulnerability level, climate change adaptation in smallholder agriculture is vital to improve agricultural productivity and the livelihood of smallholder farmers (Deressa et al. 2011). Adaptation to climate change is a two-step process which requires that farmers first perceive climate change and respond to the changes in the second step through adaptation (**Chapter 3**). The dry and the wet lowland agro-climatic zones of the Dabus sub-basin share some exogenous variables that commonly affected climate change perception and adaptation. The two agro-climatic zones also diverge in terms of other exogenous variables that affect perception and adaptation to climate change and this divergence dictate the need to have location-specific intervention to enhance smallholder farmers' perception and adaptation to climate change (**Asrat and Simane 2018a**).

The problem of climate change is well perceived and adaptive responses are being made to minimize the negative effects that compromised farm productivity in the Dabus sub-basin. Climate change perception is more pronounced in the dry lowland agro-climatic zone owing to the occurrence of repeated extreme climate events and other environmental changes that cause reduced water availability and agricultural yield in the dry lowland agro-climatic zone. However, the implementation of adaptation measures is more prevalent in the wet lowland agro-climatic zone attributed better subjective and objective adaptive capacity (**Chapter 3**).

The relevance of climate-smart agricultural practices as adaptation strategy is increasing over years in the Dabus sub-basin to lessen the vulnerability of the agricultural livelihood to climate challenge. Climate-smart agricultural practices such as adjusting planting date and early maturing crop varieties are flattering in both agro-climatic zones of the Dabus sub-basin in response to the late onset of the rainy season and the incidence of terminal moisture stress. Crop diversification is also an emerging climate-smart adaptation strategy attributed to the enhanced farmers' risk aversion behaviour being induced by climate change factors. Particularly, diversifying crop types into high-value horticultural crops is a new development in the sub-basin aiming at intensifying the use of scarce farm resources (**Asrat and Simane 2018a**).

In the Dabus sub-basin, smallholder farmers are more likely to implement structural and non-structural soil conservation measures as adaptation strategy on a part of their agricultural land that are more susceptible and where they expect more risk from climate hazards (**Chapter 4**). The knowledge gained through training and education make smallholder farmers far-sighted to look for long-term benefits rather than immediate gains and equip them with the technical know-how required for implementing climate-smart land management practices as adaptation strategy in their agricultural production system. In the sub-basin, like any rural livelihood system in Ethiopia, women-headed-households are constrained by labor shortage as they bear more burdens of the family responsibilities. They also lack access to resources, information and economic opportunities, which ultimately jeopardize their subjective and objective adaptive capacity (**Asrat and Simane, 2017b**).

8.2.1 Causality of climate-smart land management decisions

In the Dabus sub-basin smallholder farmers implement climate-smart land management practices in response to perceived hazards of climate risks although the implementation is not to the adequate level owing to various impeding factors (**Chapter 5**). Two categories of short-term land management strategies that involve the application of external inputs and modification of existing cultivation practices are examined for their causality and interdependence in the context of the Dabus sub-basin (**Asrat and Simane 2018b**).

Fertilize and manure

The two external inputs, fertilizer and manure, being used by the smallholder farmers in the Daubus sub-basin, are proved to have a negative reciprocal causation on one another (**Chapter 5**). The implication of the negative causality is that that the two inputs are substitutes to one another, and hence more use of one input renders less of the other and vice versa (**Asrat and Simane 2018b**). The application of manure is labor intensive while that of fertilizer is capital intensive and hence if farmers can afford to buy fertilizers, they may reduce the labor intensive manure; and if they are endowed with sufficient labor they may not opt for the capital intensive fertilizers. Better use of these short-term land management strategies is revealed in the wet lowland agro-climatic zone owing to more years of farming experience and better access to institutional services.

Beyond the reciprocal relationship, application of these two external inputs is commonly affected by farm household' resource endowments, plot characteristics, and farm distance. Manure application is affected by parcel size, physical land management measures, farming experience, labor endowment, slope of a parcel, fertility level, farm distance and size of farm holding. Use of fertilizer is positively affected by parcel size, livestock holding, perennial crops, and institutional services. Livestock ownership does not affect manure use indicating that availability is not a limiting factor in the Daubs sub-basin. However, livestock holding is a limiting factor for fertilizer use, for it helps to relax the financial constraint that may hider fertilizer purchase (**Chapter 5; Asrat and Simane 2018b**).

Intercropping and conservation tillage

Intercropping and conservation tillage are modifications to the conventional sole cropping and intensive tillage practices in the sub-basin (**Chapter 5**). The intercropping practice involves multiple cropping systems with more intensive and efficient use of agricultural land while offering higher land productivity, enhanced soil fertility and lower crop yield variability as compared to the conventional practices. Conservation tillage is a land cultivation practice with minimum disturbance of the soil aiming at reducing the adverse effects of soil loss while inducing minimal use of external inputs (**Asrat and Simane 2018b**). The two practices are interdependent in terms of sharing the resources at the disposal of the farm households. Intercropping is affected by farm and plot characteristics, household characteristics, institutional variables and implementation of long-term land management practices, which complement the short-term land management practices. The conservation tillage practice is also affected by farm and plot characteristics, complementary long-term soil conservation measures, household characteristics, and institutional factors (**Chapter 5**).

Both the external inputs and the modified farming practices have supplementary and complementary relationships with long-term land management investments that are aimed at reducing the risks from climate-change intensified land degradation problems. This implies that a prior investment in the long-term land management practices induces current decision on the use of the short-term climate-smart agricultural practices. Moreover, parcel size is a crosscutting determinant across manure application, fertilizer use and intercropping practices, which may imply the need to move towards farm consolidation (**Asrat and Simane 2018b)**. The proportion of female members in a household has a positive role on the use of manure as a land management practice implying that the gender role assigns soil fertility management practices partly to female members of a family while male members are more engaged in other agricultural activities.

8.3 Impact of Climate-smart Land Management Decisions

8.3.1 Managing crop yield variability

In the Dabus sub-basin, climate-smart agricultural practices helped smallholder farmers to increase crop productivity through offsetting the yield variability at plot level (**Chapter 6**). In this regard, a range of climate-smart agricultural practices are identified although extensive use of the practices is not common among farmers in the sub-basin. The smallholder farmers are diversifying away from cereal dominance into cash crops cultivation significant part of the diversification being towards drought-tolerant crops. However, there is also market oriented switch towards vegetables being induced by the use of small scale irrigation, and improved access to market, which at the same time helped farmers to intensify the use of increasingly scarce resources such as land and peak period labor (**Asrat and Simane 2017c)**.

The smallholder farmers in the wet lowland agro-climatic zone responded to moisture stress problems through adjusting planting date, having a better perception about the change in the onset of rainfall and possible terminal moisture stress. Similarly, farmers in the wet lowland use physical soil conservation measures better than their counterparts in the dry lowland owing to better awareness they have about these adaptation strategies. The use of the climate-smart agricultural practices generally helped the smallholder farmers to reduce the risks that may lead to crop yield variability in both agro-climatic zones as indicated by the negative yield variance and positive productivity coefficients associated to the practices (**Chapter 6; Asrat and Simane 2018b)**. The present study mainly focuses on the role of the individual climate-smart agricultural practices. However, it is expected that the synergetic effect of the practices could be higher in reducing crop yield variability and this is an important area of focus for the future research endeavor.

