DISSERTATION

PROSPECTS FOR SUSTAINABLE INTENSIFICATION OF SMALLHOLDER FARMING SYSTEMS IN ETHIOPIAN HIGHLANDS

Submitted by

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ABSTRACT

PROSPECTS FOR SUSTAINABLE INTENSIFICATION OF SMALLHOLDER FARMING SYSTEMS IN ETHIOPIAN HIGHLANDS

This dissertation examines the prospects of sustainable agricultural intensification by rural farming households in Ethiopia. Although widely accepted as the new paradigm for agricultural development in sub-Saharan Africa, several research and empirical questions still surround the concept of sustainable intensification, particularly its operationalization. Efforts to promote, measure and monitor progress towards sustainable intensification are hampered by the lack of quantifiable indicators at the farm level, as well as the uncertainty over the relationship between intensification and sustainability. This dissertation contributes to this knowledge gap by examining the relationship between agricultural intensification and sustainability, with a view to determine if sustainable paths of agricultural intensification are possible within the smallholder farming systems of Ethiopian highlands. To help better execute the research inquiry, and achieve the main goal of this study, the themes of this dissertation are addressed through three separate but interrelated essays, on top of the introductory and conclusion chapters.

The first essay, presented in chapter two, examines the drivers and processes shaping agricultural intensification by smallholder farmers. This chapter contributes to the literature by providing evidence of how agricultural intensification depends on a wide range of factors, whose complex interactions give rise to different intensification pathways. The implication is that, even in a region that is undergoing the process of agricultural intensification, households are likely to

respond differently to intensification incentives and production constraints, and thus pursue different paths of agricultural intensification.

The second essay, chapter three, develops a methodological framework for defining elements of sustainability based on observed, context-specific priorities and technologies. Farm-level indicators of agricultural sustainability are developed using insights drawn from literature, and adapted to the Ethiopian context through consultations with agricultural experts and key stakeholders in the agricultural sector. A Data Envelopment Analysis (DEA) framework is applied to synthesize the selected indicators into a relative farm sustainability index, thus reducing subjectivity in the sustainability index. A generalized linear regression model applied on the computed sustainability scores shows that farm size, market access, access to off farm income, agricultural loans, access to agricultural extension and demonstration plots are key drivers of agricultural sustainability at the farm level. Despite being applied to the Ethiopian context; the methodology has broader policy implications and can be applied in many contexts.

The third essay, chapter four, examines the relationship between agricultural intensification and relative farm sustainability, and identifies four clusters of farmers depending on their relative levels of intensification and sustainability. The main thrust of this essay is to examine whether farmers who are highly productive are also sustainable, and whether systems that are relatively more sustainable are mostly on the highly productive farms. The results show that of the farms that are relatively most intensive, in terms of the gross value of crop output per hectare, only 27 percent are relatively more sustainable. Of the farms that are relatively most sustainable, about 60 percent are more intensive. Overall, only 10 percent of the farms were both highly intensive and

relatively more sustainable. In order to understand the typology of farmers that are likely to embark on sustainable paths of agricultural intensification, multivariate methods of Principal Components Analysis (PCA) and Cluster Analysis (CA) were used to cluster farmers according to their common characteristics. Multinomial Logit (MNL) regression models were used to model the probability of cluster membership as well as the likelihood of farmers embarking on different intensification trajectories. is used to analyze the odds of embarking on a sustainable intensification path. The results suggest that increasing farmers' access to technical information through demonstration plots and government extension services, addressing farm liquidity constraints, improving market access, as well fostering crop-livestock interactions, significantly increases the likelihood of sustainable intensification.

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DEDICATION

To my mom and sisters-

For their endless love, support and prayers

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CHAPTER 1

INTRODUCTION

1.1 Background

1.1.1 The challenge of feeding the world

There are growing concerns over the ability of the global food systems to meet the growing food demands of a burgeoning world population, which is projected to reach nine billion by 2050 (FAO, 2012). The World Development Report (World Bank, 2008) projected that global cereal production would have to rise by 50% between 2000 and 2030, while the Food and Agriculture Organization of the United Nations (2009) estimated that a 70% increase in global food production by 2050 will be required to satisfy the increasing food demands. Several factors, including increasing water and land scarcity, growing demand for biofuels, declining agricultural productivity, increasing per capita incomes, as well as the adverse impacts of climate change (Von Braun, 2007), have compounded this already daunting challenge. Technological innovations have seen the doubling of global cereal production between the 1960s and the 1990s, and hence increases in the global per capita food supply (Tilman et al., 2002; World Bank, 2008). However, in most African countries, growth in agricultural output has largely come from expansion of the areas cultivated, albeit with little or no improvements in yields (Evenson and Gollin, 2003). While it is still common in relatively land-abundant countries such as the Congo (Reardon et al., 1999), the extensification path is fast becoming untenable across most Sub-Saharan Africa (SSA), due to high rural population density and declining per capita farm size (Josephson, Ricker-Gilbert and

Florax, 2014). It is estimated that about 65% of agricultural land in SSA is prone to degradation (GEF Secretariat, 2003), with yields across major cereals averaging one tonne per hectare (Rockström and Falkenmark, 2000). Accordingly, meeting the growing food challenge will require intensifying production on the existing land, while investing in measures to reverse the trend of soil fertility depletion and environmental degradation (Rockström et al., 2009), as well as adoption of technologies to improve nutrient and water use efficiency (Tillman et al., 2011).

1.1.2 The quest for sustainable agricultural intensification

Amidst growing concerns that production systems in Africa will not be able to meet the rapidly growing food demands, the research and policy agenda for food production in sub-Saharan Africa is converging towards Sustainable Intensification (SI) of smallholder farming systems as a pathway to achieving agricultural productivity growth in the face of growing population pressure, arable-land scarcity and climate variability. Sustainable intensification is defined as a production process or system aimed at producing more output per unit area while minimizing the negative environmental impacts of agricultural practices, and at the same time enhancing contributions to natural capital and the flow of environmental services (Pretty, Toulmin and Williams, 2011; Godfray et al., 2010; Royal Society, 2009; Pretty, 2008). The concept of sustainable intensification is seen as the new paradigm for agricultural development in Africa (Montpellier Panel, 2013), and is increasingly regarded as the future of agriculture and food security (Garnett and Godfray, 2012). A better understanding of the notion of sustainable intensification requires dissecting the fundamental concepts of sustainable agriculture and sustainable development.

Sustainability is often used interchangeably with sustainable development (Wu, 2013) and owes its origins in the Brundtland Commission report of 1987. The Commission defined sustainable development as one that "meets the needs of the present without compromising the ability of future generations to meet their own needs" (WCED, 1987). The key elements of sustainability in this definition are the need to balance human development with environmental integrity (Loos et al, 2014), maintenance of resources over time (Kuhlman and Farrington, 2010) and achieving intergenerational justice (Pearce, 1988). The National Research Council (2010) defined the concept of agricultural sustainability in terms of the continued ability to meet core societal needs without significant negative effects, and thus advancing and securing goals such as human needs for food, feed and fiber, enhancing environmental quality and the resource base, sustaining the economic viability of agriculture, as well as enhancing the quality of life for farmers, farm workers, and society as a whole. Though a variety of definitions of agricultural sustainability exist, the consensus is that agricultural sustainability should involve the simultaneous pursuit of three pillars: economic, social and environmental goals (Kuhlman and Farrington, 2010; Helming et al., 2008; Strange and Bailey, 2008; Kates et al., 2005, Hansen, 1996). This dissertation draws on concepts of the three pillars of sustainable development and sustainable agriculture in order to explain the concept of sustainable intensification.

1.2 Research problem and study significance

Although the importance of sustainable intensification of Africa's smallholder farming is widely acknowledged in literature, relatively little has been done to empirically measure and quantify practical indicators of agricultural sustainability at the farm level. As such, sustainable intensification has largely remained an abstract concept, due to several factors. First, there is no consensus on what sustainable intensification looks like on the ground because of the multidimensional nature of sustainability. There are many pathways towards ensuring agricultural sustainability, and there are generally no prescribed sets of technologies, inputs or management practices that will guarantee sustainable intensification (Pretty and Bhachura, 2014). Consequently, sustainable intensification has generally been regarded as a policy goal and not a blueprint (Garnett et al., 2013). Secondly, the relationship between intensification and sustainability is not always clear-cut, making it necessary to investigate conditions under which the two are complementary or competitors. The drivers and process shaping agricultural intensification will vary by specific socioeconomic, institutional settings, market conditions and agro-ecological circumstances of different agricultural systems. Therefore, understanding the different intensification paths and the different factors and processes shaping specific pathways will be crucial in projecting the likely intensification outcomes and their implications on agricultural sustainability. Thirdly, measuring the extent to which farming systems are sustainably intensifying is extremely difficult and challenging given the lack of quantifiable indicators. Heterogeneity of policy and stakeholder preferences often implies that under different contexts, stakeholders will have different criteria for selecting indicators and assessing agricultural sustainability. This makes it difficult for researchers and policymakers to assess and compare the sustainability of regional agricultural systems. Finally, the general lack of a theoretical model and conceptual framework that could be used to project the likely intensification and sustainability scenarios possible under given socio-economic, institutional and agro-ecological conditions, also makes it difficult for policy to design appropriate and effective instruments to ensure widespread adoption of technologies and practices supportive of sustainable intensification.

Therefore, this dissertation seeks to address these knowledge gaps and to better understand mechanisms, determinants, and constraints to sustainable intensification of smallholder farming systems of Ethiopia. The general goal is to better understand what sustainable intensification implies in the Ethiopian context, and under the specific socioeconomic and agro-ecological circumstances faced by smallholder farmers in Ethiopian highland farming regions. The study seeks to contribute to the development of a pragmatic methodological approach to assess and compare sustainability of smallholder farming systems. The study develops a composite farm-level sustainability measure that can be used to evaluate the relative performance of individual farms as well as assess progress towards sustainability goals. The study also explores the relationship between intensification and sustainability, and explores tradeoffs and/or synergies between the two concepts. The research models different scenarios to help identify an appropriate mix of policy strategies, incentives and interventions to foster the sustainable intensification of smallholder farming systems in Ethiopia.

In general, this dissertation will provide a clearer picture on the issues surrounding the sustainable intensification of smallholder farming systems. The key research orientation is to deconstruct and clarify the ‘sustainable’ and the ‘intensification’ sides of the phrase ‘sustainable intensification’. Regarding the ‘intensification’ component, the dissertation focuses on the drivers and processes shaping agricultural intensification by smallholder farmers. It provides evidence of how agricultural intensification depends on a wide range of factors, whose complex interactions give rise to different intensification pathways, depending on the nature of incentives and constraints facing households. A key hypothesis embedded in the dissertation is that in a particular region undergoing intensification, not all smallholder farmers will intensify in the same way. While agricultural intensification could follow various pathways, the main argument is that it must be sustainable. Perhaps the greatest contribution of this dissertation is developing a methodological framework for defining elements of sustainability based on observed, context-specific priorities and technologies. In addition, this work demonstrates when and how intensification and sustainability are compatible through the methods and empirical example. Despite being applied to the Ethiopian context; the methodology has broader policy implications and can be applied in any context.

1.3 Project purpose, objectives and research questions

Purpose

To develop SI practices, society has to have clear goals about what it means to be "sustainable" while seeking "intensification. There is also need for a comprehensive conceptual framework and a system of measurement that aid our understanding of the mechanisms, determinants, and constraints to sustainable intensification of smallholder farming systems, as well as forecasting the impacts of recommended technologies. The purpose of this study, therefore, is to investigate the relationship between sustainability and intensification in systems currently used by Ethiopian farmers, and to infer the implications of intensification on sustainability at the community level.

Study Objectives:

1. To examine the different intensification pathways pursued by smallholder farmers in Ethiopia and identify the driving factors;
2. To assess the sustainability of the production systems prevalent in Ethiopia's highland areas;
3. To examine the relationship between intensification and sustainability, and explore the how policy instruments can be used to enhance sustainable intensification of smallholder farming systems.

Research Questions

1) What are the pathways to agricultural intensification?
2) What is the sustainability of current, and intensified, production systems?
3) What are the tradeoffs and/or synergies between agricultural intensification and sustainability?
4) What are opportunities for policy to enhance sensible sustainable intensification?

1.4 Description of the study area

This study uses cross-sectional household-level data on smallholder farmers in the Ethiopian highlands to examine the prospect for sustainable intensification of smallholder farming systems. Ethiopia presents an interesting case study for sustainable intensification research, given the significance of the farming sector to the economy, as well as the nexus of natural resources degradation and food security issues in the Ethiopian highlands. Ethiopia is located in East Africa, between 3° 249 and 14° 539 N and 32° 429 and 48° 129 E (Mulatu and Kassa, 2001). The agricultural sector in Ethiopia accounts for about 40 percent of total Gross Domestic Product (GDP), and provides employment to 85 percent of the population (World Factbook, 2012). The sector is dominated by smallholder farmers who account for 95 percent of total cropped area and produce around 90-95 percent of cereals, pulses and oilseeds (Mengistu, 2006). Agricultural production is predominantly subsistence in nature, carried out almost entirely under rain-fed conditions, with very limited areas of irrigation where small streams are diverted seasonally for limited dry season cropping (Mengistu, 2006). Landholdings[1] are generally small and increasingly fragmented (Gebreselassie, 2006). A survey by the country's Central Statistics Agency (CSA) in 2012 showed that the average landholding per households was 1.2 hectares (CSA, 2012). Land is owned by the federal government (Headey et al., 2013), and the existing land policy does not allow for the sale of land, although intra-family inheritance of land is legally permissible (Ali et al., 2011). However, with a population of 92 million, that is projected to reach 160 million by 2050 (Josephson et al., 2014), there are concerns that younger generations will inherit much smaller farms (Headey et al., 2013).

[1] According to the Central Statistics Agency of Ethiopia, landholding is the total land in different uses that a person or household exercises management control over. The land can be under any crops, fallow, grazing or woodland (CSA, 2012)

Ethiopia is generally classified into 18 major agro-ecological zones and 49 sub zones (MOA, 1998). The study was conducted in four regions – Tigray, Amhara, Oromia and Southern Nations, Nationalities, and Peoples (SNNP), representing the South Tigray, North Shewa, Bale and Hadiya zones, respectively. A total of 12 Kebeles (or villages), which are the lowest administrative units in Ethiopia, were selected based on opportunities for sustainable intensification. A total of 50 households were surveyed in each village, giving a total sample of 600 households across the four regions. The composition of the sample is shown in Table 1.1. The highland regions in Ethiopia are characterized by soils of high agricultural potential, as well as relatively steady rainfall, ranging from 600 to 2,700 millimeters per year (IDEELS, 2016). A variety of farming systems have evolved over time, reflecting a combination of factors, such as agro-ecological potential, general climate, soils and market conditions (Christopher et al., 2014). Agriculture in the highlands is mainly characterized by mixed crop-livestock farming systems (Kindu et al., 2014). Apart from the good agricultural potential, Ethiopian highlands support vast biodiversity and offer a range of ecosystem services (IDEELS, 2016). Thus, over 85 percent of the country's population live in the Highlands (IDEELS, 2016). The per capita land area in the highlands was estimated to have dropped from about 0.5 ha in the 1960s to merely 0.2 ha by 2005 (World Bank 2005). The high population densities impose significant pressures for agricultural intensification, while at the same time posing a real threat to natural resources such as forests, soils, water and biodiversity. Consequently, the highlands are also characterized by land degradation and soil erosion, attributable to overgrazing and deforestation induced by the need to clear more land for crop production (Pender, 2002).

Table 1.1: Distribution of study sample

Zone	Region	Woreda	Kebele	Total households
South Tigray	Tigray	Endamahoni	Tsebet	50
			Embahasti	50
			Mehan	50
North Shewa	Amhara	Basona-Worana	Goshe-Bado	50
			Gudo-Beret	50
			Bakello	50
Bale	Oromia	Senana	Selka	50
			Sanbitu	50
			Shallow	50
Hadiya	SNNP	Lemmo	Jawe	50
			Upper Gana	50
			Mesena	50
Total sample				600

1.5 Dissertation Organization

This dissertation consists of five chapters (Figure 1.1). Apart from this introductory chapter and the conclusion, the dissertation is structured in a way that each chapter addresses a given theme of the research.

As articulated in this chapter, this dissertation starts by presenting a general overview of the global challenges facing food production system amidst calls for production and productivity growth in the face of numerous threats. It builds a case for sustainable intensification of smallholder farming systems in sub-Saharan Africa, and provides basis for choosing Ethiopian highlands as a befitting case study. The chapter also articulates the goal of the dissertation, its objectives and overall significance of the study.

Chapter two identifies the factors influencing agricultural intensification, as well as drivers that shape different intensification strategies pursued by smallholder farming households in Ethiopia. The significance of the different sets of socioeconomic, institutional and agro-ecological factors was tested using a robust econometric model. Data for the analyses was collected through a cross sectional household survey, while further information on contextual issues shaping agricultural intensification incentives, as well as the intensification strategies pursued by households was collected through a mixture of key informant interviews and focus group discussions. Findings presented in this chapter indicate that the size of landholding, access to agricultural loans, farm mechanization, household wealth, livestock ownership, access to agricultural demonstration plots, as well as agro-ecological factors are important drivers of agricultural intensification.

Chapter three compares relative farm sustainability of smallholder farmers in four regions of Ethiopian highlands. To do this, a multi-dimensional perspective is adopted to identify relevant farm-level sustainability indicators relevant to the Ethiopian smallholder farming sector. The chapter describes the process of selecting farm-level sustainability indicators, and how different frameworks adapted from the agricultural literature, are used to enhance the appropriateness of the chosen indicators. A Data Envelopment Analysis (DEA) framework is applied to synthesize the selected indicators into a relative farm sustainability index, after which a generalized linear regression model is applied to identify factors explaining differences in relative farm sustainability. Significant variables are prioritized and discussed, along with their policy implications. The analyses show that farm size, markets access, access to off farm income, agricultural loans, access to agricultural extension and demonstration plots, are key drivers of agricultural sustainability at the farm level.

Chapter four builds on chapters two and three, and examines the relationship between agricultural intensification and relative farm sustainability. The chapter classifies farms into eight categories based on relative levels of intensification and farm sustainability. Principal components analysis (PCA) and Cluster Analysis (CA) are used to develop distinct farm typology clusters and therefore profile farmers according to their common characteristics. Multinomial Logit (MNL) regression models are used to predict membership in farm clusters as well as the likelihood of farmers embarking on alternative paths of agricultural intensification.

Chapter five summarizes and concludes the key findings of the research. It also discusses the policy implications for sustainable intensification efforts in Ethiopia, as well as the broader implications for other contexts, particularly sub-Saharan Africa in general. The chapter then discusses the limitations of the study, and points out important areas worth considering regarding future research.

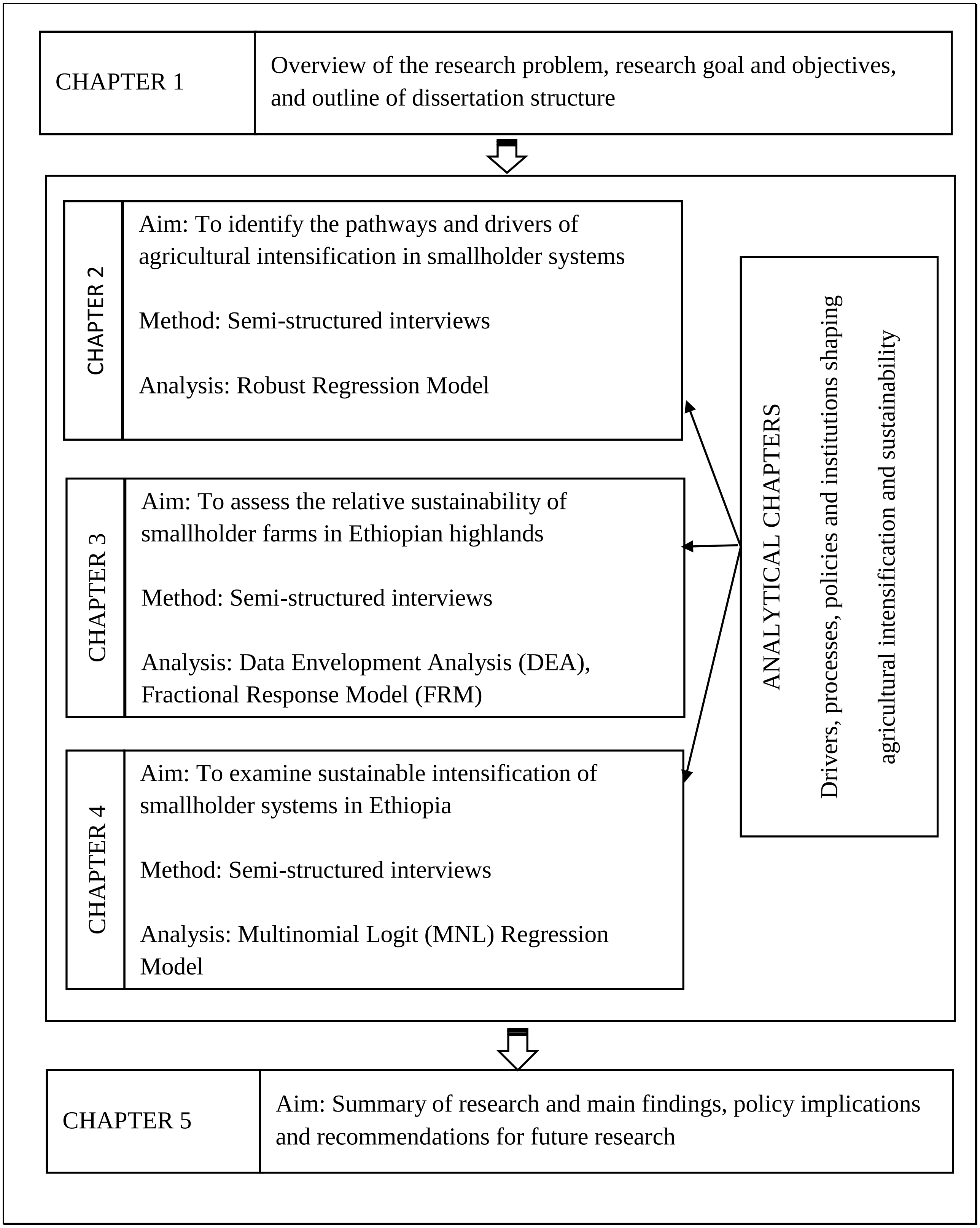

Figure 1.1: Visual representation of dissertation structure and contents

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CHAPTER 2

UNDERSTANDING DRIVERS AND PATTERNS OF AGRICULTURAL INTENSIFICATION IN ETHIOPIAN HIGHLANDS

Summary

The study investigates the factors that facilitate or hinder the process of agricultural intensification by smallholder farmers in four regions of Ethiopia's Highlands. The chapter begins by examining the factors affecting agricultural intensification, measured by the gross value of crop output per hectare. As measured in this study, agricultural intensification in the sub regions of Ethiopia, proxied by the gross value of crop output per hectare, averaged 11,421 ETB/ha, which is roughly US$ 571 per hectare. It was highest in Tigray (15,707 ETB/ha), followed by Amhara (11,733 ETB/ha), while farms in Oromia region averaged 10,885 ETB/ha and the Southern Nations, Nationalities, and Peoples (SNNP) region had the lowest average of 7,393 ETB/ha. The degree of intensification was influenced most by land size, as increasingly binding land constraints force people into more intensive patterns of production. Consistent with the inverse productivity hypothesis (Carter, 1984), the results also show that smaller farms invested more in inorganic fertilizer, improved crop seeds, and used more family and hired labor per hectare. Intensification was also significantly influenced by market access, farm mechanization as well as the use of agricultural loans. There are also significant differences in agricultural intensification across the four regions, owing to the importance of differences in general climate and other biophysical determinants of agricultural potential in the four zones. Additionally, the paper investigates determinants and factors that shape different intensification strategies pursued by households in their quest to increase agricultural output, or to save costs, in the face of increasing land constraints.

The main critical factors influencing intensification paths were farm size, levels of household wealth, production mechanization and differences in agroecological conditions. The results indicated that levels of fertilizer- and labor-use intensities, as well as cropping intensity, were generally hired on smaller farms. Levels of household wealth and general asset endowments positively influenced capital-led intensification paths through increased investments in seed, fertilizer and other agricultural inputs. Production systems that were mostly mechanized had marginally lower levels of fertilizer, seed and general capital expenditures per hectare, indicating the cost-saving potential of agricultural mechanization.

2.1. Introduction

Achieving sustained productivity growth in agriculture remains high on the policy and research agenda in sub-Saharan Africa (SSA) (Nin-Pratt and McBride, 2014). The region's agricultural productivity growth continues to lag behind the rest of the world (Fuglie and Rada, 2012). Consequently, the Global Harvest Initiative (2012) projected that, on the current trend, the region would only produce 13 percent of its food needs. A rapidly growing population, estimated at 900 million people, and projected to double by 2050 (Population Reference Bureau, 2012), has compounded the food security situation. An estimated 230 million suffers chronic malnutrition (FAO, 2012). There is, therefore, a growing consensus that farmers in SSA must intensify their production systems for the region to improve its food security situation (Wood, Tappan and Hadj, 2004). However, there remains a huge debate about how intensification in smallholder agriculture should best be achieved. Traditionally, African farmers pursued shifting cultivation in response to declining yields (Reardon et at., 1999). However, a growing pressure to address land and soil degradation implies that production growth on the extensive margin is increasingly becoming infeasible and unviable (Jayne and Munyanga, 2012; Wood, Tappan and Hadj, 2004; Tilman et al., 2002; Clay, Reardon and Kangasniemi, 1995). Thus, the FAO (2009) projected that 80 percent of growth in crop production in developing countries would come from intensification, particularly higher yields and increased cropping intensity, while only 20 percent would come from expansion of arable land.

Agricultural intensification refers to an increase in the average inputs of labor and/or capital on land already under cultivation, for the purposes of increasing the value of output per hectare (Muller, 2004; Tiffen et al, 1994). An increase in the gross value of agricultural output can occur through an increase in yields per hectare, increasing cropping intensity per unit of land or shifting towards high value crops (Pretty, Toulmin and Williams, 2011). For intensification to occur, an increase in the demand for output is necessary (Carswell, 1997). Boserup (1965) argued that increasing population density pushes farmers towards more intensive production systems, and a shift away from long-fallow periods (Pender, 2001; Turner and Shajaat, 1996). Studies in Ethiopia found that higher population densities and land constraints were associated with more intensive use of labor and other agricultural inputs such as fertilizer and improved seeds (Pender and Gebremedhin, 2006; Heady et al., 2014; Josephson et al., 2014; Benin, 2006). Other theories, however, explain intensification as a production response to changes in land values (von Thünen, 1826) and relative factor scarcities (Hayami and Ruttan, 1970; Binswanger and Ruttan, 1978). For instance, Josephson et al (2014) notes that increases in land prices push farmers to switch to higher value crops in order to maximize value produced per hectare. While farmers have historically responded to intensification incentives and drivers in a variety of ways, the specific intensification path that farmers will take in a given context is not known with certainty. Generally, the agro-ecological and policy environment, market conditions and institutional factors will shape the incentives available to farmers, and hence the choice of intensification path (Netting et al, 1989; Brush and Turner, 1987; Lele and Stone, 1989; Reardon et al., 1999; Lee et al., 2001; Kruseman, Ruben and Tesfay, 2006; Angelsen and Kaimowitz, 2001; van Soest et al. 2002; Reardon et al., 1999; Binswanger and Pingali, 1988).

Against this backdrop, the purpose of this chapter is to examine the drivers of agricultural intensification in smallholder farming systems of Ethiopian Highlands, as well as the factors that shape the choice of intensification paths smallholder farmers can potentially embark upon as they attempt to increase the gross value of their output per unit of land. Generally, much of the empirical work on the subject has focused on how land constraints and population density influence agricultural intensification in Ethiopia (Pender and Gebremedhin, 2006; Heady et al., 2014; Josephson, Ricker-Gilbert and Florax, 2014; Benin, 2006). I adopt a broader perspective, and examine how a wide range of socioeconomic, agro-ecological, policy and institutional factors influence agricultural intensification in the Ethiopian highlands. Furthermore, there has been limited empirical research on what determines the specific intensification paths taken by households. Therefore, the study further examines how the selected set of factors shape different intensification strategies and paths smallholders can potentially embark on. The study uses cross-sectional data of 600 households, drawn from Tigray, Amhara, Oromia and the Southern Nations, Nationalities, and Peoples (SNNP) regions of Ethiopia. A robust regression model is used to examine the relative importance of socioeconomic, agro-ecological and institutional factors on agricultural intensification.

Agricultural intensification is a highly relevant subject in the Ethiopian context. The agricultural sector in Ethiopia accounts for about 40 percent of national GDP, 90 percent of exports, and 85 percent of employment (World Factbook, 2012), making agricultural growth the focus of the government's poverty reduction strategy (Spielman et al., 2010). The country is densely populated, and projected to reach 160 million people by 2050 (Population Reference Bureau, 2012). Farm sizes are generally small and have been declining; averaging about one hectare per farm (Pender and Gabremedhin, 2006). Most Ethiopia's population resides in the highland regions, which are characterized by steady rainfall and good soils (Josephson, Ricker-Gilbert and Florax, 2014). This implies that most of the arable land in the highlands is already under cultivation. On top of that, despite the agricultural potential of the highlands, these areas are characterized by low and declining agricultural productivity (Pender, Place and Ehui, 1999). Productivity is compounded by land degradation, with an annual average erosion of 42 tons per hectare observed in the highland areas (Pender, 2002), and recurrent droughts (Byerlee et al, 2007). Thus, cereal yields average less than one ton per hectare (Pender and Gabremedhin, 2006).

Given several attempts to adapt lessons of the Green Revolution and achieve productivity growth in the smallholder-dominated African agriculture, this chapter has several significant contributions. First, while several hypotheses have been postulated to explain the drivers of agricultural intensification in developing countries, the exact intensification paths are still not clear. Depending on resource endowments, a particular group of households may choose a labor-led intensification path, committing higher levels of labor inputs per unit of land for critical farm activities such as land preparation; while others may embark on capital-led intensification, which involves increased investments in non-labor inputs such as fertilizer, herbicides and agricultural equipment (Carswell, 1997; Reardon et al., 1999; Clay, Reardon and Kangasniemi, 1998). Furthermore, a better understanding of the factors shaping the different intensification paths will help in the design of appropriate policy and institutional innovations to support the process. Second, as most farming in Ethiopia is conducted by smallholder farmers who face significant land constraints (Headey et al, 2013), there is growing debate about how farm size influences intensification and agricultural productivity in general (Larson et al, 2012; Carter, 1984). Therefore, examining how farm size influences agricultural intensification will provide interesting insights for land policy.

The chapter proceeds as follows: Section 2 discusses the theoretical framework and empirical model used in the study. Section 3 discusses the sampling procedure and data collection techniques, as well as a brief description of the sample. Section 4 presents the descriptive and econometric results. Section 5 discusses the implications of the study results and concludes.

2.2 Empirical Approach

2.2.1 Data

The study is based on data collected from household surveys in four regions in the Ethiopia highlands. The households were selected using a combination of stratified and systematic sampling techniques. At the initial stage, one district was selected from each of the four regions. The second stage involved selecting three wards from each of the four districts for study purposes. Finally, 50 farm households were randomly selected from each ward, using farmer lists provided by government extension officers and field facilitators. Overall, 150 farm households were randomly selected from each of Tigray, Amhara, SNNP and Oromia regions, to give a total sample of 600 households. The study regions are characterized by relatively steady rainfall, averaging an annual range of about 600 mm in the northern highlands to over 2,000 mm in the southwestern highlands. Annual average temperatures range from 20 to 22°C in the lower elevations to 10-12°C in the higher elevations. The soils are predominantly nitisols, vertisols, cambisols and luvisols, which have very good agricultural potential (Pender, Place and Ehui, 1999). Data analysis utilizes primarily the cross-section sample of 600 farming households.

2.2.2 Theoretical model

Synthesizing different theoretical perspectives on agricultural intensification, a general model was developed to assess the factors driving agricultural intensification at household level. The model specifies agricultural intensification as a function of demographic variables, as suggested by Chayanov's conceptual framework (Netting, 1993), market access variables as suggested by Von Braun's (1995) commercialization model, institutional and policy variables (Nin-Pratt and McBride, 2014, Lee et al., 2001; Binswanger and Rosenzweig, 1986; Binswanger and Ruttan, 1978) and agro-ecological variables (Mortimore and Turner, 2005). The general model is follows:

$$Y = f(X, M, P, Z) \qquad 2.1$$

Where *Y* represents a measure of agricultural intensification at household level. For the purposes of this study, agricultural intensification at the farm-level is represented by the gross value[2] of crop output per hectare. It is obtained by aggregating the main crops produced by

[2] All monetary values are in Ethiopian Birr (ETB) unless otherwise stated. An exchange rate of USD1:20 ETB is used for comparative purposes.

households, then weighting them by their respective producer prices obtained from the Ethiopia Central Statistical Agency. *X* represents a set of variables depicting the demographic characteristics such as farmers age, farming experience, family size and access to off-farm income. *M* is the market access variable, measured by the distance to the nearest village market. *P* represents the policy and institutional variables; these include farm size, access to agricultural loans and access to government extension services. Finally, *Z* represents agro-ecological factors, whose effects are captured by three regional dummies. These variables represent the incentives facing farming households, as well as their capacity to intensify the production processes. Demographic characteristics of households are expected to influence agricultural intensification in many ways. Farmers age and farming experience are expected to affect agricultural intensification through their overall impacts on technology adoption decisions. The hypothesis concerning farmers' age is ambiguous, as its effects are likely complex. While younger farmers are expected to have a higher propensity to adopt new technologies, the more experienced farmers are likely to implement soil management practices that have an impact on productivity. Family size is hypothesized to positively influence agricultural intensification, since bigger households mean more labor resources (Pender and Gabremedin, 2007).

Recognizing that farmers are more likely to pursue different strategies to intensify their production systems, another set of equations are also specified, to identify factors that affect specific intensification paths. The intensification strategy model is specified as follows:

$$S_i = \mathrm{f}(\mathrm{X}, \mathrm{M}, \mathrm{P}, \mathrm{Z}) \qquad 2.2$$

Where S_i represents the respective intensification strategy or indicator, such as fertilizer use per hectare, improved seed use per hectare, capital expenditure per hectare, total labor use per hectare, hired labor per hectare and cropping intensity.

Market access is expected to positively influence agricultural intensification. Improved access to markets provides positive incentives to intensity of agricultural input use (Lee et al., 2001), as well as reduces the need for land expansion (Reardon et al., 1999). Farm size is expected to negatively affect intensification. Farmers with smaller landholdings, and hence are more land constrained, tend to have more pressure to embark on more intensive production practices. Studies have found evidence of higher input use per ha and cropping intensity on small farms (Pham and Smith, 2014). Access to off-farm income and agricultural loans are expected to help alleviate liquidity constraints, which is a common challenge among smallholder farmers in Ethiopia. They are both expected to have a positive impact on agricultural intensification. Increased access to government extension services, which is a main source of farming information and technical advice to farmers, is expected to positively impact on agricultural intensification.

2.2.3 Empirical model

A multivariate regression model was used to examine the significance and relative importance of the factors influencing agricultural intensification at household level. The gross value of crop output was regressed on a set of demographic, socio-economic and agro-ecological, policy and institutional variables. Exploratory analyses using a Breusch-Pagan / Cook-Weisberg test indicated that heteroscedasticity was a problem in the data. Therefore, a Robust Regression Model was used instead of the traditional Ordinary Least Squares (OLS), to obtain heteroscedasticity-robust standard errors. The multivariate regression is specified as follows:

$$Y = \beta_0 + D_1 + D_2 + D_3 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_n X_N + \mu \ldots \ldots \ldots (2.3)$$

Where Y is the measure of agricultural intensification, the gross value of crop output per hectare. The Xs are the explanatory variables hypothesized to affect agricultural intensification. In this model, these explanatory variables are land size, distance to the nearest market (km), use of agricultural loans, frequency of visits to demonstration plots, household wealth index, agricultural mechanization, tropical livestock units (TLU), animal vaccinations and years of farming experience. D_1, D_2 and D_3 are dummy variables for the three regions representing Tigray, Amhara and Oromia regions, respectively. A similar specification is formulated for the intensification strategies model. The multivariate intensification strategies regression model would therefore look as follows:

$$S_i = \beta_0 + D_1 + D_2 + D_3 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_n X_N + \mu \ldots \ldots \ldots (2.4)$$

Where S_i represents the intensification strategies and the repressors are as earlier defined.

In order to ascertain in any of the estimated slope coefficients differ across regions, a similar multivariate regression model was used, but this time incorporating multiplicative dummies for each of Tigray, Amhara and Oromia regions. The SNNP was the reference region. The model is specified as follows:

$$Y = \beta_0 + D_1 + D_2 + D_3 + \beta_{11}D_1X_1 + \beta_{12}D_1X_2 + \beta_{13}D_1X_3 + \dots + \beta_{1n}D_1X_N + \mu \dots \dots \dots (2.3)$$

Where Y is the gross value of crop output per hectare and the X's are the explanatory variables as described for equation 2.2. For any variable of interest, if the coefficient of the variable multiplied by a regional dummy (i.e. the multiplicative term) is significantly different from zero, that the variable behaves differently than outside the region (Guhl, 2004).

2.2.4 Key variables

A household questionnaire was used to gather data for computing indicators of agricultural intensification (Table 2.1), as well as map the different intensification strategies pursued by households as they seek to intensify their farming systems. Key variables used in the analysis were mainly based on a review of similar studies assessing intensification and agricultural productivity in general.

Variables capturing household characteristics include household size, the age as well as farming experience of the household head. Household asset holdings, which has a bearing on their productive capacity and liquidity, were synthesized into a household wealth index, computed using principal components analysis (PCA). The PCA is a multivariate statistical method used to reduce data dimensions, transforming a set of correlated variables into a set of uncorrelated variables called ‘principal components’ (Filmer and Pritchett, 2001). The procedure is applied on a set of variables that are indicators of socio-economic status or well-being of rural households. While socio-economic status of rural households involves many dimensions, variables used in this study were based on literature review and synthesis of variables used in similar research, such as Vyas and Kumaranayake (2006). Variables used included ownership of production assets such as animal carts, sprayers, ox ploughs, harrows, yokes and ridgers; ownership of household assets such as radio and television; quality of housing (floors, roofs and walls); sources of drinking water (river, protected wells, tape); access to sanitation facilities; as well as livestock ownership. PCA was used to aggregate these variables into a single socioeconomic index, which was used as a proxy for household wealth.

The gross value of output per hectare was measured in Ethiopia Birr. To capture intensification strategies or input intensification, data on input quantities and costs was also collected. Fertilizer use was given by the sum of all the fertilizer, including Diammonium phosphate (DAP), Urea, and New Pricing Scheme (NPS) fertilizers applied across all crops, in kilograms per hectare. The variable on labor use captured all the labor, including family and hired labor, used in crop production processes such as land preparation, weeding, fertilizer application and harvesting. It is measured in person-days per hectare. Capital costs represents total amount, in Ethiopian Birr, incurred in purchases of fertilizers, seeds, herbicides and pesticides. It excludes payment for labor services.

Institutional factors are represented by variables capturing access to agricultural loans (binary), distance to nearest market (kilometers), frequency of visits by extension officers and visits to agricultural demonstration plots, as well as size of farm plots owned by the household (hectares). Land size can be potentially endogenous[3] to the dependent variable, since there could be some unobserved factors that affect both the dependent variable (intensification) and changes in land size. However, in the Ethiopian context, land ownership is fairly exogenous because of State ownership. The absence of a land market makes buying and selling of land almost impossible. Regional dummy variables are included to capture the effects of variations in agro-ecological conditions and other region-specific policies that vary across the four regions.

[3] Most of the variables used in the model are exogenous. Variables such as labor hiring and capital costs will mostly depend on the going wage for hiring labor, market prices for fertilizer and machinery hiring costs, which are exogenous to the household. Extension services are also provided by the State, and their availability will depend on budgetary provisions and mobility of agents.

Table 2.1: Definition of key intensification indicators and variables used in the study

Variable	Description
Intensification measures	
Gross value of crop output per hectare (ETB/ha)	Total value of crop production per hectare
Intensification strategies	
Total improved seed use per hectare (kgs/ha)	Sum of improved seeds used in production of main crops in both main (meher) and second (belg) seasons
Total fertilizer-use per hectare (kgs/ha)	Total inorganic fertilizer used during the main (meher) and second (belg) seasons
Labor use intensity (person-days/ha)	Total labor (family and hired) in crop production, including land preparation, weeding, fertilizer application and harvesting.
Total hired labor per hectare (persons/ha)	Total hired labor used in crop production
Total labor costs per hectare (ETB/ha)	Total labor costs incurred in crop production
Total capital costs per hectare (ETB/ha)	Total of fertilizer, seeds, herbicides, pesticides costs, excluding labor expenses
Cropping intensity (CI)	A measure of cropping intensity, computed from the data
Institutional and policy variables	
Total land holding (ha)	Total land owned by the household
Distance to nearest market (km)	Estimates of average distance (km) to nearest market town
Access to agricultural loans (0-1)	Binary variable whether household obtained agricultural loans during cropping year
Frequency of visits to demonstrations and research plots (0-1)	Number of time the farmer visited agricultural demonstration plots during the cropping year.
Household controls	
Total household size	Total number of household members
Household head age (years)	Age of the household head in years
Household head farming experience (years)	Total years of farming experience in completed years
Household wealth index	An index of household assets, computed using principal components analysis.
Agro-ecological controls	
Oromia dummy	Binary variable whether household is in Oromia region
Amhara dummy	Binary variable whether household is in Amhara region
Tigray dummy	Binary variable whether household is in Tigray region

2.4 Results

2.4.1 Descriptive results

In the study sample, the average land size across the four regions is 1.80 hectares. Land holdings were largest in the Oromia region, which averaged 3.5 hectares, compared to 0.56 hectares in Tigray, 1.44 hectares in Amhara and 1.46 hectares in SNNP regions. According to the 2011–2012 agricultural sample survey of the Ethiopian Central Statistical Agency (CSA), the average land size is 1.15 hectares in Oromia, 0.91 hectares in Tigray, 1.09 in Amhara and 0.49in the SNNP region; while the national average is 0.96 hectares. For the purposes of exploring how intensification varies by farm size, the study classified farms into three distinct size categories based on landholdings, with small-sized farms having less than one hectare, medium-sized farms with one hectare to 1.5 hectares and large farms having more than 1.5 hectares of land. About 25.6% of the farms are in the small category, while 44.4% make up the medium-sized farms and 30% are in the large category. Average farm sizes for each category were 0.66 hectares for the small-sized farms, 1.67 hectares for the medium-sized farms and 2.97 hectares for the large-sized farms. Table 2.2 provides descriptive statistics of the main production inputs utilization by farmers.

Table 2.2: Means and standard deviations of main intensification indicators by farm size

Variable	Small farms	Medium farms	Large farms	Overall
Total cultivated land (ha)	0.61 (0.23)	2.101 (0.92)	5.11 (3.03)	2.63 (2.48)
Total fertilizer use (kgs/ha)	212.25 (371.15)	99.81 (71.50)	81.89 (95.90)	123.19 (206.94)
Total improved seed use (kgs/ha)	111.93 (196.92)	79.38 (77.13)	86.02 (123.31)	89.70 (131.20)
Total labor (person-days/ha)	125.34 (94.08)	67.38 (55.77)	45.43 (46.46)	75.62 (721.19)
Total hired labor (person-days/ha)	21.49 (42.32)	6.67 (11.51)	3.80 (9.08)	9.60 (24.26)
Total labor costs (ETB/ha)	1,028.98 (1,826.54)	567.88 (1,030.66)	294.24 (585.30)	603.68 (1,223.38)
Total crop capital input costs (ETB/ha) (excl. labor)	3,829.02 (5,992.10)	2,134.06 (1,417.47)	1,545.56 (1,521.50)	2,390.98 (3,388.83)
Total crop variable costs (ETB) per hectare	4,857.99 (7,301.37)	2,701.94 (1,863.01)	1,839.79 (1,656.47)	2,994.66 (4,152.03)
Gross value of crop output (ETB/ha)	16,650.31 (15,620.29)	9,838.31 (6,469.14)	9,304.24 (6,811.40)	11,420.58 (10,192.91)

Note: standard deviations and in parentheses.

Average inorganic fertilizer use by households was 123.2 kgs/ha, of which DAP was the most used (73kgs/ha). Fertilizer use was highest among farmers in the Tigray region (172.2 kgs/ha), followed by farms in the SNNP region (145 kgs/ha). Average fertilizer use was 98 kgs/ha in Amhara and 85.5 kgs/ha in Oromia regions. Fertilizer use per hectare was highest among the small farms (212.2 kgs/ha), followed by the medium size farms (99.8 kgs/ha). The large farms had an average fertilizer use of 82 kgs/ha. About 79% of the farmers utilized improved seeds in their cropping enterprises. Total improved seeds use across main crops was 90 kgs/ha, and was highest among small farms (112 kgs/ha). Medium size farms used a total of 79.4 kgs/ha of improved seeds, while large farms used 86 kgs/ha of the same inputs.

On average, total labor utilization was 75.6 man-days per hectare. The overall labor-use intensity is higher among small farms (125.3 man-days/ha) than that of medium size (67.4 man-days/ha) and large farms (45.4 man-days/ha). Total hired labor averaged 9.6 man-days/ha, implying that family labor accounts for the biggest share of farm labor. Small farms utilized more hired labor (21.5 man-days/ha) compared to medium size (6.7 man-days/ha) and large farms (3.8 man-days/ha). These results are consistent with the inverse productivity literature that shows an inverse relationship between farm size and productivity (Larson et al, 2012; Carter, 1984). Studies have also found evidence of inverse relationships between labor intensity and farm size, as well as between capital input intensity and farm size (Masterson, 2007).

Overall, farmers incurred 603.7 ETB (roughly US $30.2) in labor costs per hectare. They made a total capital investment in fertilizer, improved seeds and other agro-chemicals, of about 2,391 ETB, which is roughly US$ 119.6 per hectare. The capital investments were highest among small farms (3,829 ETB/ha), followed by medium size farms (2,134.1 ETB/ha), while large farms had the least investments per hectare (1,545 ETB/ha). The general investments in production inputs varied considerably across households. Overall, 56.9% of the farmers had hired some additional labor, 63.3% used herbicides while 40.2% purchased pesticides, 78.9% invested in improved crop seeds, and 65.7% had used some mechanization services. In terms of access and utilization of agricultural services, about 24.5% had access to agricultural credit, 53.3% had membership in farmer groups, 55.9% were visited by an agricultural expert, 81.4% received some specialized agricultural training, and only 21.3% had access to some irrigation facilities. About 54% of the farmers indicated they had invested in soil erosion control using stone bunds. Overall, the average gross value of output per hectare was 11,421 ETB, roughly US$ 571 per hectare, and varied considerably across the four regions (figure 2.1).

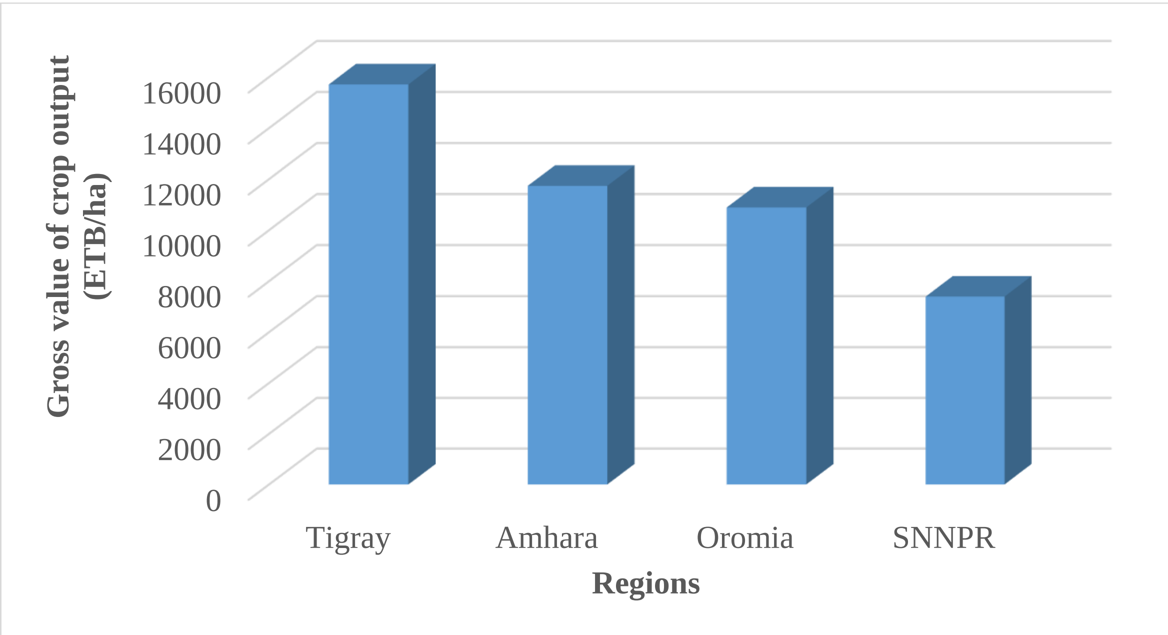

Figure 2.1: Distribution of agricultural intensification measures over regions

Farmers were categorized into three classes of intensification levels (low, medium and high) based on the three quantiles of gross value of output per hectare. Overall, the Tigray region had the highest number of farmers in the high intensification level (37%), followed by Oromia region (31%), while Amhara and SNNP regions had 25% and 8%, respectively. Generally, farmers in the high intensification level class had invested the most in labor, improved seed and capital inputs per hectare (Table 2.3). Higher levels of gross value of output were associated with higher input-use intensities. Agricultural intensification, as measured by the gross value of crop output per hectare, was higher on relatively smaller farms.