8.3.2 Productivity impacts

In smallholder agriculture, the prospect for extensification is very limited or non-existent. Thus the only viable option available to increase agricultural output is through sustainable intensification. Nevertheless, the options to increase agricultural productivity through sustainable intensification are determined by several factors in the Dabus sub-basin (**Chapter 6**). Manure application, intercropping, and conservation tillage are among the climate-smart agricultural practices identified to positively contribute to enhanced crop productivity. The positive effect of manure on crop productivity justifies the crop-livestock sectors complementarity in the smallholder agriculture. The positive role of intercropping practice on crop productivity implies the possibility that intercropping can substitute the less accessible and capital intensive external inputs in the smallholder farming situation. Conservation tillage contributed sustained and increased productivity through conserving soil moisture in the face of critical water shortage, particularly the terminal moisture stress, for crop cultivation (**Asrat and Simane 2017c**).

The positive association between crop diversification and productivity is the reflection of the fact that diversification helps to offset part of farmers' exposure to production and price risks. Sometimes, crop diversification is at the expense of high value crops and this may lead to low income although it helps to increase production and to minimize crop yield variability. The positive role of livestock ownership on crop productivity justifies the complementarity between livestock and crop enterprises in the context of the smallholder agriculture, and this may call for an integrated approach that maximizes benefit from both enterprises. Parcel size has positive effect on crop productivity while land fragmentation negatively contributes to crop productivity. In this regard, the positive effect of parcel size on crop productivity is associated with economies of scale. Conversely, land fragmentation compromised the possibility of economies of scale in smallholder agriculture. The resultant implication from the effects of parcel size and land fragmentation is that land consolidation is a viable option to enhance crop productivity in the Dabus sub-basin (**Asrat and Simane 2017c**).

8.3.3 Livelihood impacts

Physical land management practices require longer time horizon to realize benefits in terms of productivity both at household and plot-level. For this reason, this study assessed crop productivity impact of the physical land management practices taking into account the variation due to time lag (**Chapter 7**).

First, the land management impact is assessed considering households that implemented the practice for the entire period under consideration (2004 and 20160). Second, the impact is assessed categorizing the users into early users (2004-2009) and late users (2010-2016). The assessment revealed that early users of the land management practices gained a higher value of production over the non-users, while the late users are not. The implication is that adequate time is required to allow the practice replenish soil nutrients that could help increase agricultural production (Asrat and Simane 2017d). The productivity impact analysis at plot-level also generated a result consistent with household-level analysis. The plot-level disaggregated result confirmed that plots that received the physical land management measures experienced a higher value of production over the plots that did not receive the practices. In line with this, the sensitivity analysis made for the estimated household and plot-level productivity impact confirmed that the impact is entirely the effect of the physical land management measures (**Chapter 7; Asrat and Simane 2017d**).

The impact of the physical land management measures is evaluated in terms of payoff periods and marginal effects on crop productivity. Maintenance of the land management structures at least for six years is crucial to acquire a benefit out of the practices. A positive increase in value of production is realized after the fifth year in the context of the present study and it is only after the fifth year that marginal benefit start to increase at an increasing rate and leading to a higher gain in value of production. This calls for an intervention that motivate smallholders' investment decision in long-term physical land management measures and an incentive mechanism that make them accept longer time horizons in terms of payoff periods (**Asrat and Simane 2017d**).

8.4 Implication for Sustainable Smallholder Agriculture

The climate vulnerability analysis provide a worthy policy connotations for heightening smallholder farmers' subjective and objective adaptive capacity to climate change and variability. The exposure, sensitivity, adaptive capacity, and the overall vulnerability indices generated can provide useful information to set location specific priorities for intervention that is most needed to cope up with the effects of climate variability and change. Based on the indices of the vulnerability contributing factors and the overall vulnerability, both agro-climatic zones of the Dabus sub-basin should be given due attention in terms of climate specific extension/ training opportunities and agricultural input supply. The exposure levels can be reduced through timely provision of climate specific information that leads to enhanced preparedness amid anticipated extreme events. Availing infrastructural facilities that include input and output market, human health facilitates, and veterinary services can contribute to enhanced autonomous adaptive capacity of smallholder farmers.

Since the vulnerability assessment presented in study followed agro-ecology specific approach, it can only provide an indicative vulnerability for the context under consideration. Moreover, the directionality of most of the indicators used in any venerability assessment is context specific and arguable. Indicators that revealed increased adaptive capacity or reduced vulnerability to climate impacts in a given context may show a different result in a different context or location. Therefore, there may be a need for more detailed agro-ecosystem specific vulnerability analysis through further research.

The factors affecting farmers' perception and adaptation to climate change are directly related to institutions, infrastructure, and technologies. Therefore, policy intervention should gear to ensuring the institutional services, infrastructural facilities and delivering effective adaptation technologies. Ensuring effective and reliable access to climate information and improving farmers' awareness of potential benefits of autonomous adaptation are suggested areas of policy measures. Availability of adaptation technologies should be aligned to agro-ecology-specific contexts to address the negative impacts of climate change on the already weak subsistence agriculture. Development and promotion of farm-level autonomous adaptation should be through effective participation of farmers to ensure its sustainable implementation taking into account specific factors relevant to the nature of the adaptation practices. The process of autonomous adaptation is knowledge and resource intensive, and its implementation could be beyond the capacity of smallholder farmers given the limited awareness and resource endowment at their disposal. These call for a shared vision of all potential stakeholders and public-private partnership.

Direct relationship is explored among decision variables (climate-smart land management practices and their determinants) and outcome variables (crop yield variability and crop productivity). In this regard, increasing parcel size and reducing land fragmentation leads to a win-win outcome of increasing agricultural productivity and reducing land degradation. Parcel size has positive effect on crop productivity while land fragmentation negatively contributes to crop productivity. The positive effect of parcel size on crop productivity is associated with economies of scale. Conversely, land fragmentation compromised the possibility of economies of scale in the smallholder agriculture. The resultant implication from the effects of parcel size and land fragmentation is that land consolidation is a viable option to ease implementation of climate-smart land management practices for lowering crop yield variability and enhancing land productivity. Generally, parcel size deserves a special mention as it is positively associated with most land management decisions and crop productivity. Besides, the negative effects of land fragmentation index (expressed as SI index) on the use of the physical land management measures and productivity prompts policy decisions and dictates the need for policy action towards land consolidation in the rural economy.

Perennial crops are important climate-smart investments which lead to ‘win no loss’ outcomes through enhancing soil fertility and reducing degradation without affecting short term productivity. Fertility level of farm plots is among the variables that resulted in a ‘win-win’ outcome of increasing productivity at household level. The soil fertility level positively affects the intercropping practices implying that any effort to improve fertility levels of a soil improves the livelihood of smallholder farmers through enhancing productivity levels. Livestock ownership is positively related to adoption of fertilizer, implying that livestock are important components in a mixed crop-livestock farming systems. Consequently, achieving improvement in agricultural productivity and farm income requires due consideration of the interaction between crops and livestock enterprises.

Contrary to this, there are also decisions that would likely lead to trade-offs between production and sustainability objectives. For instance, involvement in off/non-farm activities generate income for a farm household that may ease immediate liquidity constraint but decreases productivity through diverting the labor input unless the proceeds are re-invested in agriculture. Crop diversification has a positive outcome of increasing productivity through minimizing crop yield variability. However, diversification is sometimes made at the expense of high value crops that may result in more production but less income, which is a typical feature of a dualistic and subsistence agricultural production system in developing countries. This calls for alternative or complementary risk minimizing strategies such as irrigation, drought resistant crop varieties, and crop insurance scheme aligned to the major sources of crop production risk. Parallel to this, there is also a need to look for possible markets linkages for the currently less marketable crops but that are being used in the diversification process.

Complementary and supplementary interactions are confirmed between long-term and short-term climate-smart land management practices. Implementation of the physical land management measures induces the application of short-run climate-smart agricultural practices like manure and conservation tillage. Moreover, increase in proportion of perennials promotes fertilizer application and use of physical land management measures. Parallel to these, access to credit, size of a parcel, use of manure, and conservation tillage have a 'win-no loss' outcome of increasing productivity. The positive effects of extension on the use of fertilizer, intercropping, conservation tillage and use of physical land management measures; and positive effects of training and education on conservation tillage and physical land management measures, calls for public investment in improving extension services, expanding rural education programs and providing farm trainings. The results of this study also provide suggestive evidence that long-term land management investments are complementary with short-term soil fertility management interventions.

The policy implications and the lessons that are drawn from the empirical results of this study are briefly summarized as follows.

1) Supporting short-term and long-term climate-smart land management practices

The long-term physical land management measures increase the probability of implementing the short-term climate-smart agricultural practices. In addition, measures that maintain or improve soil fertility have a positive effect on agricultural productivity as revealed from the significant positive impact of manure, intercropping and conservation tillage on crop productivity. Therefore, the issue of climate-smart land management practices has to receive due attention in an effort to ensure sustainability of the rural livelihood system and the food security goal of the country in the face of climate change. In this regard commitment of every stakeholder is required in fostering the use of the practices through supporting those who already implemented the measures for sustainability; and increasing awareness among non-users to encourage them to adopt in the practice.

It is indispensible that the climate-smart land management measures need to be implemented incrementally based resource endowment of the smallholder farmers and local institutional capacity to support the implementation. Hence, first one can emphasis the short term climate-smart agricultural practice like intercropping and conservation tillage practices that require less of the farm household resources and institutional capacity, followed by manure application that require less of the financial resources but more of the labor input along with concomitant institutional capacity. Finally, long term physical land management measures can be introduced in piecemeal as these require more resources for putting them in place while benefits are only be expected for the years to come. This type of approach may finally lead to a sustainable solution to climate change aggravated land degradation problem.

2) Devising alternative climate-risk management approaches

The study result indicated that crop diversification is an important climate-smart agricultural practice that induces increased crop productivity. However, diversification could affect farm income as it may compromise high value crops as farmers mostly decide diversification in order to minimize production risk at the expense of high value marketable crops. Hence, there is a need to look for other complementary ways of risk minimizing techniques that may include irrigation/water harvesting schemes, introducing drought tolerant varieties, and crop insurance schemes along with creating market linkage for less-marketable crops that are being used for diversification Moreover, it is necessary to identify the specific source of the climate-risk so as to design a relevant intervention for risk minimization.

3) Optimization of climate-smart land management practices

The result of this study showed that the decision to use manure and fertilizer are negatively related to one another. But both of these inputs have merits and demerits in terms of labor and capital requirement. Fertilizer is expensive and inadequate in supply but less demanding of labour in its application. Manure in most of the cases is freely available but is labor intensive in transportation and application. As a result, the choice between the two is mostly based on labor endowments and income levels of farmers. But farmers are traditionally using different levels of both inputs in combination and yet optimum combination of these inputs is not known. Therefore, it is necessary to revisit the traditional combinations and look for a sensible blend of both.

4) Motivation for long-term land management investments

Physical land management measures have longer payoff periods in terms of realizing their effect on crop productivity and household income. This involves both installation and maintenance costs until the benefits are realized out of the practices. This calls for an intervention that motivate the smallholders farmers to make investment in the long-term physical land management measures and an incentive mechanism that make them accept longer time horizons in terms of payoff periods.

5) Farmland consolidation

Fragmentation of farm lands is a widespread phenomenon in the Ethiopian smallholder agriculture system. The fragmentation of farmland into small-sized plots is also becoming an increasing phenomenon in the study area owing to rural population pressure. The findings of this study revealed that parcel size has a positive effect on different climate-smart land management practices and on land productivity. Fragmentation of farm lands as measured in terms of Simpson index resulted in low productivity and lesser payoff from using the land management practices. Therefore, these are indicators for the need to have a program of consolidation that leads to the creation of viable-sized farms, reduction of production costs and cost per unit for constructing the physical land management structures. Under the existing land policy framework, this may be realized through legalizing voluntary exchange of farmlands among farmers that can lead to consolidation and enlargement of parcels. The other option could be creation of farmers innovative platform and production groups where farmers mange, and finance production and management costs together as per parcel sizes and divide the produce among themselves according to the size of parcels. Furthermore, enacting legislation that support consolidation and restrict fragmentation is also a possible option.

6) Non-agricultural employment opportunities

Involvement in off-/non-farm activities may decrease productivity and deter the land management decisions in the short run, for it keeps away farm labor from the agricultural activity. However, it helps to generate additional income that may ease the liquidity constraint for long term investments in climate-smart land management if farmers are persuaded to re-invest the proceeds from non-agricultural employment into agriculture for productivity enhancement. Added to this, given the growing rural population dependent on the agricultural sector, creation of non-agricultural employment alternatives may help to reduce the pressure on the agricultural land resource by pulling-out the surplus agricultural labour, which in turn has the potential to increase marginal productivity and returns to the agricultural labor.

7) Public investment in education/training extension services, and credit schemes

Both training and educational attainment of household heads are found to be important determinants in enhancing farmers knowledge of using climate-smart land management practices. Given the diversified cropping and livestock systems, several natural resource components, and the pressing climate change issues, diversified extension services are supposed to be provided. Therefore, trainings tailored to the impact of climate change intensified land degradation and the benefits of climate-smart agricultural practices need to be launched and/or strengthened. The positive influence of extension service on the implementation of different climate-smart agricultural practices is revealed from this study. More effective benefit can be realised through strengthening and modifying the extension services to address climate-change, natural resource and conservation issues. It is necessary to provide climate-change tailored extension services through equipping the extension agents with appropriate skills, communication and information facilities. Institutional support in terms of facilitating access to input credit is also an important intervention as rural credit is very helpful in relieving capital constraints faced by farmers in using different climate-smart land management practices.