Table 2.3: Distribution of intensification indicators by intensification levels

Variable	Intensification Levels (average)			Overall (average)
	Low	Medium	High	
Total cultivated land (ha)	3.36 (2.93)	2.35 (2.01)	2.15 (2.26)	2.62 (2.48)
Total fertilizer use (kgs/ha)	77.77 (70.33)	128.64 (280.68)	163.42 (203.84)	123.42 (206.94)
Total improved seed use (kgs/ha)	62.72 (85.96)	78.02 (71.19)	128.60 (192.73)	89.70 (131.20)
Total labor (person-days/ha)	57.57 (55.62)	68.43 (49.40)	101.02 (95.74)	75.62 (72.19)
Total hired labor (person-days/ha)	4.81 (9.36)	8.65 (14.98)	15.38 (37.55)	9.60 (24.26)
Total labor costs (ETB/ha)	419.45 (783.70)	618.95 (966.76)	773.72 (1,704.67)	603.68 (1,223.38)
Total crop capital input costs (ETB/ha) (excl. labor)	1,588.39 (1,267.98)	2,047.57 (1,144.77)	3,549.30 (5,447.83)	2,390.98 (3,388.83)
Total crop variable costs (ETB) per hectare	2,002.84 (1,626.89)	2,666.52 (1,549.63)	4,323.03 (6,648.19)	2,994.66 (4,152.03)
Gross value of crop output (ETB/ha)	4,642.46 (1,904.91)	9,366.55 (1,287.77)	20,308.99 (13,368.40)	11,420.58 (10,192.91)

Note: standard deviations are in parentheses.

2.4.2 Drivers of agricultural intensification

A multivariate linear regression model was used to determine the drivers of agricultural intensification at the household level. The intensification variable, gross value of crop output per hectare, was regressed on the set of variables hypothesized in Table 2.1, as well as other determinants such as household size, herd size, farm size, agricultural mechanization, number of years of farming, access to agricultural demonstration plots, among others. Two diagnostic tests were carried out. First, the variance inflation factor (VIF) option in Stata 13.0 was used to identify variables that exhibited a great degree of multicollinearity. The test was negative, meaning that mulicollinearity is not a problem. Second, a Breusch-Pagan / Cook-Weisberg test was used to test for heteroscedasticity. The null hypothesis of constant variance was rejected, thus confirming heteroscedasticity. Therefore, heteroscedasticity-robust standard errors were used to deal with heteroscedasticity. The results of the robust regression model for intensification are shown in Table 2.4 below.

Table 2.4: Robust regression results

Variables	Coefficients (b)	Standardized coefficients (Beta)
Crop area (ha)	-1,092***	-0.395
	(186.4)	
Distance to market (km)	-23.34	-0.015
	(83.17)	
Use of agricultural loans	2,123**	0.125
	(1,067)	
Demonstration plot visits	497.5***	0.180
	(165.8)	
Wealth index	1,286***	0.356
	(281.9)	
Production mechanization	3,269*	0.215
	(1,663)	
Tropical livestock units (TLU)	301.3*	0.124
	(153.9)	
Animal vaccinations	2,209**	0.095
	(1,090)	
Years farming	-90.29***	-0.144
	(32.26)	
Oromia region	4,187***	0.259
	(1,490)	
Tigray region	4,479***	0.234
	(1,347)	
Amhara region	2,424**	0.145
	(1,159)	
Constant	2,684	
	(3,089)	
Observations	232	
R-squared	0.332	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The results show a significant negative relationship between gross value of crop output per hectare and land size. According to these results, a one-hectare reduction in land area is associated with a 1,092 ETB (or US$55) increase in the gross value of crop output per hectare. A related study exploring effects of land constraints on agricultural intensification in Ethiopia (Headey et al, 2013) found that a one-hectare reduction in village farm size leads to a 4,216 ETB (or US$250) increase in net crop income per hectare. This indicates that households tend to intensify more as farm sizes become smaller and land constraints are more binding. This result is consistent with the inverse productivity hypothesis, which observes that small farms are more productive than large farms in Africa (Larson et al, 2012; Carter and Wiebe, 1990; Carter, 1984). This is often attributed to the higher input-use intensity on small farms (Pham and Smith, 2014; Masterson, 2007). However, other studies argue that small farmers are often resource poor and therefore less likely to invest in soil fertility improvements (Havenevik and Rune, 1997) or adopt modern technologies (Bhalla, 1979), and other non-labor inputs that larger farms usually use as a substitute for labor (Adesina, Djato, and Pegatienan, 1994).

The market distance variable carries the expected negative sign, which should imply that the nearer to the market the more the intensification incentives, and hence the more the gross value of crop output per hectare. However, surprisingly, this variable is not statistically significant. This is somewhat counterintuitive, since market access is expected and well documented in literature as a critical driver of agricultural commercialization and intensification (von Braun 1995). This could be due to the way the market distance variable was measured. Due to lack of GPS coordinates, the study relied on farmers' estimates of the distance of their homesteads to the nearest market. Other institutional-related variables are significant and positive drivers of agricultural intensification. The results show that the gross value of crop output per hectare was 2,123 ETB (or US$106) higher for farmer who had access to agricultural loans compared to those without access. The results also show that visiting agricultural demonstration plots more often increases agricultural intensification. This is attributable to the knowledge that farmers acquire from visiting demonstration plots, which are essentially platforms for field schools that showcase different technologies from which farmers can learn and adapt good agricultural practices onto their own farms.

Household and farm characteristics are significant drivers of agricultural intensification at the household level. The results show that the household wealth index positively and significantly influences agricultural intensification. Thus, this result reflects that the higher the resource endowment, in terms of productive assets, the higher the intensification performance. Consistent with this inference, the results show that mechanized systems are more productive than those that are predominantly manual. The gross value of crop output per hectare was 3,269 ETB (or US$163) higher on farms where land preparation, weeding and harvesting are mostly mechanized (e.g. through animal drawn implements). Herd size, measured by tropical livestock units (TLU), positively and significantly affects agricultural intensification. The result provides evidence of the positive relationship between crop–livestock interactions and agricultural intensification. Positive gains come from increased supply of manure as well as draught power for critical farm operations. Unsurprisingly, farmers who had their livestock vaccinated had more intensification performance, with the gross value of crop output per hectare 2,209 ETB (or US$110) higher than those who didn't have access to the same facility.

The effects of agro-ecological conditions on agricultural intensification and productivity in general are captured by regional dummies. Three dummy variables were included in the regression model and they are all significant. The results show the value of crop production per hectare in Oromia region is 4,187 ETB (or US$209) lower than that in the SNNP region. Also, compared to the SNNP region, value of crop production per hectare is 4,479 (or US$223) higher in Tigray and 2,424 ETB (or US$121) higher in the Amhara region. These results probably point to differences in general climate and other biophysical determinants of agricultural potential in the four zones. A regional regression model was also estimated, to ascertain if any of the estimated slope coefficients differed across regions. The model also showed how the effects of the different factors on agricultural intensification were mediated by the region in which the farm is located. The results show that land size, agricultural loans, and access to government vaccination services had greater impact on agricultural intensification when the farm is in Tigray compared to the SNNP region. Tropical livestock units had a significantly higher impact on agricultural intensification when the farm is in Oromia compared to SNNP region. The full results of the regional regression model are displayed in Appendix 1.

The estimated coefficients of the multiple regression model were also standardized to get beta coefficients. Standardized coefficients (betas[4]) help to ascertain the relative importance of the set of independent variables on the agricultural intensification variable. This is especially important given that the independent variables had different units of measurement. Generally, controlling for the other regressors in the model, the closer to the absolute value of the beta coefficient is to one, the stronger the influence of the particular independent variable on agricultural intensification. In this case, the results in Table 2.4 show that land size (0.40) had the strongest effect on agricultural intensification, followed by household wealth (0.36), while distance to the market had the smallest effect (0.02). For every standard deviation unit decrease in land size, agricultural intensification would increase by 0.40 standard deviation units, with other factors held constant. Following Piedra-Muñoz, Galdeano-Gómez and Pérez-Mesa (2016), the standardized coefficients were also index out of 100, thus giving a clearer picture on the relative importance of each value (figure 2.2).

[4] Standardized beta coefficients are obtained by weighting the unstandardized coefficients by the ratio of the standard deviation of the dependent variable to the standard deviation of the dependent variable. They are also the coefficients that one would otherwise obtain if dependent variables in the regression were converted to z-scores before running the regression.

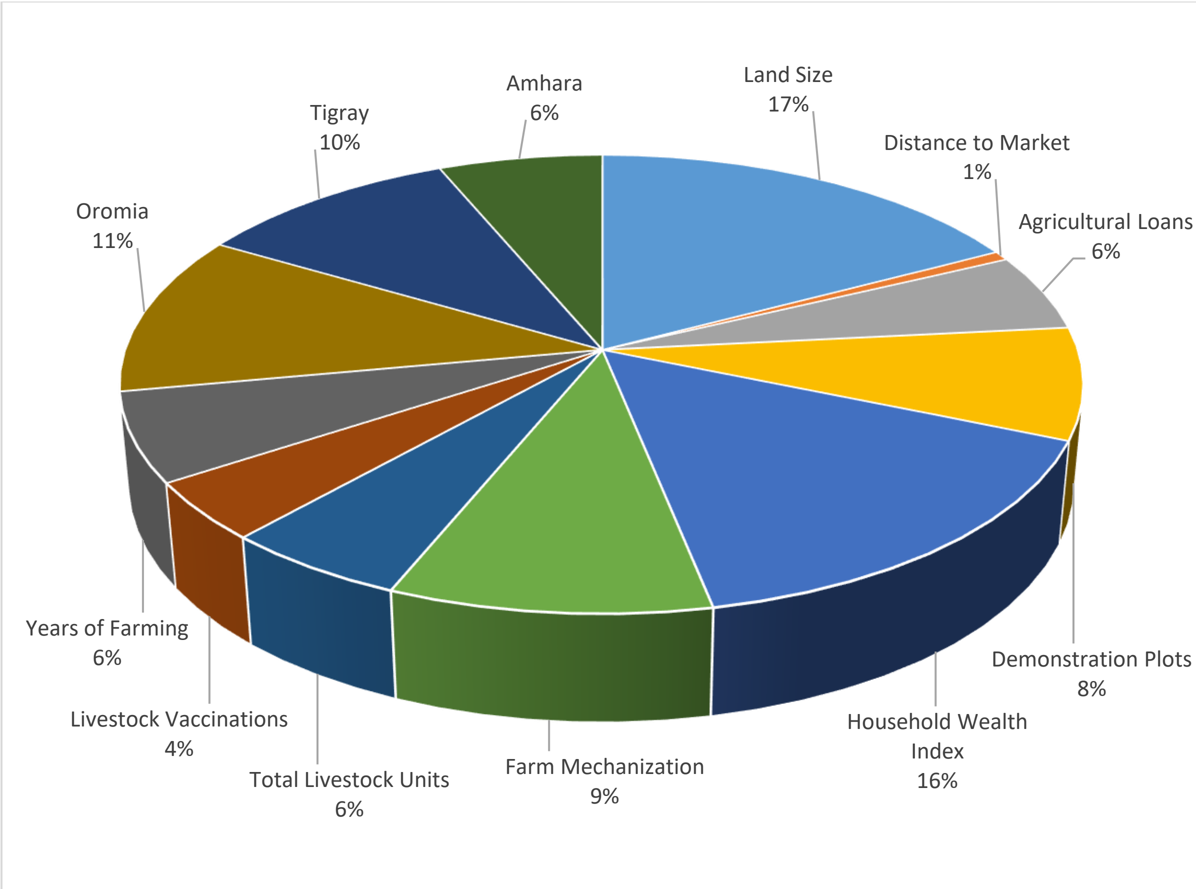

Figure 2.2: Relative importance of each variable on agricultural intensification

4.2.2 Drivers of different intensification strategies

Having determined the factors driving agricultural intensification at household level, the next step was to determine how the same factors affect different intensification strategies that households can potentially pursue in their attempts to increase the gross value of their crop output per hectare. It is expected that the decisions regarding the implementation of the different intensification strategies are related, and thus failure to capture the interrelationships among the intensification strategies will lead to bias and inefficient estimates (Greene, 2008). Ideally, a system of equations, rather than ordinary least squares (OLS), would be more appropriate to model the factors driving the different intensification strategies, preferably using a seemingly unrelated regression (SUR) model (Cameron and Trivedi, 2010). However, the efficiency gains of SUR compared to OLS were very modest. Therefore, robust regression models were estimated for each of the intensification strategies. The results are shown in Table 2.5 below.

Table 2.5: Robust regressions of determinants of intensification strategies

Dependent Var.	Fertilizer intensity (kg/ha)	Improved seed-use (kg/ha)	Capital expenditure (ETB/ha)	Total labor (man-days/ha)	Hired labor (man-days/ha)	Cropping intensity (score)
Crop area (ha)	-8.103***	-7.198**	-385.3***	-8.625***	-1.761**	3.629*
	(2.297)	(2.931)	(107.5)	(1.465)	(0.703)	(1.889)
Distance to market (km)	0.471	-0.142	25.55	1.551	-0.405*	-1.431**
	(1.324)	(1.554)	(35.02)	(1.081)	(0.244)	(0.725)
Use of agricultural loans	4.263	-3.096	1,967*	12.61	12.87*	-16.28*
	(11.21)	(20.05)	(1,163)	(13.18)	(7.088)	(9.253)
Demonstration plot visits	1.177	2.686	-110.9	-0.479	-0.881*	3.180
	(1.630)	(2.147)	(76.40)	(0.939)	(0.515)	(3.639)
Wealth index	14.20***	15.68***	838.0*	4.266	5.300*	2.379
	(4.993)	(5.745)	(452.9)	(2.967)	(2.758)	(3.003)
Production mechanization	-61.68***	9.282	-2,020*	-19.39	-16.40**	-39.56
	(20.54)	(25.26)	(1,165)	(12.04)	(7.644)	(32.43)
Tropical livestock units (TLU)	0.220	-1.429	-302.7*	-0.784	-1.257	0.474
	(2.898)	(3.295)	(172.5)	(1.391)	(1.083)	(1.480)
Animal vaccinations	-34.92*	-57.27**	-2,100	-4.523	-12.82	13.09
	(19.35)	(26.68)	(1,696)	(11.76)	(10.22)	(10.43)
Years farming	0.564	-0.0242	-14.33	-0.291	-0.145	0.0748
	(0.628)	(0.509)	(10.58)	(0.247)	(0.0987)	(0.235)
Oromia region	-1.178	14.28	77.47	-8.119	2.877	-50.74
	(15.74)	(18.58)	(793.2)	(9.499)	(5.013)	(38.67)
Tigray region	2.250	19.17	-1,376	20.76	0.503	-36.64***
	(20.02)	(30.50)	(967.3)	(15.31)	(6.094)	(10.45)
Amhara region	-33.36**	-18.23	4.448	-1.561	7.615	-38.02***
	(12.86)	(18.93)	(1,039)	(9.573)	(6.737)	(13.68)
Constant	167.5***	148.3***	7,977***	105.8***	38.79**	214.5***
	(32.45)	(49.65)	(2,997)	(20.96)	(18.37)	(69.90)
Observations	237	232	237	237	237	231
R-squared	0.133	0.129	0.210	0.321	0.190	0.279

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Very few variables were significant. However, the results show that farm size has a significant impact on most intensification strategies. The intensity of fertilizer, capital expenditure, improved seed use and labor-use per hectare tend to decrease as the size of cultivated area increases. A 1-hectare increase in farm size (cultivated area) reduces fertilizer-use intensity by an average of nine kilograms (Table 2.5). An increase in farm size also results in a reduction in capital-use intensity by about 330 ETB/hectare, which is roughly US$17/hectare. Total labor-use intensity decreases by roughly eight man-days/hectare, while hired labor decreases by one man-day/ha with an increase in cultivated area. The results suggest that farmers tend to be less intensive in terms of use of key production inputs as farm size gets bigger. Conversely, reduction in farm size induces more intensive production practices. Interestingly, cropping intensity tends to increase with farm size. These results are consistent with the inverse productivity hypothesis discussed earlier.

Furthermore, distance to the village market significantly influences hired labor and cropping intensity. The results show that an additional kilometer further from the village market reduces labor hiring by 0.4 mandays/hectare and reduces cropping intensity by 1.4 scores. This result implies that farmers who are closer to the market hires more labor per unit of land and embark more in intensive cropping programs. Fertilizer-use intensity is positively affected by the household's socio-economic status, measured by the wealth index. Wealthier households tend to use about 14 kilograms more fertilizer per hectare than their less endowed counterparts. Consistent with the fertilizer-intensity results, the use of improved seeds increases by 16 kilograms per hectare with the improvement in a household's socioeconomic status. An improvement in the household's average wealth increases their capital investments by 838 ETB/ha, which is roughly US$42 per hectare. Households would increase hired labor use by 5.3 man-days per hectare with an improvement in their wealth status.

Agricultural mechanization has a significant impact on fertilizer and hired labor use intensity, as well as the overall capital investments per hectare. The results show that mechanizing the production system reduces fertilizer use intensity by 62 kilograms per hectare, while hired labor use falls by 11 man-days per hectare. These results suggest that agricultural mechanization has labor-saving benefits, and could be an important strategy for intensifying smallholder production systems in Ethiopia. The reduction in fertilizer use per hectare could be because mechanization, especially use of equipment such as direct seeders, allows for precision in fertilizer application and hence reduce wastage. Overall, the results show that mechanizing production systems reduces capital expenditure per hectare, probably due to the savings on hired labor and fertilizer use per hectare. Exploring feasible options for small scale mechanization and enhancing the availability of mechanical implements should, therefore, be part of an intensification strategy for smallholder agriculture.

The results also show that farmers with access to agricultural demonstration plots hire less labor per hectare, probably because they learn and implement management practices such as conservation agriculture that are known to save on labor requirements of farming. Total livestock herd, measured by the tropical livestock units (TLU), is also shown to reduce capital costs in crop production. More livestock could mean more draught power and manure, meaning the farmer can use mechanical weeding options instead of purchasing chemical herbicides. It also means the farmer may also save on hired labor. More manure can also enable the farmer to save on inorganic fertilizers.

The study captures the effects of biophysical factors by dummy variables for the agro-ecological zones. The results show that households in Tigray and Amhara regions embark less on cropping intensity than those in the SNNP region and use about 24 man-days more labor per hectare than those in Oromia region. The results show that cropping intensity among households in the SNNP region was 37 units higher than in Tigray region, and 38 units higher than in Amhara region. The results also show that being in Amhara region reduces fertilizer use intensity by 33 kilograms per hectare compared to the SNNP region.

2.5 Discussion and concluding remarks

This study explored the general nature of agricultural intensification among smallholder households in Ethiopia's highland areas. With a high population and well documented land constraints, Ethiopia presents an interesting case study for agricultural intensification. There is strong evidence that smaller, land-constrained farms are associated with higher input-use intensity, a trend confirmed by several studies in Africa and across the developing world. The results showed that smaller farms applied more fertilizer and improved seed, and invested more in hired labor and capital expenses per hectare. This result supports the inverse productivity hypothesis that shows a negative relationship between farm size and agricultural productivity. This hypothesis has been used to argue for a smallholder-led strategy for agricultural development in Africa. It will be interesting for land policy, therefore, to determine what would be the optimal farm size to achieve sustained agricultural intensification and agricultural productivity growth.

It is noted that, while smaller farms are more intense, analysis of the relative importance of different variables in the intensification model has also demonstrated the existence of other factors that make farms more intensive. For instance, a one standard deviation increase in household wealth, captured by productive assets endowments, would lead to a 0.36 standard deviation increase in predicted agricultural intensification, while for every standard deviation unit increase in farm mechanization, or agricultural intensification would increase by 0.22 standard deviation units. This information can be helpful to intensify on larger farms, and to sustain productivity growth on smaller farms. While the results identified household wealth as the prominent driver of agricultural intensification, raising household wealth levels would probably require complimentary developmental programs. However, improving access to capital, farm mechanization and agricultural extension should help speed up agricultural intensification at the farm level.

While most studies tend to focus on the incentives and drivers that induce agricultural intensification in general, this study acknowledges that even when facing similar incentives to intensify, households are likely to embark on different intensification paths depending on their resource endowments. There is usually a temptation to assume that in a particular region undergoing intensification, farm households would respond to intensification incentives in the same way and follow similar patterns of agricultural intensification. Yet, the ultimate intensification path pursued by farmers will depend on their resource endowments and adaptive capacity, and the relative sustainability of the chosen paths will be governed by the agricultural potential and the degree to which farmers are integrated to markets. For instance, in a region with a combination of high agricultural potential and good market access, farmers can easily embark on capital-led agricultural intensification and commercialization through high-value crops. However, if conditions are unfavorable, farmers may end up choosing to migrate out of farming in search of better opportunities off-farm.

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CHAPTER 3

ASSESSING THE RELATIVE SUSTAINABILITY OF SMALLHOLDER CEREAL-LEGUME FARMING SYSTEMS IN ETHIOPIAN HIGHLANDS

Summary

This chapter develops a composite index for assessing the relative sustainability of smallholder farms. A set of indicators relevant for the smallholder farming system setting in Ethiopian highlands are developed to depict the social, economic and environmental dimensions of agricultural sustainability. A Data Envelopment Analysis (DEA) model that uses endogenous weights is then used to construct the relative farm sustainability index, aggregating a set of 15 indicators farm sustainability. This analytical tool is applied to a sample of 600 farmers in four regions of Ethiopia's highlands. A Generalized Linear Model (GLM) was used to investigate how a set of socioeconomic, agro-ecological and institutional variables influence relative farm sustainability. The results show that farm size, markets access, access to off farm income, agricultural loans, access to agricultural extension and demonstration plots, are key drivers of agricultural sustainability at farm level. Differences in agroecological conditions and region-specific factors, captured by regional dummies, were also significant determinants of relative farm sustainability. This underscores the importance of geographical targeting and tailoring of interventions to bolter farm sustainability.

3.1 Introduction

The global food system faces a daunting task of meeting the growing food demands of a burgeoning population, projected to reach nine billion people in 2050 (FAO, 2009). The FAO (2009) estimated that food production must increase by at least 70 percent to supply enough food. Achieving such productivity growth without exacerbating environmental problems in already fragile farming systems remains a major concern (Tilman et al., 2002). In the past, technological innovations, through investments in high yielding crop varieties, chemical fertilizers, resilient technologies to water-stress, pests and diseases resulted in massive productivity gains in developing and developed countries alike (Nin-Pratt and McBride, 2014; Binswanger, 1986). However, agricultural intensification often has been associated with adverse environmental and social effects, especially under the flagship "Green Revolution" (Lee et al., 2001; Shiva, 1991; Li, Wu and Deng, 2013; Ali, 2007; Tilman et al., 2002). There is a broad consensus that sustainability should encompass three important pillars, namely economic, social and environmental dimensions (Kuhlman and Farrington, 2010; Kates, Parris & Leiserowitz, 2005). The concept of maintaining all pillars of sustainability has thus emerged as an important dimension when exploring intensification pathways that can increase agricultural productivity.

The ability to measure and monitor farm sustainability constitutes an important step towards designing policies and interventions for bolstering the sustainability of current production systems. However, sustainability assessments are limited by the ability to find and agree upon common indicators and to apply these indicators to create indices. The multi-dimensional nature of sustainability makes it difficult to both operationalize (Rigby and Caceres, 2001) and to develop appropriate indicators that can be applied to diverse spatial and temporal scales and socioeconomic contexts (Dantsis et al., 2011; Hayati, Ranjbar and Karami, 2010; Speelman et al. 2007; Rigby et al., 2001; Lopez-Ridaura et al., 2005). Developing appropriate indices is also compounded by embedded social values (Lele and Norgaard, 1996), conflicting goals and multiple interactions between sustainability dimensions (Morse et al., 2001), as well as general heterogeneity in societal preferences (Robinson et al., 2015; Loos et al., 2014; Garnet and Godfray, 2012). The complexity and uniqueness of farming systems also implies that indicators can be meaningful in one system, but irrelevant in another (Speelman et al., 2007). Therefore, it is often appropriate to use local farming, system-specific indicators and to consider the farm as the basic unit for sustainability assessment (Rigby et al., 2001; Van der Werf and Petit, 2002).

Sustainability assessments typically involve many indicator variables across economic, social and environmental sustainability dimensions. The methods used to integrate and aggregate indicators into composite indices are of paramount importance so that they reflect social and individual values (Dong, Mitchell and Colquhoun, 2015). Composite indices allow for the comparison of relative sustainability between farms (Gomez-Limon and Sanchez-Fernandez, 2010; Rigby et al., 2001; Nambiar et al., 2001), but cannot avoid subjectivity in how they weight indicators (Perisic, 2015; Shen et al., 2013; Cherchye et al., 2006; Lopez-Ridaura et al., 2005; Nardo et al., 2005). Subjectivity is involved since expert judgements are often used to assign indicator weights (Zhou, Ang and Poh, 2007). Many studies have turned to data-based methods such as Data Envelopment Analysis (DEA), Principal Component Analysis (PCA) and Factor Analysis (FA) to add more structure to the way weights are assigned in composite indices (Perisic, 2015). The primary goal of this chapter is use Data Envelopment Analysis (DEA) to construct composite farm-level sustainability indices (FSI) on nearly 500 Ethiopian farms. The second goal is to examine the different factors driving relative sustainability of smallholder farmers, thus helping explore potential policies, interventions and institutional innovations for improving the sustainability of the sector. The relationship between relative farm sustainability and driving variables is analyzed using a Fractional Response Model (FRM). The applicability of the DEA approach in construction of composite indices has been widely explored in several studies, such the human development index (Despotis, 2004), the technology achievement index (Cherchye et al. 2008), and the sustainable energy index (Zhou, Ang and Poh, 2007). It has also been recently applied to develop composite indices of agricultural sustainability (Dong, Mitchell and Colquhoun, 2015; Gerdessen and Pascucci, 2013; Reig-Martinez, Gomez-Limon and Picazo-Tadeo, 2011; Gomes et al., 2009).