Finally, given the limitations of this study, there are some implications that do deserve further research so as to make the signified recommendations more robust. These include:

- ❖ The need to have time series information for assessing over time, long-term effects, and dynamic linkages among the variables considered in this study;
- ❖ The need to make cost-benefit analysis of the different climate-smart/physical land management practices so as to prioritize them based on their potential benefits and profitability, both at individual and community level;
- ❖ The necessity to consider the broader aspects of the environment, beyond agricultural land conservation including conservation of water, forests, wetlands, biodiversity, and the environment in general;
- ❖ The need for further research that could come up with policy options that encourage farmers to accept longer time horizons and to provide an estimated envelope of long term benefit and marginal returns of the physical land management measures;
- ❖ The need for future research that gear to investigate and quantify the possible complementarities among different climate-smart agricultural practices and the synergetic effect thereof; and
- ❖ The need to have wider and diverse coverage of the same issue across the entire Blue-Nile River basin.

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Appendices

Appendix I: Household Survey Questionnaire

Part 1: Household Information											
1. Name		2. Sex((√)	Female		3. Age	4. Marital status(√)	Married	Single	Divorced	Widowed
			Male							
5. Farming experience in years											
6. Educational status (√)	Literate		7. If literate, number of years of formal education completed? ________________							
	Illiterate									
	Non-formal education									
8. Family size	Male		Female		9. Total family size					
10. Members of the household in age group	**Age group**	**0-14**	**15-64**	**65+**						
	Male									
	Female									
11. Members of your household (age 15 and above) that can read and write	Male									
	Female									
12. Children (age 6-15) that attend school	Male									
	Female									
13. Ethnic group (specify)										

14. Religion	Tick (√)	15. What is your responsibility in the community	Tick (√)
Muslim		Religious leader	
Orthodox		Coordinator of community development work	
Protestant		Member of the kebele administration	
Other (specify)___________________		Other (specify)___________________	

Part 2: Involvement in Farm and Off-farm Activities (2007 E.C 2014/15)

Age group	Number		Working hours per day				Type of off farm activity	Tick (√)
			On farm/agriculture		Off farm			
	Male	Female	Male	Female	Male	Female		
<14							Firewood collection and sale	
15-30							Charcoal making and sale	
31-45							Casual work/daily laborer	
46-65							Petty trade	
>65							Permanent employment	
							Pottery	
							Tanning	
							Wavering	
							Material making from bamboo	
							Jewelry and Welding	
							Other (specify)________________	

Part 3: Income from Farm and Off-farm Activities (2007 E.C or 2014/15)

Type of farm activity	**Income per year (Birr)**	**Type of off farm activity**	**Income per year (Birr)**
Crop production		Firewood collection and sale	
Livestock production		Charcoal making and sale	
Agroforestry		Casual work	
Poultry		Petty trade	
Bee keeping		Permanent employment	
Other (specify)_______________		Pottery	

Part 4: Land Ownership

1. Do you own land? Tick (√)	Yes	2. If yes, what is the size of total land you have in hectares?	Number of plots:
		3. What is the size of your fertile land in hectares?	Size of each plot
	No	4. What is the size of your marginal/in fertile land in hectares?	

5. Indicate size of different land uses in hectare(ha)	Cultivated land	Grazing land	Irrigated land	Homestead	other
Size of plots	Plot 1:	Plot 2:	Plot 3:	Plot 4:	Plot 5:
6. How is the change in the size of farm land in the last 10 years? Tick (√)			Increased	Decreased	No change

7. If the size of your land increased, what are the reasons	1.
	2.
	3.
8. If the size of your land decreased, what are the reasons	1.
	2.
	3.

9. Do you share crop on others land? Tick (√)	Yes		No	
10. If yes how much land do you share crop in hectares?				
11. Do you give out land for share cropping? Tick (√)	Yes		No	
12. If yes how much land do you give for share cropping in hectares?				
13. Do you irrigate your farm land? Tick (√)	Yes		No	
14. If yes, what is the size of your irrigated land in hectares?				

15. How do your rate the relative slope of your farm land Tick (√)	Plain	
	Gently hilly	
	Hilly	

Part 5: Land Allocation and Crop Production (E.C)

1. Type of crop produced	2. Area in hectare and production in quintals									
	2009		2008		2007		2006		2005	
	Plot Area	Qt	Plot Area	Qt	Plot Area	Qt	Plot Area	Qt	Plot Area	Qt
a.										
b.										
c.										
d.										
e.										
f.										
g.										
h.										

3. Have you ever experienced crop failure? Tick (√)	Yes		No	
3. If yes, how many times in the last 10 years?				
4. What is the major cause of the crop failure?				
5. How many months does your own farm production last to cover the food requirements of your family?				
6. What is the reason for not able to cover the annual food requirement?				

7. During the last production season, which of the following constrained your crop production activity? ***(more than one option possible)***	Constraint	Tick (√)
	Cash shortage	
	Rain/water shortage	
	Soil erosion	
	Labor shortage	
	Lack of input	
	Lack of knowledge/awareness	
	In fertile soil	
	Lack of market access	
	Lack of farm tools	
	Crop pest/disease	
	Low market price	
	Land shortage	
	Wild animal attack	

8. What are the main crops and forest products produced during last production season and their quantity?

Production	Product 1	Quantity	Product 2	Quantity	Product 3	Quantity

Main food crops (in quintal)						
Main cash crops (in quintal)						
Vegetables (in kilogram)						
Fruits (in kilogram)						
Main dairy products ((in kilogram or in liters)						
Honey (in kilogram)						
Main forest products for food (in kilogram)						
Main forest products for market						

Part 6: Land Productivity and Management

1. How is the change in productivity of cultivated land over the last five years (tick (√)	Increasing	Decreasing	No change

2. If increasing, reason (tick (√)	Increased soil fertility		2. If decreasing, reason (tick (√)	Land degradation	
	Strong extension service (advise)			Lack of timely input supply	
	Suitable weather conditions			Lack of oxen	
	Soil and water conservation practices			Rain/water shortage	
	More use of technologies (improved seed, fertilizer, chemicals)			Drought	
	Other (specify)__________________			Pests and crop diseases	
				Lack of extension advise	
				Other (specify)_____________________	

3. Do you have land use certificate? (tick (√)	Yes		4. If yes, has this caused you apply better land management practices than before? (tick (√)	Yes	
	No			No	

5. If you apply land management practices, which of the following type? (tick (√)	Soil and water conservation		6. How is the fertility status of your cultivated land? (tick (√)	Fertile	
	Terracing			Medium	
	Agro forestry			Infertile	
	Crop rotation		7. How is the slope of your cultivated land? (tick (√)	Plain	
	Minimum tillage			Sloppy	
	Other (specify)______________			Medium	

8. What type of soil is your cultivated land? (tick (√)	Black	
	Brown	
	Red	

8.How do you apply the following Land management activities	Plot zise	Year started	Production (qt)	Code for the problem	
Check dam				Harbor rodents (mouse)	01
Stone band				Reduce farm size	02
Soil band				Difficulty while plowing (turning oxen)	03
Agro-forestry				High labor requirement	04
Crop rotation				Impracticable	05
Minimum tillage				Less knowledge about it	06
Animal manure				Less advice on the practice	07
Use of crop residue				Other (specify)	08
Conservation tillage					
Intercropping					
Organic fertilizer					

9. What is the total size of land in which soil and water management practices were applied last year (hectare)?	

10. Do you practice crop rotation? (tick (√)	Yes		11. If yes, what is the sequence of rotation?			
	No					

12. Do you use conservation tillage practice? (tick (√)	Yes	
	No	

Part 7: Agricultural Input Use

1. Please indicate your use of agricultural inputs in the last production season

Type of crop	plot size (ha)	Input utilization							Production (Qt)	Market price per quintal (birr)
		Chemical fertilizer (kg)		Natural fertilizer (kg)		Improved seed (kg)	Local seed (kg)	Weed and pest protection chemicals (lit)		
		DAP	Urea	Compost	Crop residue					

2. If you are not currently using improved agricultural inputs, specify your reason(write in the space)	1	
	2	
	3	
	4	
	5	

3. How do you manage seed? (tick (√)	Seed management	Tick (√)	Source (write)	How often ((tick (√))		
				Always	Sometimes	Never
	Buys seed					
	Saves seed					
	Receives seed for free					
	Borrow seed					
	Through credit					

Part 8: Livestock Production

1. How many of the following animals do your household currently own?	**Type of animal**	**Number**
	Oxen	
	Cows	
	Young bulls	
	Heifers	
	Sheep	
	Goats	
	Hoarse/mule	
	Donkey	
	Poultry	
	Bee colony	
	Camel	
	Other (Specify: _______________)	

2. Indicate source of feed for livestock

Type of livestock	Source of feed (write the code)	Code for source of feed	
		Source	Code
Oxen		Private grazing land	01
Cows		Communal grazing land	02
Young bulls		Crop residue	03
Heifers		Buying fodder	04
Sheep		Other (specify)	
Goats		1.	05
Hoarse/mule		2.	06
Donkey		3.	07
Poultry		4.	08
Bee colony		5.	09
Camel			
Other (Specify: _______________)			

3. Do you want to have improved breeds of livestock? Tick (√)	Yes	
	No	
4. If yes, specify the livestock type for which you want improved breed? (Tick (√)	Type of livestock	Tick (√)
	Cattle	
	Sheep	
	Goat	
	Poultry	
	Bee hive	
5. During the last one year, which of the following constrained your livestock rearing activity? ***(more than one option possible)***	Constraint	Tick (√)
	In sufficient cash	
	Water shortage	
	Feed shortage	
	Labor shortage	
	Lack of market access	
	Animal disease	
	Low market price	
	Lack of access to veterinary service	

	Wild animal attack	

6. Indicate the number of livestock that you own in the last 5 years									
Year (E.C)	cattle	sheep	goat	camel	horse	donkey	mule	poultry	
2007									
2006									
2005									
2004									
2003									

7. What are the main livestock products and honey produced during last production season and their quantity?						
Production	Product 1	Quantity	Product 2	Quantity	Product 3	Quantity
Main dairy products ((in kilogram or in liters)						
Honey (in kilogram)						

Part 9: Livelihood

		Tick (√)
1. What is the primary source of livelihood/income for your household? (tick (√)	Source of livelihood	Tick (√)
	Agriculture	
	Livestock	
	Forest products (specify)	
	Non-farm (off-farm income) (what type:_____________________________)	
	Business (trade)	
	Support (Mention:____)	
	Other (Specify): ____	
2. During the last 12 months, how many members of your family involved in off-farm activities	Number of male household members involved	
	Number of female household members involved	
3. Do you or any one of your household member own a mobile phone? (tick (√)	Yes	
	No	
4. How many number of rooms does your dwelling house has?		
5. What is the primary construction material of your housing unit?	Type	Tick (√)
	Grass/straw	
	Bamboo	
	Stone	
	Galvanized iron (corrugated sheet)	
	Mud	
	Wooden	
	Other (Specify: ______________)	
6. What is the primary source of light your home uses?	Source of lighting	Tick (√)
	Electricity	
	Firewood	
	Gas (kerosene)	
	Other (Specify: ______________)	
7. What is the primary source of fuel your household uses for cooking?	Source of cooking fuel	Tick (√)
	Fire wood	
	Charcoal	
	Kerosene	
	Dung cake	
	Crop residue	
	Other (Specify: ______________)	
8. If you use firewood, indicate the source	Source	Tick (√)
	Community owned forest	
	Privately grown trees/ forest	
	Naturally grown trees on farmland	
	Buying from market	
	Others (specify: ______________)	
	No	

Part 10: Access to Infrastructure	
How long does it take to reach to all weather road from your home (in walking hours)	
How long does it take to reach to the nearest school from your home (in walking hours)	
How long does it take to reach to health service from your home (in walking hours)	
How long does it take to reach to veterinary service from your home (in walking hours)	
How long does it take to reach to water source from your home for human consumption (in walking hours)	
How long does it take to reach to water source from your home for livestock consumption (in walking hours)	
How long does it take to reach to saving and credit institution (in walking hours)	
How long does it take to reach to market (in walking hours)	

Part 11: Social Networks and Social Capital

	Type of help	Help received (√)	Help given (√)
1. In the last one year, which of the following types of help did you receive or provide to others ***(more than one option possible)***	Land preparation		
	Planting		
	Weeding		
	Harvesting		
	Attending sick animals		
	During human sickness		
	Building/maintenance of house		
	Borrowing money		
	Borrowing or Providing seed		
	During death		
	During marriage		
	Mediating conflicts		
	Other (Specify:_______)		

2. In the past one year, how many times did you borrow or lent money?	Activity	Number of times
	Borrow money	
	Lent money	
3. If you want to borrow money, whom would your approach first?	Source	Tick (√)
	Relatives	
	Friends	
	Credit cooperatives	
	Local money lenders	
4. Which source is easy to borrow money from?	Source	Tick (√)
	Relatives	
	Friends	
	Credit cooperatives	
	Local money lenders	

5. Are you a member of social institution in your village? Tick (√)	Yes		No	
6. If yes, to which of the following institutions. Tick (√)	Idir			
	Ekub			
	Religious group			
	Other (Specify)			
7. In any of the above institutions indicated, do you discuss about climate change? Tick (√)	Yes		No	
8. If yes, do you participate in identification and adoption of adaptation strategies? Tick (√)	Yes		NO	
9. Are you a member of farmers' cooperative?	Yes		No	
10. Are you a member of saving and credit association?	Yes		No	
11. Have you borrowed money from any credit and saving institution? Tick (√)	Yes		No	

Part 12: Climate change

1. Is the current climate condition the same to that of the situation before 20 years? Tick (√)	Yes		No	
2. If no, how is the condition of the temperature of the day in the last 20 years? Tick (√)	Increasing			
	Decreasing			

3. What are the indicators that show the change in temperature in your locality? Tick (√)	Frequency of occurrence of drought	
	Human diseases that have not been seen before	
	Crop diseases/pests that have not seen before	
	Animal diseases that have not been seen before	
	Emergence of new species of animals	
	Emergence of new species of plans	
	Degradation of land	