This chapter is structured as follows: Section 2 presents the proposed analytical model for computing composite relative sustainability indices. Section 3 describes the methodological aspects of the study, including the selection of indicators, normalization, weighting and aggregation techniques. Section 4 presents research results and their empirical applications. Finally, section 5 summarizes and concludes, highlighting the policy implications of key research results.

3.2 Empirical models

3.2.1 Adopting DEA to compute a composite relative farm sustainability index

Data Envelopment Analysis (DEA) is a mathematical programming technique that was originally developed to estimate the efficiency of decision making units (Banker, Charnes and Cooper, 1984; Charnes, Cooper and Rhodes, 1978). For each decision making unit (DMU), DEA maximizes the ratio of weighted outputs to weighted inputs (Gerdessen and Pascucci, 2013). For instance, given production data for a group of farms, DEA could be used to examine relative technical efficiency of farms by creating a nonparametric production frontier, from which it identifies the most efficient farms, which are assigned a score of unity. The efficiency scores of the remaining farms can be taken as relative measures, benchmarked against the most efficient farms (Cooper et al., 2007). DEA assigns weights to the various inputs and outputs such that the efficiency of the DMU under consideration is maximized (Gerdessen and Pascucci, 2013). In this study, a total of 15 indicators of economic (Table 3.1), social (Table 3.2) and environmental (Table 3.3) sustainability are developed from a cross-sectional data of 600 households. The study then adapts the DEA model, helping to aggregate the indicators into a composite measure of agricultural sustainability at the farm-level. To achieve this, the adapted DEA model, sometimes called the benefit-of-the-doubt approach, uses the indicators as "outputs", and ignores the input-side (Cherchye et al., 2006). Despotis (2005) notes that representing indicators as outputs and allocating a single 'dummy input' with value unity to each DMU, results in the original constant-returns-to-scale DEA model postulated by Charnes, Cooper and Rhodes (1978).

The objective function in this case maximizes the weighted sum of the indicators, based on an endogenously determined set of optimal weights. The weights derived by the DEA model reflect the relative importance of each indicator (Adler, Yazhemsky and Tarverdyan, 2010), such that greater weight is given to components considered more important for farm sustainability (Munda and Nardo, 2003; Cherchye et al., 2006). The basic assumption in this model is that each farm maximizes its composite sustainability, subject to the level of priority given to each of the sustainability indicators.

We consider a set of m (= 15) sub-indicators of the economic, social and environmental dimensions of agricultural sustainability for each of n (= 600) farming households. Our objective is to aggregate these individual sub-indicators into a single-valued composite index, which represents the weighted average of the m sub-indicators. Denoting w_i as the weight of the m^{th} sub-indicator of sustainability of the farmer j, the DEA-based composite indicators of farm-level sustainability are obtained by solving the following constrained optimization problem:

$$FSI_j = \max_{wij} \sum_{i=1}^{m} y_{ij} w_{ij} \qquad (3.1)$$

Subject to

$\sum_{i=1}^{m} y_{ij} w_{ij} \leq 1 \qquad \forall j = 1, \ldots, n$ (normalization constraint)

$w_{ij} \geq 0 \qquad \forall i = 1, \ldots, m$ (non-negativity constraint)

Where FSI_j is the Farm Sustainability Index for farm j, y_{ij} is the value of sub-indicator *i* for individual farm *j*, and w_{ij} is the weight of the sub-indicator i on the farm *j*. The model combines multiple sub-indicators, endogenously selecting weights that maximize the sustainability score for each DMU (Zhou, Ang and Poh, 2007). Each entity obtains its own best possible set of indicator weights (Shen et al., 2013), with the highest relative weights assigned to those indicators where the farm under consideration achieves the best performance (Cherchye et al., 2006). Non-negativity constraints are added so that every indicator is used in computing the composite sustainability index, and thus removes the possibility of farms choosing to assign zero weights to indicators that perform relatively poorly and putting all their weights on the indicators for which they perform best (Gerdessen and Pascucci, 2013). A normalization constraint ensures that the resultant composite indices range from zero to unity for each farm *j*.

3.2.2 Fractional Response Model

Two-stage DEA regression analysis was used to analyze how contextual factors influence relative sustainability scores of individual decision making units (DMUs) (Ramalho, Ramalho and Henriques, 2010). The general approach involves using DEA techniques to compute relative sustainability scores for individual farms and then regressing the DEA-generated sustainability scores on a set of variables of interest (Simar and Wilson, 2007). However, there has recently been growing concerns over the use of standard censored regression (Tobit), ordinary least squares (OLS) and the transformed logistic normal models for fractional data (Ogundari, 2014; Ramalho, Ramalho and Henriques, 2010; Simar and Wilson, 2007; Kieschnick and McCullough, 2003). DEA-generated scores are typically bounded and confined to the [0,1] interval, and thus the data generating process (DGP) for the sustainability scores is fractional response data, and not censored data by construction (Ramalho, Ramalho and Henriques, 2010; McDonald, 2009). Therefore, the standard OLS model fails to provide the best description of how an explanatory variable x influences a fractional response variable, since is does not guarantee that the predicted values of the dependent variable lie in the unit interval (Ogundari, 2014; Papke and Wooldridge, 1996). The traditional Tobit model is also inappropriate for fractional data because observations at the boundary values of unity are a natural consequence of the way DEA-generated sustainability scores are defined, and not the result of censoring (Ramalho, Ramalho and Henriques, 2010).

This chapter thus adopts the fractional response model (FRM), proposed by Papke and Wooldridge (1996), which extends the generalized linear model (GLM), and uses the logistic function as the link function between a linear prediction and the conditional mean $E[y|x]$. The model is estimated with a quasi-maximum likelihood estimator (QLME)[5] (Ramalho, Ramalho and Henriques, 2010). This modeling approach only requires the correct specification of the conditional mean and there is no need for an *ad hoc* transformation of the boundary values (Oberhofer and Pfaffermayr, 2014). The basic assumption underlying the FRM is given by:

$$E(y_i|x_i) = G(x_i\beta) \quad \forall i \qquad 3.2$$

Where $0 \leq y_i \leq 1$ denotes the dependent variable and x_i refers to the explanatory variables of observation i. The G(.) is some non-linear distribution function satisfying 0 < G(.) < 1. Typically, G(.) is similar to the logistic function $G(z) = \exp(z)/(1 + \exp(z)$. Parameters of the

[5] The QMLE is estimated in STATA v13, using generalized linear model (glm) command with family (binomial), link (logit), and robust standard error option. The robust option ensures robust standard errors, which is essential in case the distribution family is misspecified (McDowell and Cox, 2016).

FRM are estimated by a quasi-maximum likelihood estimator, based on the following Bernoulli log-likelihood function:

$$l_i(\beta) = y_i \log[G(x_i\beta)] + (1 - y_i) \log[1 - G(x_i\beta)] \qquad 3.3$$

The function is well defined for 0 < G(.) < 1. Given that the Bernoulli distribution belongs to the linear exponential family, the quasi-maximum likelihood estimator of β is obtained by maximizing equation (3.3). Papke and Wooldridge (1996) showed that the quasi-maximum likelihood estimator (QMLE) of β is consistent and asymptotically normal, regardless of the distribution of y conditional on x, provided that $E(y_i|x_i)$ in (2) is correctly specified.

3.2.3 Potential Explanatory variables

A number of explanatory variables were included in the GLM regression, based on economic theory and previous empirical sustainability studies. Variables included to depict farm and farmer characteristics are farm size, farmer age and farming experience, which are hypothesized to influence farmers' decisions relating to the use of sustainable farming practices. Farm size is expected to positively influence sustainability; as bigger farms are requisites for adoption of sustainable farming practices, and are generally associated with scale economies through its impact on scale economies (Karagiannis and Sarris, 2005). Doss (2006) also notes that farmers in Ethiopia must have at least 0.5 hectares under maize to participate in the credit scheme for maize. Farmers' age and farming experience are expected to influence sustainability through their impacts on farm technology adoption decisions (Teklewold, Kassie and Shiferaw, 2013). Family size is expected to positively influence sustainability. It is expected that the bigger the household size, the more the potential labor endowment and hence the greater the propensity to adopt more sustainable agricultural practices (Pender and Gabremedin, 2007).

Socio-economic drivers of agricultural sustainability include credit access, contact with agricultural extension services, as well as access to off-farm income. In developing countries, credit constraints are seen as critical drivers of agricultural technology adoption (Feder and Umali, 1993), and hence influences productivity in general (Dong, Lu and Featherstone, 2012). A credit constraint variable is included to distinguish between farmers who choose not to use credit, and those who do not have access to credit. Following Feder et al. (1990), the study was designed such that farmers were asked whether credit was needed or not, and if yes, whether credit was obtained for farming operations or not. Credit constrained farmers are thus those who needed credit but were unable to get it; while unconstrained farmers included those who did not need credit and those who needed credit and were able to get it. Off-farm income is expected to positively influence farm sustainability, since households with alternative sources of income are more likely to adopt new technologies and have more capacity to finance new investments (Pender and Gebremedhin, 2007). However, participating in off-farm activities may potentially affect the availability of household labor for critical farm operations (Kassie et al., 2012).

Other variables included in the regression model are market access, access to information and agro-ecological controls. Market access is expected influence farm sustainability through its impacts transaction costs (Sadoulet and de Janvry, 1995) and the degree of farmers' participation in input and output markets (Kassie et al, 2012), as well as the opportunity costs of labor (Pender and Gebremedhin, 2007; Jansen et al. 2006). Distance to village markets, measured in minutes of walking time, is used as a proxy for market access. The hypothesis is that distance from the village market negatively affects farm sustainability. Access to information is critical to making informed production and management decisions. The chapter thus includes variables for access to extension, measured by the frequency of extension contact; as well as a variable measuring the number of times the farmer visited demonstration plots. Having access to extension and demonstration plots is expected to positively impact on farm sustainability. Regional dummies were also included to as proxies for differences in agro-ecological conditions and, potentially, differences in temperature and rainfall regimes.

3.3 Empirical approach

3.3.1 Data

Data for the sustainability index and driving factors came from an in-person survey of over 600 households in the Ethiopian Highlands. The household questionnaire included a set of questions covering the general characteristics of the farmers (such as age, gender, household size, farming experiences, main occupation, membership of groups, agricultural training), farm operations (such as farm size, cultivated area, crops grown, livestock ownership, agricultural input use, general husbandry practices, crop and livestock sales), management practices (such as tillage types, crop rotations, organic manure use, soil erosion control measures), and general questions such as interaction with extension officers, use of agricultural loans, living conditions, asset ownership, and access to off-farm income.

The survey population comprised farming households located in Tigray, Amhara, Oromia and the Southern Nations Nationalities and Peoples' *(*SNNP) regions of Ethiopian highlands. The data thus covers a wide geographical area, which allows for variation in farming practices, farm sizes, agro-ecological potential as well as other variables such as market access and institutional services. Generally, Ethiopian highlands range in annual average temperatures from 20-22°C in the lower elevations to 10-12°C in the higher elevations, while annual rainfall ranges from about 600 mm in the northern highlands to over 2,000 mm in the southwestern highlands (Pender, Place and Ehui, 1999). The soils are predominantly nitisols, vertisols, cambisols and luvisols, which have very good agricultural potential.

The sample comprises of 600 farming households, drawn from the four regions. One study district was chosen per region. In each district, stratified sampling was used to select two wards where the International Livestock Research Institute (ILRI) had some ongoing projects and one non-project ward. A total of 50 farmers were randomly selected in each ward, based on the farmer lists provided by ILRI field coordinators and government extension officers. Government extension officers, ILRI field facilitators and agricultural research officers administered household interviews. This information was complimented with secondary information. Table 3.1 provides a summary descriptive information of these indicator variables.

Table 3.1: Descriptive statistics of sustainability indicators in the Ethiopian Highlands

Indicators	Obs	Original Values		Normalized Values	
		Mean	Std. Dev.	Mean	Std. Dev.
Agricultural income	473	6,729.98	8,408.35	0.12	0.15
Labor productivity	473	214.72	212.10	0.09	0.09
Capital productivity	472	6.76	6.28	0.13	0.13
Crop diversification	473	0.57	0.20	0.65	0.23
Diversity of income	473	0.17	0.22	0.23	0.30
Family workforce	453	2.28	1.26	0.23	0.13
Membership in farmer organizations	473	0.53	0.50	0.53	0.50
Gender equity	473	0.96	0.21	0.96	0.21
Use of chemical fertilizers	473	123.19	206.94	0.97	0.06
Use of pesticides	473	561.15	1,373.70	0.96	0.10
Erosion control	473	0.54	0.50	0.54	0.50
Crop rotations	473	0.74	0.44	0.74	0.44
Livestock density	473	4.83	6.88	0.95	0.07
Organic farming	473	0.75	0.43	0.75	0.43

3.3.2 Development of indicators

To develop a farm-level relative sustainability index (FSI), the study followed the OECD (2008) guidelines for computing composite indicators, as well general principles for selecting and organizing sustainability indicators (Van Cauwenbergh et al., 2007; Nambiar et al., 2001; Von Wiren-Lehr, 2001). The chapter adapts the Framework for Assessing the Sustainability of Natural Resource Management Systems (MESMIS), a system-based framework that allows for the systematic derivation of indicators that describe the key attributes of the farming systems under consideration (Cauwenbergh et al 2007). The framework helps identify appropriate, coherent and consistent indicators of sustainability. MESMIS defines sustainability in terms of seven attributes, namely productivity, stability, reliability, resilience, adaptability, equity and self-reliance (López-Ridaura et al., 2005). Insights from this framework help in the initial stages of sustainability indicators development.

The first stage in the construction of a composite index of relative farm sustainability involved the selection of a set of indicators that cover the economic, social and environmental components of sustainability. A general catalogue of indicators of agricultural sustainability was developed, based on an extensive review of the literature, which synthesized the common indicators used in previous studies on farm sustainability (Vitunskiene and Dabkiene, 2016; Dantsis et al., 2010; et al., 2010; Hayati, Ranjbar and Karami, 2010; Gomez-Limon and Sanchez-Fernandez, 2010). This process resulted in a mixture of outcome-based and practice-based farm-level indicators of sustainability. A series of key informant interviews were organized with agricultural experts representing research institutions, farmer organizations, national agricultural research staff, district agricultural extension coordinators, as well as personnel from nongovernmental organizations (NGOs) involved in agricultural and natural resources management. The expert selection process considered experience in sustainability-related work, as well as familiarity with the smallholder agricultural sector in Ethiopia. These consultations helped map the key attributes important for sustainability of smallholder farming systems, as well as classify them according to the dimension of sustainability. The most appropriate indicators were selected based on their relevance to the agricultural systems under consideration, measurability, policy relevance, and the general ease with which they can be computed with information easily obtainable from farmers. The final set of indicators for relative farm sustainability included fifteen quantitative and qualitative indicators.

The economic dimension of farm sustainability is represented by five indicators, relating to farm economic stability, productivity and profitability (Table 3.2). Agricultural income (AGINCOME) captures total income from crop and livestock sales, measured in Ethiopian birr. With liquidity constraints and limited employment opportunities in most rural areas, sales income forms a significant source of household income, hence expected to have a positive impact on sustainability of farm operations. Capital productivity (CAPITALPRODT) represents the total value generated by a given input of capital. It can be measured as total kilograms of crops per dollar spent agricultural inputs (Kamanga et al., 2010), or as the value of crop sales obtained per dollar spent on inputs (Snapp et al., 2010). In this study, capital productivity is the gross value of crop produced per unit of capital invested in production inputs. Labor productivity (LABORPRODT) is a crucial indicator of sustainable agricultural intensification (Struik et al., 2014; Kamanga et al., 2014). Economically viable farms must have the capacity to remunerate labor (Ryan et al, 2014). In this study, labor productivity is the total value of crops per person day of labor (Silici, 2010; Twomlow et al., 2006). Crop diversity (CROPDIV) is often cited as a measure for increasing agricultural productivity, enhancing resilience in agroecosystems, as well as reducing variability of agricultural income (Rai et al., 2011; Dantsis et al., 2010). Crop diversity can be measured in terms of number of the different crops cultivated at a given time (Valet and Ozier-Lafontaine, 2014; Riesgo and Gomez-Limon, 2006). Income diversity (INCOMEDIV) represents the importance of off-farm, non-agricultural activities (Dantsis et al., 2010). In this study, the degrees of crop and income diversification are measured using Herfindahl-Hirschman index (HHI)[6], following Sichoongwe et al. (2014).

Table 3.2: Indicators for assessing the economic sustainability of smallholder agriculture

Notation	**Indicators**	**Description**	**Indicator type**
e1	Agricultural income (AGINCOME)	Total income from crop and livestock sales (ETB/ha).	More is better
e2	Labor productivity (LABORPRODT)	Farm gross value added per labor input (ETB/man-day).	More is better
e3	Capital productivity (CAPITALPRODT)	Ratio of gross value added to capital inputs (ETB).	More is better
e4	Crop diversification (CROPDIV)	An index of crop diversification (score).	More is better
e5	Diversity of income (*INCOMEDIV*)	An index of income diversification, showing the diversity of income sources for the households.	More is better

[6] The Herfindahl-Hirschman index (HHI) computed as:

$HHI = 1 - \sum_{i=1}^{n} P_i^2$ and $P_i = \frac{A_i}{\sum_{i=1}^{n} A_i}$

Where P_i is the proportion of ith crop, A_i is the area under the ith crop, $\sum_{i=1}^{n} A_i$ is the total cropped area and i are the individual crops. The same model was modified to calculate and income diversification index for each household.

Moving on to the next pillar, a total of four indicators were selected for the social dimension of farm sustainability (Table 3.3). The social dimension is represented by indicators relating to farmers' general wellbeing, gender equity and empowerment, household labor supply and social capital. Household wealth (WEALTH) is generated by a Principal Components Analysis (PCA[7]) on asset data. Social capital, which refers to the value of human relationships, is frequently cited as an indicator of social sustainability (Pretty et al, 2011). In a rural setup, social capital encompasses who the number of people a household regularly interacts with, their membership in formal organizations, as well as general participation in collective land management activities (Smith et al, 2015). In this study, social capital is captured by membership in farmers' groups or producer associations (ASSOCIAT). Leading agencies promoting sustainable agricultural intensification emphasize the need to foster gender equity and create opportunities for women in agriculture (The Montpelier Panel, 2013). A gender equity (GENDEREQUITY) indicator captures whether women are involved in making production and marketing decisions. Household labor supply (HHLABOR) represents the total number of household members that are available for farm operations.

[7] PCA is a multivariate statistical method used to reduce data dimensions, transforming a set of correlated variables into a set of uncorrelated variables called 'principal components' (Filmer and Pritchett, 2001). The procedure is applied on data depicting household asset ownership, housing characteristics, as well as access to utilities and infrastructure such as water sources and sanitation facilities, to create an index of household wealth (Vyas and Kumaranayake 2006).

Table 3.3: Indicators for assessing the social sustainability of smallholder agriculture

Notation	Indicators	Description	Indicator type
s1	Household wealth (WEALTH)	A measure of household socio-economic status, computed from principal component analysis of assets	More is better
s2	Membership in farmer organizations (ASSOCIAT)	A dummy variable capturing whether the farmer belongs to a farmer group. This is a proxy for social capital.	More is better
s3	Gender role (GENDEREQUITY)	A dummy variable capturing whether female members of the household are actively involved in production and marketing decisions	More is better
s4	Family workforce (HHLABOR)	Total number of household members that provide labor in farming activities.	More is better

Finally, for the environmental pillar, six indicators of farm sustainability were considered (Table 3.4), namely, use of chemical fertilizers (kgs/ha), use of pesticides and herbicides, livestock density, erosion control measures, use of crop rotations and organic farming. Due to data constraints, the study resorted to readily available variables such as the use of chemical fertilizers, use of agrochemicals such as pesticides and herbicides, and livestock density, as well as the adoption of environmentally friendly practices such as soil erosion control, crop rotations and the use of organic manure; to assess the environmental sustainability of farm operations. Sustainable agricultural intensification entails the progressive reduction of chemical inputs (Schreinemachers et al., 2011), with farmers applying more biologically-sound fertility management options such as animal manure (Fungo et al, 2013). It is estimated that the overuse of synthetic fertilizers and pesticides, along with deforestation, are responsible for about 22 % of total greenhouse gas emissions (World Bank, 2008). Therefore, in this study, use of chemical fertilizers, pesticides and herbicides are included as 'less is better' indicators of environmental sustainability. Use of chemical fertilizers (TOTFERT) was the rate of use of Diammonium phosphate (DAP), Urea and New Pricing Scheme (NPS) fertilizers across all crops in kilograms per hectare. Due to lack of data on physical quantities, the use of pesticides and herbicides (CHEMCOSTS) was captured by total expenditures (costs) on the chemicals. Livestock stocking rates relative to the carrying capacity of the range can be used to depict the pressure exerted on the grazing resources, and thus a good indicator of agricultural sustainability (Smith et al, 2015). This study uses livestock density (LDENSITY), measured by the tropical livestock units per hectare, to depict pressure on the grazing resources. Tropical livestock units are computed using FAO (1987) guidelines[8]. Environment-friendly farming practices (erosion control, rotations and organic manure) were captured by dummy variables. Soil erosion and degradation are issues of concern in smallholder farming systems, particularly in areas where population pressure and land constraints force farmers onto steep slopes (Schmitt-Olabisi, 2012, Clay, Reardon and Kangasniemi, 1999). The study includes an erosion control variable (EROSIONCONT) to capture whether farmers have employed erosion control measures such as stone buds. Adoption of environmentally friendly practices such as use of organic manure (ORGANICMANURE) and legume crop rotations (ROTATIONS) is considered desirable for environmental sustainability.

[8] Tropical Livestock Units (TLU) conversion factors: Cattle = 0.7; Goats = 0.1; Sheep = 0.1; Donkeys = 0.5; Horses = 0.8; Mules= 0.7; Pigs = 0.2; Chicken = 0.01

Table 3.4: Indicators for assessing environmental sustainability of smallholder agriculture

Notation	Indicators	Description	Indicator type
v1	Use of chemical fertilizers (TOTFERT)	Amount of chemical fertilizers per hectare (kgs/ha).	Less is better
v2	Use of chemicals (CHEMCOSTS)	Costs of pesticides and herbicides per hectare (ETB/ha).	Less is better
v3	Livestock density (LDENSITY)	Tropical livestock units per hectare (TLU/ha).	Less is better
v4	Erosion control (EROSIONCONT)	Dummy variable whether farmer use soil erosion control measures such as stone buds, contours or terraces.	More is better
v5	Crop rotations (ROTATIONS)	Dummy variable whether farmer practiced legume crop rotations.	More is better
v6	Organic farming (ORGANIC)	Dummy variable whether farmer uses organic manure in farming operations.	More is better

3.3.3 Indicator normalization

The chosen indicators have different measurement units; hence normalization was needed to render comparability and allow for summing across the different indicators. This chapter uses the min-max normalization techniques, following Reig-Martínez, Gómez-Limón and Picazo-Tadeo (2011) and Nardo et al. (2008). Normalization was done using the following formulas:

$$I_{ij} = \frac{(y_{ij} - y_{imin})}{(y_{imax} - y_{imin})} \quad 3.4$$

$$I_{ij} = \frac{(y_{imax} - y_{ij})}{(y_{imax} - y_{imin})} \quad 3.5$$

Where I_{ij} is the normalized value of the indicator and y_{ij} is the original value of indicator *i* for farm *j*. The elements y_{imin} and y_{imax} are, respectively, the minimum and maximum of the original values of indicator *i* found in the sample. The values of the normalized indicators (I_{ij}) vary within the range [0,1], where a value of 0 represents the lowest possible value of the indicator and 1 corresponds to the best. Equation (3.4) is used for indicators of the type ‘‘more is better’’, and hypothesized to have a positive impact on sustainability. In cases where indicators are of the type ‘‘less is better’’ are hypothesized to negatively affect farm sustainability, equation (3.5) is adopted. Indicators representing livestock density (LDENSITY), use of chemicals (CHEMCOSTS) and use of inorganic fertilizer (TOTFERT) are such that the lower the crude value, the more the farm sustainability, hence they were normalized using expression (5). The rest of the indicators were normalized using expression (4).

After normalization, a basic exploratory analysis of the indicators is performed to ascertain the nature of their relationships. There is concern that aggregating variables that are highly correlated will effectively introduce some element of double counting into the resultant index (Jacobs et al, 2004). A common practice is to exclude strongly correlated indicators before aggregation (Vitunskiene and Dabkiene, 2016). However, Smith (2002) noted correlation among indicators is a common feature with sustainability indicators, and that as long as indicators weights are selected properly, there will not be technical problems. Feedback loop relationships are highly anticipated, especially among indicators of the same sustainability dimension (Pham and Smith, 2014).

3.4 Results

3.4.1 Farm-level sustainability indices

Composite indices of relative farm sustainability (FSI) were computed at the farm level, aggregating a set of indicators across the economic, social and environmental dimensions of sustainability. A DEA benefit-of-the-doubt model was run in GAMS (equation 3.1), selecting a set of idiosyncratic indicator weights that maximize the sustainability index for each farmer. The overall composite index of sustainability was also developed, considering all the 15 sustainability indicators selected. The computed indices are relative measures used to rank farmers according to sustainability performances. From a benchmarking perspective, a composite sustainability score below unity implies that there are other farms in the sample with relatively higher sustainability performance than the farm under consideration. The higher and closer to unity the value of the composite sustainability index, the higher the level of relative sustainability. Figure 3.1 below shows Kernel density distributions of the composite farm sustainability indices.