	Degradation/disappearance of water resources	
	Cultivation of new crops	
	Change in planting time	
	Other (specify):________________________	
4. How is the condition of rainfall in the last 20 years? Tick (√)	Increasing	
	Decreasing	
	No change	
	Other (specify): _______________________	
5. What are the local indicators that show the variability/change in rainfall through time in your surrounding? Tick (√)	Change in cropping season	
	Change in the season of rainfall	
	Increase in the frequency of drought	
	Early onset of rainfall	
	Late start of rainfall	
	Shortened rainy season	
	Long rainy season	
	Increased volume of rainfall	
	Change in crop type	
	Change in productivity	
	Other (specify): ________________________	
6. Which of the following are your important responses to adapt and protect the problems caused due to climate change/variability in your locality? Tick (√)	Plowing along the contour	
	Planting along the contour	
	Stone/soil band/terracing	
	Fallowing	
	Crop rotation	
	Intercropping	
	Use of chemical fertilizer	
	Use of improved seed	
	Use of compost	
	Agroforestry	
	Draining of vertisols	
	Establishing protected area	
	Irrigation	
	Water harvesting	
	Other (specify):______________________	
7. Tell us (list) major problems that hinder the implementation of the above listed adaptation strategies	1.	
	2.	
	3.	
	4.	

8. How many times did drought occur in the last 20 years?	
9. How many times did drought occur in the last 10 years?	
10. How many times did drought occur in the last 5 years?	
11. How many times did flood occur in the last 20 years?	
12. How many times did flood occur in the last 10 years?	
13. How many times did flood occur in the last 5 years?	

14. Have you ever participated in climate change related training? Tick (√)	Yes		No	
15. If yes, did the training help you in increasing productivity? Tick (√)	Yes		No	

16. What is your source of climate related information? Tick (√)	Radio	
	Television	
	Neighbor	
	Extension agent	
	Social institution	
	Local administration/meeting	
	Other (specify)	

Part 13: Extension Service				
1. Is there any agricultural extension service in your locality? Tick (√)	Yes		No	
2. If yes, do you have extension contact? Tick (√)	Yes		No	
3. Did the extension contact help you improve productivity? Tick (√)	Yes		No	
4. Do you get information on climate change from the extension agent? Tick (√)	Yes		No	
4. Do you get market information from the extension agent? Tick (√)	Yes		No	

5. How often do you get advice from the extension agent? Tick (√)	Weekly	
	Once in two weeks	
	Once in three weeks	
	Once in a month	
	Other (specify)	
6. If you do not have extension contact, reason? (write)		

Part 14: Health sensitivity

1.In the last one year, how many of your household members were ill and miss work or school	Frequency	Number of members who missed school	Number of members who missed work
	Once/twice		
	Once a month		
	More than a week		
	More than a month		
	Whole year		

2. In the past one year, how many members suffered from the following diseases?	Disease	Male number	Female number	In which months?
	Malaria			
	Typhoid			
	Diarrhoea			
	Common cold			
	Fever			
	Other (Specify)			

3. Does your household use the following disease prevention methods?

Do you filter water? Tick (√)	Yes		No	
Do you boil drinking water? Tick (√)				
Do you have mosquito nets? Tick (√)				

4. How many mosquito nets are available in your household? (indicate the number)	

Part 15: Food Sensitivity

1. For how many months do you face shortage of food in a year? (***tick the appropriate box***)	More than 6 months	4-5 months	2-3 months	Less than 1 month	No food shortage
2. What are your main sources of food supplies? Tick (√)	Self-sufficient from own farm	Mainly buy from market	Mainly exchange for labor	Mainly borrow from neighbors	Remittance from household members living in other areas

Part 16: Water sensitivity

1. What is the main source of water for your household consumption?	Source	Tick (√)
	Public stand pipe	
	Piped water inside house	
	Protected spring	
	Unprotected spring	
	Rain water collection	
	Pond	
	Stream/river	
	Well	
2. What is the main source of water for livestock	Source	Tick (√)
	Public stand pipe	
	Piped water inside house	
	Protected spring	
	Unprotected spring	
	Rain water collection	
	Pond	
	Stream/river	
	Well	
3. How much time in (minutes) does it take to collect water from the nearest source	Season	Time
	During the rainy season	
	During the dry season	
	During most of the year	

4. How do you rate the availability of drinking water during the last 5 years? Tick (√)	Increasing	Decreasing	Same
5. How do you rate the quality of drinking water during the last 5 years? Tick (√)	Improving	Worsening	Same
6. How do you rate the volume of water available for livestock? Tick (√)	Increasing	Decreasing	Same

7. Are there a conflicts over the use of water in your community for different purposes (irrigation, livestock…) Tick (√)	Never	Rarely	Sometimes	Often	Always

Part 17: Exposure Sensitivity						
1. Have you faced the following problems in your village?	(√) if yes	2. Did you get warning of such incidence? (√)		3. How sever the problems are? (√)		
		Yes	No	Low	Medium	High
Drought						
Flood						
Excess/too much rainfall						
Early rainfall						
Late rainfall						
Erosion						
Strong wind						
Extreme cold						
Extreme heat						
Crop disease and pest						
Lack of access to disease and pest control						
Lack of access to improved seed						
Bad seeds						
Lack of access to fertilizer						
Expensive fertilizer						
Weed infestation						
Soil fertility problem						
Livestock disease						
Irrigation problem						
Labor shortage						
Fuel shortage						
Lack of access to market						
Low market price for crops						
Low market price for livestock						
Water borne diseases						
Death of family members due to natural disaster						
Local conflict						
Lack of access to credit facilities						
Lack of access to human health services						
Lack of access to veterinary services						
Human disease						

Part 18: Copping mechanisms					
1. Type of problem/shock	Copping mechnizm used (enter code of copping meachnism by placing the most important one first			Codes for coping mechanisms	
	1st copping strategy	2nd copping strategy	3rd copping strategy	Copping mechanism	Code
Drought				Rely on less expensive food	01
Flood				Spent savings on food	02
Excess/too much rainfall				Restricted consumption	03
Early rainfall				Reduced number of meals	04
Late rainfall				Selling firewood	05
Frost				Consumes seed stock	06
Erosion				Involving children on work	07
Land slide				Send children to live with relatives	08
Strong wind				Send children to work off-farm	09
Extreme cold				Withdraw children from school	10
Extreme heat				Stop planting some crops	11
Crop disease and pest				Move livestock to other places	12
Lack of disease and pest control				Migrated for work	13
Lack of improved seed				Involve in off farm activities	14
Bad seeds				Bough food on credit	15
Lack of access to fertilizer				Collected wild food	16
Expensive fertilizer				Sold assets	17
Weed infestation				Rent in/share in land	18
Soil fertility problem				Rent out/shared out land	19
Livestock disease				Reduced spending on health	20
Irrigation problem				Introduced new crop types	21
Labor shortage				Used new varieties	22
Fuel shortage				Introduced new type of livestock	23

Lack of access to market				Sold livestock	26
Low market price for crops				Borrowed money from relatives	25
Low market price for livestock				Other coping mechanisms	
Water borne diseases				a)	26
Death due to natural disaster				b)	27
Debt				c)	28
Local conflict				d)	29
Lack credit facilities				e)	30
Lack of human health services				f)	31
Lack of veterinary services				g)	32
Human disease				h)	33
Food shortage				i)	34
Water shortage				j)	35
Feed shortage				k)	36
Grazing land shortage					

2. How do you rate the occurances of the following events in the past 10 years? ((tick (√) ***the appropriate box***)

Event	**Increaing**	**Decreasing**	**Same**
Drought			
Flood			
Excess rainfall			
Early rainfall			
Late rainfall			
Extrem heat			
Extrem cold			
Strong wind			
Soil erosion			
Land slide			
Crop disease and pest			
Poor market access			
Low market price crop/livestock			
Cost of inputs			
Livestock disease			
Death rate			
Human disease			
Impoverishment			
Labor shoratge			
Fuel shortage			
Wild animal attack			

Part 19: Specific copping strategies	
1. Mention three major crop production problems	Mention copping strategies for each crop production problem
a.	
b.	
c.	
Mention three major livestock production problems	Mention copping strategies for each livestock production problem
a.	
b.	
c.	
Mention three major land realted problems	Mention copping strategies for each land related problem
a.	
b.	
c.	
Three major forest related problems	Mention copping strategies for each forets related problem
a.	
b.	
c.	
Three major rainfall related problems	Mention copping strategies for each rainfall relaated problem
a.	
b.	
c.	
Three major temperature related problems	Mention three copping strategies for temperature related problems
a.	
b.	
c.	

Part 20: General

1. How do you rate the following factors as source of stress to your agricultural activity? (Rate them by the scale indicated)

Source of stress (uncertainty) factor	Not a source of concern (1)	Limited source of concern (2)	Moderate source of concern (3)	High source of concern (4)	Very highly a source of concern (5)
Lack of inputs (seed, fertilizer)					
High price of input					
Lack of road					
Lack of market					
Lack of credit					
Lack of extension service					
Drought					
Flood					
Insufficient rain					
Irregular/ unpredictable rain					
Heavy rain occurrence					
Delay (late start) of rain					
Early start of rainfall					
Terminal moisture stress (early cessation of rain)					
Warmer days than before					
Malaria					
Lack of oxen					
Limited availability of farm land					
Low level of soil fertility					

2. How do you rate the effectiveness of the following actions in reducing the risks in crop farming associated with climate variability and change?

Activity	**Ineffective(1)**	**Moderately effective (2)**	**Effective (3)**
Use of different crop varieties			
Changing planting dates			
Adopting drought resistant crop			
Use of soil and water conservation			
Off- farm activities			
Water harvesting			
Agroforestry (planting trees)			
Use of irrigation			
Use of fertilizer			

3. How do you rate in your resource capacity (financial, technical) to be able to perform the following actions?

Activity	**Not confident(1)**	**Moderately confident**	**Confident (5)**
Use of different crop varieties			
Changing planting dates			
Adopting drought resistant crop			
Increased use of soil and water conservation			
Involving on non- farm practices			
Water harvesting			
Planting trees/agroforestry			
Use of irrigation			
Use of fertilizer			

4. How do you evaluate the importance of soil and water conservation measures? **(tick √)**							
Very important		Important		not important		Don't know	
Are you willing to adopt soil and water conservation measure? (tick √)				Yes		No	
Have you ever implemented the measures?				Yes		No	

5. Indicate soil and water conservation measure applied on any of your plot in 2007

Plot number	Conservation? Yes/No	Type of conservation	Equipment cost (birr)	Labor (person days)	Area cover by the conservation (ha)	Impact on soil degradation (High/medium/low)

6. Soil conservation practice and crop production

Type of crop	Total area (ha)	Size of land on which land management is practiced			Size of land on which no land management practiced	
		Area (ha)	Production (Qt)	Type of land management practiced	Area (ha)	Production (Qt)

7. Access to information

Type of information	Do you have access Yes/No	Source of the information	Were you able to use this information Yes/No	If you did not use the information, reasons
Forecast of extreme events (drought, flood)				
Forecast for the start of the rains				
Information on climate change				
Information on crop production and management				
Information on livestock production and management				
Information on tree management and agroforestry				
Information on marketing of crop/livestock products				
Information on land Management				

8. Food security

Are there months in the last one year in which you did not have enough food to meet your family's needs? **(tick √)**															
Yes		No													
If yes, which are the months during which you did not have enough food to meet your family's needs? **(tick √)**															
January		February		March		April		May		June					
July		August		September		October		November		December					

9. Technology adoption

Practice	Do you know the practice? Yes/No	Have you ever used the practice? Yes/No	Do you use the practice now? Yes/No	When did you first adopt this practice?	Major constraints to adopt the practice
Improved Crop Varieties					
Recommended Fertilizer Application Techniques					
Intercropping					
Planting along the contour					
Water Harvesting					
Agroforestry					
Degraded Land reclamation					
Compost preparation					
Building Terraces					
Row planting					

Appendix 2: Conversion factor of various classes of livestock to TLU

Animal Category	Tropical Livestock Unit TLU)
Calf	0.25
Donkey (young)	0.35
Weaned calf	0.34
Camel	1.25
Heifer	0.75
Goat/sheep (adult)	0.13
Cow and ox	1.0
Goats/sheep (young)	0.06
Horse	1.10
Donkey (adult)	0.70
Chicken	0.013

Source: Strock et al. (1991)

Appendix 3: Conversion factor for Adult Equivalent (AE)

Sex		
Age group (years)	Male	Female
<10	0.60	0.60
10-13	0.90	0.80
14-16	1.00	0.75
17-50	1.00	0.75
>50	1.00	0.75

Source: Strock et al. (1991)

Appendix 4: Variance Inflation Factors (VIF) for variables used in the Heckman probit selection model

Variables	VIF	1/VIF
Education level of HH head	2.35	0.893
HH head age	1.25	0.74
Climate change information	1.25	0.892
Frequency of drought	1.26	0..915
Frequency of drought	1.15	0.512
Number of crop failures	1.72	0.369
Duration of food shortage	1.60	0.384
Mean VIF	1.51	

Appendix 5: Summary results for stage regression of IV Model

Variables	**Shea Partial R^2**	**Partial R^2**	**F**	**P-value**
Ln(labor)	0.721	0.910	41.67	0.000
Plowing technics	0.793	0.861	85.21	0.000
Intercropping	0.896	0.934	215.21	0.000
Fertilizer use	0.415	0.921	377.13	0.000
Manure application	0.901	0.951	834.43	0.000

Appendix 6: Variance Inflation Factors (VIF) for variables used in the Heckman probit outcome model