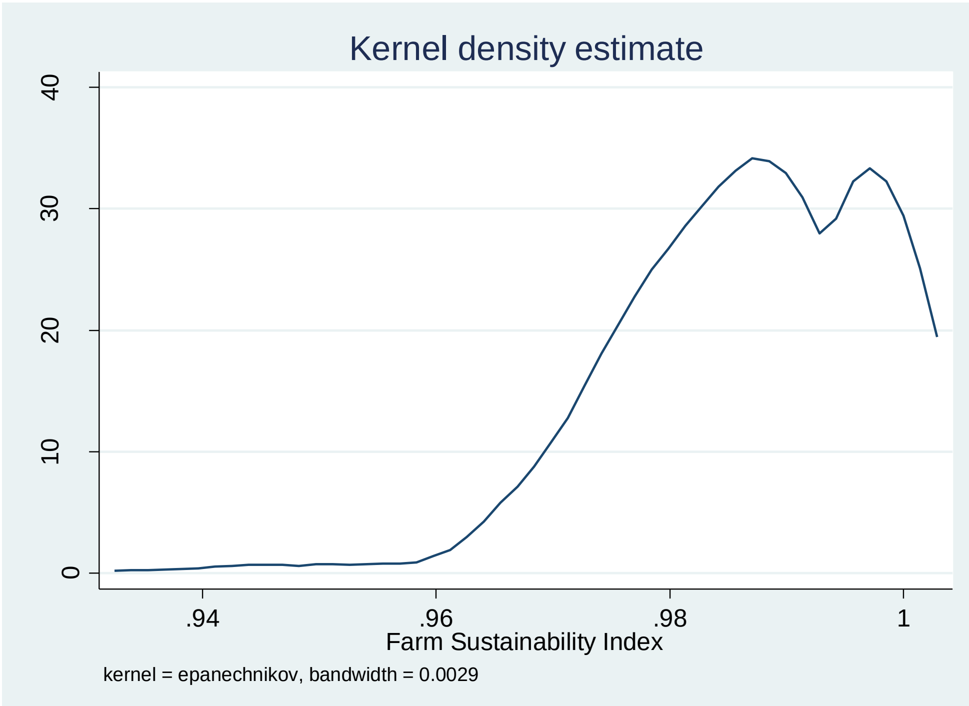

Figure 3.1: Distribution of composite relative farm sustainability indices

Overall, 16% of the farms had composite relative sustainability scores of unity (FSI = 1). These farms were significantly larger, averaging 2.8 hectares, compared to farms with relative sustainability less than 1, which averaged 1.6 hectares in farm size. It is also interesting to examine how mean composite relative sustainability scores varied between different variables of interest. A one-way analysis of variance (ANOVA) was conducted to determine if mean composite relative sustainability index was different among small (less than 1 hectare), medium (1 to 1.5 hectares) and large (more than 1.5 hectares) farms in the sample. The results are presented in Table 3.5 below.

Table 3.5: ANOVA tests for differences in composite relative farm sustainability indices

	Contrast	Standard Error	Significance (p-values)
Farm size groups:			
Medium vs Small	0.001	0.001	0.577
Large vs Small	0.004	0.001	0.004
Large vs Medium	0.003	0.001	0.023
Regions:			
Amhara vs Tigray	0.005	0.001	0.009
Oromia vs Tigray	0.003	0.001	0.234
SNNP vs Tigray	0.003	0.001	0.301
Oromia vs Amhara	(0.002)	0.001	0.517
SNNP vs Amhara	(0.002)	0.001	0.508
SNNP vs Oromia	0.000	0.001	1.000

The ANOVA test runs pairwise comparisons of overall sustainability scores across the different categories, and a p-value of less than 0.05 indicates significance in the differences. The results show a significant difference in relative sustainability from the large farm to the medium or small farm, and between the Amhara and Tigray regions. A post-hoc Tukey's test revealed that relative sustainability was significantly higher in the larger farms compared to the small and medium sized farms. The mean composite relative sustainability index was also statistically significant between the different regions, with a post-hoc Tukey's test showing that mean relative sustainability of farms in Amhara was significantly higher than that of farms in Tigray.

Comparisons were also made in relative economic sustainability across farm size groups and over the four regions (Table 3.6). The results show that large farms exhibited significantly higher relative economic sustainability than medium and small farms. Relative economic sustainability of farms varied significantly across the four regions. Post-hoc Tukey tests show that relative economic sustainability of farms in SNNP region was statistically significantly higher than that of farms in Tigray and Oromia regions. Relative economic sustainability of farms in Amhara was statistically significantly higher than that of farms in Tigray and Oromia regions.

Table 3.6: ANOVA tests for differences in relative economic sustainability indices

	Contrast	Std. Error	Sig.
Farm size groups:			
Medium vs Small	0.054	0.020	0.020
Large vs Small	0.046	0.022	0.085
Large vs Medium	(0.008)	0.019	0.916
Regions:			
Amhara vs Tigray	0.085	0.022	0.001
Oromia vs Tigray	(0.039)	0.021	0.270
SNNP vs Tigray	0.108	0.022	0.000
Oromia vs Amhara	(0.124)	0.021	0.000
SNNP vs Amhara	0.022	0.022	0.736
SNNP vs Oromia	0.147	0.021	0.000

Table 3.7 shows results of comparisons of environmental sustainability. The results indicate that smaller farms have higher relative environmental sustainability than large and medium sized farms. Environmental sustainability also varies significantly across the four regions. Post-hoc tests showed that farms in Amhara region have relatively higher environmental sustainability than farms in Oromia and SNNP regions. The results also show that farms in the Tigray region have higher relative environmental sustainability compared to farms in Oromia and SNNP regions. Relative environmental sustainability is higher in the SNNP region than over farms in Oromia region. Relative social sustainability did not vary significantly across farm size categories, but significantly differed across the regions. The results showed that farms in Oromia region had higher relative social sustainability compared to farm in Tigray and SNNP regions.

Table 3.7: ANOVA tests for differences in relative environmental sustainability indices

	Contrast	**Std. Error**	**p-values**
Farm size groups:			
Medium vs Small	(0.002)	0.001	0.047
Large vs Small	(0.003)	0.001	0.000
Large vs Medium	(0.001)	0.001	0.104
Regions:			
Amhara vs Tigray	0.000	0.001	0.986
Oromia vs Tigray	(0.006)	0.001	0.000
SNNP vs Tigray	(0.002)	0.001	0.073
Oromia vs Amhara	(0.006)	0.001	0.000
SNNP vs Amhara	(0.002)	0.001	0.027
SNNP vs Oromia	0.004	0.001	0.000

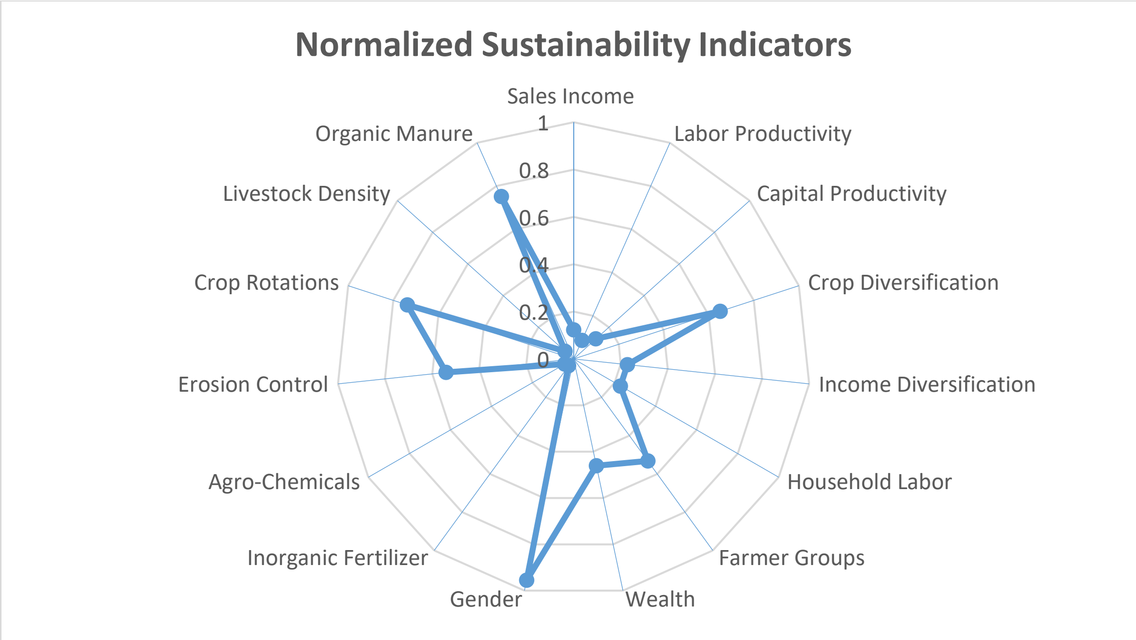

Figure 3.2: Normalized average farm sustainability indicator weights for farmers in the Ethiopian Highlands (1=maximum weight, 0= no weight)

To get a picture of the relative importance of the 15 indicators of farm sustainability, the individual indicators were normalized and plotted using Radar graphs. Figure 3.2 shows the drivers of relative sustainability across the different dimensions. Indicators with the most influence on sustainability were gender, crop rotation and diversification, and organic matter. Indicators with the least influence were inorganic fertilizer, labor and capital productivity and livestock density. This implies that the smallholder systems in Ethiopia perform relatively better in social and environmental aspects than the economic dimension. The low levels of fertilizer use, for instance, could be favorable for environmental sustainability, but such system tends to be associated with low levels of agricultural productivity. An interesting observation in Figure 3.2 is that the average values of normalized economic indicators such as labor and capital productivity are very low, a trend that is generally observed in sub-Saharan Africa (Nin-Pratt and McBride, 2014). Low labor productivity could be attributed to the lack of technological innovations in production as well as limited capital to purchase complimentary inputs. In the sample, only 21% of the farmers had access to irrigation facilities, while only 24% had access to credit. Income from crop and livestock sales is also considerably very low. On average, households sold only 20% of the crop produce, indicating that production is more geared towards subsistence. Consequently, the average economic sustainability score is relatively low compared to the other dimensions. On the other hand, farmers seem to be making considerable efforts towards adopting environmentally friendly practices such as soil erosion control, legume crop rotations and use of organic manure. Relative to the other sustainability dimensions, the average environmental sustainability index was higher. It was driven by the very low levels of chemical fertilizer usage by the farmers. The average values of normalized indicators for pesticides and herbicides, as well as livestock density, were also very low on the smallholder farms.

3.4.2 Factors determining relative farm sustainability

An important component in sustainability assessments is identifying the critical variables and drivers explaining farm-level sustainability performance. The study examines the significance and relative importance of a set of socio-economic variables. It also determines whether the relative importance of these variables vary across different agro-ecological contexts, as represented by the four regional dummies. Literature identifies several factors that can influence agricultural sustainability in developing countries, including demographic, agro-ecological, socioeconomic, political and institutional, as well as management factors (Pham and Smith, 2014). A generalized linear regression model is used to explain the variation in the composite farm sustainability index scores related to farm-specific factors and other socio-economic variables (Tables 3.8).

Table 3.8: Generalized linear model (GLM) regression results

	Overall sustainability model b/se	Economic sustainability model b/se	Social sustainability model b/se	Environmental sustainability model b/se
Total owned land (ha)	0.205**	0.0466	0.154***	-0.0136
	(0.0864)	(0.0438)	(0.0484)	(0.0469)
Distance to markets (km)	-0.0287***	0.00532	-0.0248	-0.0187
	(0.0107)	(0.0137)	(0.0173)	(0.0126)
Oromia region	-0.195	0.00857	-0.425*	0.233
	(0.327)	(0.320)	(0.233)	(0.311)
SNNP region	-0.235	0.585***	-0.351**	-0.495***
	(0.162)	(0.209)	(0.179)	(0.174)
Amhara region	0.270*	0.481**	-0.0366	0.250
	(0.158)	(0.191)	(0.0954)	(0.176)
Agricultural loans	0.0680	0.0911	-0.0893	0.204*
	(0.123)	(0.161)	(0.0833)	(0.111)
Off-farm income (ETB)	3.19e-05***	2.14e-05***	1.63e-05***	-7.10e-06
	(1.13e-05)	(8.22e-06)	(3.80e-06)	(4.98e-06)
Agricultural mechanization	0.524*	0.762***	-0.398**	1.619***
	(0.276)	(0.239)	(0.160)	(0.288)
Frequency of extension	0.151***	0.0993*	0.0189	0.0724
	(0.0575)	(0.0577)	(0.0293)	(0.0605)
Frequency of demonstration visits	0.0544**	0.0276	-0.0223	0.0213
	(0.0261)	(0.0337)	(0.0138)	(0.0225)
Livestock vaccination	0.212	0.494**	0.508	-0.671***
	(0.171)	(0.221)	(0.318)	(0.173)
Age of household head	0.000838	0.00683	-0.00575	0.0155***
	(0.00603)	(0.00554)	(0.00554)	(0.00582)
Constant	2.546***	-1.580**	3.351***	2.583***
	(0.677)	(0.696)	(0.380)	(0.660)
Observations	224	224	224	224

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The results show that both the social and the composite relative sustainability of farms were positively and significantly influenced by farm size. Larger farmers tend to be more sustainable because of the efficiency gains from economies of scale (Reig-Martinez, Gomez-Limon and Picazo-Tadeo, 2011). Having larger farms also allows the farmer more room to implement environmentally friendly practices such as crop rotations, crop diversification and agro-forestry, among other environmental programs. Benin (2006) observed how land constraints negatively affect land management in Ethiopia, particularly noting that land-constrained households had a lower likelihood of using reduced tillage.

The results also show that the composite relative sustainability was negatively associated with the distance from the village markets, which was used as a proxy for market access. Conversely, relative sustainability tends to increase as market access improves. Studies have shown that improved market access is an important driver of agricultural intensification (Pingali and Binswanger 1988), and that distance from the markets negatively affects the adoption of sustainable farming practices (Kassie et al, 2012). Therefore, improving farmers' access to input and produce markets should be a critical driver of agricultural sustainability at farm-level. With more access to markets, farmers are likely to switch to high crops instead of attempting to increase the gross value of their output through opening up new land for cultivation, which often carries steep environmental costs (Tillman et al., 2011).

The study shows a positive and significant relationship between off-farm income and agricultural sustainability. The coefficient of the off-farm income was also positive and significant in the economic and social sustainability models. The implication of this result is that increasing households access to off-farm income will have a positive impact on their relative farm sustainability. Given the liquidity constraints in the smallholder farming sector, off-farm activities provide an invaluable source of income to purchase farm inputs and technology, which are important requisites for production intensification, farm modernization and commercialization (Reardon et al,1994). Beyene (2008) also observed that a significant number of smallholder farmers in Ethiopia rely on off-farm activities to augment their agricultural incomes, which are persistently low due to low productivity levels and subject to fluctuations due to climatic shocks.

Agricultural mechanization had a positive impact on environmental, economic, as well as overall relative sustainability of farms. Farm mechanization positively influences economic sustainability of farm operations through increased land and labor productivity, improved timeliness in performance of critical activities, as well as reduction in post-harvest loses (Kienzle, Hancox, and Ashburner, 2010). Through its labor-saving ability, farm mechanization frees up more time for household members to seek off-farm work and thus improved general household incomes, another variable that was shown to positively affect farm sustainability.

Frequency of contact with agricultural extension had a positive and significant impact on farm sustainability. This is an expected result, since extension services are the primary source of information and technical advice to smallholder farmers in developing countries. Agricultural extension has been shown to positively influence the adoption of sound management practices and knowledge-intensive investments that often translate into efficiency and productivity gains (Teklewold, Kassie and Shiferaw, 2013; Nyagaka et al., 2010; Binam et al, 2008). Number of visits to agricultural demonstration plots also has a similar effect on farm sustainability. These demonstrations are like field schools, showcasing different technologies where farmers can learn by doing, which is a crucial facet of adult learning. The results also show a significant positive relationship between older age and environmental sustainability, possibly suggesting that older farmers have more experiences and knowledge with sustainable agricultural practices.

Relative farm sustainability varied significantly across the regions, which underscores the importance of agro-ecological factors. The results show that being in Amhara region increases the relative sustainability of farms relative to the Tigray region. In terms of the sustainability dimensions, the results showed that farms located in SNNP region had relatively higher economic sustainability but relatively lower social and environmental sustainability scores relative to the Tigray region. Being in Oromia region decreases the social sustainability, while being in Amhara increases the economic sustainability of farms, relative to the Tigray region.

3.5 Discussion and concluding remarks

This chapter shows how the DEA-inspired benefit-of-the-doubt modelling approach can be used to evaluate the sustainability of smallholder farming systems. Given the multi-faceted nature of sustainability and the heterogeneity of preferences across decision-making units, Data Envelopment Analysis (DEA) becomes a useful tool for constructing composite farm sustainability indices, aggregating across several indicators and endogenously determining optimal weights that maximize individual sustainability index scores. The computed index is interpreted as a relative measure, quantifying the farm-level sustainability performance of individual farms relative to the best performing farmers in the study sample. It is, however, not an absolute measure. The benefit-of-the-doubt model was applied to a total of 600 smallholder farmers in four regions of Ethiopia's highland areas, aggregating a total of 15 economic, social and environmental indicators into a composite relative farm sustainability index (FSI) score. Dimensional index scores are also computed for each of the economic, social and environmental pillars of sustainability.

Results show that composite farm sustainability is positively associated with size of land holding. Bigger farms are associated with scale economies, improvements in general household wealth that allows them to acquire productive assets, increased access to off farm income and to agricultural loans, which allows for investments in agriculture, and improved access to off-farm income, which strengthens income diversity and augments working capital. With land constraints being well documented in Ethiopia (Headey et al., 2014), policies and institutional innovations that increase average landholding, or at least enhance security of land tenure, should form the nexus of sustainability discussions in the country. Several studies in Ethiopia, have shown how land size and tenure insecurity affects the adoption of sustainable agricultural practices and natural resource management (Kassie et al., 2010; Kassie and Holden, 2008). Sustainability is a long-term concept, and addressing land ownership and tenure security issues should encourage long term investments in land improvements, and generally encourage farmers to navigate towards sustainable paths of agricultural intensification.

Another interesting result of this study is the observed positive relationship between agricultural sustainability and off-farm income. However, there exists a divergence of views in literature pertaining the exact nature of relationship between off-farm income and the farm sector. One body of studies contends that off-farm activities compliments agricultural productivity through helping alleviate liquidity constraints; another school observes a potentially negative relationship. The consensus is that this relationship depends on the prevailing conditions in the rural labor markets. Generally, participation in off-farm activities competes with agriculture for labor resources, and if returns to labor are relatively higher in the off-farm sector compared to the farm sector, then farmers would have less incentives to invest in land-improving technologies. Therefore, achieving sustainable intensification in the smallholder farming sector requires a better understanding of the rural labor market and calls upon policy makers to come up with strategies that foster synergies and optimize tradeoffs between the farm and non-farm sectors of the rural economy.

One important innovation is farm mechanization. The agricultural sector in Ethiopia is generally characterized by low levels of agricultural mechanization. The Ethiopian Agricultural Transformation Agency (2016) notes that, while most countries in Sub-Saharan Africa and Asia use more than 1 kw mechanical power index per hectare, Ethiopia's mechanical power index is a paltry 0.1 kw/ha. Consequently, production processes are characterized by high labor drudgery. Small scale mechanization will help address farm power constraints caused by loss of draught animals to diseases or recurrent droughts, as well as reduce the labor burden of farm operations, which is mostly borne by women. Undoubtedly, sustainable intensification in smallholder farming systems will require addressing farm power constraints, through the development of appropriate mechanization options that are economically viable, environmentally non-disruptive and compatible with the prevailing socio economic circumstances of smallholder farmers in Ethiopia.

Overall, these results provide valuable insights into the ongoing debate on sustainable intensification of smallholder farming system. Firstly, a synthetic and composite measure of farm sustainability helps to reconcile the multi-dimensional nature of sustainability, simplifying sustainability assessments and helping policy makers to easily benchmark and rank farm performances, as well as monitor progress over time. Secondly, findings on the key drivers of agricultural sustainability help policy makers and other agricultural stakeholders to identify effective programs and interventions to improve farm-level sustainability. Dimensional indices and our assessments of interrelationships among sustainability dimensions will help guide policy simulations and scenario analysis, especially where development programs involve preference of one sustainability dimension over another.

The major challenge encountered in this research was the lack outcome-oriented environmental indicators, such as levels of soil erosion, greenhouse gas emissions, nutrient leaching and biodiversity. Due to lack of these variables, I resorted to practice-based indicators that capture farmers' investments towards minimizing the negative impacts of their agricultural practices on the environment.

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CHAPTER 4

SUSTAINABLE INTENSIFICATION IN ETHIOPIAN HIGHLANDS

Summary

The main thrust of this paper is to investigate sustainable intensification of smallholder farming systems in Ethiopian highland areas. To achieve this, the relationship between agricultural intensification and sustainability is examined with a view to identify cases where there two are competing or complimentary. Eight categories of farmers are derived based on farmers' relative levels of intensification and sustainability. The study shows that most the farmers (22.8%) are low intensification and low sustainability (LILS) while only 8.3% of the farmers were high intensification and high sustainability (HIHS). On the other hand, 2.3% of the farms were low intensification and high sustainability (LIHS), while 16.7% were high intensification and low sustainability (HILS). In order to get a picture of what typologies of farmers fall into what categories of intensification and sustainability, multivariate statistical techniques of Principal Components Analysis (PCA) and Cluster Analysis (CA) were used to groups farmers into four distinct clusters. Out of the derived clusters, the results showed that Cluster three farmers were characterized by larger landholdings, high productive capacity, livestock ownership (TLU), as well as significant crop sales. This is the cluster that contains the largest percentage of farms (30%) in the high intensification and high sustainability category (HIHS). Factors found to significantly influence cluster membership were mostly access to agricultural loans, distance to markets, household wealth and regional factors.

This paper explores the different intensification pathways possible under the given circumstances facing smallholder farmers in Ethiopia, and examines the odds of sustainable intensification. A cross-sectional survey was carried out, covering 600 households in four regions of Ethiopia's Highlands. A logistic regression model was used to determine the factors influencing the odds of farmers embarking on a sustainable path of agricultural intensification. The results show that access to technical information through demonstration plots and government extension services; more off-farm income; improved market access; as well as livestock ownership, significantly increases the likelihood of sustainable intensification. Also, significant were the influences of the age and farming experience of the head of the household, as well as differences in agro-ecological conditions. Results of this paper will contribute to the ongoing debate on sustainable intensification and help policy makers to explore alternative options for managing different intensification and sustainability scenarios to achieve agricultural development goals.

4.1 Introduction

Sustainable intensification (SI) of agriculture is receiving growing attention as a viable pathway to addressing the challenge of feeding a rapidly growing world population in the face of a changing climate and increasing environmental concerns (Barnes, Lucas and Maio, 2016; Tilman et al., 2011; Foresight, 2011; Royal Society, 2009). While there is no commonly agreed upon definition, sustainable intensification generally refers to a system aimed at enhancing agricultural productivity while simultaneously reducing the negative impact of farming on the environment, and without cultivating additional land (Pretty and Bharucha, 2014; Muller, 2014; Pretty, Toulmin and Williams, 2011; Godfray et al., 2010; Pretty, 2008). Although widely viewed as the new paradigm for agriculture development in Africa (The Montpellier Panel, 2013), a number of studies have argued that the quest for sustainable intensification will involve trade-offs in economic, social and ecological goals (Godfray and Garnett, 2014; Barnes, 2012; Pretty, Toulmin and Williams, 2011; Godfrey et al., 2010). There is an ongoing debate on what really constitutes sustainable intensification of agriculture (Petersen and Snapp, 2015; Rockström et al., 2016; Tittonell, 2014; Garnett et al., 2013; Garnett and Godfray 2012). There are also concerns that environmental goals tend to be overwhelmingly emphasized (Robinson et al., 2015; Garnet and Godfray, 2012), while other developmental aspects, such as food and nutrition security (Godfray and Garnett, 2014), welfare of farm animals and wellbeing of farm workers (Garnet and Godfray, 2012), as well as equity and distributive justice (Loos et al., 2014; Agyeman and Evans, 2004), are not given equal prominence.

Within the sustainable intensification discourse, the largest debate is centered on the relationship between agricultural intensification and sustainability (Pretty and Bharucha, 2014; Garnett and Godfray, 2012). Much of this debate emanates from differences in the economist's and ecologist's views of intensification and sustainability (Russell, 2005). From an economic perspective, agricultural intensification involves increasing the use of variable inputs to produce higher agricultural output, or value, per hectare (Basset-Mens *et al*., 2007; Carswell, 1997). However, several authors have expressed concern that some types of intensification, such as increased use of chemical fertilizers, is detrimental to the environment (Tilman et al., 2011; Tilman et al., 2002; Tilman et al., 2001). Parallel to these arguments, are concerns that calls to reduce levels of input usage may reduce farm productivity and undermine competitiveness (de Prada, Bravo-Ureta and Shah, 2003). The goals of intensification and sustainability are generally viewed as incompatible (Garnett and Godfray, 2012). Studies have highlighted cases where intensification of production systems has led to negative environmental and social outcomes (Petersen and Snapp, 2015; Tilman et al., 2011; The Royal Society, 2009; Pretty, 2008; Shiva, 1991), as well as lost ecosystem services provided by agriculture (Firbank et al., 2011). However, some scholars instead argue that intensification can support ecological goals, especially in cases where land-sparing gains from intensification-induced productivity growth could reduce the need for land expansion (Garnett et al., 2013; Borlaug, 2007; Waggoner and Ausubel, 2001). Generally, the relationship between intensification and sustainability is not always clear-cut (Robinson et al., 2015; VanWey et al., 2013), and for any given intensification path, there are trade-offs between productivity, environmental sustainability and social objectives (Muller, 2004). Accordingly, understanding the synergies and tradeoffs between agricultural intensification and sustainability, as well as the relationships between different sustainability dimensions will be crucial to crafting appropriate policies to support sustainable intensification of agriculture within any given context.

Perhaps there is no more important place to understand the synergies and tradeoffs from sustainable intensification than smallholder farming systems. These systems exhibit considerable variability and diversity, largely owing to differences in agro-ecological conditions, socioeconomic circumstances, technological levels, access to markets and infrastructure, as well as differences in resource endowments, technology use and production orientation (Goswami, Chatterjee and Prasad, 2014). The cost of undesirable tradeoffs can be more devastating due to the already venerable positions most of these farm owners already face. To study these complex systems, however, requires some way to track and manage multiple dimensions of sustainability and intensification, while simultaneously accounting for individual preferences for trade-offs for those people managing the smallholder farms.

The purpose of this study is to assess how sustainability and intensification are related in the case of smallholder agriculture in Ethiopia. The first objective is to define and measure sustainability and agricultural intensification on individual farms so they can be compared. The second objective is to characterize the attributes of smallholder farms that effect intensification or sustainability. The goal is to relate intensification and sustainability vis-à-vis the different farm characteristics to determine which affect agricultural intensification and relative farm sustainability. The contributions of this work to the current sustainable intensification discourse are twofold. First, the paper gives evidence of both synergies and conflicts of sustainable intensification in an empirical setting with data from over 600 farmers. Secondly, the results can help guide farmers and their advisers into situations where both objectives can be realistically pursued, and indicate when more serious incompatibility in the two objectives will lead to choosing one over the other. Finally, these results can help policy makers offer effective incentives and instruments for nudging farmers towards more sustainable paths of agricultural intensification.

The rest of the paper is organized as follows: Section 2 provides a brief description of the model and variables used in the analysis. Section 3 describes the general characteristics of the sector of the study, the data used and methodology for data collection. Section 4 presents the descriptive and econometric results. Finally, section 5 concludes with a discussion of main findings and their implications.

4.2 Conceptual Model

Farmers are driven by different constraints and incentives to intensify, and the intensification path they pursue will be shaped by an interplay of agro-ecological, socioeconomic, and institutional conditions (Kruseman, Ruben and Tesfay, 2006), nature of existing farming systems (Binswanger and Pingali, 1988), and farmers’ circumstances (Ringler et al, 2014; Harrington and Erenstein, 2005; Von Wirén-Lehr, 2001), as well as access to markets, infrastructure and agricultural potential (Pender, Place and Ehui 1999). The type of intensification path that emerges in each given context will have implications on sustainability (Reardon et al., 1999, Clay et al. 1998). Sustainable intensification paths will therefore vary between locations, farming systems and individual farms. Figure 3.1 provides a conceptual framework, depicting the likely cases.

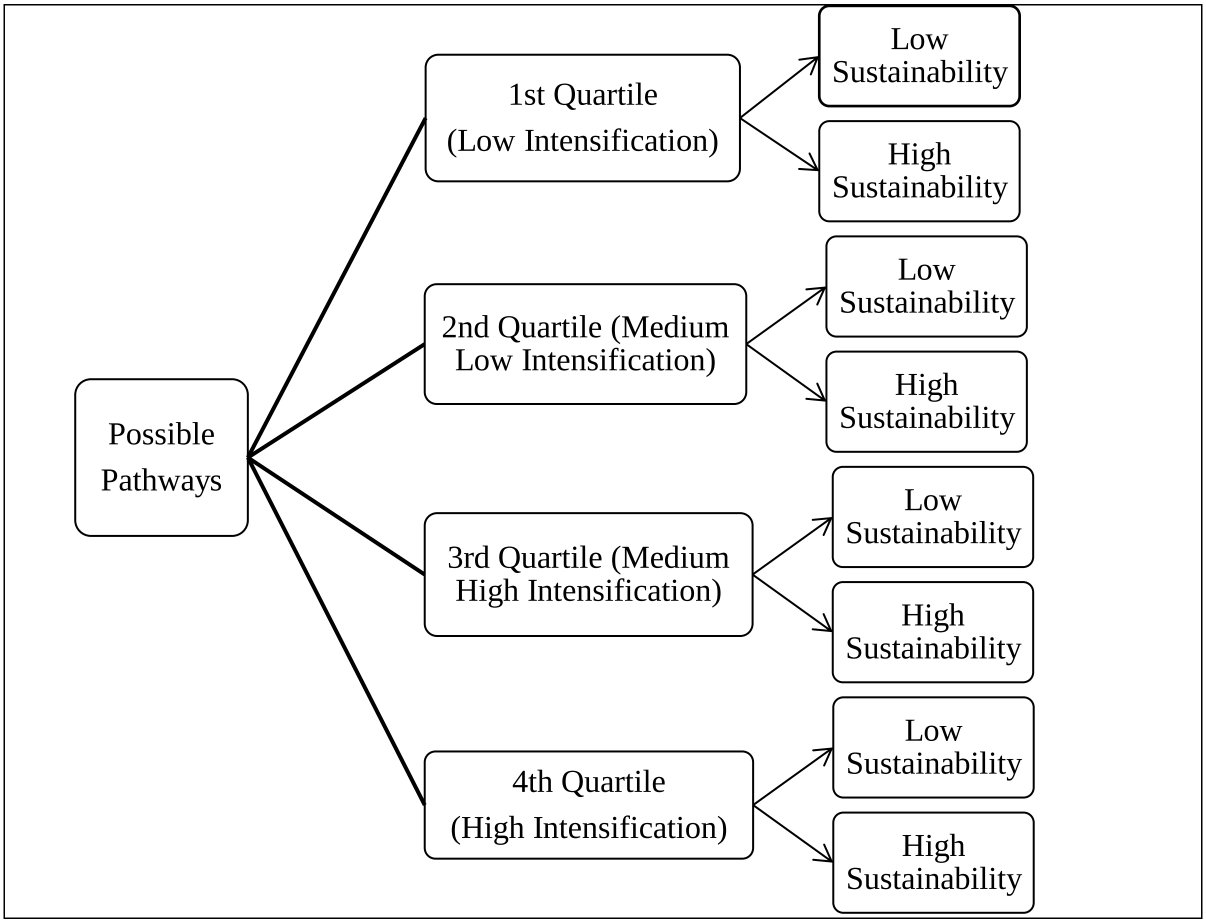

Figure 4.1: Conceptual pathways for agricultural intensification and sustainability (farm pathway clusters)

For simplicity, the levels of intensification are depicted in Figure 4.1 in four quartiles of gross value of crop output per hectare, from most to least. Tradeoffs with sustainability can be easily depicted next to each quartile as high and low on any farm. When both are high or both are low, intensification is synergistic or complementary to sustainability. However, when one is high and the other is low, they may be antagonistic. Eight broad farm pathway clusters are described in Figure 4.1. The first scenario is a case where intensification is low and sustainability is low (LILS), which is undesirable for both farmers and policy makers alike. This is a typical case of resource constrained households, with very limited investments in both productivity-enhancing inputs and in soil fertility management. This scenario likely depicts systems where farmers operate very low or negative levels of net farm income, with increasing debt to asset ratios (Barnes, 2012). The second case involves a tradeoff between agricultural intensification and sustainability (LIHS). This scenario is similar to the low input sustainable agriculture systems described by de Prada, Bravo-Ureta and Shah (2003), which typically involve use of less chemical inputs such as fertilizer and more ecological management practices to produce food (Gold, 1999). The third scenario also represents tradeoffs between intensification and sustainability, but this time intensification is high and sustainability is relatively low (HILS). This is probably the case of high input systems, where farms are highly productive and competitive but with less investments in environmentally friendly practices and land improvements. The fourth scenario would be high intensification and high sustainability (HIHS). The other four pathways include medium high (MH), or second quartile, intensification or medium low (ML) intensification paired with high and low sustainability.

4.3 Empirical Models

4.3.1 Farm Typology Clusters

The study applies a multivariate approach that combines Principal Components Analysis (PCA) and Cluster Analysis (CA) to characterize households into distinct farm typology clusters, a technique that is widely recognized in literature (Goswami, Chatterjee and Prasad, 2014; Dossa et al., 2011; Ding and He, 2004). PCA is first applied on the set of selected variables (Table 4.1) to reduce dimensionality of the data (Jolliffe, 2002). A total of 22 variables were included in the Principal Components Analysis (PCA). Applying the Kaiser's (1970) criteria, 8 principal components eigenvalues of at least 1 were retained for further analysis. The screen plot of eigenvalues after PCA is shown in figure A4 in the annex. Kaiser-Meyer-Olkin (KMO) measures of sampling adequacy are also shown in the annex (Table A4). The retained eight principal components were used for K-means cluster analysis, in order to classify households into four distinct clusters. The K-means procedures performs better than the hierarchical methods for larger data sets, and is less affected by outliers in the data or the inclusion of irrelevant clustering variables (Kaur and Kaur, 2013). Hence, given the sample size, this study employed the K-means iterative partitioning method, which assigns cases to clusters in a way that minimizes within-cluster variation. The four clusters identified represent groups of farms that are alike in a subset of dimensions from Table 4.1.

Table 4.1: Variables used in farm typology characterization

Variable	Description
Cropping system	
Total owned land	Total land owned by the households (hectares)
Cultivated land	Total land cultivated by households (hectares)
Land renting	Binary variable whether household rented land (1= Yes, 0 = No)
Land leasing	Binary variable whether household leased land (1= Yes, 0 = No)
Gross value per hectare	Gross value of crop production (ETB/ha)
Sales volume	Total volume of crop sales per cropping year (kgs)
Cross sales income	Total incomes from crop sales (ETB/ha)
Livestock system	
Livestock incomes	Total incomes livestock and livestock products sales (ETB/ha)
Livestock purchases	Total expenditures on livestock purchases (ETB/ha)
Fodder production	Binary variable whether grows livestock fodder (1= Yes, 0 = No)
Tropical livestock units	Total number of livestock owned (TLU)
Overall input intensity	
Total fertilizer	Total fertilizer use (kgs/ha)
Improved seeds	Total improved seed use (kgs/ha)
Hired labor	Total labor hired by household (man-days/ha)
Capital costs	Total capital expenditures, excluding labor (ETB/ha)
Labor costs	Total labor expenses (ETB/ha)
Cropping intensity	A measure of cropping intensity
Crop diversification	Measured by Herfindahl index; varies from 0 to 1
Household economy	
Asset index	Index of productive assets, using Principal Components Analysis.
Household labor	Number of family members in farm activities
Off farm labor	Number of household members involved in off-farm activities
Off farm income	Total off-farm incomes, including remittances (ETB)

4.3.2 Multinomial Logit (MNL) regression model

A multinomial logit (MNL) regression model was used to identify farm and other characteristics that drive both farm typology and pathway cluster membership. Several household demographics, socioeconomic, institutional and agro-ecological variables (Table 4.2) were considered, with the goal of predicting the likelihood of a farm household, with given characteristics, being a member of a particular farm typology or pathway cluster. The MNL model uses maximum likelihood (ML) estimation to evaluate the probability of cluster membership. Following Cameron and Trivedi (2010), the multinomial logit (MNL) model is specified as follows:

$$p_{ij} = \frac{\exp(x_i'\beta_j)}{\sum_l^m (x_i'\beta_l)}, \qquad j = 1, \dots, m$$

Where px_i are the regressors, $\beta_i$are the parameter estimates and m is the number of clusters. Therefore, in the cluster membership model, m equals 4. To ensure model identification, cluster 1 was treated as the base category. Therefore, the estimated coefficients are interpreted with respect to cluster 1, and depict the comparative likelihood of the household belonging to given cluster relative to cluster 1. A positive sign of the parameter estimate implies that the particular variable increases the likelihood of the cluster under consideration relative to the reference cluster (Cameron and Trivedi, 2010). The (rr) option of the mlogit command in Stata version 13.0 was used to obtain odds ratios (relative-risk ratios) of membership in cluster j rather than cluster 1. The same model was extended to analyses membership to the eight categories of agricultural intensification and sustainability.

Table 4.2: Description of variables used in the MNL model

Variable	Category	Description
Dependent variables		
Farm Typology Clusters	Categorical	Depicts the four clusters computed by cluster analysis
Farm Pathway Clusters	Categorical	Represents the 8 categories of farms based on levels of intensification and relative farm sustainability
Independent variable		
Land size (ha)	Continuous	Total land owned by the household
Distance to markets (km)	Continuous	Total distance, in kilometers, to the nearest village market
Demonstration plots visits	Continuous	Number of times the farmer visited agricultural demonstration plots during the cropping year.
Extension frequency	Continuous	Number of times the farmer had extension contact
Off farm income (ETB)	Continuous	Amount of off-farm income received by the household (Ethiopian Birr)
Household head age (years)	Continuous	Age of the household head in years
Household head farming experience	Continuous	Total years of farming experience in completed years
Tropical livestock units	Continuous	Total livestock ownership, in tropical livestock units
Oromia dummy	Binary	1 = Oromia region 0 = otherwise
Amhara dummy	Binary	1 = Amhara region 0 = otherwise
Tigray dummy	Binary	1 = Tigray region 0 = otherwise

The explanatory variables include a mixture of household and farm characteristics, institutional factors and agro-ecological variables. Household and farm characteristics are represented by the age and farming experience of the household head, who happens to be the principal decision maker, as well as off-farm income, livestock ownership and farm size. The farmer’s age may have an ambiguous influence on sustainable intensification. While younger farmers have a higher propensity to adopt new technologies (Howley, Donoghue and Heanue, 2012), older people are more likely to invest in soil fertility and land improvements, due to more savings and farming knowledge (Romero and Groot, 2008). Farming experience is expected to positively influence both intensification and sustainability. Households' off-farm income is expected to provide an important source of income for the liquidity-constrained rural households, and thus positively affect the odds of sustainable intensification. Livestock ownership, measured by the tropical livestock units, will positively affect both agricultural intensification, through increased availability of draught power, and sustainability, through manure for organic farming. Farm size will likely have an ambiguous effect on the odds of sustainable intensification. Smaller farms in developing countries tend to be more intensive and highly productive, consistent with the inverse productivity hypothesis (Carter, 1984), while larger farms have a higher propensity to invest in sustainable farming practices and soil fertility management. However, farm size could have varying impacts on agricultural technology use depending on the characteristics of the technology in question and other institutional factors such as tenure arrangements (Feder, Just and Zilberman, 1985).

Institutional factors are represented by the distance of the households from the nearest markets, frequency of access to extension services, as well as number of times the farmer received government extension services. Distance to markets is a proxy for market access, hence the odds of sustainable intensification are likely to fall with distance from the markets. The number of farmers' visits to demonstration plots is expected to increase the likelihood of both agricultural intensification and sustainability, since farmers are exposed to improved technologies and sustainable farming practices. Improved access to extension services will help farmers adapt the technological packages to their own farms and hence increasing the odds of sustainable intensification. Three regional dummies are included represented Tigray, Amhara and Oromia regions, while the SNNP region is treated as the reference group. These dummies will act as proxies for differences in agro-ecological conditions, and hence expected to influence both intensification and sustainability. For instance, (Ehui et al., 2002) observed differences in total factor productivity across Tigray, Amhara and Oromia regions of Ethiopian highland regions, due to differences in climate and other biophysical determinants of agricultural potential.

4.3 Data

4.3.1 Study area

The study is carried out in Tigray, Amhara, SNNP and Oromia regions of the Ethiopian highlands. The Highlands are characterized by relatively steady rainfall, averaging an annual range of about 600 mm to over 2,000 mm, while average annual temperatures range from 20 to 22°C in the lower elevations to 10-12°C in the higher elevations (Pender, Place and Ehui, 2006). However, climatic conditions vary across regions. For instance, the Tigray region, which lies in northern Ethiopia, is characterized by frequent droughts. On the other hand, the Oromia region, located in the central and southern part of Ethiopia, receives rainfall ranging from 200 mm to 2000 mm annually. This is the region where most of Ethiopia's coffee is grown. The Oromia and Southern Nations, Nationalities and Peoples' Regions (SNNP), which makes up the southwest highlands, also has relatively good agro-ecological potential (Headey et al., 2013). The Amhara region, located in the central and northwestern part of Ethiopia, receives annual rainfall ranging from 300 mm in the east to over 2000 mm in the west (Benin, Pender and Ehui, 2003). However, despite the agricultural potential, these areas face productivity and soil degradation issues, attributable to limited investments in soil and water conservation measures (Pender, Place and Ehui, 1999).

4.3.2 Data collection

A cross-sectional survey of 150 smallholder farmers in each of Tigray, Amhara, Oromia and the Southern Nations, Nationalities, and Peoples (SNNP) regions of the Ethiopian highlands was conducted from March through May of 2015. To ensure that relevant information was collected, participating households owned some agricultural land and had planted and harvested crops over the previous twelve months. Most respondents made most production and marketing decisions on the farm, unless it was a spouse of the household head who was aware of most operational decisions on the farm. Households were randomly selected from farmer lists provided by government extension officers in the respective wards (woredas). The selected farmers were interviewed face-to-face using a structured questionnaire that contained mostly closed questions regarding the farmers' land ownership, size of cultivated land, crop grown, yields, livestock activities, levels of inputs use, crop and livestock sales, as well as area under soil erosion control and other environmentally friendly practices. A pilot study with twenty smallholder farmers was carried out to pre-test the questionnaire, gauge farmers' response time and thus refine the questionnaire in terms of wording, ordering of questions and skip patterns. Before administering the survey, the revised questionnaire was assessed for content validity through consultation with experts in the field. Farmer interviews were carried out by government extension officers, field facilitators and agricultural research officers from the International Livestock Research Institute (ILRI) who were selected based on their familiarity with the study areas and ability to speak the local language. Survey teams were comprised of five enumerators and a supervisor in each of the four districts, who were all subjected to an intensive three-day training session prior data collection.

4.3.3 Intensification and sustainability measures

Gross value of crop output per hectare was used as a measure of agricultural intensification at the farm level. This was obtained by summing all the main crops produced, namely white and black teff, barley, wheat, maize, sorghum, field peas and faba beans, multiplied by average producer prices. The producer prices were obtained from the Ethiopian Central Statistical Agency (CSA). Farms were divided into four quartiles according to their performance relative to the average gross value of output per hectare, the first quartile being the lowest and the fourth quartile being the highest level of agricultural intensification, as measured by the gross value of crop output per hectare. The average gross value per hectare was ETB 3,930 in the first quartile, ETB 7,790.6 in the second quartile, ETB 11,241.8 in the third quartile and ETB 22,783 in the fourth quartile.

Composite sustainability scores were created from a set of 15 indicators of economic, social and environmental sustainability. Labor and capital productivity, crop and income diversification indices, and agricultural income were the indicators for the economic dimension of farm sustainability. Agricultural income represents the total income from crop and livestock sales, measured in Ethiopian birr (ETB). Labor productivity is measured as the gross value of crops per person day, while capital productivity is measured as the total value generated by a given input of capital. A Herfindahl-Hirschman index was used to compute indicators for crop and income diversification. Social sustainability was depicted by indicators representing membership in farmer organizations, women's participation in production and marketing decisions, family labor availability, and household wealth, computed by Principal Components Analysis (PCA) on households' assets and living conditions data. Six indicators were used to capture environmental sustainability of farming operations, namely, use of chemical fertilizers, use of pesticides and herbicides, livestock density, erosion control measures, use of crop rotations and organic farming. Chemical fertilizer use was measured in kilograms per hectare of total inorganic fertilizers used by the farmers, while use of pesticides and herbicides was captured by total expenditures (Ethiopian Birr) on the chemicals. Livestock density was measured by the tropical livestock units per hectare. Erosion control, rotations and organic farming were captured by binary variables, indicating whether the farmer used the environment-friendly farming practices. A Data Envelopment Analysis (DEA) model was used to aggregate the indicators into composite farm sustainability scores, using endogenously determined optimal weights (see Chapter 3). Farmers were categorized according to their relative levels of farm sustainability. High sustainability farms were those with a relative farm sustainability index (FSI) score of unity (i.e. FSI = 1).

4.4. Results

4.4.1 Descriptive results

To better understand how farmers are intensifying and the potential sustainability of current production practices, the study examined the general farming practices, farm economics and the extent to which farmers were adopting and implementing commonly recommended management practices. Besides the household surveys, the study was complimented by focus group discussions and key informant interviews to get a view of the system characteristics, production constraints, potential intensification pathways and their implications on sustainability. The study showed that, on average and inclusive of the main (meher) and second (belg) seasons, households cultivated 2.62 hectares under crop production. The size of the cultivated land was mainly determined by the drive to produce enough food for the family, as reported by 30.5% of the households. Other factors influencing the size of cultivated area were the availability of seed (16.9%) and other inputs (16.9%), and the availability of draught power (13.9%). Cultivation of land was mostly done using own draught animals, as reported by 90.7% of the farmers. Operations such as weeding are mostly done manually using hand implements (66%); however, 32% of the households surveyed indicated use of herbicides for weed control. Labor for farm operations is mostly from household members, although about 56.9% of the households reported that they hired additional labor from within the villages. Almost all the households used some inorganic fertilizers, at varying intensities, while 79% used improved seed varieties. Table 4.3 below summarizes general variables relating to farm economics, farm and household characteristics, as well as access to key institutional services, which are later used in subsequent analyses.

Table 4.3: Descriptive statistics of key farm characteristics[9]

Variables	Mean	Std. Dev.
Farm economics		
Total owned land (ha)	1.80	1.66
Total cultivated land (ha)	2.62	2.48
Gross value of crop output (ETB/ha)	11,420.58	10,192.91
Net value of crop output (ETB/ha)	8,425.92	9,620.01
Total labor (man-days/ha)	75.62	72.19
Capital expenditure (ETB/ha)	2,390.98	3,388.84
Total inorganic fertilizer (kgs/ha)	123.19	206.94
Tropical livestock units (TLU)	4.94	2.83
Off-farm household income (ETB)	3,547.47	8,671.33
Household characteristics		
Total household members	6.79	4.49
Age of household head	44.85	12.20
Household head's farming experience (years)	23.742	12.02
Institutional factors		
Frequency of extension visits	2.571	1.156
Demonstration plots visits	2.580	2.595
Distance to village markets (km)	5.364	4.639

[9] Production data covers both the main (meher) and second (belg) seasons, which represents one cropping year.

The study also explored the extent to which farmers utilized farming technologies and practices that are commonly recommended by extension services that are integral to sustainable agriculture. 75% of the farmers reported that they used legume crop rotations, 22.4% left some land fallow, but only 12% practiced intercropping. In terms of the other fertility management practices, 77% reported using organic manure, 57.1% reported following recommended fertilizer application rates, while only 17.7% practiced green manuring. In terms of practices to reduce soil erosion, conserve soil and water, only 9.9% of the farmers reported using minimum tillage. However, 60% indicated implementation of soil erosion control measures such as soil and stone buds and 59.4% used soil and water conservation techniques. 48.8% of the farmers were growing fodder and 27.3% reported planting trees on their plots. Only 21.3% had access to irrigation while as little as 8.2% had soil testing done on their fields to ascertain fertility status and pH levels.

4.4.2 Intensification and sustainability

The average gross value of output per hectare, my measure of intensification, was 11,421 ETB, which is roughly US$ 571 per hectare. Intensification varied considerably by farm sizes and across the four regions. The average gross value of output per hectare was 16,650 ETB (US$ 832) on small farms, 9,838 ETB (US$ 492) on medium and 9,304 ETB (US$ 665) on relatively larger farms. Intensification was highest in the Tigray region, with an average gross value of crop production of 15,707 ETB (roughly US$ 785). The average gross value of crop production per hectare were 11,733 ETB (roughly US$ 587), 10,885 ETB (roughly US$ 554) and 7,393 ETB (roughly US$ 370) in Amhara, Oromia and SNNP regions, respectively. When compared to sustainability, based on the sustainability index computed by a DEA model, only 16% of the farms had composite relative sustainability scores of unity (FSI = 1). From a benchmarking perspective, these were the highest performing farms.

A generalized Lorenz curve was constructed to depict the relationship between intensification and sustainability variables, plotting the cumulative percentage of the intensification variable against the cumulative percentage of sustainability (figure 4.2). The results indicate that the lowest 20% of intensification has 40% of the lowest sustainability. The second, third and fourth 20% of intensification contains 23%, 17% and 12% of sustainability, respectively. Interestingly, the highest 20% of intensification has only 6% of the highest sustainability. This indicates that intensification and sustainability are not linear functions of each other, and policy makers should be alerted to the potential tradeoffs between intensification and sustainability. Policy makers may want to explore questions of how to make systems that are relatively sustainable more productive and more competitive without compromising sustainability. They may also want to encourage, and possibly 'nudge' farmers who are already highly productive and competitive to adopt sustainable practices and land management measures without imposing a penalty on their current productivity.

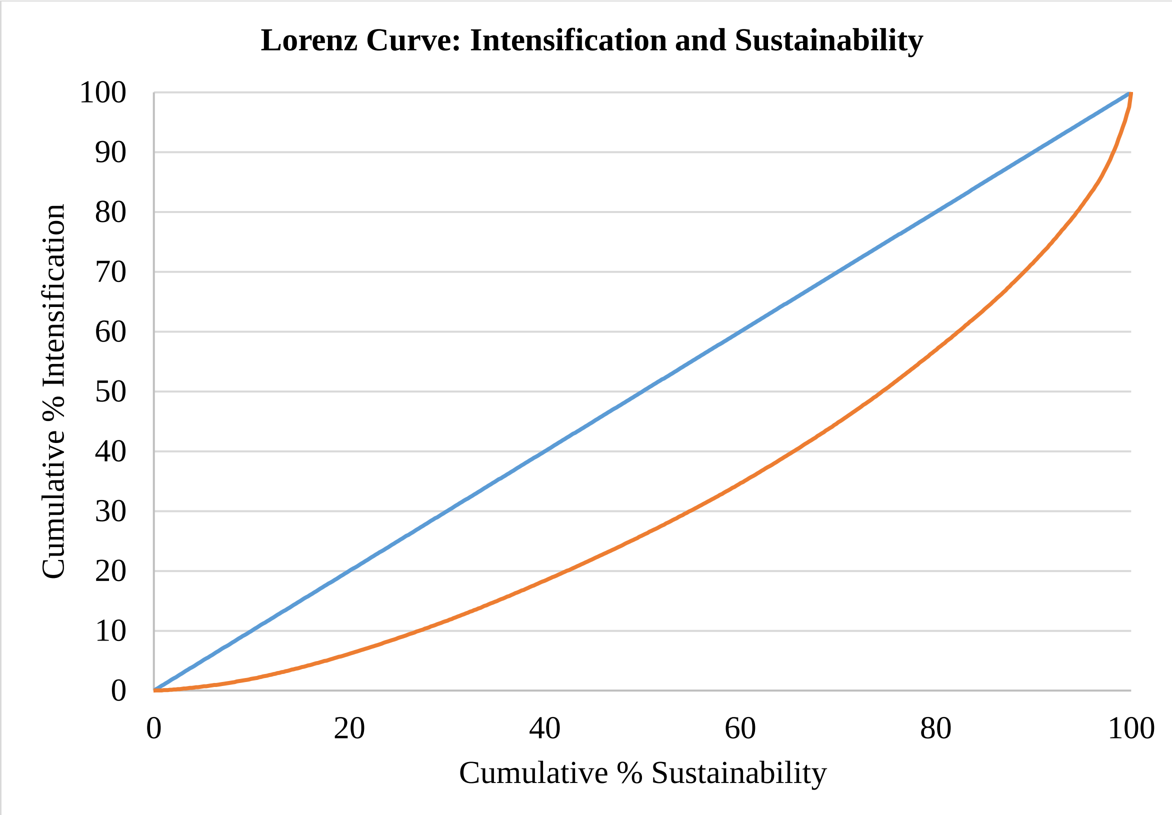

Figure 4.2: Lorenz curve plot of intensification and sustainability

A cross tabulation of the intensification and sustainability variables shows how the households are distributed across the two variables (Table 4.4). A chi-square test of homogeneity of proportions showed that differences across the categories of intensification and sustainability were statistically significant at 5%. Overall, eight typologies are evident, viz, low intensification and low sustainability (LILS), medium low intensification and low sustainability (MLILS), medium high intensification and low sustainability (MHILS), high intensification and low sustainability (HIHS), low intensification and high sustainability (LIHS), medium low intensification and high sustainability (MLIHS), medium high intensification and high sustainability (MHIHS), as well a high intensification and high sustainability (HIHS). Farms where sustainability and intensification are complementary are shown in the light shaded region of Figure

4.4 (31.1% in total), while farms at the extreme end of conflict are in the darkly shaded cell (19% in all). Therefore, 30% of farms show complementary relationships in SI and 20% show a conflict. The remaining half of farms show mixed effects.

Table 4.4: Distribution of households by intensification and sustainability

		Intensification levels			
		Low Quartile	Low Medium Quartile	High Medium Quartile	High Quartile
Relative farm sustainability	Low	108 (22.8) **LILS**	105 (22.2) **MLILS**	103 (21.8) **MHILS**	79 (16.7) **HILS**
	High	11 (2.3) **LIHS**	13 (2.8) **MLIHS**	15 (3.17) **MHIHS**	39 (8.3) **HIHS**

** in parenthesis are percentages of households

Interestingly, only 2.3% of the farms are in the lowest quartile of intensification but exhibiting relatively high sustainability levels (LIHS), while 16.7% of the farms are in the highest quartile of intensification but relatively less sustainable (HILS). Only 8.3% of the farms are in the fourth quartile of agricultural intensification and relatively high sustainability (high intensification and high sustainability). Figure 4.3 below shows that most LILS (low intensification and low sustainability) farms are in SNNP region (45.3%), most MHILS (medium high intensification and low sustainability) farms are situated in Oromia region (35.9%), while most HILS (high intensification and low sustainability) farms are in Tigray region. On the other hand, Oromia has the highest percentage of relatively more sustainable farms, housing 54.6% of LIHS farms, 46.7% of MHIHS farms and 46.2% of HIHS farms.

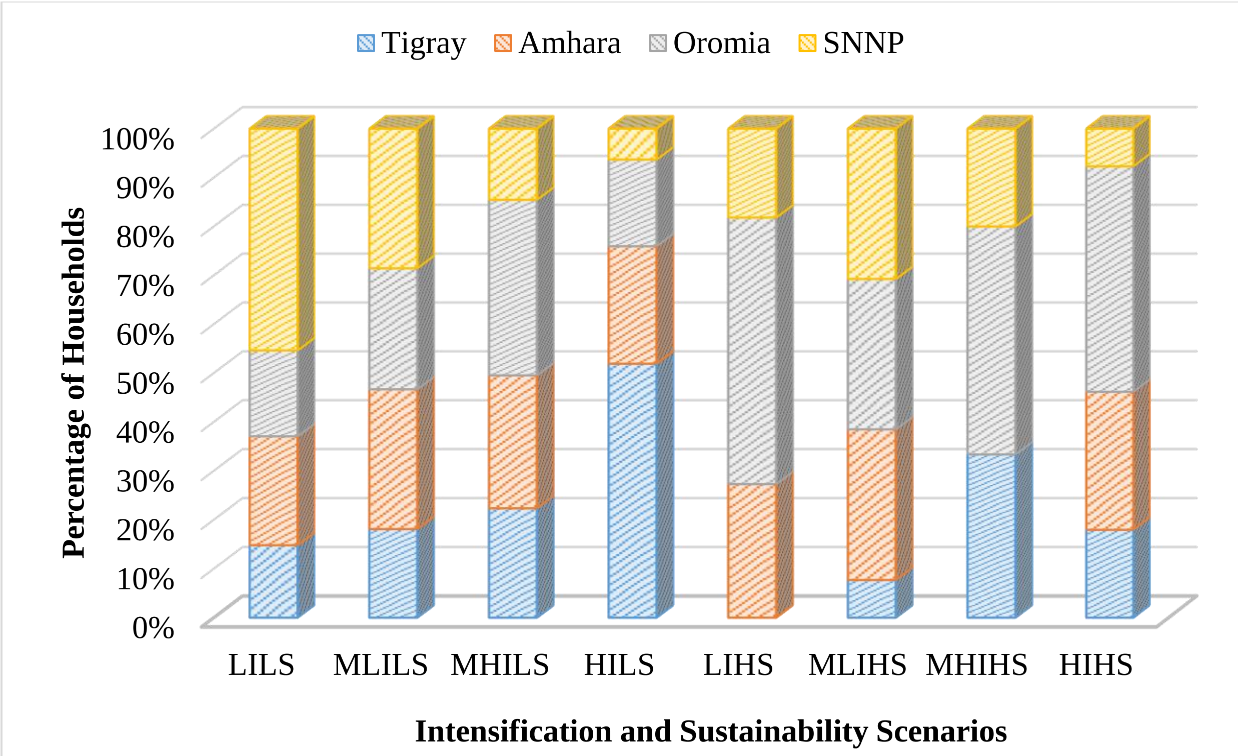

Figure 4.3: Distribution of intensification and sustainability classes in each region

4.4.3 Principal components analysis

Table 4.5 below shows the factor loadings for each of the variables used in the analysis. A Varimax rotation matrix was also used to examine which variables were associated with each of the 8 principal components. Overall, the retained principal components explained 66% of the total variability in the data. The first three components had relatively more importance in explaining the variation in the data. The first component explained 15% variance, and was correlated with total landholding, cultivated area, crop sales income and household asset index. The second component, which explained 8.7% of the variance, was correlated with labor use variables (total hired labor and total labor expenses). Principal component 3 explained 8.5% variance and was correlated with fertilizer use, total improved seeds and capital investments. Principal components 4, 5 and 6 explained 7.7%, 7.3% and 7.1% variance respectively, while components 7 and 8 explained 6% of the variance each.

Table 4.5: Principal components analysis factor loadings (scoring coefficients)

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Total owned land	0.40	0.16	0.16	-0.03	0.03	0.07	0.18	-0.13
Cultivated land	0.39	-0.01	0.20	-0.01	-0.13	0.28	-0.02	0.08
Land renting	-0.14	0.17	0.15	-0.14	-0.51	-0.01	-0.04	0.29
Land leasing	-0.24	0.10	0.19	-0.10	-0.33	-0.10	0.31	0.22
Gross crop value	-0.03	0.36	-0.21	-0.03	0.25	-0.12	0.17	0.11
Sales volume	0.04	0.21	-0.12	-0.02	0.30	0.06	-0.22	0.62
Crops income	0.28	0.26	0.08	-0.15	-0.02	0.08	0.16	0.22
Livestock incomes	0.05	0.13	-0.06	0.50	-0.08	-0.26	-0.13	0.19
Livestock purchases	0.13	0.07	-0.06	0.35	-0.15	-0.30	-0.17	-0.14
Fodder production	0.07	0.12	0.37	0.22	0.02	0.07	-0.28	0.24
Tropical livestock units	0.29	0.21	0.09	0.34	0.00	-0.09	0.08	-0.09
Total fertilizer	-0.11	0.33	0.04	-0.13	0.13	-0.04	-0.31	-0.24
Improved seeds	0.12	0.26	0.05	-0.28	0.01	-0.22	-0.15	-0.33
Hired labor	-0.21	0.33	-0.20	0.23	-0.16	0.43	0.12	-0.15
Capital costs	-0.15	0.33	-0.11	-0.26	0.30	-0.04	0.00	0.07
Labor costs	-0.22	0.34	-0.05	0.22	-0.14	0.43	0.02	-0.20
Cropping intensity	0.20	-0.13	0.12	-0.11	0.13	0.48	-0.06	0.00
Crop diversification	-0.17	-0.15	0.22	0.30	0.40	0.18	-0.07	0.01
Asset index	0.39	0.17	-0.09	-0.06	-0.07	-0.02	0.10	-0.06
Household labor	-0.07	0.06	0.28	0.15	0.32	-0.16	0.59	-0.06
Off farm labor	-0.19	0.08	0.49	-0.03	0.01	-0.05	0.14	0.04
Off farm income	-0.12	0.14	0.46	-0.11	0.04	-0.07	-0.34	-0.19
Eigen values	3.76	2.68	1.84	1.61	1.39	1.19	1.04	1.02
Cumulative explained variance	0.15	0.23	0.32	0.40	0.47	0.54	0.60	0.66

4.4.4 Farm Typology Clusters

Figure 4.4 shows the distribution of farm typology clusters by region. Overall, cluster 1 comprised 41.5% of the households, cluster 2 constituted 25.2 of the households, while 9.9 of the households were in cluster 3. The remainder 23.3% of the households were in cluster 4.

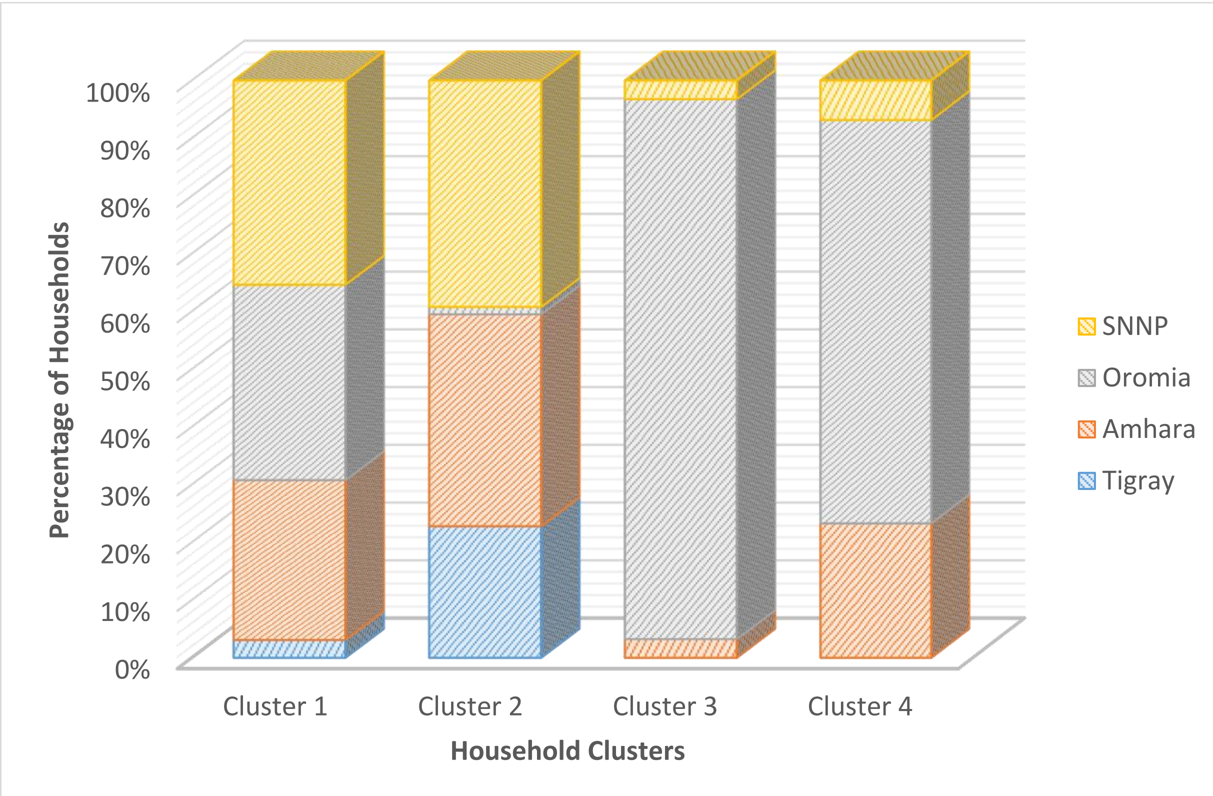

Figure 4.4: Distribution of clusters by region

The proportion of household types in each region is shown in each bar. Geographically, most Cluster 1 farms are in SNNP (34.4%) and Oromia (33.9%) regions. Cluster 2 farms are mostly in SNNP (39.2%) and Amhara (36.7%) regions, while Cluster 3 farms are predominantly in Oromia (93.6%). Most Cluster 4 farms are in Oromia (69.9%). The Tigray region did not have any of the farms in clusters 3 and 4. Chi-square tests showed that the distribution of farms across the four clusters differed significantly. Table 4.6 below helps explain the characteristics of each of the clusters in terms of the underlying variables. One-way analysis of variance (ANOVA) was used to test for significance of differences in cluster means, and hence to ascertain the authenticity of the clustering procedure. The resulting p-values are also reported in Table 4.6. All the clustering variables showed significant differences between the cluster means, suggesting that the profile variables were successful in discriminating between generated clusters.

Table 4.6: Characteristics of identified clusters

	Cluster 1 (N = 130)	Cluster 2 (N = 79)	Cluster 3 (N = 31)	Cluster 4 (N = 73)	P-value[10]
Total owned land (ha)	1.74	1.22	6.16	2.70	0.00
Cultivated land (ha)	3.30	1.30	7.99	3.79	0.00
Land renting (binary)	12.5	19.5	4.5	12.8	0.00
Land leasing (binary)	9.3	19.2	1.9	3.2	0.00
Gross crop value (ETB/ha)	7,417.18	12,087.60	11,395.32	12,363.70	0.00
Sales volume (kgs)	6.47	7.33	48.13	42.14	0.02
Cross sales income (ETB/ha)	4,076.15	5,101.54	40,357.52	12,544.78	0.00
Livestock incomes (ETB/ha)	3,333.49	5,145.76	5,589.81	9,830.90	0.00
Livestock purchases (ETB/ha)	2,330.60	1,952.70	3,865.16	7,816.03	0.00
Fodder production	17.6	12.5	7.0	9.3	0.02
Tropical livestock units (TLU)	4.61	4.38	8.87	6.48	0.00
Total fertilizer (kgs)	68.19	136.32	105.56	94.03	0.00
Improved seeds (kgs)	55.90	89.05	154.42	115.94	0.00
Hired labor	2.21	15.93	3.40	3.48	0.00
Capital costs (ETB/ha)	1,487.72	3,088.92	2,126.72	1,810.53	0.00
Labor costs (ETB/ha)	147.43	1,071.13	190.75	285.09	0.00
Cropping intensity index	161.00	114.00	198.68	141.27	0.00
Crop diversification index	0.67	0.64	0.46	0.44	0.00
Asset index	-0.33	-0.83	3.80	2.13	0.00
Household labor	2.22	2.91	2.52	1.81	0.00
Off farm labor	0.49	1.67	0.68	0.22	0.00
Off farm income (ETB)	1,985.54	9,213.39	4,625.81	1,470.96	0.00

[10] Significance values from ANOVA tests of significance in cluster means differences (F-test) for continuous variables and Chi-square tests for binary variables (i.e. land renting, land leasing and feed production).

Variables in each cluster that stand out for being higher than they are in other clusters are highlighted in light gray, while variables that were lower than other clusters are highlighted in darker gray. These shaded variables represent what is unique about the cluster. In cluster 1, the gross value of crop output per hectare, crop sales, livestock sales incomes, hired labor, fertilizer intensity and improved seed use were all very low, compared to the other clusters. The cluster has a negative score on production assets index, hence the low productive capacity of these households. However, fodder production and crop diversification index were highest in this cluster. These factors point to low levels of agricultural productivity and a predominantly subsistence orientation. This cluster comprises the biggest number of the households (41.5%) in the study area.

Cluster 2 is characterized by very high input use intensity per hectare (fertilizer, hired labor, capital and labor costs), as well as significant land transactions (renting and leasing). Farms in this group had the highest number of household members available for both agricultural and off-farm activities than any other group, earning on average 9,213 ETB per year (roughly US$ 460) in off farm work, petty trade and remittances. Thus, they are biggest earners of off-farm income. On average, this group has the least landholding, averaging 1.22 hectares per household. Thus, the group is more actively involved in the renting (19.5%) additional land for cultivation. Probably in order to offset the land constraints, this group has the highest fertilizer use intensity per hectare, averaging 136 kgs/ha. However, this group has the least, and negative, score on productive assets. Consequently, average cultivated area is lowest in this cluster. Cluster 2 comprises 25.2% of the farm households.

Cluster 3 is characterized by high levels of landholdings, household assets, cropping intensity and high capital expenditure per hectare. Households in this clusters have the largest landholding, averaging 6.2 hectares per household. The cluster members also boast the highest score in productive assets, which represents high productive capacity. A combination of land access and high productive capacity means the group cultivates the largest area on average. They also exhibit the highest cropping intensity, indicating their ability to make use of the production possibilities in both the main (Meher) and second (belg) cropping seasons. The groups also make the most investments in improved seeds, averaging about 154 kgs/ha. The systems in this cluster are also highly productive, with an average gross value of crop output of 11,395 ETB/ha (roughly US$ 569). Farmers in this group have the highest earnings from crop sales, averaging 40,358 ETB per cropping year (roughly US$ 717). These households have the largest tropical livestock units (TLU), and make the second largest earnings from sales of livestock and livestock products. Further analysis also show that this cluster comprises households located nearer to the village markets than any other group. This through therefore represents the highest potential for agricultural intensification and commercialization through diversification into high value cropping enterprises. The cluster comprises 9.9% of the farming households.

Cluster 4 is characterized by relatively high gross value of crop output per hectare. However, because the average landholdings are fairly small, compared to Cluster 3, households in this cluster engage in renting-in (12.8%) additional land for cultivation, more than those in clusters 1 and 3. Incomes from crop sales are also fairly high, significantly higher than in clusters 1 and 2. Members of this group also have the highest earnings from livestock sales, and also seem to plough back these incomes into the livestock system, as shown by the significantly high expenses incur in livestock purchases, probably to replenish their stock. This group characteristically has the least number of household members available for both farm and off-farm work. Consequently, it is the group that relies the least on off-farm income, only averaging about 1,471 ETB per year (roughly USD$ 74) from off farm activities and remittances. The fourth cluster comprises 23.3% of the farm households

4.4.5 Relative performance of clusters vis-à-vis intensification and sustainability

The previous section examined the relationship between intensification and sustainability, thus coming up with potential scenarios that have implications for sustainable intensification. The preceding discussion looked at the various typologies of farm households based on the multivariate analysis of the key themes characterizing smallholder crop-livestock farming systems. However, to draw insights for sustainable intensification and help identify the kinds of farms that are more likely to embark on sustainable path of agricultural intensification, this section relates the farm typology cluster with the intensification and sustainability scenarios. Table 4.7 below shows the overall differences between intensification levels and relative farm sustainability across the four farm clusters. Overall, ANOVA tests show that levels of intensification and relative farm sustainability were significantly different across the clusters. A post-hoc Tukey’s test was used to show where these differences lie.

Table 4.7: Differences in intensification and relative sustainability levels across clusters

	Contrast	Standard Error	p-value
Intensification levels			
Cluster 2 vs Cluster 1	4,670.42	1,005.09	0.000
Cluster 3 vs Cluster 1	3,978.14	1,408.24	0.026
Cluster 4 vs Cluster 1	4,946.52	1,030.46	0.000
Cluster 3 vs Cluster 2	-692.27	1,493.21	0.967
Cluster 4 vs Cluster 2	276.10	1,143.84	0.995
Cluster 4 vs Cluster 3	968.38	1,510.40	0.919
Relative farm sustainability			
Cluster 2 vs Cluster 1	0.002	0.002	0.465
Cluster 3 vs Cluster 1	0.008	0.002	0.004
Cluster 4 vs Cluster 1	0.000	0.002	0.998
Cluster 3 vs Cluster 2	0.005	0.002	0.110
Cluster 4 vs Cluster 2	-0.003	0.002	0.480
Cluster 4 vs Cluster 3	-0.008	0.002	0.006

The results showed that Cluster 1 had the lowest intensification level, significantly lower than the averages in all the other three clusters. The average gross value of crop output in Cluster 1 was 4,670 ETB/ha lower than Cluster 2, 3,978 ETB/ha lower than Cluster 3 and 4,947 ETB/ha lower than Cluster 4. The results also show that relative farm sustainability among farms in Cluster 3 were significantly higher than those in clusters 1 and 4. Table 4.8 below shows the distribution of the different intensification and sustainability scenarios across the farm typology clusters.

Table 4.8: Distribution of households by intensification, relative sustainability and farm clusters

Clusters	Intensification and sustainability typologies (% of total households)							
	LILS	MLILS	MHILS	HILS	LIHS	MLIHS	MHIHS	HIHS
Cluster 1	71.25	41.27	35.21	18.92	45.45	27.27	10	20
Cluster 2	18.75	31.75	19.72	43.24	18.18	18.18	30	23.33
Cluster 3	2.5	9.52	8.45	2.7	0	36.36	30	30
Cluster 4	7.5	17.46	36.62	35.14	36.36	18.18	30	26.67

Table 4.8 shows that most farm households in the first quartile (lower 25%) of intensification and relatively low sustainability (LILS) are in located in Cluster 1 (71.3%). The same cluster also contains 41.3% of households in the second quartile of intensification and relatively low sustainability (MLILS). It also has the least number of households (20%) in the relatively high sustainability class and fourth quarter of intensification (HIHS). However, Cluster 1 also contains the majority (45.5%) of farms that are relatively more sustainable but in the first quartile of intensification (LIHS). On the other hand, Cluster 3 contains a significant number of farm who are in the relatively high sustainability category. Cluster 3 comprises of 36.4% of households in the relatively high sustainability and second quartile of intensification (MLIHS), 30% of households MHIHS farms and 30% of HIHS farms.

4.4.6 Multinomial logistic (MNL) regression

A multinomial regression model was estimated to determine how exogenous drivers effect SI in the various clusters. The results are summarized in Table 4.9 below.

Table 4.9: Multinomial model prediction of cluster membership

	Cluster 2		**Cluster 3**		**Cluster 4**	
	Coefficient	Odds ratio (e^{β})	Coefficient	Odds ratio (e^{β})	Coefficient	Odds ratio (e^{β})
Market distance	0.0795 (0.0847)	1.083	0.0647 (0.104)	1.067	0.117* (0.0700)	1.124
Agricultural Loans	1.742** (0.883)	5.711	-1.813 (1.560)	0.163	-0.867 (0.801)	0.420
Years of farming	0.0340 (0.0287)	1.035	0.0412 (0.0338)	1.042	0.0181 (0.0227)	1.018
Demonstration plots	-0.912*** (0.306)	0.402	-0.106 (0.269)	0.899	0.129 (0.104)	1.137
Wealth Index	1.065*** (0.353)	2.901	1.698*** (0.424)	5.461	0.654*** (0.217)	1.923
Household Size	0.135 (0.130)	1.145	0.417** (0.191)	1.517	-0.0662 (0.115)	0.936
Mechanization	19.36 (2,091)	2.56e+08	-10.80 (1,136)	0.000	1.237 (1.270)	3.445
Oromia	-2.044 (2,564)	0.129	15.21 (1,303)	4018787	2.409** (1.125)	11.120
Tigray	0.867 (1.179)	2.379	13.92 (10,813)	1112899	-16.51 (10,598)	0.000
Amhara	-1.116 (0.836)	0.328	13.66 (1,303)	856221.7	0.993 (0.940)	2.698
Constant	-38.63 (4,182)	0.000	-13.42 (1,729)	0.000	-5.198** (2.579)	0.006
Observations	161		161		161	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The estimated model shows that households with access to agricultural loans are more likely to be in Cluster 2 of farm typologies compared to Cluster 1. Also, compared to Cluster 1, households that are wealthier and have more access to production assets, are associated with a higher likelihood of being members of Cluster 2. However, households that have greater frequency of access to on-farm demonstration plots are less likely to be in Cluster 2 category of farm typologies. Factors that were significant in predicting Cluster 3 membership were household size and wealth index. The results show that bigger and wealthier households are more likely to be in Cluster 3 rather than Cluster 1 Finally, the results indicate that households who are wealthier have a higher likelihood on being members of Cluster 4 rather than Cluster 1, and so are households located in Oromia region. Interestingly, the results suggest that households that are further from the markets are more likely to be in Cluster 4 rather than Cluster 1.

In order to get a different dimension of the ongoing discussion, a similar multinomial logistic (MNL) regression model was also used to model membership in the eight farm pathway clusters, based on levels of agricultural intensification and relative farm sustainability. A set of socioeconomic variables were used as regressors in the MNL model. The results are presented in Table 4.10 below. Generally, off farm income, production mechanization, land size and regional variables emerged as dominant predictors of higher level of agricultural intensification and relative farm sustainability.

Table 4.10: Multinomial logit model prediction of intensification and sustainability scenarios

VARIABLES	**Model 2** (MLILS)	**Model 3** (MHILS)	**Model 4** (HILS)	**Model 5** (LIHS)	**Model 6** (MLIHS)	**Model 7** (MHIHS)	**Model 8** (HIHS)
Land size	0.367	0.156	-0.133	1.024**	0.373	0.197	0.356
	(0.236)	(0.254)	(0.316)	(0.501)	(0.341)	(0.335)	(0.282)
Market distance	0.0524	0.0962	0.114*	0.297**	0.0353	0.0211	0.00835
	(0.0571)	(0.0592)	(0.0628)	(0.146)	(0.115)	(0.0985)	(0.0871)
Agricultural Loan	-1.107	-1.448*	-0.891	-0.716	-14.04	-1.062	0.285
	(0.686)	(0.757)	(0.736)	(1.947)	(1,464)	(1.267)	(1.186)
Credit Constraint	-0.0355	-0.00281	-0.206	2.203	-13.33	-1.420	-0.836
	(0.656)	(0.732)	(0.756)	(2.218)	(1,487)	(1.541)	(1.244)
Demonstration plots	-0.316*	-0.0637	0.179*	0.138	-0.100	-0.185	0.329**
	(0.165)	(0.130)	(0.107)	(0.207)	(0.272)	(0.343)	(0.129)
Household wealth	0.337*	0.529***	0.721***	0.609	1.325***	1.397***	1.338***
	(0.188)	(0.200)	(0.226)	(0.573)	(0.438)	(0.416)	(0.316)
Household size	0.0653	-0.0227	-0.118	-0.160	0.291*	0.0887	-0.0326
	(0.101)	(0.106)	(0.118)	(0.264)	(0.166)	(0.162)	(0.146)
Mechanization	2.250*	1.866	1.564	-0.691	3.825*	2.643	4.204**
	(1.285)	(1.334)	(1.379)	(2.979)	(2.236)	(2.431)	(1.818)
Oromia	1.754	3.069**	2.589*	-4.114	-0.434	0.536	2.469
	(1.316)	(1.384)	(1.393)	(3.119)	(1.859)	(1.784)	(1.830)
Tigray	1.765*	3.338***	4.590***	-12.11	-11.99	4.384***	3.423**
	(0.935)	(1.024)	(1.053)	(1,506)	(1,933)	(1.503)	(1.437)
Amhara	0.941	2.180***	1.546*	-0.0332	0.519	-14.50	2.177*
	(0.676)	(0.794)	(0.889)	(2.018)	(1.263)	(1,568)	(1.155)
Off-farm income	-3.52e-05	2.94e-05	7.00e-05**	7.36e-05	-1.66e-06	7.45e-05*	5.68e-05*
	(3.60e-05)	(3.45e-05)	(3.15e-05)	(7.54e-05)	(6.55e-05)	(3.92e-05)	(3.45e-05)
Constant	-4.810*	-5.246*	-4.919*	-5.266	-11.46**	-8.144*	-12.02***
	(2.577)	(2.681)	(2.714)	(5.277)	(4.505)	(4.352)	(3.936)
Observations	229	229	229	229	229	229	229

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The estimated results compare the likelihood of membership to a given intensification and sustainability class (farm pathway cluster) relative to the first farm cluster, which represented farms that are relatively less sustainable and less intensive. Comparing model 5 (farm type LIHS) to model 1 (farm type LILS), shows that with access to more land, households in the first quartile of intensification could be more sustainable. The results also show that access to more land increases the likelihood of households being members of HIHS rather than farm LILS. This is generally consistent with studies that have shown that larger farms are associated with more environmentally sustainability because they tend to implement more extensive productive techniques implemented (Burton and Walford, 2005) and have a higher propensity to participate in agro-environmental programs (Muniz and Hurle, 2006).

Off farm income was one of the significant predictors of classes comprising higher levels of both agricultural intensification and relative farm sustainability. Results show that access to off-farm income increases the likelihood of being HILS, MHIHS and HIHS, rather than LILS, indicating that off-farm income increases the likelihood of farmers embarking on more sustainable paths of agricultural. This is consistent with several other studies that show that off-farm income is an essential source of liquidity for the resource-constrained farming households who are faced with imperfect rural credit markets. Off-farm income provides the much-needed capital for smallholder farmers to invest in land improvements (Clay, Reardon and Kangasniemi, 1998), as well as purchase complimentary inputs required for sustainable farming. Most of the technologies promoted under the banner of sustainable intensification tend to involve considerable upfront investment costs (McCarthy, Lipper and Branca, 2011; Shiferaw, Okello and Reddy, 2009). Access to off-farm income will be important for sustainable agricultural intensification in Ethiopia and most sub-Saharan Africa, where a combination of imperfect credit markets and limited access to rural financing imposes significant constraints on smallholder farmers.

The results also showed that, relative to LILS farms, regular visits to agricultural demonstration plots increases the likelihood of HILS and HIHS farms, which are categories of relatively higher intensification and higher farm sustainability, respectively. Sustainable intensification will require a paradigm shift in farmers' production behavior, increased awareness to the environmental consequences of the production practices and hence the adoption of improved farming technologies that are consistent with the tenets of sustainable agriculture. Increased access to demonstration plots will enhance farmers' exposure to such technologies. Since most sustainable farming technologies are knowledge-intensive by nature, requiring considerable skills and knowledge from farmers (Pretty and Bharucha, 2015; Wall, 2007; Giller 2009), availing more extension services will be crucial in shortening the farmers learning curves and ensuring that technologies showcased at demonstration plots are adapted to farmers' fields.

The analyses also showed that systems with higher degrees of farm mechanization has a higher likelihood of being in categories MLIHS and HIHS, both of which are characterized by higher levels of agricultural intensification ad relative farm sustainability compared to LILS. Production mechanization is important for addressing draught power constraints and labor bottleneck, as well as make farm operation less arduous. Affordable and tailored small scale mechanization will therefore be an important innovation for promoting sustainable intensification of smallholder farming systems in Ethiopia.

Agro-ecological factors were also significant predictors of intensification and sustainability categories. The results showed that households located in Oromia region have a higher likelihood of being in categories MHILS and HILS, both of which are associated with relatively higher levels of agricultural intensification, than LILS. The results also indicate that, relative to LILS, farmers in Tigray and Amhara regions were much more likely to be in HIHS, which is a class associated with higher levels of both agricultural intensification and relative farm sustainability. The significance of these regional dummy variables underscores the importance of geographic targeting as an effective strategy for both encouraging and enhancing sustainable intensification in smallholder farming systems.

4.5 Conclusions

The study has managed to classify smallholder farmers in the highland regions of Ethiopia into four clusters of farm typologies, thus helping to answer the question of what typologies of farmers are in what categories of agricultural intensification and sustainability. This approach helps in targeting of interventions and development of technological innovations that are tailored to specific farmer profiles. Based on the analyses from this study, the essential ingredients of a sustainable intensification strategy for Ethiopia, and for smallholder farming systems in general, appear to be enhancing farmers' access to off-farm income, through increased integration into the non-farm rural economy and addressing liquidity constraints through appropriate rural financing schemes and smallholder-tailored credit facilities, increased access to agricultural training and technical services, agricultural mechanization, and finally improved access to productive land through measures to address the revolving land ownership and tenure security questions. Achieving sustainable intensification may also require coming up with some 'nudges' and appropriate measures and incentives to encourage farmers that are already highly intensive to adopt sustainable farming practices. Table 4.11 summarizes the key findings of the paper.

Table 4.11: Typologies of smallholder farmers in Ethiopian highlands

Cluster	Key features	Drivers
1	- Low gross value of crop output per hectare - Low improved seed, fertilizer, hired labor per hectare - Low crop sales - Low livestock incomes - Low productive assets index - Comprise 41.5% of total households - Predominantly located in SNNP (34.4%) and Oromia (33.9%) regions - Most of the households (43.9%) are low intensification and low sustainability (LILS)	Reference group
Cluster 2	- High hired labor, capital and labor cost expenditures per hectare - High land rentals and leasing - High household labor for farm and off-farm work - High off-farm income - Low and negative assets index - Comprises 25.2% of households - Mostly in SNNP (39.2%) and Amhara (36.7%) regions - Mostly of the households (25.3%) are medium low intensification and low sustainability (MLILS)	Agricultural loans Household wealth index Agricultural demonstration plots
Cluster 3	- High land holdings and cultivated area - High cropping intensity - High improved seed use per hectare - High productive assets index - High livestock ownership (TLU) - High crop sales income - Low land leasing - Mostly in Oromia (93.6%0 region - Contains largest percentage of farmers who are HIHS (30%) - Comprises 9.9% of total households	Household wealth index Household size
Cluster 4	- High livestock incomes - High livestock purchases - Mostly in Oromia (69.9%) region - Constitutes 23.3% of households - Majority of households are MHILS (35.6%)	Market distance Household wealth Oromia dummy

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CHAPTER 5

CONCLUSIONS

Summary

Over the years, the Ethiopian government has pursued several programs, such as the Agricultural Development Led Industrialization (ADLI), in an attempt to stimulate agricultural growth and achieve food security for its people. Agriculture, particularly the smallholder farming sector, is the mainstay of the country's economy, accounting for about 90 percent of total exports and 85 percent of employment. However, the sector is characterized by low agricultural productivity, attributable to severe land degradation, and most smallholder farming systems are facing severe threats from the effects of climate change. It is increasingly recognized that farming systems must adapt to climatic shocks, and productive capacity must be enhanced to achieve food security. To attain this goal, agricultural intensification is key, but it must be sustainable. The policy and research agenda for achieving food security has therefore coalesced around sustainable intensification of smallholder farming systems. The goal of this dissertation is to assess the prospects for sustainable intensification of smallholder agriculture in Ethiopia. The study represents one of the few attempts to incorporate a more holistic approach to assessing the performance of smallholder farming system, integrating the economic, social and environmental aspects of agricultural sustainability, particularly in the Ethiopian context.

The multifaceted nature of agricultural intensification and the heterogeneity in individual farmers' motivations and constraints regarding agricultural sustainability, raises important research questions. Do farming households, facing relatively the same incentives and pressures to intensify, embark on the same path of agricultural intensification? What accounts for the differences in the relative levels of agricultural sustainability performance at farm-level? Are farmers who are highly intensive and more productive, also relatively more sustainable? These questions form the basis of this dissertation, and were examined in three separate but interrelated chapters, using different econometric methods. This chapter concludes the dissertation, synthesizing all the research findings and drawing attention to the overall contributions of this study to the existing body of knowledge pertaining sustainable intensification of smallholder farming systems.

5.1 Main findings

Chapter two examines the drivers of agricultural intensification as well as the factors influencing alternative intensification paths that can be pursued by farm households in Ethiopian households. Data used in the analyses were based on a cross-sectional survey of 600 households drawn from 12 villages (kebeles) in four regions of Ethiopia highlands. A robust regression was used to test the relative importance of different socioeconomic, institutional and agro-ecological factors in influencing both the level of agricultural intensification and in shaping different intensification strategies. Regression results showed that size of landholding, access to agricultural loans, farm mechanization, household wealth, livestock ownership (tropical livestock units), access to agricultural demonstration plots, and agro-ecological factors were significant drivers of agricultural intensification, manifested both through higher gross value of crop output per hectare and the intensity of use of key production inputs such as labor, inorganic fertilizers, improved seed and capital investments in general. The results indicated that policies to address revolving land ownership and tenure security issues, enhance farmers' access to markets for both their produce and farm inputs, alleviate liquidity constraints, enhance access to information and technical advice, promote integrated crop–livestock systems, and appropriate smallholder mechanization; policies that effect these issues will effectively facilitate the process of agricultural in smallholder farming systems. Regional regression analysis also showed the relative importance of some of these factors, particularly household wealth, farm size, agricultural loans and tropical livestock units, varied across the four regions. This underscores the importance of geographical targeting and a greater attention to the biophysical and market conditions in which smallholder farmers operate, and how it shapes their options for, and incentives and constraints to agricultural intensification.

In Chapter three, indicators of agricultural sustainability were developed using methodological frameworks drawn from literature, and adapted to the smallholder farming sector in Ethiopia through interviews with agricultural experts. A DEA methodology was adopted to aggregate the several indicators of the economic, social and environmental dimensions into an index of agricultural sustainability at farm-level. The computed sustainability score is interpreted as a relative measure, quantifying the sustainability performance of individuals relative to the best farmers within the sample. The DEA methodology allowed the research to cope with the complexity and multidimensional nature inherent in the concept of sustainability. Indicator weights are chosen endogenously, thus removing subjectivity that is inherent in other aggregation methods. While agricultural sustainability can be assessed at regional or country level, focusing on the farm as the basic unit for sustainability assessment provides more practical information relevant for agricultural policy. Sustainability outcomes are a manifestation of the aggregate effects of many individual actions executed at the farm-level. The results showed that only 16% of the farms were relatively more sustainable (farm-level sustainability scores of unity). The indicators were also aggregated into economic, social and environmental sub-indices, in order to examine how the system generally performed with respect to the three essential sustainability dimensions. The results showed that the economic sustainability score was relatively low compared to the other dimensions, which underscores the need for policies and measures that increases the productivity, competitiveness and profitability of the current production systems in Ethiopia. A Generalized Linear Model (GLM) was used to investigate how a set of socioeconomic, agro-ecological and institutional variables influence relative farm sustainability. The results showed that relative farm sustainability was positively influenced by farm size, markets access, farm mechanization, access to off farm income, agricultural loans, as well as access to agricultural extension and demonstration plots. Enhancing agricultural sustainability will involve a combination of strategies, including improving the relevance and effectiveness of current agricultural extension services, enhanced access to technical services such as farmer field schools and participatory demonstration plots, insuring farmers are integrated within the markets for both agricultural inputs and commodity markets, enhancing access to agricultural finance and affordable credit schemes, and access to complimentary technical inputs and services such as farm mechanization and irrigation infrastructure.

Finally, chapter four built on chapters two and three to examine the relationship between agricultural intensification (I) and relative farm sustainability (S) by analyzing the prospects for sustainable intensification in Ethiopian highlands. Given that the relationship between intensification and sustainability is not always known with certainty, a framework for analyzing conditions under which tradeoffs or synergies exist, is vital for policy makers to identify relevant intentions for each given scenario. Farmers were grouped into eight farm pathway clusters that defined their relative agricultural intensification and sustainability. These SI combinations were then compared across farmers to better understand what drives S and I and to determine when they are complementary and when they are in conflict. To make the comparison more manageable, farms were first grouped in typology clusters, using multivariate methods to derive four distinct typology clusters of farm households based on their common characteristics. The results showed that the majority (22.8%) of the farms exhibited low levels of agricultural intensification as well as relatively low sustainability performance. This situation is undesirable for both farmers, whose main concern is mainly profitability, and the policy and social planners. Only about 8.3% of the farms were both highly intensive and relatively more sustainable, indicating that a lot still need to be done in order to achieve widespread sustainable intensification of smallholder farming systems in Ethiopia. Two scenarios represented cases of intense tradeoffs between intensification and sustainability. The first case involves 2% of the farms, which were low in intensification but relatively high in sustainability. The high sustainability was attributable to the adoption of environmentally friendly farming practices such as organic farming, conservation tillage, crop rotations and soil erosion control measures. For these farms, there is potential for increasing agricultural productivity and closing yield gaps through appropriate competitiveness-enhancing measures. The second scenario involved 16.7% of the farmers, who were highly intensive, but relatively less sustainable. This represents high input intensive farming systems, where productivity is often enhanced at the expense of environmental sustainability. Since farmers are already highly productive and probably near the maximum attainable yields, the policy focus should be of strategies to incentivize farmers to adopt more environmentally friendly practices.

5.2 Limitations and suggestions for future research

As in any scientific research, this dissertation is not without limitations. Perhaps the most important drawback was the lack of availability of some relevant indicators, particularly those related to the environmental dimension. Environmental indicators such as biodiversity and measures of environmental impacts such as greenhouse gas emissions and eutrophication potential were not readily available. Though they are essential in sustainable intensification assessments, computing these indicators is often highly data intensive. However, while this additional information would improve the completeness of the sustainability index, the main thrust of this dissertation was to demonstrate how the DEA methodology can be used to operationalize the complex concept of agricultural sustainability, and how the same approach can be applied to any context where data are available. In terms of future research, sustainable intensification assessments could also benefit from panel data, which allows for the tracking of indicators and monitoring progress over time. This research relied on cross-sectional data. Measuring progress towards sustainable intensification will require establishing system benchmarks. The performance of agricultural systems depends on the interaction between biophysical, socioeconomic, institutional and market conditions. Therefore, understanding and defining system benchmarks in terms of what is achievable for a given soil type, climate, levels of technical inputs and market access domains, will be crucial in determining scope for sustainable intensification. Related to this, is the need to come up with ecological thresholds, beyond which agricultural intensification should not exceed if ecological services are to be safeguarded. Use of integrative frameworks and behavioral approaches should also allow us to better understand farmers' motivations and perceptions, as well as their general ambivalence towards sustainable intensification.

Appendix A: Descriptive statistics for the indicators of agricultural intensification

Variable	Mean	Std. Dev.	Min.	Max.	No. of obs.
Farm size (ha)	1.79	1.64	0.03	12.50	489
Total cultivated land	2.580	2.456	0.035	18.8	489
Gross value of crop production (birr)	23,916.01	26,283.48	523.00	170,426.50	489
Gross value of crop production (birr) per hectare	11,338.04	10,062.01	262.81	131,885.70	489
Total agricultural income (birr) per hectare	6,887.87	8,584.08	81.08	54,335.26	489
Net farm income (birr) per hectare	1,745.35	8,254.65	-35,781.25	48,631.98	489
Total crop sales income (birr) per hectare	3,247.05	4,692.97	0.00	42,196.53	489
Total livestock sales income (birr) per hectare	6,456.66	20,970.21	0.00	276,992.00	489
Wealth index	0.01	2.15	-4.98	5.98	489
Total fertilizer use (kgs) per hectare	119.16	204.70	0.00	3,522.86	489
Total improved seed use (kgs) per hectare	87.60	129.71	0.00	1,571.43	489
Total labor per hectare (person-days)	75.87	71.77	6.00	600.00	489
Total hired labor per hectare (person-days)	9.98	25.16	0.00	265.63	489
Total labor costs (birr) per hectare	618.49	1,279.84	0.00	10,625.00	489
Total crop capital input costs (birr) per hectare (excl. labor)	2,372.85	3,355.17	0.00	45,468.75	489
Total crop production costs (birr) per hectare	2,991.34	4,133.12	150.00	56,093.75	489
Total livestock production costs (birr) per hectare	3,504.32	7,611.10	0.00	90,576.00	489
Total variable costs (birr) per hectare	5,142.52	5,533.19	167.50	56,093.75	489
Cropping intensity	136.10	62.01	100.00	752.00	488

Notes: See Table 2.1 for definitions of variables.

Appendix B: Intensification model regression with regional interactive dummies

VARIABLES	Coefficients
Amhara	4,240
	(7,512)
Oromia	1,411
	(3,557)
Cultivated Land	-869.9***
	(197.7)
Village Market Distance	-137.5
	(97.04)
Agricultural Loans	425.1
	(1,354)
Demonstration plots Times	204.7
	(279.0)
WEALTH	1,042*
	(589.2)
Mechanization	2,141
	(2,464)
TLU	78.07
	(214.4)
Vaccination	740.6
	(1,120)
Years Farming	6.361
	(33.93)
Tigray*Cultivated Land	-3,102***
	(1,040)
AMHARA*Cultivated Land	-1,460
	(1,005)
OROMIA*Cultivated Land	412.6
	(318.0)
TIGRAY*VillageMarketDistance	81.25
	(208.9)
AMHARA*VillageMarketDistance	10.72
	(249.1)
OROMIA*VillageMarketDistance	130.5
	(157.0)
TIGRAY*AgricLoans	6,386**
	(3,012)
AMHARA*AgricLoans	2,052
	(3,186)
OROMIA*AgricLoans	869.4
	(2,120)
TIGRAY*DemoTimes	127.8
	(1,139)
AMHARA*DemoTimes	302.5
	(384.7)
OROMIA*DemoTimes	383.5
	(431.9)
TIGRAY*WEALTH	85.86
	(1,066)
AMHARA*WEALTH	1,302
	(977.9)
OROMIA*WEALTH	-497.7

	(690.3)
TIGRAY*Mechanization	-2,744
	(1,853)
AMHARA*Mechanization	300.6
	(3,281)
TIGRAY*TLU	138.4
	(493.4)
AMHARA*TLU	-288.8
	(510.1)
OROMIA*TLU	622.0*
	(321.0)
TIGRAY*VACCINATE	13,094***
	(4,033)
AMHARA*VACCINATE	7,089**
	(3,152)
OROMIA*VACCINATE	-163.8
	(1,430)
TIGRAY*YearsFarming	-93.68
	(160.1)
AMHARA*YearsFarming	-171.6*
	(103.1)
OROMIA*YearsFarming	-153.7***
	(55.67)
Constant	5,189
	(5,146)
Observations	232
R-squared	0.443

Appendix C: Intensification model regression with land quality controls

Variables	Coefficients
Cultivated Land	-1,368***
	(426.6)
Village Market Distance	-8.843
	(81.37)
Agricultural Loans	2,340**
	(1,097)
Demonstration plot Times	572.8***
	(167.4)
WEALTH	1,318***
	(279.3)
Mechanization	4,086**
	(1,766)
TLU	294.4*
	(159.5)
VACCINATE	2,437**
	(1,122)
Years Farming	-94.75***
	(32.95)
Oromia	4,137***
	(1,537)
Tigray	3,585**
	(1,382)
Amhara	2,166*
	(1,163)
CultivatedLand*Flat	-55.91
	(309.0)
CultivatedLand*Medium slope	-739.0**
	(335.2)
CultivatedLand*Good fertility	265.0
	(253.1)
CultivatedLand*Medium fertility	161.5
	(255.2)
CultivatedLand*Shallow soils	55.58
	(315.4)
CultivatedLand*Medium deep soils	350.7
	(268.4)
Constant	1,584
	(3,350)
Observations	232
R-squared	0.355

Appendix D: Kaiser-Meyer-Olkin (KMO) measures of sampling adequacy

Variable	**KMO**
Total owned land	0.7556
Cultivated land	0.7409
Land renting	0.5836
Land leasing	0.6968
Gross crop value	0.6767
Sales volume	0.683
Crops income	0.8139
Livestock incomes	0.5672
Livestock purchases	0.7288
Fodder production	0.7138
Tropical livestock units	0.7384
Total fertilizer	0.7176
Improved seeds	0.7097
Hired labor	0.5854
Capital costs	0.7234
Labor costs	0.6033
Cropping intensity index	0.7295
Crop diversification index	0.6218
Asset index	0.8296
Household labor	0.5277
Off farm labor	0.6959
Off farm income	0.6178
Overall	0.6992

Appendix E: Screen plot of eigenvalues after PCA