Variables	VIF	1/VIF
Education of HH head	1.16	0.511
Household size	2.26	0.211
HH head sex	1.11	0.395
Farming experience	1.26	0.557
HH head age	1.13	0.448
Crop income	1.21	0.349
Livestock income	1.35	0.693
Non-farm income	1.25	0.174
Extension advice	1.01	0.801
Climate change information	1.22	0..515
Cultivated land size	1.31	0.412
Plots with steep slope	1.33	0.269
Plots with mixed slope	1.31	0.284
Semi-fertile plots	1.13	0.304
Non-fertile plots	2.01	0.365
Shared out land	1.12	0.511
Farm-home distance	1.02	0.394
Number of parcels	1.11	0.201
Past knowledge of adaptation	1.22	0.405
Mean VIF	1.29	

Appendix 7: Variance Inflation Factors (VIF) for two-stage probit model estimates (manure and fertilizer)

Variables	VIF	1/VIF
Age	2.12	0.437
Adult equivalent ratio	1.13	0.695
Proportion of female	2.02	0.457
Education 1	1.43	0.519
Education 2	2.25	0.853
Size of land holding	1.35	0.641
Parcel size	1.05	0.492
Land fragmentation (SI)	1.06	0..815
Farm distance	1.45	0.412
Fertility 1	1.63	0.322
Fertility 2	1.13	0.374
Slope 1	1.13	0.681
Slope 2	1.35	0.394
Slope 3	1.56	0.401
Physical soil conservation	1.24	0.405
Proportion of fruits	1.38	0.426
Livestock holding (TLU)	1.34	0.472
Off-farm/non-farm activities	1.74	0.568
Extension	1.12	0.421
Mean VIF	1.45	

Appendix 8: VIF for bivariate probit model estimates (intercropping and conservation tillage)

Variables	VIF	1/VIF
Age (years)	1.35	0.593
Sex (dummy)	2.25	0.343
Adult equivalent	1.01	0.892
Dependency ratio	1.22	0..415
Education (cf. no formal education)	1.11	0.712
Primary	1.23	0.569
Secondary	1.41	0.884
Extension (dummy)	1.13	0.494
Training (dummy)	2.01	0.565
Size of land holding (ha)	1.26	0.781
Parcel size(ha)	1.55	0.594
Land fragmentation (simpson index)	1.46	0.611
Farm distance (km)	1.19	0.405
Fertility level (cf. poor)	1.16	0.556
Good	1.33	0.432
Medium	1.23	0.468
Slope (cf. flat)	1.74	0.471
Gentle	2.16	0.537
Steep	1.54	0.393
Very steep	1.22	0.495
Physical soil conservation (dummy)	2.05	0.657
Proportion of fruits/trees	1.97	0.308
Livestock holding (TLU)	1.13	0.633
Market distance (km)	1.35	0.663
Mean VIF	1.40	

Appendix 9: Heteroskedasticity Test Results (Breusch-Pagan/Cook-Weisberg)

Econometric Model	**Ho:**	**Variables**	**Chi2(1)**	**Prob>chi2**
Heckman probit perception model (Chapter 3)	Constant variance	Fitted values of perception	8.08	0.0018
Heckman probit outcome model (Chapter 3)	Constant variance	Fitted values of adaptation	9.94	0.0047
Single equation Probit Regression (Chapter 4)	Constant variance	Fitted values of adaptation through physical measures	9.55	0.0014
Two-stage probit model + logarithmic transformation)	Constant variance	Fitted values of determinants of fertilizer and manure use	9.98	0.0047
Bivariate probit model + logarithmic transformation)	Constant variance	Fitted values of determinants of intercropping and conservation tillage practices	9.43	0.0076
IV estimation (Huber-White robust + logarithmic transformation)	Constant variance	Fitted values of determinants of productivity		0.000

Appendix 10: Variance Inflation Factors (VIF) for variables used in productivity analysis (IV estimation)

Variables	**VIF**	**1/VIF**
Ln(labor)	1.65	0.512
Manure	1.13	0.758
Fertilizer	2.04	0.671
Intercropping	2.16	0.537
Conservation tillage)	1.26	0.693
Physical soil cons	1.28	0.795
Crop rotation	2.26	0.557
Improved crop variety	1.55	0.608
Irrigation	1.63	0.619
ln(oxen-pair)	2.35	0.893
ln(parcel size)	1.25	0.74
Slope 1	1.25	0.892
Slope 2	1.26	0..915
Slope 3	1.15	0.512
Fertility level 1	1.72	0.369
Fertility level 2	1.60	0.384
Fertility level 3	1.13	0.394
ln(farm distance)	2.15	0.465
ln(size of land holding)	1.12	0.581
ln(TLU)	1.45	0.594
Land fragmentation (SI)	1.36	0.601
Proportion of fruits	1.29	0.605
Ln(number of crops)	1.18	0.626
Off-farm/non-farm	1.22	0.772
Credit	1.13	0.668
Mean VIF	1.51	

Note: Using the Rule of Thumb (average VIF has to be less than 2; individual VIF has to be less than 10), there is no sever multicollinearity problem

Appendix 11: Comparison of IV and OLS estimates on determinants of productivity

Explanatory variables	Ordinary least square		Instrumental Variables	
	Coefficient	**S.E**	**Coefficient**	**S.E**
Ln(labor)	0.321**	0.054	1.134**	0.376
Manure (dummy)	0.181***	0.068	0.477***	0.301
Fertilizer (dummy)	0.343*	0.071	0.089	0.191
Intercropping (dummy)	0.322***	0.074	0.344***	0.132
Conservation tillage (dummy)	0.121*	0.085	0.342***	0.134
Physical soil and water conservation measures (dummy)	0.164*	0.042	0.212**	0.207
Crop rotation (dummy)	0.034	0.122	0.101	0.122
Improved crop variety (dummy)	0.075	0.173	0.221*	0.236
Irrigation (dummy)	0.134	0.135	0.311**	0.321
ln(oxen-pair)	0.041	0.045	0.110	0.121
ln(parcel size)	0.212	0.071	0.231*	0.101
Slope (cf. flat)				
Gentle	0.022	0.055	0.033	0.210
Steep	-0.112	0.211	-0.155*	0.131
Very steep	-0.211	0.132	-0.312	0.222
Fertility level (cf. poor)				
Good	0.066	0.086	0.012	0.111
Medium	0.232*	0.023	0.228*	0.149
ln(farm distance)	0.033	0.041	0.121	0.043
ln(size of land holding)	0.022	0.116	0.041	0.150
ln(TLU)	0.144**	0.057	0.241*	0.117
Land fragmentation (simpson index)	-0.343*	0.241	-0.588*	0.242
Proportion of fruits	0.065	0.141	0.211	0.202
Ln(number of crops)	0.146*	0.124	0.982**	0.243
Credit (dummy)	0.114*	0.043	0.321*	0.434
Off-farm/non-farm activities (dummy)	-0.131*	0.071	-0.156*	0.178
Wet lowland (dummy)	0.221*	0.0431	0.443*	0.240
Dry lowland (dummy)	-0.211	0.007	-0.132	0.041
Relevance test of excluded variables (p-value)$^{\Phi}$				
Ln(labor)			0.000	
Conservation tillage			0.000	
Intercropping			0.000	
Fertilizer use			0.000	
Manure application			0.000	
Hansen's J-test of overid. restrictions (p-value) $^{\varphi}$			0.7465	

***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively