RECONCILING FOOD, ENERGY, AND ENVIRONMENTAL OUTCOMES: THREE ESSAYS ON THE ECONOMICS OF BIOMASS MANAGEMENT IN WESTERN KENYA

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RECONCILING FOOD, ENERGY, AND ENVIRONMENTAL OUTCOMES: THREE ESSAYS ON THE ECONOMICS OF BIOMASS MANAGEMENT IN WESTERN KENYA

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This dissertation explores human-environment interactions, focusing on on-farm biological resources (biomass) and crop residues, in particular, and how they can meet the competing demands of food production, energy generation, and environmental conservation in Sub-Saharan Africa. The empirical setting is rural western Kenya, where maize residues, one of the largest sources of on-farm biomass, constitute a large portion of livestock diets, contribute to household energy needs, and are fundamental in maintaining and improving soil fertility. The three dissertation essays analyze the uses and value of crop residues in tropical smallholder agriculture from several different perspectives and using different methodological approaches, all based on data from the western Kenyan highlands.

The first essay (Chapter 2) treats non-marketed crop residues as factors of household production, accounting for their long-term benefits when used for soil fertility management. Empirically, the essay estimates a household-level maize production function and calculates the shadow value of maize residues as suggested by the theoretical framework and empirical estimates. This estimated value is substantial—$0.06-08 per kilogram and $208 per average farm—and is higher for poorer households. The second essay (Chapter 3) analyzes crop residue use in an intertemporal setting and develops a dynamic bioeconomic model of agricultural households. The model combines an econometrically estimated production function and a calibrated soil carbon flow equation in a maximum principle framework to determine the optimal application rates of mineral fertilizer and crop residues. The results yield an estimated equilibrium value of soil carbon in the research area—$138 per metric ton—and highlight the significant local private benefits of soil carbon sequestration, and the potential

to simultaneously increase food production and sequester carbon. Finally, the third essay (Chapter 4) considers one of the primary challenges in small-scale second-generation biofuel development—the provision of feedstocks. The essay estimates the potential availability and cost of purchasing maize residues from smallholder farmers and transporting them to a hypothetical small-scale pyrolysis-biochar plant in western Kenya. Feedstock provision costs depend on regionally specific agro-ecological and socio-economic conditions, with implications for economic viability in Kenya and, by extension, other rural settings.

BIOGRAPHICAL SKETCH

Julia Berazneva was born in Minsk, Belarus. She graduated from the Belarusian Humanitarian Lyceum in Minsk in 1998 and the United World College of the Adriatic in Duino, Italy in 2000. After spending a year working at the British School of Lomé in Togo, she attended Mount Holyoke College in South Hadley, MA, where she received her BA degree in 2004, majoring in Economics and minoring in Romance Languages. Julia also holds an MSc degree in Development Studies from the School of Oriental and African Studies in London, United Kingdom.

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CHAPTER 1

INTRODUCTION

1.1 Biomass and crop residues

A strong link among poverty, natural resources, environmental sustainability, and climate-related outcomes is present throughout the rural areas of developing countries. These areas are home to the world's poorest billion people who derive substantial portions of their incomes from farmland, forests, and fisheries (Hassan, Scholes, and Ash 2005). At the same time, the natural resources on which the livelihoods of the poor are based are often facing highly intensive use and degradation (Dasgupta 2010). Moreover, climate change and climate variability are threatening agricultural production and household food security (Boko et al. 2007). For the rural poor living in fragile environments in Africa and some parts of Latin America and Asia, the resulting degraded soils, depleted fisheries, deforested lands, and the deteriorated ecosystem services frequently translate into lower food production and declining incomes. These conditions also discourage investments in adopting sustainable technologies and maintaining the natural resource base, further endangering the resilience of the rural poor.

The objective of this dissertation is to explore the link between natural resources, agriculture, and environmental sustainability, and to understand how natural resources can meet the competing demands of poverty alleviation, energy sufficiency, and environmental conservation in African smallholder agriculture. The focus here is on on-farm biological resources ("biomass") in general and on crop residues in particular. Biomass is broadly defined as biological material from living or recently living organisms, consisting of vegetation, cultivated crops, livestock products, and their residues. Together with land and labor, biomass constitutes a critical productive resource for farm households and contributes to satisfying their basic needs, including food security and income generation. The research reported in this dissertation is part of a larger multi-disciplinary research project of social scientists, soil scientists, agronomists, and engineers at Cornell, collaborating on finding sustainable solutions to food and energy insecurity in rural communities of the developing world. The project "Fueling Local Economies and Soil Regeneration: Biofuels and Biochar Production for Energy Self-sufficiency and Agricultural Sustainability" explores the potential and feasibility of producing biofuels and biochar, a soil amendment, from local biomass in a rural African context.

For many farmers in developing countries, crop residues—cereal and legume straws, leaves, stalks, tops of vegetables, sugar, and oil crops, etc.—constitute the largest source of on-farm biomass. An estimated 60 percent of crop residues (2.25 Pg, petagrams, or billion metric tons) are produced in developing countries, almost 45 percent in the tropics (Smil 1999; Lal 2005). Crop residues make up about 50 percent of livestock diets (Thornton, Herrero, and DeFries 2010), and are fundamental to the implementation of many sustainable agricultural practices. They contribute to household energy needs for an estimated 730 million people in Sub-Saharan Africa (SSA) who rely on solid biomass for cooking (IEA 2014), and are also of great interest as second-generation bioenergy feedstocks (Eisentraut 2010).

The removal of crop residues from the fields for other uses, however, contributes to soil degradation in the tropics and subtropics. Depletion of soil fertility is, in turn, one of the main biophysical causes of poor yields and low per capita food production in Sub-Saharan Africa (Sanchez 2002), contributing to extensive food insecurity and rural poverty. An estimated 414 million people in the region—up from 290 million people in 1990—live in poverty, and SSA remains the region with the highest prevalence of undernourishment (UN 2014). In addition, the degradation of soil resources in SSA leads to many environmental problems precipitated by the conversion of marginal lands and natural environments to agriculture, increased greenhouse gas emissions, and many others. Moreover, some estimates suggest a 36 percent decline in cereal yields due to climate change by the end of the century (Ward, Florax, and Flores-Lagunes 2014).

Crop residues and other biological resources also play a major role in the global carbon cycle. Since soil carbon is primarily derived from plant matter, any land use or agricultural practice has a direct effect on soil carbon. Despite the fact that agriculture accounts for 20-30 percent of total global greenhouse gas emissions (WB 2012), it can take advantage of the role of soils as a carbon sink and for carbon storage. Agricultural practices that fall under the umbrella of "climate smart" or "low emissions" agriculture can simultaneously increase agricultural productivity, reduce emissions, and enhance the resilience of those relying on agriculture who face the impacts of climate changes. These practices include the retention of crop residues, mulching, the use of manures, composting, agroforestry, applications of biochar, and many others (Lal 2006; WB 2012). By some estimates it is possible to sequester 0.4-1.2 Pg of carbon per year on the world's agricultural and degraded soils, an amount equivalent to 5-15 percent of global emissions from fossil fuels (Lal 2004).

The management of on-farm biological resources by smallholder farmers in the tropics thus has important implications for current and future socio-economic and environmental outcomes at household, national, and global scales. For example, leaving crop residues on the field—a simple climate-smart practice—improves soil fertility and increases crop yields for current households. At the same time it creates off-farm benefits through providing soil erosion protection and enhancing the soils in neighboring farms, maintaining the agricultural resource base for future generations, and helping to mitigate climate change through sequestering carbon. However, if the environmental benefits accumulate slowly or if they accrue to others, farming households may be unwilling to invest in sustainable agricultural practices. Moreover, competing demands for crop residues, farm households' time and risk preferences, and outside market forces may prevent adoption of this climate-smart practice. Consequently, understanding farmers' decision-making with respect to crop residue management and the tradeoffs and challenges they face can help jointly address critical questions of food security, poverty alleviation, and environmental sustainability.

In the essays that follow, I analyze the management and value of crop residues in tropical smallholder agriculture from several different perspectives and using different methodological approaches, but the analysis in each essay is based on data from the western Kenyan highlands. In the first essay (Chapter 2), I investigate the current uses of maize residues and estimate their value to smallholder farmers, using econometric techniques. In the second essay (Chapter 3), I develop a bioeconomic model to analyze the optimal application rates of crop residues and their potential to increase maize yields and sequester carbon. Finally, in the third essay (Chapter 4), I study the cost of sourcing maize residues from smallholder farmers for bioenergy production. These essays contribute to a rich body of research in development and environmental and resource economics that aims to understand the complex linkages between human behavior and biophysical resources, and thereby contribute to agricultural growth, poverty alleviation, sustainable resource use and climate mitigation (Lee, Ferraro, and Barrett 2001).

1.2 Challenges in analysis of natural resources

Analyzing natural resources in developing countries is a challenging task. Smallholder subsistence agriculture involves a large number of interlinked activities, the outcomes of which often depend directly on natural resources. Subjected to considerable uncertainty, both in terms of the economic and biophysical environments, missing markets and large transaction costs, smallholder farmers link their production and consumption decisions to satisfy multiple objectives of food security, income generation, and risk reduction (de Janvry, Fafchamps, and Sadoulet 1991). These decisions in turn have significant impacts on natural resources (Holden and Binswanger 1998), with implications that often go beyond farm boundaries, both temporally and geographically (Barbier and Bergeron 2001) and are difficult to quantify with available data. Moreover, the lack of markets for many natural resources leads to difficulties with their valuation and optimal allocation. These conditions, together with other characteristics of natural resource management—environmental externalities, a multiplicity of benefits, and payoffs generated over time—all imply methodological challenges.

The first challenge lies in quantifying natural resources and their benefits. Measuring crop residue production is rarely done even in developed countries (Smil 1999), where agronomic systems are better understood and data sources are usually more complete. Most studies that estimate crop response models in developing countries, however, rely on rough indicator variables for crop residues and animal manures (see, for example, Gavian and Fafchamps (1996), Sheahan, Black, and Jayne (2013), and Marenya and Barrett (2009b)). When it comes to demonstrating natural resource values, the few studies that exist use either a production or a substitution approach. The production approach establishes the value by calculating changes in overall farm profits or physical changes in production by including biomass as a production input (see, for example, Lopez (1997), Goldstein and Udry (2008), Klemick (2011)). The substitution approach derives the value of natural resources using the observed prices of marketed agricultural inputs (see Teklewold (2012) and Magnan, Larson, and Taylor (2012)).

These static methods, however, potentially underestimate the true value of natural resources. Since their use in the current period imposes a reduction in net benefits on the future generation, they ideally need to be evaluated within an intertemporal framework. Yet, the lack of data available to economists and complexity of the agricultural systems have limited the dynamic analysis of natural resources in developing countries. Some existing studies, for example, simulate the effects of land degradation by incorporating biophysical soil parameters estimated in separate biophysical models into models of economic behavior (see, for example, Barbier (1998) and Wise and Cacho (2011)). Only with detailed biophysical and socio-economic data, however, can bioeconomic models truly internalize the linkages between natural resources and household intertemporal decisions. Without access to detailed micro-level data, it is easy to overestimate natural resource availability and thus mask the high degree of geographic variation in biomass production that commonly exists. This is the case, for example, in the estimation of crop residue availability as a feedstock for modern bioenergy production (see, for example, Senelwa and Hall (1993), Jingura and Matengaifa (2008), Milbrandt (2009), Duku, Gu, and Hagan (2011), and Ackom et al. (2013)).

This research attempts to overcome these methodological challenges. These three essays are grounded in applications of microeconomic theory, however, they build on multi-disciplinary collaborations with agronomists and soil scientists, use a variety of methods (summarized below and discussed at length in Chapters 2-4), and employ detailed biophysical and socio-economic data from multiple sources—all collected in the same research area.

1.3 Research sites and data

The study area for this dissertation is the western Kenyan highlands (Western, Nyanza, and Uasin Gishu provinces) in the Yala and Nyando river basins, two of the major seven influent rivers feeding Lake Victoria in Kenya. The highlands area is one of the most densely populated regions of the country (100-300 people per square kilometer), with over 55 percent of the population living below the national rural poverty line (WRI 2007). Average farms are about 0.5-2 hectares in size and originally formed part of the Guineo-Congolese forest system that has became converted to agricultural land. Farmers practice subsistence agriculture following two cropping seasons: the long rains from March to August and the short rains from September to January. Maize (*Zea mays* L.) is the most commonly grown and consumed grain in the area, having established itself as a dominant food crop in Kenya at the beginning of the twentieth century (Crowley and Carter 2000). While farmers' main objective is increasing their supplies of food (Waithaka et al. 2006), subsistence farmers also strive to earn income and satisfy household energy needs.

Farms in the study area have medium to high agricultural potential (WRI 2007), but suffer from severe soil degradation. Low levels of soil carbon are one of the most limiting factors to agricultural productivity. The incorporation of crop residues at plowing, crop rotations, and short fallows were among the principal means of maintaining soil fertility in crop fields in western Kenya until the 1960s (Crowley and Carter 2000). As population increased and average farm size declined, however, crop rotations and fallowing periods were reduced and most farmers have stopped planting woodlots, making cereal residues the principal on-farm source of fuel. Only wealthier households with larger land holdings have continued fallowing and/or using crop rotations (Crowley and Carter 2000). As a result, the amount of organic material returned to the soil after harvest has significantly declined in the area and maize monoculture has hastened soil deterioration (Solomon et al. 2007).

The household survey research on which my dissertation papers are based was conducted in 2011 and 2012 in five research sites in the Nyando and Yala basins, respectively identified as Lower Nyando, Mid Nyando, Lower Yala, Mid Yala, and Upper Yala (the map of the research area accompanies each of the essays). These 10x10 kilometer research sites formed part of the original geographic coverage of the Western Kenya Integrated Ecosystem Management Project, implemented between 2005-2010 by the Kenya Agricultural Research Institute and the World Agroforestry Center. The research sites are similar in terms of agricultural practices, but vary in altitude, rainfall, soils, and socio-economic characteristics, and thus represent the diversity of the East African highlands. Within each research site, 21 farm households were surveyed in each of three randomly sampled villages, comprising a total sample of about 315 households.

To account for the bi-modal rain pattern and two distinct cropping seasons in several of the research sites, the household survey was split into two rounds and covered a wide range of standard topics, common to the World Bank's Living Standards Measurement Survey format. The topics included household production activities of the two seasons in 2011, income sources, household resource endowments in terms of land, labor, and biomass, residential energy uses, access to information, socio-economic characteristics such as household composition, educational background and labor market participation, and others. To supplement the data from the household surveys, my fieldwork team and I also collected soil samples, identified, counted, and measured on-farm trees, measured plot and farm area with hand-held GPS units, and collected village-level data from questionnaires with village elders, and collected market data (market prices for main commodities and measurements of local units). The choice of the research area, sampling methods, timing of the household survey, interviewing procedures, and other fieldwork details are described in Appendix A.

In addition, I use two other datasets. The biophysical dataset used in Chapter 3 comes from agronomic experiments in Vihiga and Nandi districts of western Kenya, established by the Lehmann Soil Biogeochemistry and Soil Fertility Management Lab at Cornell. The experimental sites were established in 2005 and maintained until 2012 as a part of a chronosequence experiment designed to analyze the long-term effects of land conversion from primary forest to continuous agriculture (Ngoze et al. 2008; Kinyangi 2008; Kimetu et al. 2008; Guerena 2014). The commercial center data used in Chapter 4 are from a survey of 56 centers in western Kenya conducted in April-June 2012 that described the demand and supply patterns of available energy and transportation (Cadogan and O'Sullivan 2012; Lane 2013). This survey collected market price data from energy sellers and buyers, and estimated the demand for modern energy services from small businesses in each of the commercial centers.

1.4 Overview of dissertation

My first essay (Chapter 2), "Allocation and Valuation of Non-marketed Crop Residues in Smallholder Agriculture: The Case of Maize Residues in Western Kenya," analyzes the use, management, and valuation of crop residues in smallholder agriculture. The theoretical framework treats non-marketed crop residues as factors of production, accounting for the long-term benefits of crop residues used in soil fertility management and highlighting important tradeoffs when it comes to their use. It also allows estimation of their shadow value. Using the household data, I estimate the shadow value of maize residues using the coefficients from an econometrically estimated household-level maize production function and household-specific fertilizer prices. The estimated value is 5.49-6.90 Kenyan shillings per kilogram or US$0.06-0.08. This value extends beyond the effects of fertilizer substitution, and is higher for poorer households. Quantifying the contribution of crop residues to smallholders' production helps in assessing agricultural technology options and in measuring the effects of policies on farmers' incomes and agricultural sustainability.

My second essay (Chapter 3), "Agricultural Productivity and Soil Carbon Dynamics: A Bioeconomic Model," develops a dynamic bioeconomic model of agricultural households to investigate the likely effects of changes in agricultural practices on the natural resource base and on farmer livelihoods. The theoretical modeling framework extends the traditional agricultural household model to incorporate the dynamic nature of natural resource management and to integrate biophysical processes through soil carbon management. Using an eight-year panel dataset from an agronomic "chronosequence" experiment and data from household and market surveys in the western Kenyan highlands, my empirical model combines an econometrically estimated production function and a calibrated soil carbon flow equation in a maximum principle framework. I use the model to determine the optimal management of the farming system over time in terms of the application rates of mineral fertilizer and crop residues, taking into consideration initial resource endowments and prices. The optimal management strategies lead to soil carbon stocks of 20.2-40.2 Mg/ha (in the top 0.1 m) and maize yields of 3.5-4.2 Mg/ha, with discount rates of five to fifteen percent. The optimal application rates of mineral fertilizer and organic resources are, however, considerable—higher than the current practices of western Kenyan farmers. These also depend on the initial condition of soil fertility, with more depleted soils requiring higher application rates at the outset. The equilibrium value of soil carbon is high and ranges between 108 and 148 US$/Mg, depending on the discount rate used, which highlights the considerable local private benefits of soil carbon sequestration. Annual soil carbon sequestration rates of 630 and 117 kg/ha can be achieved on depleted and medium-fertility soils, respectively.

The third essay (Chapter 4), "Small-scale Bioenergy Production in Sub-Saharan Africa: The Role of Feedstock Provision in Economic Viability," considers one of the primary challenges in small-scale second-generation biofuel development—the provision of feedstocks—and offers some of the first estimates of feedstock provision costs from Sub-Saharan Africa. Using detailed household-level and market data, I provide a detailed *ex ante* assessment of one particular case in Kenya and draw implications for small-scale bioenergy development in other rural settings. I consider the availability and cost of purchasing maize residues from smallholder farmers, as well as the cost of transporting them to a small-scale pyrolysis-biochar plant in rural western Kenya. I demonstrate that, contrary to much of the recent literature that emphasizes geographically aggregated estimates, feedstock provision costs depend significantly on regionally specific agro-ecological and socio-economic conditions. Crop yields, planting density, and the value of crop residues to farmers exhibit a high degree of heterogeneity even in the limited geographic area considered. Together, these result in highly varying feedstock purchase and transportation costs, depending on the location of the pyrolysis-biochar system. Only under the best-case scenario (that with the lowest provision costs), do I find that a pyrolysis-biochar plant with 15 Mg of feedstock per hour capacity has positive net present value. Initial capital investment, feedstock cost, final product prices, and interest rates have the highest impacts on net present value estimates. If developing country governments want to promote small-scale bioenergy production, initial government support may be required to account for the social and environmental benefits of rural bioenergy production. Accounting for the diversity of agro-ecological and socio-economic constraints is necessary to match the global enthusiasm about bioenergy and its potential to deliver access to modern energy services, spur economic growth, and mitigate climate change.

Overall, these three essays describe the current and potential management of maize residues in the western Kenyan highlands. They quantify the annual production of residues, describe their uses across different households, and estimate their economic value, both as a climate-smart strategy to maintain and improve soil fertility, and as a possible feedstock for modern bioenergy and biochar production. They also suggest the potential of crop residues to increase food production and sequester carbon. Although the essays highlight one research area, many of the implications are likely applicable to other developing countries. The last chapter (Chapter 5) summarizes the conclusions and implications of the dissertation, and suggests topics for future research.

CHAPTER 2

ALLOCATION AND VALUATION OF NON-MARKETED CROP RESIDUES IN SMALLHOLDER AGRICULTURE: THE CASE OF MAIZE RESIDUES IN WESTERN KENYA

2.1 Introduction

Crop residues[1] are an invaluable resource in smallholder agriculture. An estimated 60 percent of crop residues are produced in developing countries, and almost 45 percent in the tropics (Smil 1999; Lal 2005). They are an essential ingredient to maintaining and sustaining long-term soil fertility, and thereby contribute fundamentally to agricultural productivity. Crop residues also account for up to 50 percent of livestock diets in developing countries (Thornton, Herrero, and DeFries 2010), and they contribute to satisfying household energy needs for those who rely on solid biomass for cooking. This includes an estimated 730 million people in Sub-Saharan Africa (IEA 2014).

The multiple uses and competing applications of crop residues also create many challenges. The removal of crop residues for use as feed for domestic animals and fuel is, for example, a driving force behind the depletion of the soil organic matter pool in the tropics and subtropics, leading to soil degradation, a decline in soil structure, severe erosion, emission of greenhouse gases, and water pollution (Lal 2006). These soil fertility-depleting processes not only decrease agronomic productivity, but also reduce crop response to chemical fertilizer and other inputs. Depletion of soil fertility is considered to be one of the main biophysical causes of poor yields and low per capita food production in Sub-Saharan Africa (Sanchez 2002), contributing to widespread food insecurity and rural poverty.

Given the tradeoffs among alternative uses as well as the long lag in realizing the agro-

[1] Crop residues are defined as all inedible phytomass of agricultural production (cereal and legume straws, leaves, stalks, and tops of vegetables, sugar, oil, and tuber crops, etc.).

nomic benefits of leaving residues on the fields, the management and value of crop residues have important implications for current and future socio-economic and environmental outcomes. Yet quantifying crop residue production and accounting for its uses are rarely done even in developed countries (Smil 1999), where agronomic systems are better understood and data sources are typically more complete. There are also significant methodological challenges in valuing crop residues since organic resources are often non-marketed, entail multiple long-term benefits, and create environmental externalities (Shiferaw and Freeman 2003). Careful analysis of the allocation of crop residues to different uses, however, can improve our understanding of smallholder choices with respect to these resources. Moreover, deriving their monetary values as factors of production can help assess agricultural technology options (Magnan, Larson, and Taylor 2012) and measure the effects of technologies and policies on smallholder incomes and agricultural sustainability (Lopez 1997).

In this paper we study the allocation and value of crop residues in smallholder agriculture. We extend the crop-livestock farming model of Magnan, Larson, and Taylor (2012) to account for the long-term benefits of crop residues used in soil fertility management and to allow for the uses of residues as animal feed and household energy. The "full marginal value" of leaving crop residues on the field in our simple two-period model includes their contribution to the current period production and its contribution to the increased yields and the amount of residues available in the following period. Our theoretical model also shows that the allocation of crop residues to soil fertility management depends on the value of alternative uses, as well as household-specific wealth, liquidity constraints, time preferences, and market interest rates. We infer the monetary value of crop residues from the households shadow price—the households internal price for nontradable residues (de Janvry, Fafchamps, and Sadoulet 1991).

Empirically, we estimate a household-level maize production function using detailed input and output data, including measurements of crop residues and household-specific environmental variables to calculate the shadow value of maize residues, using data from the highlands of western Kenya. In this densely populated rural part of the country, maize residues constitute one of the largest sources of on-farm organic resources (Torres-Rojas et al. 2011) and have competing applications. Our econometric estimates suggest that the shadow price of one kilogram of maize residues left on the fields is 5.49-6.90 Kenyan shillings or US$0.06-0.08, extends beyond fertilizer substitution, and is higher for poorer households. Using the average shadow price, we also show that maize cobs and stover make up around 37 percent of the total value of annual maize production and constitute about 22 percent of the median household income.

The following section briefly describes the links between soil organic matter management, soil fertility, and agricultural productivity, as well as the existing literature that analyzes the use of agricultural residues. Section 3 presents the extended model and our empirical strategy. Section 4 describes crop residue management in the western Kenyan highlands and the data used. Section 5 discusses the empirical estimation results, shows the economic importance of maize residues, and explains how residue values differ across farming households. Section 6 concludes the paper.

2.2 Value of organic resources in smallholder agriculture

Despite considerable progress in agricultural innovations and successes of the Green Revolution in other regions of the world, by the year 2013, cereal yields in Sub-Saharan Africa (SSA) remained at less than 1.5 metric ton per hectare, less than half the average yields in other developing country regions (FAOSTAT 2015). The reasons for this are many and complex but they include low levels of fertilizer use, the systematic removal of crop residues by farmers, and the region's widespread soil degradation and decline in soil fertility, among other factors (Sanchez 2002; Jayne and Rashid 2013). To address these challenges, research in agronomy, soil science, and farming systems ecology has widely called for initiatives promoting the sustainable intensification of SSA agriculture (see, for example, Lee and Barrett (2001) and Tilman et al. (2011)).

One of the most frequently cited priorities in increasing agricultural productivity in SSA—relieving soil fertility constraints—will require increased combined applications of chemical fertilizer and organic resources. Fertilizers and organic resources—which include traditional organic inputs such as crop residues and animal manures, as well as trees, shrubs, cover crops, and composts (Palm et al. 2001)—have different functions. While chemical fertilizers address short-term crop nutrient demands, organic inputs are fundamental for soil fertility management through their longer-term contribution to soil organic matter formation (Lal 2009). Moreover, both chemical fertilizers and organic resources are often not widely available or affordable in sufficient quantities, suggesting another practical reason for their combined application (Vanlauwe and Giller 2006). Fertilizer application rates are limited by high costs, restricted availability, and household liquidity constraints, while organic resources face numerous competing applications. Even if fertilizer use were to be widely expanded, chemical fertilizers alone are not capable of restoring soil fertility and increasing agricultural productivity across all soil types, and especially on "non-responsive" soils (Tittonell and Giller 2013).[2]

In recent years, organic resource management has also increasingly been viewed as contributing not just to agricultural productivity but to wider environmental and economic goals. Reducing greenhouse gas emissions, increasing agricultural carbon sequestration, and enhancing farmers' resilience to climate change have become imperatives for the promotion of many agricultural practices that rely on organic resources (e.g., "climate-smart" or "low emissions" agriculture). Increasing the soil carbon pool through recommended practices

[2]Discontinuous, limited or no fertilizer application, combined with continuous cultivation over time, leads to severe soil degradation through nutrient depletion and the loss of organic matter, thus rendering many soils "non-responsive" to the renewed application of nutrients or improved varieties (Tittonell and Giller 2013).

(mulching, retention of crop residues, use of manures and biosolids) has the promise to sequester carbon, reverse soil degradation processes, improve soil quality and increase food production, with a potentially strong impact on offsetting fossil fuel emissions (Lal 2006).

Despite the prominence of crop residues in the agronomic literature, they have been the subject of limited attention in economics research. Contrast this, for example, with the long recognized importance of chemical fertilizers and modern seed varieties to increasing crop yields and the constraints underlying their adoption and use in SSA and other developing countries (see, for example, recent work from Kenya by Marenya and Barrett (2009a); Suri (2011); Duflo, Kremer, and Robinson (2011)). One of the reasons for this neglect is the difficulties associated with quantifying organic resources. As a result, most studies that estimate crop response models rely on rough indicator variables for crop residues and animal manures. For instance, Gavian and Fafchamps (1996) and Sheahan, Black, and Jayne (2013) include indicator variables for manure use, while Marenya and Barrett (2009b) rely on the value of livestock as a control for unobserved manure application rates. Only a few studies include the quantities of animal manure in their estimation of production functions: Teklewold (2012) in his work in Ethiopia and Matsumoto and Yamano (2011) in their work in Kenya and Uganda.

The existing literature, though limited, nonetheless confirms important tradeoffs among different uses of crop residues. Wealthy households in Kenya, for example, use chemical fertilizers, practice fallowing on a portion of their farm, or incorporate maize residues for soil fertility management to achieve higher crop yields, while poorer households obtain higher returns from using maize residues as fuel or livestock feed (Crowley and Carter 2000; Marenya and Barrett 2007). It is also often thought that agricultural residues are substitutes for fuelwood in consumption. The empirical evidence as to whether fuelwood and dung, or fuelwood and crop residues, are substitutes or complements, however, is mixed (Amacher, Hyde, and Joshee 1993; Mekonnen and Kohlin 2008; Cooke, Kohlin, and Hyde 2008).

In order to demonstrate the value of organic resources in developing countries, the existing literature uses either a production or a substitution approach. The production approach establishes the value by calculating changes in overall farm profits or physical changes in production by including biomass as a production input (see, for example, Lopez (1997); Goldstein and Udry (2008); Klemick (2011)). Two recent studies use, alternatively, the substitution approach, deriving the value of biomass using the observed prices of agricultural inputs. Teklewold (2012) examines the role of returns to manure as energy and farming inputs in smallholder agriculture in Ethiopia, while Magnan, Larson, and Taylor (2012) analyze the value of cereal stubble in a mixed crop-livestock farming system in Morocco. Both of these studies extend the method of estimating shadow wages and labor supply functions in the context of non-separable agricultural household models developed by Jacoby (1993) and Skoufias (1994). One of the strengths of the dataset used here lies in the reliable estimates of quantities of both inputs and outputs, which dictates our choice of the substitution approach.

2.3 Conceptual framework and empirical strategy

Since leaving crop residues for soil fertility is a long-term agricultural management strategy, it needs to be evaluated in an intertemporal setting. Extending the model of Magnan, Larson, and Taylor (2012) to account for the intertemporal nature of residue management, we propose a simple two-period model to develop the intuition for a dynamic allocation problem.[3] A farming household maximizes net present value from two main household production activities: crop production (f) and all other household production activities (h) that include energy generation and livestock maintenance, using both market ($\mathbf{x}$) and non-market ($\mathbf{z}$) inputs. The net value from these two production activities represents the

[3] Potential market failures in rural Sub-Saharan Africa call for the use of a non-separable agricultural household model (de Janvry, Fafchamps, and Sadoulet 1991). To simplify our exposition, we specify a model focusing on the production behavior of agricultural households, but accounting for full income, income from producing both traded (crops) and non-traded (household energy) goods, and endogenous traded and non-traded inputs.

amount of profits the household could earn if all production activities resulted in marketable outputs. Given that crop residues in rural western Kenya are not typically traded, resource constraints are required to ensure that the amount of maize residues allocated to the two activities does not exceed the total residues produced during the previous season. And since liquidity constraints and transaction costs can introduce a wedge between market and shadow prices of inputs, we add a liquidity constraint.

To simplify the exposition, let each production activity be a function of one market input (x_{it}) such as chemical fertilizer or purchased animal feed or fuel and one non-market input (z_{it}) such as crop residues for $i = f, h$ and $t = 1, 2$. Then, the constrained maximization problem can be written as:

$$\begin{aligned} \max_{x_{it}, z_{it}} \; & p_f f(x_{f1}, z_{f1}) + p_h h(x_{h1}, z_{h1}) - w_f x_{f1} - w_h x_{h1} \\ & + \rho[p_f f(x_{f2}, z_{f2}) + p_h h(x_{h2}, z_{h2}) - w_f x_{f2} - w_h x_{h2}] \\ & \text{subject to} \\ & z_{f1} + z_{h1} \leq z_1^{max}, \\ & z_{f2} + z_{h2} \leq z_2^{max} \equiv \alpha f(x_{f1}, z_{f1}), \\ & w_f x_{f1} + w_h x_{h1} + \beta(w_f x_{f2} + w_h x_{h2}) \leq W, \end{aligned} \tag{2.1}$$

where p_f is the price of crops, p_h is the value of one unit of other production activities, w_f and w_h are the prices of market inputs, $\rho = 1/(1+\delta)$ is the household's discount factor for the discount rate δ, $\beta = 1/(1+r)$ is the market discount factor for the market rate r, z_t^{max} is the total amount of non-market input z_t available, and W is the household's two-period wealth available to spend on production inputs. Note that $z_2^{max} \equiv \alpha f(x_{f1}, z_{f1})$, where α is the product to grain ratio used to convert the amount of crops produced in period $t = 1$ to the amount of crop residues to allocate in period $t = 2$.

The Lagrangian is thus specified as:

$$\begin{aligned}\mathcal{L} = p_f f(x_{f1}, z_{f1}) + p_h h(x_{h1}, z_{h1}) - w_f x_{f1} - w_h x_{h1} \\ +\rho[p_f f(x_{f2}, z_{f2}) + p_h h(x_{h2}, z_{h2}) - w_f x_{f2} - w_h x_{h2}] \\ +\mu_1(z_1^{max} - z_{f1} - z_{h1}) + \rho\mu_2(\alpha f(x_{f1}, z_{f1}) - z_{f2} - z_{h2}) \\ +\lambda(W - (w_f x_{f1} + w_h x_{h1}) - \beta(w_f x_{f2} + w_h x_{h2})) \\ +\eta_{it} x_{it} + \zeta_{it} z_{it}.\end{aligned} \tag{2.2}$$

Here, μ_t is the shadow price of non-market input z_{it}, λ is the cost of liquidity, and η_{it} and ζ_{it} are multipliers on market and non-market inputs, for $i = f, h$ and $t = 1, 2$.

Assuming that all production activities are increasing in x_{it} and z_{it} and the farm household is liquidity constrained, the constraints will bind such that $z_1^{max} = z_{f1} + z_{h1}$, $z_2^{max} = z_{f2} + z_{h2}$, $W = w_f x_{f1} + w_h x_{h1} + \beta(w_f x_{f2} + w_h x_{h2})$, and $\mu_1 > 0$, $\mu_2 > 0$, and $\lambda > 0$. The Karush-Kuhn-Tucker (KKT) first order conditions (FOC) for Equation 2.2 with respect to x_{it} and z_{it} are the inverse demand functions for market and non-market inputs, respectively, and are as follows:

$$(p_f + \alpha\rho\mu_2)\frac{\partial f(x_{f1}, z_{f1})}{\partial x_{f1}} = w_f(1+\lambda) + \eta_{f1}, \tag{2.3a}$$

$$(p_f + \alpha\rho\mu_2)\frac{\partial f(x_{f1}, z_{f1})}{\partial z_{f1}} = \mu_1 + \zeta_{f1}, \tag{2.3b}$$

$$\rho p_f \frac{\partial f(x_{f2}, z_{f2})}{\partial x_{f2}} = w_f(\rho + \lambda\beta) + \eta_{f2}, \tag{2.3c}$$

$$\rho p_f \frac{\partial f(x_{f2}, z_{f2})}{\partial z_{f2}} = \rho\mu_2 + \zeta_{f2}, \tag{2.3d}$$

$$p_h \frac{\partial h(x_{h1}, z_{h1})}{\partial x_{h1}} = w_h(1+\lambda) + \eta_{h1}, \tag{2.3e}$$

$$p_h \frac{\partial f(x_{h1}, z_{h1})}{\partial z_{h1}} = \mu_1 + \zeta_{h1}, \tag{2.3f}$$

$$\rho p_h \frac{\partial h(x_{h2}, z_{h2})}{\partial x_{h2}} = w_h(\rho + \lambda\beta) + \eta_{h2}, \tag{2.3g}$$

$$\rho p_h \frac{\partial h(x_{h2}, z_{h2})}{\partial z_{h2}} = \rho\mu_2 + \zeta_{h2}, \tag{2.3h}$$

$$x_{it} \geq 0,\ \eta_{it}x_{it} = 0, \tag{2.3i}$$

$$z_{it} \geq 0,\ \zeta_{it}z_{it} = 0 \text{ for } i = f, h \text{ and } t = 1, 2. \tag{2.3j}$$

Several observations follow from the FOCs. FOCs 2.3a-2.3h equate marginal value to marginal cost for market inputs x_{it} and non-market inputs z_{it}. However, since x_{f1} and z_{f1} not only contribute to higher yields in $t = 1$, but also increase the amount of crop residues available for allocation in period $t = 2$, "full marginal value" in 2.3a and 2.3b includes the term $\alpha\rho\mu_2$. Since $\mu_2 = p_f \frac{\partial f(x_{f2}, z_{f2})}{\partial z_{f2}}$ (from 2.3d), $\alpha\rho\mu_2$ is the discounted marginal value of having more crop residues in $t = 2$.

Marginal cost for x_{ft} includes the market price w_f, as well as the cost of liquidity λ in $t = 1$ and $\rho + \lambda\beta$, the discounted cost of liquidity, in $t = 2$. The shadow price of non-market input z_{ft} is μ_t. When in $t = 1$ crop residues are allocated to both production activities, f and h, so that z_{f1} and z_{h1} are non-zero (and $\zeta_{f1} = \zeta_{h1} = 0$), FOCs 2.3b and 2.3f imply

$\mu_1 = (p_f + \alpha\rho\mu_2)\frac{\partial f(x_{f1}, z_{f1})}{\partial z_{f1}} = p_h \frac{\partial f(x_{h1}, z_{h1})}{\partial z_{h1}}$ and the household allocates crop residues to equate the marginal value across two uses, accounting for the fact that crop residues also contribute to crop production in $t = 2$.

The amount of the allocation in $t = 1$, however, depends not only on the shadow price of crop residues, but also the output value of the two production activities, the household-specific and market discount factors, and household wealth and cost of liquidity: $z_{i1}^* = z_{i1}^*(\mu_1, \mu_2, p_f, p_h, \rho, \beta, W, \lambda)$. These allocations thus necessarily reflect the tradeoffs that households make among alternative uses of crop residues, household-specific liquidity constraints and time preferences, and existing market interest rates.

FOCs 2.3a and 2.3b also give us a way to estimate the value of crop residues in $t = 1$ empirically. When both x_{f1} and z_{f1} are non-zero (and $\eta_{f1} = \zeta_{f1} = 0$), we can derive the shadow price of crop residues allocated for soil fertility management:

$$\mu_1 = w_f(1 + \lambda)\frac{\partial f(x_{f1}, z_{f1})}{\partial z_{f1}} \Big/ \frac{\partial f(x_{f1}, z_{f1})}{\partial x_{f1}}. \tag{2.4}$$

The shadow value μ_1 is the amount of fertilizer required to compensate for the loss of one unit of crop residues times the cost of fertilizer—its market price w_f adjusted by the cost of liquidity λ. Because both x_{f1} and z_{f1} contribute to the future availability of crop residues and the unit value of their contribution $(p_f + \alpha\rho\mu_2)$ is the same, we can derive μ_1 using the period $t = 1$ marginal value product of x_{f1} and z_{f1} and the period $t = 1$ value of market input only.

Estimation of the shadow price of a non-market good using a household production model requires the assumption of at least one well-functioning market (Jacoby 1993; Skoufias 1994; Le 2009).[4] Moreover, given the cross-sectional nature of our dataset, unfortunately

[4] The assumption of well-functioning input markets is reasonable in the context of western Kenya. In the sample of households used in the empirical estimation, 84 percent of households engage in off-farm

we cannot estimate the value of non-market inputs in different periods and we thus treat the amount of crop residues in any given year as exogenous. The problem collapses from dynamic to static; equation 2.4, however, still holds. We also do not observe household wealth W and thus cannot measure λ with our data. And although we add household-specific transportation costs to the cost of fertilizer, similar to Magnan, Larson, and Taylor (2012), we likely underestimate the shadow price of crop residues for liquidity-constrained farmers.

The choice of functional form for the estimation of the crop response function with respect to different inputs has received substantial attention in the agronomic and economic literature. Several studies that use a household production model to calculate the shadow price of a non-market good use the Cobb-Douglas specification (see, for example, Magnan, Larson, and Taylor (2012); Arslan and Taylor (2009); Skoufias (1994); Jacoby (1993)). Yet in a smallholder setting such as ours, not all farmers use fertilizer and crop residues in positive quantities thus creating the "zero-observation" problem for estimation (Battese 1997). We also suspect interactions between different inputs as the agronomic literature argues (Chivenge, Vanlauwe, and Six 2011). Moreover, we focus on household-level maize production function, aggregating output and inputs for all plots and across two seasons and disregarding potential spatial and temporal variation in the use of one or more inputs. In this setting a smooth "aggregate" production function is appropriate (Berck and Helfand 1990). We are cautious to assume unitary elasticity of substitution necessary for the Cobb-Douglas estimation. Instead we use a quadratic specification as a second-order local approximation of the unknown true maize production function. The same functional form is used in some recent studies focusing on maize production across Sub-Saharan Africa (see, for example,

employment, 62 percent hire agricultural laborers, 60 percent purchase fertilizer, and about 15 percent participate in land markets, either renting in or renting out parcels of land for cultivation.

Sheahan, Black, and Jayne (2013) and Harou et al. (2014)):

$$y_i = \alpha_0 + \sum_{i=1}^{m} \alpha_i x_i + \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} \alpha_{ij} x_i x_j + \epsilon_i, \tag{2.5}$$

where y_i is household-level annual maize production from all plots, x_i is a vector of production inputs, α are parameters to be estimated, and ϵ_i represents the iid, mean zero, normally distribution error.

Particular concerns in the literature on the estimation of primal production functions in developing countries are the possibilities of measurement error, omitted variables (e.g., environmental production conditions), and/or simultaneity bias due to unobserved heterogeneity. The dataset used in this study includes plot area measured with hand-held Global Positioning System (GPS) units, quantities of crop residues estimated using actual measurements, household-specific measures of soil quality and altitude to capture variation in maximum and minimum temperatures (as in Tittonell and Giller (2013))—all variables which should attenuate potential measurement error and omitted variable bias. Simultaneity bias, however, is still of concern: managerial ability (imperfectly captured by the age and education of a household head), for example, can lead to higher maize yields and higher residue retention. In the absence of credible instruments and with inevitable unobserved heterogeneity, however, we rely on the estimation of the production function, acknowledging the potential bias of our estimates.

2.4 Research area and data

The research sites are five 10-kilometer sites located in the Nyando and Yala river basins of western Kenya, two of the major seven rivers feeding the Kenyan side of Lake Victoria (see figure A.1.2).[5] A socio-economic and household production survey of a sample of 309 households in 15 villages (three in each site) across the Nyanza, Rift Valley and Western counties was conducted in two rounds in 2011-2012 to account for the bi-modal annual precipitation pattern and associated two distinct cropping seasons. The survey covered a wide range of standard Living Standards Measurement Survey topics and, in addition, collected soil samples and detailed spatial and market data. Table 3.1 shows selected summary statistics for the sample households.

A typical household in the sample has six members and owns 4.53 acres of land. The household head is on average 51 years old, has seven years of schooling, and for over 80 percent of households is male. Maize is the most popular grain crop in the area and is cultivated on almost half of the land owned. Maize established itself as the dominant food crop at the beginning of the 20th century due to its relatively higher yields per unit of land and the possibility of two crops per calendar year (Crowley and Carter 2000). The average maize plot in the sample is 0.61 acres (across 801 plots and two cropping seasons) and is rainfed. Differences in geographic location and associated rainfall availability, maximum and minimum temperatures (proxied by altitude), and the possibility of two cropping seasons of varying length, as well as variations in farmer management practices together account for a high variance in maize grain yields, which average 670 kg/acre among sample farms.[6]

Dominant soil types in the Yala and Nyando river basins are acrisols, ferralsols and nitisols (Jaetzold and Schmidt 1982). Acrisols and ferralsols are strongly leached or weathered; indeed, farmers in the sample identified their soil fertility as mostly of moderate quality. The soil analysis, however, showed that the average soil nitrogen content and soil pH on the

[5] The sites formed part of the original geographic coverage of the Western Kenya Integrated Ecosystem Management Project, implemented between 2005-2010 by the Kenya Agricultural Research Institute and the World Agroforestry Center and funded from the Global Environmental Facility of the World Bank.

[6] The farm and household characteristics are similar to those of the households in the representative panel dataset from Kenya collected by the Tegemeo Institute of Agricultural Policy and Development at Egerton University and Michigan State University. See, for example, Mathenge, Smale, and Olwande (2014).

sample farms are "very low" and "low," respectively.[7] Nitrogen content, a critical macronutrient for plant growth and yield, is 0.16 percent by weight. Soil pH measures the degree of soil acidity or alkalinity (from 0 to 14); optimum pH for plant growth is 6.5. The average pH in the sample is lower than optimal—5.82.[8]

About 60 percent of households in the sample apply some chemical fertilizer. Di-ammonium phosphate (DAP) is commonly applied during planting, while urea and calcium ammonium nitrate (CAN) are applied as top dressing. To account for all types of chemical fertilizer applied and their different compositions without introducing too many variables, we create a "plant nutrient" measure, NPK, that aggregates the quantity of the active ingredients (rather than the total quantity of fertilizer), giving equal weight to the three most important plant nutrients: nitrogen (N), phosphorous (P) and potassium (K).[9] Application of 25.28 kg of NPK across all maize plots and two seasons, or 17.42 kg of NPK per acre, is the sample average. This represents a very low level of fertilizer usage. More than 8 in 10 (83 percent of) farmers in the sample left maize residues on their fields for soil fertility management, and 162 households (52 percent) used both chemical fertilizer and maize residues as organic soil amendments.

Herd size is measured in Tropical Livestock Units (TLU), where 1 TLU is equivalent to 250 kg of animal body mass (0.7 cattle or 0.1 sheep/goat). Ninety four percent of house-

[7]Soil samples were collected during the first household visit in the end of the long rains season of 2011 from the largest maize plot on each farm. The laboratory analysis was carried out at the World Agroforestry Center's Soil-Plant Spectral Diagnostics Laboratory in Nairobi using near infrared spectroscopy (NIRS), a rapid nondestructive technique for analyzing the chemical composition of materials, following protocols developed by Shepherd and Walsh (2002) and Cozzolino and Moron (2003). The three classification tiers used in the empirical analysis were "good," "low," and "very low," based on recommendations from the Kenya Agricultural Research Institute (Mukhwana and Odera 2009) and from the Cornell Soil Health Test (Moebius-Clune 2010).

[8]Soil organic carbon or soil organic matter contents have also been used in the literature to account for overall soil quality (Goldstein and Udry 2008; Marenya and Barrett 2009a). In the sample of farms considered, it is the nitrogen content and soil pH that are the limiting factors. Moreover, the correlation between organic carbon and nitrogen content is very high (correlation coefficient of 0.96) and both serve as indicators of overall soil fertility.

[9]The NPK composition of the most common fertilizers used by farmers in the sample is the following: DAP (with N-P-K composition of 18-46-0), urea (46-0-0), CAN (26-0-0), TSP (0-46-0), NPK mixes (20-10-10, 23-23-0, 20-20-0).

holds keep farm animals with the average TLU in the sample being 2.38. Following Sahn and Stifel (2003), we create an asset index for each household derived from a factor analysis on household durables and housing quality. Household durables include assets such as radios, televisions, furniture, improved and gas/electric stoves, bicycles, motorcycles and cars; housing quality incorporates indicator variables for construction material (walls, roof, floor), source of drinking water, energy used for lighting, and toilet facilities.[10]

Allocation and amount of maize residues. Maize residues are used for multiple purposes, leaving none wasted. Nearly half (47 percent) of aboveground maize residues (both stover and cobs) in our sample are allocated to soil fertility management (left on the fields, mulched, or collected to be applied as organic soil amendments later on). Most livestock in smallholder systems in Kenya either graze on own or communal land, or are tethered, so that maize residues can constitute a significant portion of livestock diets—up to 24 percent of total livestock feed by dry weight (KARI 2008). Household energy sources are also predominantly from biomass, including wood and crop residues. The shares used for animal feed and household fuel are 25 percent and 22 percent, respectively (table 2.3). A minor amount of remaining residues are allocated to miscellaneous uses. Residue use also differs by household wealth (figure 2.3). Households in the first quartile of the asset index use the largest share of maize residues for soil fertility management (and the least fertilizer quantity), while households in the top two quartiles have more livestock and allocate more residues as animal feed.

The quantity of residues allocated to different uses is reported in the survey at the household level for the twelve months preceding the survey visit; this includes two cropping seasons in the areas where maize is planted twice per year. In the absence of plot-level data on crop residue use over time, we assume that a large part of the residue allocation decision is persistent from year to year, given that the household needs for energy and livestock

[10]Scoring coefficients (weights) for asset index are reported in table 2.A.1 in Appendix 2.A.

feed, on average, do not significantly change from year to year.[11] As cooking activities display significant economies of scale, small changes in household size, for example, do not materially alter energy requirements. The survey included a household member roster during both visits; only six percent of households reported that the number of their family members either increased or decreased by more than one person.

Estimating plot-level amounts of maize residues is a challenging task. No nation tracks the production of crop residues the way they track food production or chemical fertilizer use; the most reliable estimates come indirectly from studies of the harvest index (the ratio of crop edible yield to the crop's total aboveground phytomass) or the straw-to-grain ratio on experimental plots (Smil 1999; Lal 2005). We instead rely on actual measurements of maize grain and residues from 140 farmer plots in the same research sites in 2011-2012 (Torres-Rojas 2015). We first predict the within-sample plot-specific yields of maize grain and maize residues over the sample of 140 plots (see figure 2.2) and use this linear prediction (R^2=0.58) to generate plot-level residue quantities in the full sample of 309 households. The total household-level residue quantities are then the sum of predicted plot-level quantities for each household, estimated across two cropping seasons of 2011 where appropriate.[12] This generated variable presents a couple econometric problems in the later estimations, one of which concerns the standard errors from a second-stage regression (Pagan 1984). We correct the biased standard errors caused by the generated regressor of maize residue quantities by bootstrapping techniques.

[11] The assumption of time invariance in the use of crop residues deserves additional consideration that can be properly addressed only with panel data.

[12] We focus our analysis on the management of aboveground maize residues (stover and cobs) and do not consider maize root biomass. Since Kenyan farmers do not remove roots from soil after harvesting, there is no variation in use of maize roots among households. Moreover, maize roots are, on average, only about 10 percent of aboveground residues dry weight (Latshaw and Miller 1924).

2.5 Empirical results

In order to elicit the shadow value of maize residues allocated to soil fertility management, we estimate a household-level quadratic production function for maize for the whole sample (equation 2.5). Since the allocation of maize residues to different uses is a decision made at the farm household level, maize production is estimated at the household level from all maize plots cultivated during two seasons: the long rains and the short rains of 2011. Limiting the production function estimation to households that used only positive quantities of maize residues as a soil amendment would necessarily introduce selection bias into the estimates. In a small dataset there is a trade-off between allowing for full flexibility of the quadratic function and degrees of freedom; the function is estimated allowing for all squared and interaction terms for the four inputs: land planted with maize, household and hired labor, chemical fertilizer, and maize residues as soil amendments. Additional variables include a set of environmental variables to control for biophysical influences on production (soil pH, soil nitrogen content, altitude), other variables potentially influencing maize production (herd size in TLU as a proxy for unobserved manure application rates, the fraction of land planted with hybrid seeds and intercropped with legumes), and controls (characteristics of the household head such as gender, age, and years of education).

The results of the estimation are reported in table 2.4.[13] We reject the null hypothesis of the statistical insignificance of the second-order terms with a Wald test statistic of 61.06 and a P-value of zero against the $\chi^2(10)$ distribution. Joint tests of the first- and second-

[13] Addition of geographic controls—indicator variables for sites/districts or villages—does not significantly change the estimation. The results are reported in table 2.A.2 in Appendix 2.A. A Wald test statistic of 2.28/5.32 and a P-value of 0.81/0.26 against the $\chi^2(5/4)$ distribution cannot reject the null hypothesis that the sites/districts are, for example, statistically important. Moreover, since altitude does not significantly vary within households in a particular village, altitude serves as a geographic control variable. Table 2.A.3 repeats the estimation using total quantity of chemical fertilizer or nitrogen quantity only across different fertilizer types, with similar results. The results of the estimation using a Cobb-Douglas and translog specifications of the production function are reported in table 2.A.4. The joint test of the significance of all second-order terms after the translog estimation also shows their statistical significance at 1% level ($\chi^2(10)$=51.71 with p-value of zero).

order terms for the three productive inputs (land, fertilizer and crop residues) show that they are statistically significant determinants of production levels. The test of the significance of all coefficients for NPK, for example, is 50.24 with a P-value of zero. The interaction term between NPK and crop residues is positive as expected, yet statistically insignificant. While hybrid maize seeds are usually associated with increased yield when used together with nitrogen fertilizer and when rainfall stress is limited (Sheahan, Black, and Jayne 2013), their use in western Kenya does not guarantee increased returns. There have been reports of recycled hybrid seeds—seeds replanted from previous year's harvest (Matsumoto and Yamano 2011; Suri 2011), and only 60 percent of our sample reported using either both hybrid seeds and chemical fertilizer or neither. This may help explain the statistically insignificant value of the estimated coefficient for the fraction of land planted with hybrid maize.

Table 2.5 shows the estimated marginal physical productivities (MPP) for land, labor, NPK and maize residues, as well as their marginal value productivities (MVP) and benefit/cost ratios, based on the sample average maize price of 29 Kenyan shillings per one kilogram (KES/kg) and prices of inputs. The resulting estimates have the expected signs and their magnitudes are consistent with expectations. Marginal physical productivity estimates show that an additional acre of land increases output by 103 kg, on average. The estimated MPP of labor is positive, yet low and has high variance. Marenya and Barrett (2009b) note that measuring labor employed in tropical agriculture poses specific difficulties for empirical estimation, such as measurement error associated with variable effort and absorption of under-employed or unemployed household members.

Both chemical fertilizer and maize residues also positively influence output: for an additional kilogram of N, P, K nutrients and maize residues, maize grain harvest increases by 8.11 kg and 0.21 kg, respectively.[14] The estimated mean MPP of NPK is comparable to the

[14]The MPP estimate of NPK is positive for all observations, while the MPP of maize residues is positive for 90 percent of the households who used maize residues for soil fertility management. Other studies relying on the estimated coefficients of the production function, for example, Jacoby (1993) and Skoufias (1994), also find negative marginal revenue productivities. While they drop those observations or set their value

estimated returns in existing studies, giving confidence to our estimates. Jayne and Rashid (2013), for example, find the recent estimates across Sub-Saharan Africa to be around 8-24 kilograms of maize grain per 1 kilogram of nitrogen applied, with the most estimates concentrated in the lower 8-15 kg range. Specifically for Kenya, the MPP of nitrogen from chemical fertilizer is found to be 17.6 kg in the western highlands by Marenya and Barrett (2009b) and 11.1-19.8 kg in central and western regions by Matsumoto and Yamano (2011). The estimated MPP of 8.11 kg maize/kg of NPK is lower than the MPP of nitrogen alone in the referenced studies as the composite NPK measure aggregates the benefits of two other nutrients (phosphorous and potassium), the content of which in the soils of the region is not limiting. The estimated marginal benefit/cost ratio for NPK of 1.61 suggests the profitability of chemical fertilizer for households in the sample.

In order to estimate the household-specific shadow value of 1 kg of maize residues as a soil amendment, a price of 1 kg of NPK is needed. Assuming that all the value in chemical fertilizer is derived from the three essential nutrients for plant growth (N, P and K), a household-specific price of NPK is calculated as the total reported expenditure on chemical fertilizer across two cropping seasons divided by the quantity of NPK in kg. This price, however, does not account for household-specific transport and transaction costs that have been found to be significant for rural households in developing countries (de Janvry, Fafchamps, and Sadoulet 1991). While availability and access to chemical fertilizer in rural Kenya have been improving over time leading to considerable reduction in real transport costs (Sheahan, Black, and Jayne 2013), they are still significant. We include an estimated transport cost to be added to the price of purchased fertilizer by calculating the shortest round-trip distance from the household to a fertilizer seller in the nearest commercial center, using the household and center GPS coordinates. The average one-way distance is 3 km in the sample. The cost

equal to one, we retain the observations not to introduce unknown bias. The average MPP of maize residues for the observations with positive values only is, as expected, higher—0.25 kg of maize/kg of maize residues. The estimated mean MPP of N only (after the estimation of the quadratic production function with nitrogen rather than NPK) is 13.26 kg.

of transport adds about 9 KES, or 6 percent, to the price of 1 kg of NPK as reported by households. Since the estimates of the shadow price rely on input ratios, which can be large if one input is used in very small quantities, we also calculate the shadow price excluding the top and bottom tails (5 percent of the distribution).[15]

Of the total of 309 sample households, not all households, however, left maize residues on the field—17 percent of households used all of the residues for different purposes—and not all households used chemical fertilizer, only 64 percent did. Just over half (52 percent, or 162 households) used both inputs in positive quantities. The estimated shadow values for households that used positive quantities of both chemical fertilizer and maize residues as inputs in maize production are shown in table 5 (equation 4). The top panel shows the shadow values using the household-specific price of 1 kg of NPK, while the bottom panel uses this price adjusted for travel costs as described above. The average shadow values for maize residues left on the fields for soil fertility management are in the range of 5.49-6.90 KES/kg or US\$0.06-0.08/kg. Using the estimated average value of maize residues (5.49 KES), table 4 shows that the average benefit/cost ratio for maize residues is 1.10, suggesting that it is profitable to leave maize residues as soil amendments (the ratio is greater than one).

2.5.1 Economic importance of crop residues

Using the most conservative estimate of the average shadow value of one kg of maize residues allocated to soil fertility management (5.49 KES), table 2.7 shows the values of maize residues per farm and per acre (per ha). Maize residues applied as a soil amendment are valued, on average, at 8,351 KES or US\$99 per farm, which constitutes about 10 percent of the median annual household income in the sample (79,750 KES). Total maize residues per farm are valued at US\$208 (22 percent of the median income). When these values are translated to

[15] Alternatively, we calculate the shadow price replacing the top and bottom tails with the 95th and 5th-percentile values, respectively (top- and bottom-coding). The results do not significantly change.

per acre estimates, table 2.7 also shows that maize residues constitute 37 percent of the total value of cereal production (both grain and residues) in western Kenya.

Although the estimated value of maize residues seems relatively high, they are indeed close to the previously estimated value of non-market crop stubble in Morocco and farm-yard manure in Ethiopia. Magnan, Larson, and Taylor (2012) find the median and mean per hectare value of cereal crop stubble during two seasons of 2007 (drought year) and 2008 (normal rainfall year) to be US$221 and US$491, respectively. Our estimate, US$330 per hectare of maize residues produced, falls between these two values. The estimated average value of US$0.06/kg is also similar to the discounted marginal revenue product of farm-yard manure in the Ethiopian study of Teklewold (2012).

With almost all households using at least some maize residues as fuel, the value of residues can also be inferred from their preferred market substitutes—fuelwood or charcoal. Over one-third of the households in the sample reported purchasing fuelwood in 2011. Based on the reported quantities and prices, the median and mean market price of 1 kilogram of mixed fuelwood is 5.85 and 8.94 KES/kg, respectively. The specific energy—energy per unit mass measured in megajoules per kilogram (MJ/kg), often used for fuel comparisons—of mixed fuel and maize stover and cobs in western Kenya is very similar (17.2 MJ/kg for mixed wood, 17.3 MJ/kg for maize stover and 16.9 MJ/kg for maize cobs) (Torres-Rojas et al. 2011). This market price gives another indication that our estimated shadow value of maize residues is within the realistic range. This comparison also allows us to assess whether the households in our sample allocate crop residues to equate the marginal value across allocations as predicted by our theoretical model (FOCs 2.3b and 2.3f). For the 54 households who reported purchasing fuelwood and for whom we have the estimated shadow value, these two values are close. The mean (median) price of fuelwood is 9.39 (5.56) KES/kg and the mean (median) shadow value of residues is 5.34 (4.31).

It is also informative to look at the value of N, P and K found in dry maize residues in order to disaggregate their estimated values. Some estimates for the United States show that NPK accounts for about 2.5 percent of maize residues (leaves, stems and cobs), as a percentage of dry weight (Latshaw and Miller 1924). Similar estimates for nitrogen in western Kenya point to slightly lower values (for example, 0.7 percent of nitrogen (Gentile et al. 2011)). Using 2.5 percent as the highest possible NPK content of maize residues and 138 KES as the mean price of one kilogram of nutrients (NPK) in the sample, the price of NPK in one kilogram of maize residues can thus be estimated at 3.46 KES or US$0.04. Our estimates of the shadow value of one kilogram of maize residues left on the fields are higher—5.49-6.90 KES or US$0.06-0.08.

Our theoretical model shows that the full value of using crop residues for soil fertility management is not only their marginal benefit in current period production, but also the discounted marginal value of having more crop residues in the future (FOC 2.3b). A meta-analysis from 57 studies across Sub-Saharan Africa by Chivenge, Vanlauwe, and Six (2011) shows that the addition of organic resources in one season also have residual effects in the subsequent season with crop yield responses of 38 percent over the no-input control. Thus, the estimated value of 5.49-6.90 KES/kg also likely includes the residual value of maize residue applications.

While the estimated shadow value of maize residues is crop- and location-specific, these results point to the significant monetary value of using organic resources as a soil amendment. The agronomic research community largely agrees on the complementarity and necessity of using both chemical fertilizer and organic inputs for soil fertility management (Vanlauwe et al. 2002). In order to properly assess the value of organic inputs and their influence on crop yields, one also needs to account for organic resources in the estimation of production functions. Moreover, traditional practices in other regions of the world often include the burning of residues: about 25 percent of all residues are burnt in low-income countries (Smil 1999). This practice is often carried out to prepare fields for next planting and to destroy phytomass that may carry diseases or pests. Burning of residues, however, also contributes to substantial emissions from agriculture and has adverse respiratory health effects on nearby populations. Incorporating crop residues into soil instead can lead to substantial yield increases, as our findings suggest.

2.5.2 Differences in values across farming households

We also investigate the differences in the shadow value of maize residues across farming households. We regress the estimated household-specific value (KES/kg) on a set of household- and farm-level characteristics, such as gender of household head, asset index, herd size and herd size squared, household size, total land area farmed, the share of land cultivated with maize, and several farm-specific environmental characteristics capturing temperature variations and soil quality. We include village fixed effects to account for unobserved characteristics common to a given village. The sample size is 162 households across fifteen villages—these are the households that used both chemical fertilizer and maize residues for soil fertility management in positive quantities (allowing us to estimate their shadow values). Since the left-hand size variable is estimated rather than observed, we bootstrap standard errors.

Table 2.8 shows the results, with the second column repeating the estimation but excluding the households with shadow values in the top and bottom tails (5 percent of the distribution). Overall the results suggest that, controlling for natural capital in the form of soil quality, poorer households—those with a lower asset index, fewer livestock and a lower share of land in maize—derive higher values per kilogram of maize residues. This finding is consistent with previous qualitative work that shows that wealthier households can achieve higher crop yields by practicing fallowing, using chemical fertilizer, or animal manure; for poorer households, these options are more limited (Crowley and Carter 2000). Thus promotion of agricultural technologies centering on crop residues cannot presume their wide availability and no or low cost across all households.

2.6 Conclusion

Together with land and labor, organic resources are used to satisfy a variety of household needs and constitute critical productive resources for small farmers in developing countries. Yet, our understanding of their availability, uses, and monetary values is highly limited. The current research starts filling this literature gap. Given the diversity of smallholder systems in Africa and elsewhere in the developing world, quantifying the economic benefits of maize residues in western Kenya helps establish realistic bounds on the monetary values of organic resources as factors of production. These values can inform the promotion of agricultural technologies and policies.

Our theoretical framework accounts for the long-term benefits of crop residues used in soil fertility management and highlights important tradeoffs when it comes to crop residue use. Our empirical findings show that the shadow price of maize residues is significant—the average value is 5.49-6.90 Kenyan shillings per kilogram or US$0.06-0.08. The shadow price extends beyond fertilizer substitution, including the long-term benefits of leaving crop residues on the field, and is higher for poorer households. Maize stover and cobs make up around 37 percent of the total value of maize production on a typical farm in western Kenya, and constitute about 22 percent of the median household income.

The current socio-economic and policy environments of Kenya and most other nations do not fully support the adoption of sustainable agricultural practices such as retention of crop residues, use of manure and compost, no-till farming, agroforestry, and other practices that enhance soil fertility. It is important that, going forward, the sustainable management of soil resources becomes an integral component of national policies and practical actions

(Powlson et al. 2011). These could include a combination of agricultural extension, information provision, economic incentives, and government regulations. Finding alternative sources for animal feed and household fuel is also important (Lal 2005). Further research is needed to precisely measure the monetary value of organic resources, identify location-specific alternatives to crop and animal residues, and design policies aimed at promoting soil fertility management. These actions are imperative to improve agricultural productivity and assure environmental sustainability and resilience to climate change, and hereby help achieve food security in Sub-Saharan Africa.

Figure 2.1: Map of the research sites.

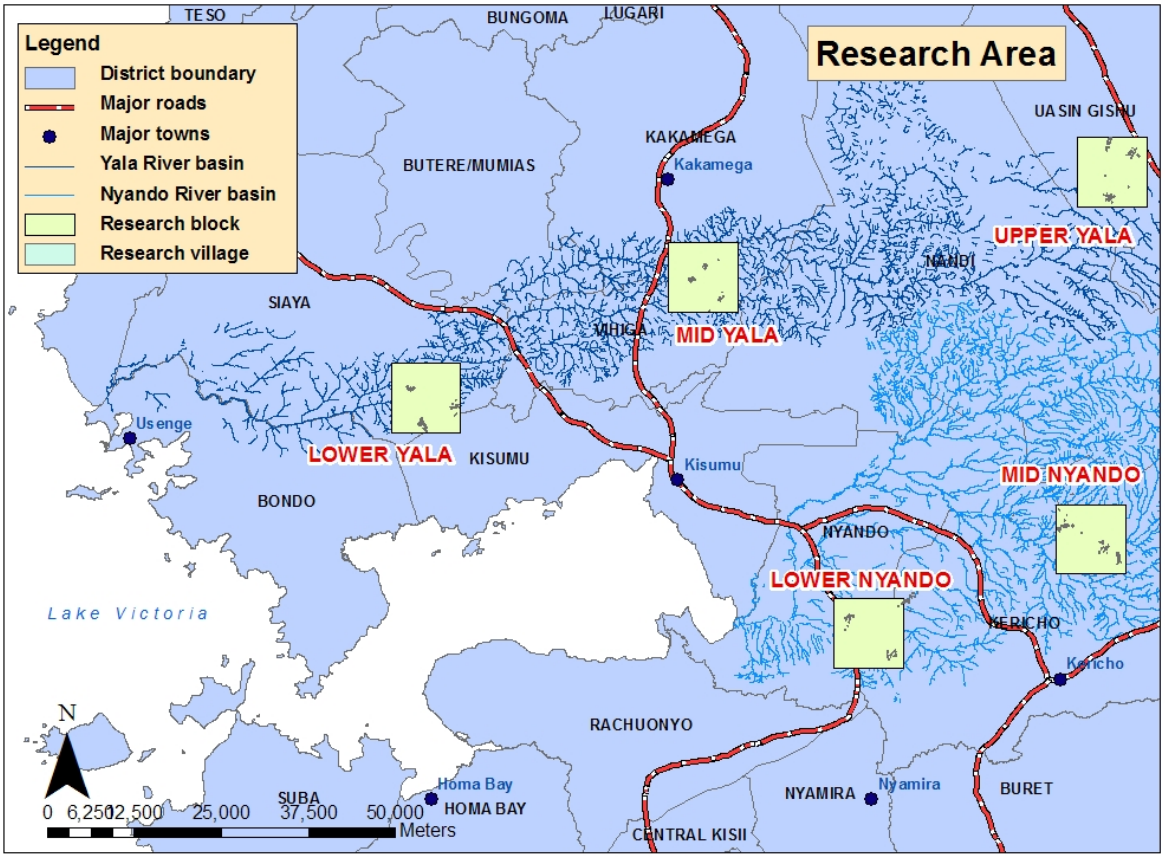

Figure 2.2: Maize grain vs. maize residues (kg/m^2), R^2=0.58.

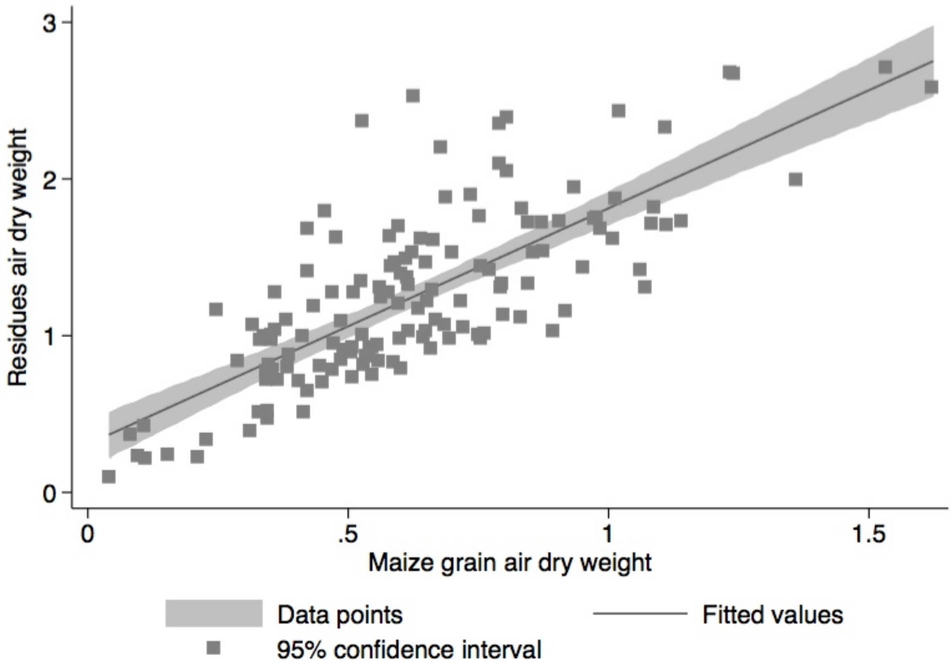

Figure 2.3: Maize residue use by asset index quartile.

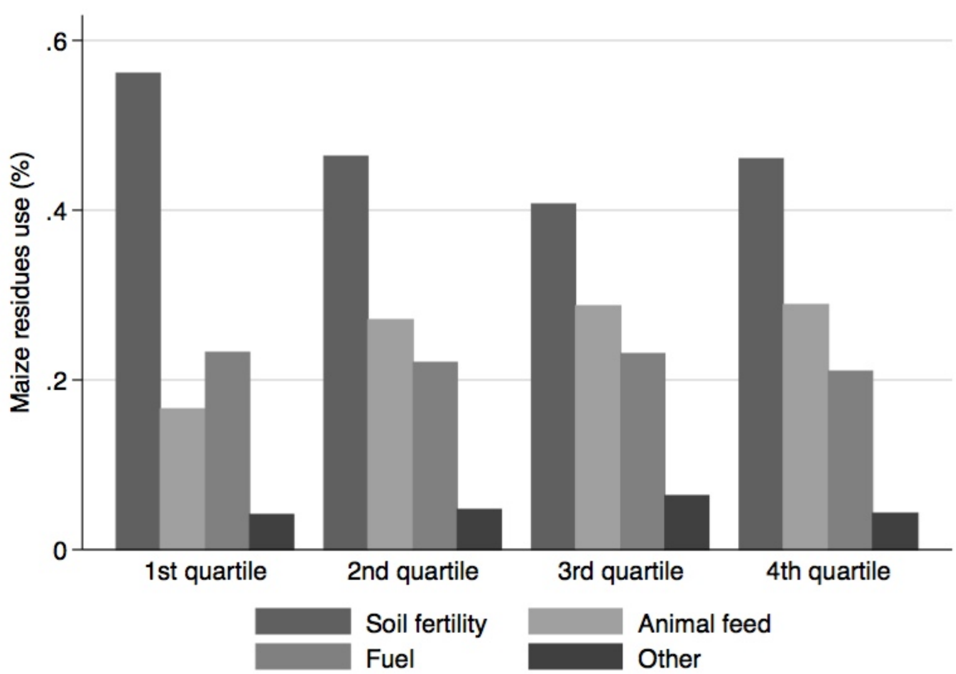

Table 2.1: Summary statistics of variables used.

Variable	Mean	Standard Deviation	Minimum Value	Maximum Value
Gender of household head: 1=male*	0.81			
Household head age	51.41	15.35	20.00	90.00
Household head years of education	6.75	4.53	0.00	18.00
Household size	6.06	2.46	1.00	13.00
Asset index	0.00	1.00	-1.00	5.95
Estimate of household annual income (KES)	146,610	262,733	0	3,674,650
Total land area farmed (acres)	4.53	9.82	0.05	110.00
Land in maize as share of total	0.42	0.27	0.01	1.00
No chemical fertilizer applied*	0.36			
No maize residues applied*	0.17			
Soil pH	5.82 (Low)	0.52	4.35	7.13
Soil nitrogen (% by weight)	0.16 (Very low)	0.09	0.06	0.87
Average plot altitude (m)	1,606	330	1,205	2,258
Herd size (TLU)	2.38	2.71	0.00	17.66
Own livestock*	0.94			
Household-level, across two seasons				
Maize grain harvest (kg)	1,001.81	1,283.24	11.50	10,453.52
Maize land (acres)	1.58	1.22	0.08	7.14
Labor (person-days)	94.14	67.97	11.00	406.00
NPK (kg)	25.28	41.33	0.00	315.00
Fertilizer (kg)	48.26	81.32	0.00	700.00
N (kg)	10.79	18.71	0.00	154.00
Maize residues (kg)	1,521.08	1,579.88	0.00	9,561.73
Fraction of acres planted with hybrid maize	0.58	0.46	0.00	1.00
Fraction of acres intercropped with legumes	0.74	0.39	0.00	1.00

Note: * indicates binary variable. N=309 households.

Table 2.2: Sample soils data by key indicator (N=309).

Indicator	Mean (Ranking)	St. Dev.	Min	Max
Organic carbon content (% by weight)	2.45 (Good)	1.30	0.81	9.45
Total nitrogen content (% by weight)	0.16 (Very Low)	0.09	0.06	0.87
Extractable P (g/kg)	0.013 (Good)	0.015	0.0006	0.1321
Extractable K (g/kg)	0.36 (Good)	0.22	0.05	1.34
Soil pH	5.82 (Low)	0.52	4.35	7.13

Table 2.3: Allocation of maize residues across the main uses.

Variable	Mean	St. Dev.	Min	Max
Share of maize residues to soil fertility management	0.47	0.31	0	1
Share of maize residues to animal feed	0.25	0.27	0	0.9
Share of maize residues to residential fuel	0.22	0.15	0	1
Share of maize residues to other uses	0.05	0.17	0	0.8

Note: N=309 households.

Table 2.4: Household-level maize production function.

Maize grain (kg)	Coefficient	Std. Err.
Maize land (acres)	65.79	(182.7)
Labor days	-0.251	(2.509)
NPK (kg)	0.659	(4.751)
Residues (kg)	0.217**	(0.102)
1/2 Maize land sq.	252.6**	(100.1)
1/2 Labor days sq.	-0.0125	(0.0233)
1/2 NPK sq.	0.0823	(0.0685)
1/2 Residues sq.	0.000133**	(5.27e-05)
Interaction: Land * Labor	-0.135	(1.132)
Interaction: Land * NPK	1.177	(2.006)
Interaction: Land * Residues	-0.250***	(0.0503)
Interaction: Labor * NPK	0.00997	(0.0367)
Interaction: Labor * Residues	0.00127	(0.000856)
Interaction: NPK * Residues	0.000979	(0.00110)
Average plot altitude (m)	0.649***	(0.150)
Soil pH	92.72	(67.85)
Soil nitrogen (% by weight)	125.5	(307.1)
Herd size (TLU)	66.31***	(19.39)
Fraction of acres intercropped with legumes	-26.62	(90.32)
Fraction of acres planted with hybrid maize	-105.9	(87.55)
Gender of household head: 1=male	-79.48	(75.93)
Household head age	-1.464	(2.072)
Household head years of education	1.574	(6.802)
Constant	-1,285**	(540.3)
Observations	309	
R-squared	0.852	
Wald tests	χ^2	Prob> χ^2
Coefficients for land: $\alpha_1 = \alpha_{11} = \alpha_{12} = \alpha_{13} = \alpha_{14} = 0$	38.66	0.00
Coefficients for labor: $\alpha_2 = \alpha_{12} = \alpha_{22} = \alpha_{23} = \alpha_{24} = 0$	3.04	0.69
Coefficients for NPK: $\alpha_3 = \alpha_{13} = \alpha_{23} = \alpha_{33} = \alpha_{34} = 0$	50.24	0.00
Coefficients for residues: $\alpha_4 = \alpha_{14} = \alpha_{24} = \alpha_{34} = \alpha_{44} = 0$	35.42	0.00
All second-order terms: = 0	61.06	0.00

Note: Bootstrapped standard errors in parentheses (1,000 replications). *** p<0.01, ** p<0.05, * p<0.1.

Table 2.5: Household-level marginal physical productivities (MPP), marginal value productivities (MVP), and benefit/cost estimates.

Variable	MPP (kg maize/ unit input)	MVP (KES)	Input price (KES)	Marginal benefit/cost (MVP/input price)
Maize land (acres)	103.36 (335.03)	2,997.44 (9,715.87)	2,110	1.42 (4.60)
Labor (person-days)	0.54 (1.91)	15.74 (55.31)	138	0.01 (0.40)
NPK (kg)	8.11 (5.93)	235.29 (172.04)	146	1.61 (1.18)
Maize residues (kg)	0.21 (0.18)	6.03 (5.33)	5.49	1.10 (0.97)

Note: Standard errors are in parentheses. MPP of NPK and MPP of maize residues are reported only for households with positive input values (N=198 and N=257, respectively). Sample average maize price is 29 KES. Input prices are based on the mean reported prices from the household survey (price of land is the sample average rental price of 1 acre of land, price of labor is the sample average price of 1 person-day of hired labor, and price of NPK is the household-level sample average price of 1 kilogram of NPK (expenditure on chemical fertilizer divided by the quantity of N, P, K in kg). Input price for maize residues is the estimated average shadow value (not adjusted for travel cost). 84 KES = 1 USD (average 2011-2012 exchange rate).

Table 2.6: Shadow price of maize residues (KES/kg).

Variable	Mean	St. Dev.	N
Using market price of NPK			
Value for full sample	6.29	7.43	162
Value for full sample, excluding top and bottom 5%	5.49	4.34	144
Using market price of NPK adjusted for travel cost			
Value for full sample	6.90	9.07	162
Value for full sample, excluding top and bottom 5%	6.05	5.06	144

Note: Calculated using household-specific price of 1 kg of NPK. 84 KES = 1 USD (average 2011-2012 exchange rate).

Table 2.7: Economic value of maize residues in Kenyan shillings (KES) and US dollars (USD).

Variable	Value in KES	Value in USD
Maize residues for soil fertility management per farm	8,351 (8,674)	99 (103)
All maize residues per farm	17,458 (19,526)	208 (232)
Value per acre		
Maize residues per acre	11,239 (6,567)	134 (78)
Maize grain per acre	19,426 (14,924)	231 (178)
Value per hectare		
Maize residues per acre	27,760 (16,219)	330 (193)
Maize grain per acre	47,982 (36,863)	571 (439)

Note: Calculated using 5.49 KES as value of 1 kg of maize residues and 29 KES as price of 1 kg of maize grain. Standard errors are in parentheses. N=309 households. 84 KES = 1 USD (average 2011-2012 exchange rate).

Table 2.8: Household- and farm-level determinants of the shadow value of maize residues.

Value of crop residues (KES/kg)	(1)	(2)
Gender of household head: 1=male	2.717*	0.520
	(1.535)	(1.027)
Asset index from first PC	-1.191*	-1.158***
	(0.638)	(0.394)
Herd size (TLU)	-1.146**	-0.204
	(0.501)	(0.312)
Herd size squared	0.0799	0.0122
	(0.0556)	(0.0323)
Household size	-0.611**	-0.222
	(0.293)	(0.186)
Total land area farmed (acres)	-0.0904	-0.0685
	(0.225)	(0.150)
Land in maize as share of total	-6.663***	-3.220*
	(2.187)	(1.690)
Average plot altitude (m)	0.0762**	0.0298**
	(0.0379)	(0.0129)
Soil nitrogen (% by weight)	15.55	1.194
	(14.22)	(7.392)
Soil pH	3.463*	1.522
	(1.800)	(1.043)
Constant	-115.3**	-42.39**
	(57.80)	(21.01)
Observations	162	144
Village fixed effects	YES	YES
R-squared	0.359	0.384

Note: Bootstrapped standard errors in parentheses (1,000 replications). *** p<0.01, ** p<0.05, * p<0.1. Sample size is the households that used both chemical fertilizer and maize residues for soil fertility management in positive quantities. Column (2) excludes the households with the shadow value in the top and bottom tails (5 percent of the distribution).

APPENDIX

2.A Additional tables

Table 2.A.1: Scoring coefficients (weights) for asset index.

Variable	Weight
Durables: number of	
House	0.411
Radio	0.389
Telephone (mobile)	0.649
Fridge/freezer	0.620
Television	0.688
Electronic equipment	0.559
Air conditioning	0.339
Furniture	0.743
Kettle/iron	0.446
Mosquito net	0.602
Computer	0.529
Internet access	0.351
Electric/gas stove	0.526
Improved stove	0.217
Bicycle	0.332
Motorcycle	0.483
Car/truck	0.568
Bank account	0.699
Generator	0.291
Large battery	0.177
Solar panel	0.338
LPG	0.636
Characteristics: indicator for	
Brick/cement walls	0.700
Mabati (corrugated iron) roof	0.379
Cement/wood floor	0.666
Private piped water	0.447
Water from neighbor	-0.068
Borehole water	0.036
River/stream water	-0.184
No toilet	-0.279
Traditional toilet	-0.293
Improved toilet	0.703
Kerosene light	-0.717
Electricity light	0.763
Solar light	0.112
Observations	309

Table 2.A.2: Specifications of the household maize production function.

Maize grain (kg)	(1) Parsimonious	(2) Quadratic	(3) Environ. vars	(4) All controls	(5) Block dummies	(6) Village dummies
Maize land (acres)	318.8***	176.9	80.63	65.79	75.70	45.51
	(95.02)	(195.2)	(184.2)	(190.5)	(189.7)	(191.5)
Labor days	-0.922	-2.031	-0.0931	-0.251	-0.508	0.0175
	(0.888)	(2.797)	(2.542)	(2.533)	(2.644)	(2.537)
NPK (kg)	19.98***	4.761	0.309	0.659	0.292	0.723
	(2.299)	(5.147)	(4.563)	(4.663)	(4.753)	(4.560)
Residues (kg)	0.0538	0.186*	0.203**	0.217**	0.221**	0.220**
	(0.0676)	(0.109)	(0.0938)	(0.0978)	(0.103)	(0.104)
1/2 Maize land sq.		225.1**	243.7**	252.6**	255.7**	267.1**
		(114.3)	(97.78)	(99.56)	(99.53)	(104.5)
1/2 Labor days sq.		-0.00586	-0.0129	-0.0125	-0.0106	-0.0131
		(0.0248)	(0.0237)	(0.0239)	(0.0243)	(0.0226)
1/2 NPK sq.		0.1000	0.0859	0.0823	0.0811	0.0806
		(0.0721)	(0.0649)	(0.0687)	(0.0682)	(0.0684)
1/2 Residues sq. / 1,000		0.151***	0.133***	0.133***	0.131**	0.136***
		(0.0537)	(0.0513)	(0.0501)	(0.0521)	(0.0507)
Interaction: Land * Labor		-0.0326	-0.109	-0.135	-0.239	-0.257
		(1.216)	(1.149)	(1.159)	(1.128)	(1.085)
Interaction: Land * NPK		0.416	1.210	1.177	1.085	1.121
		(2.240)	(1.956)	(2.004)	(1.946)	(2.046)
Interaction: Land * Residues / 1,000		-253.3***	-246.6***	-249.6***	-244.6***	-243.3***
		(55.71)	(48.50)	(48.35)	(49.44)	(51.94)
Interaction: Labor * NPK		0.0162	0.00875	0.00997	0.0142	0.0110
		(0.0397)	(0.0345)	(0.0356)	(0.0390)	(0.0359)
Interaction: Labor * Residues / 1,000		1.150	1.281	1.273	1.211	1.139
		(0.916)	(0.833)	(0.825)	(0.832)	(0.818)
Interaction: NPK * Residues / 1,000		0.588	0.976	0.979	0.972	0.893
		(1.191)	(1.051)	(1.113)	(1.058)	(1.131)
Average plot altitude (m)			0.601***	0.649***	0.385	-0.120
			(0.141)	(0.158)	(0.333)	(0.555)
Soil pH			85.88	92.72	149.1	245.1*
			(60.60)	(68.09)	(111.8)	(136.4)
Soil nitrogen (% by weight)			95.07	125.5	203.5	269.6
			(309.2)	(302.1)	(339.3)	(349.6)
Herd size (TLU)			59.96***	66.31***	68.90***	66.12***
			(17.99)	(19.15)	(19.28)	(20.14)
Fraction of acres intercropped with legumes				-26.62	-67.30	-90.71
				(92.18)	(98.79)	(95.46)
Fraction of acres planted with hybrid maize				-105.9	-76.11	-179.5
				(95.16)	(111.6)	(125.6)
Gender of household head: 1=male				-79.48	-86.98	-74.84
				(76.87)	(76.52)	(85.96)
Household head age				-1.464	-2.014	-2.425
				(2.085)	(2.077)	(2.463)
Household head years of education				1.574	-0.658	1.613
				(7.121)	(6.838)	(8.012)
Constant	-3.355	216.2**	-1,366***	-1,285**	-1,339	-1,202
	(73.59)	(108.9)	(495.6)	(541.7)	(1,071)	(1,129)
R-squared	0.722	0.826	0.850	0.852	0.854	0.863

Note: Bootstrapped standard errors in parentheses (1,000 replications). *** p<0.01, ** p<0.05, * p<0.1.

Table 2.A.3: Quadratic maize production function: NPK, nitrogen (N), and total fertilizer.

Maize grain (kg)	(1) NPK	(2) N	(3) Fertilizer
Maize land (acres)	65.79	129.8	78.40
	(188.1)	(193.2)	(187.9)
Labor days	-0.251	-0.364	-0.448
	(2.603)	(2.183)	(2.404)
NPK/N/Fertilizer (kg)	0.659	2.004	0.766
	(4.808)	(8.407)	(2.424)
Residues (kg)	0.217**	0.199**	0.202**
	(0.102)	(0.0919)	(0.0938)
1/2 Maize land sq.	252.6***	385.2***	286.4***
	(97.62)	(103.3)	(95.16)
1/2 Labor days sq.	-0.0125	0.0154	-0.00299
	(0.0234)	(0.0204)	(0.0214)
1/2 NPK/N/Fertilizer sq.	0.0823	0.645**	0.0163
	(0.0666)	(0.320)	(0.0154)
1/2 Residues sq. / 1,000	0.133***	0.181***	0.158***
	(0.0489)	(0.0445)	(0.0464)
Interaction: Land * Labor	-0.135	-1.749*	-0.542
	(1.132)	(1.027)	(1.097)
Interaction: Land * NPK/N/Fertilizer	1.177	-2.737	0.664
	(1.953)	(5.181)	(0.977)
Interaction: Land * Residues / 1,000	-249.6***	-281.4***	-258.5***
	(48.75)	(53.38)	(44.76)
Interaction: Labor * NPK/N/Fertilizer	0.00997	0.00442	0.00416
	(0.0364)	(0.0495)	(0.0176)
Interaction: Labor * Residues / 1,000	1.273	0.885	1.037
	(0.840)	(0.584)	(0.740)
Interaction: NPK/N/Fertilizer * Residues / 1,000	0.979	2.911	0.398
	(1.007)	(2.379)	(0.543)
Average plot altitude (m)	0.649***	0.783***	0.654***
	(0.157)	(0.153)	(0.149)
Soil pH	92.72	63.10	87.96
	(68.46)	(64.62)	(68.81)
Soil nitrogen (% by weight)	125.5	210.4	225.3
	(313.0)	(299.5)	(309.4)
Herd size (TLU)	66.31***	53.25***	62.47***
	(19.45)	(15.31)	(16.89)
Fraction of acres intercropped with legumes	-26.62	-46.76	-14.12
	(87.73)	(90.78)	(92.45)
Fraction of acres planted with hybrid maize	-105.9	-61.70	-110.7
	(92.07)	(81.47)	(85.57)
Gender of household head: 1=male	-79.48	-71.18	-87.21
	(76.55)	(74.16)	(75.49)
Household head age	-1.464	-0.262	-1.489
	(2.083)	(2.028)	(2.170)
Household head years of education	1.574	4.787	2.704
	(7.052)	(7.107)	(7.485)
Constant	-1,285**	-1,450***	-1,281**
	(550.0)	(520.9)	(527.5)
R-squared	0.852	0.861	0.858
Shadow price of residues (KES/kg)	6.29 (7.43)	9.74 (17.50)	5.28 (5.43)
Shadow price of residues (KES/kg), excl. top and bottom 5%	5.49 (4.34)	8.81 (8.33)	5.00 (3.74)

Note: Bootstrapped standard errors in parentheses (1,000 replications). *** p<0.01, ** p<0.05, * p<0.1. Column (1) is the same as Table 3. Column (2) repeats the estimation with N (kg) instead of NPK (kg); shadow price is calculated using household-specific price of nitrogen (depending on the fertilizer type). Column (3) repeats the estimation with Total fertilizer (kg) instead of NPK (kg); household-specific price of fertilizer is calculated as price of fertilizer divided by fertilizer amount in kg.

Table 2.A.4: Cobb-Douglas and translog maize production functions.

LN(Maize grain (kg))	(1) Cobb-Douglas	(2) Translog
LN(Maize land (acres))	0.450***	1.473**
	(0.0975)	(0.642)
LN(Labor days)	0.160*	-0.641
	(0.0911)	(0.947)
LN(NPK (g))	0.107**	-1.059*
	(0.0447)	(0.590)
LN(Residues (g))	0.313***	-0.515
	(0.0895)	(1.196)
1/2 Maize land sq.		0.112
		(0.145)
1/2 Labor days sq.		0.150
		(0.210)
1/2 NPK sq.		0.130**
		(0.0606)
1/2 Residues sq.		0.0706
		(0.0860)
Interaction: Land * Labor		-0.119
		(0.134)
Interaction: Land * NPK		0.00638
		(0.0191)
Interaction: Land * Residues		-0.0655***
		(0.0136)
Interaction: Labor * NPK		-0.0149
		(0.0208)
Interaction: Labor * Residues		0.0203
		(0.0143)
Interaction: NPK * Residues		-0.00181
		(0.00206)
Average plot altitude (m)	0.000757***	0.000583***
	(0.000175)	(0.000186)
Soil pH	-0.0890	-0.125
	(0.0969)	(0.0943)
Soil nitrogen (% by weight)	0.589	0.615
	(0.562)	(0.577)
Herd size (TLU)	0.0616***	0.0706***
	(0.0150)	(0.0143)
Fraction of acres intercropped with legumes	0.0968	0.0441
	(0.128)	(0.120)
Fraction of acres planted with hybrid maize	0.297**	0.180
	(0.125)	(0.125)
Gender of household head: 1=male	0.00388	-0.0389
	(0.108)	(0.104)
Household head age	-0.00162	-0.00158
	(0.00291)	(0.00285)
Household head years of education	0.00322	0.00239
	(0.0107)	(0.0110)
No chemical fertilizer applied: =1	0.590	-4.161*
	(0.382)	(2.224)
No maize residue applied: =1	3.871***	0.843
	(1.180)	(7.068)
Constant	-0.832	11.23
	(1.530)	(9.087)
R-squared	0.665	0.714
Shadow price of residues (KES/kg)	11.46 (17.74)	20.00 (120.00)
Shadow price of residues (KES/kg), excl. top and bottom 5%	8.72 (7.17)	7.97 (12.44)

Note: Bootstrapped standard errors in parentheses (1,000 replications). *** p<0.01, ** p<0.05, * p<0.1. Column (1) is the Cobb-Douglas specification with maize grain harvest, land, labor, NPK and residues in log forms. Column (2) is the translog specification. LN(NPK (g)) = LN(NPK (g) if NPK>0), =1 otherwise and LN(Residues (g))=LN(Residues (g) if Residues>0), =1 otherwise.

CHAPTER 3

AGRICULTURAL PRODUCTIVITY AND SOIL CARBON DYNAMICS: A BIOECONOMIC MODEL

3.1 Natural resources, poverty, and climate

The world's poorest billion people mostly live in rural areas, where their livelihoods depend directly on natural capital (Hassan, Scholes, and Ash 2005). They derive a substantial portion of their livelihoods from farmland, forests, and waterways, so that the natural capital is not only an amenity but also a primary factor of production. While natural resources are typically renewable, overuse or mismanagement leads to their depletion and deterioration (Dasgupta 2010). Crop lands stop responding to applications of fertilizer, inland and coastal fisheries become depleted, and excessive deforestation leads to loss of biodiversity. For the poor, especially in fragile environments in Africa and some parts of Latin America and Asia, the reduced stocks and the deteriorated ecosystem services they provide lead to lower land productivity and stagnating incomes, as well as discourage investments in maintaining the natural resource base or in new agricultural technologies needed for sufficient food production. Improving the management of natural resources is, therefore, fundamental to addressing rural poverty.

Management of soil resources in smallholder agriculture of Sub-Saharan Africa (SSA) is of particular concern as depletion of soil fertility is considered to be one of the major biophysical causes of low per capita food production (Sanchez 2002). About 414 million people in the region—up from 290 million people in 1990—live in extreme poverty, and Sub-Saharan Africa remains the region with the highest prevalence of undernourishment (UN 2014). The neglect of the rural sector by governments and the collapse of traditional societies and their practices (e.g., fallowing) over many decades have resulted in the removal of large quantities of nutrients from soils without sufficient quantities of fertilizer or organic resources to replenish them. Almost 40 percent of land across SSA suffer from nutrient depletion, making it the primary source of soil degradation across the continent (Tully et al. 2015). As soils depleted of organic matter and nutrients are less responsive to mineral fertilizers and changing climate, more and more resources are needed to maintain food production. As a result, smallholder farmers in SSA "cultivate marginal soils with marginal inputs, produce marginal yields, and perpetuate marginal living and poverty" (Lal 2004, p. 1626). In addition, degradation of soil resources in SSA leads to numerous environmental concerns, such as water pollution and conversion of natural environments and marginal lands to agriculture, among many others. And some estimates suggest that across SSS climate change will lead to a further 36 percent decline in cereal yields by the end of the century (Ward, Florax, and Flores-Lagunes 2014).

Soil resources also play a major role in the global carbon cycle. Soils and the biomass therein contain about 2,500 petagrams (1 Pg is equal to one billion metric tons) of carbon within a one-meter depth, making soils the largest terrestrial pool of carbon (Woodward et al. 2009). And while agriculture accounts for 20-30 percent of total global greenhouse gas emissions, agricultural soils and biomass also sequester carbon out of the atmosphere (WB 2012). "Climate-smart" farming practices can take advantage of the soil role as a carbon sink and a carbon store and simultaneously reduce emissions. These practices include mulching, retention of crop residues, use of manures, agroforestry, and many others. Lal (2004) estimates that soil carbon sequestration from sustainable use and agriculture could sequester 0.4-1.2 Pg of carbon per year. This amount is equivalent to 5-15 percent of global emissions from fossil fuels.

In this paper, we ask the following questions: what is the optimal management of soil resources in smallholder agriculture in the tropics, what is the potential for increasing yields and sequestering carbon, and what is the value of soil carbon? To answer these questions, we develop a dynamic bioeconomic model of agricultural households in the western Kenyan highlands. Our theoretical bioeconomic modeling framework extends the traditional economic agricultural household model to incorporate the dynamic nature of natural resource management and to integrate biophysical processes through soil carbon management. Using an eight-year panel dataset from an agronomic "chronosequence" experiment in Vihiga and Nandi districts in Kenya and data from household and market surveys, our model combines an econometrically estimated production function and a calibrated soil carbon flow equation in a maximum principle framework. The unique nature of our dataset—a "false" time series, comparable to a quasi-natural experiment and not often available for economic research—allows for estimation of site-specific dynamic relationships between agronomic productivity, land use management decisions, and soil carbon.

We use the model to determine the optimal management of the farming system over time in terms of the application rates of mineral fertilizer and crop residues, taking into consideration initial resource endowments and prices. The combined application of mineral fertilizer and organic resources is required to overcome soil fertility depletion across SSA (Vanlauwe and Giller 2006) and to sequester carbon (Lal 2014). The two inputs fulfill different functions. While the main role of mineral fertilizer is to supply nutrients, organic resources replenish soil carbon and soil organic matter stocks that enhance soil physical, chemical, and biological processes and properties, fundamental for long-term soil fertility and nutrient use efficiency (Blanco-Canqui et al. 2013). The improvement of soil properties not only sustains yields, but also enhances the inherent capacity of soils to buffer against extreme climatic events such as droughts, heat waves, and floods. Moreover, the limited availability and high cost of external inputs, as well as competing uses for on-farm organic resources (fuel and fodder) often discourage the applications of either in sufficient quantities (Vanlauwe and Giller 2006). At the same time, decomposition of crop residues into soil carbon may require additional nutrients, such as nitrogen, phosphorus, and sulfur (Richardson et al. 2014). Understanding how soil resources respond to the combined applications and determining the optimal application rates is, therefore, important for improved resource allocation at the farm level, for national agricultural policy, and for global climate change mitigation.

We find that the optimal management strategies lead to carbon stocks of 20.76-33.28 Mg/ha (in the top 0.1 m) and maize yields of 3.74-4.17 Mg/ha, with discount rates of five to fifteen percent and given the prevailing price levels. Reaching and sustaining these carbon stocks and maize yields, however, requires different applications rates of mineral fertilizer and crop residues for farms with different initial resource endowments, with more depleted soils requiring higher application rates at the outset. Our focus on soil carbon allows us to assess its value and, moreover, permits us to estimate the potential for and impacts of carbon sequestration in the research area. The equilibrium value of soil carbon is high and ranges between 119 and 168 US$/Mg of carbon or 32 and 46 US$/Mg of carbon dioxide equivalent, depending on the discount rate used, highlighting the considerable local private benefits of soil carbon sequestration and suggesting a lower bound on the societal value of soil carbon. Annual soil carbon sequestration rates of 440 and 240 kg/ha can be achieved on depleted and medium-fertility soils, respectively.

The remainder of this paper is organized as follows. Section 3.2 provides a brief review of the existing literature focusing on valuing natural resources and agricultural production in Sub-Saharan Africa, discusses the implications of the static and dynamic analyses, and outlines our paper's contribution. Section 3.3 discusses the soil carbon resources and Section 3.4 introduces our research area, the western Kenyan highlands. Section 3.5 presents our theoretical model. The farmer's objective is to maximize the discounted present value of annual profits from a representative hectare planted with maize over an infinite horizon. Section 3.6 reports the construction of our empirical model, focusing on the econometric estimation of the underlying maize production function, calibration of the soil carbon equation, and the prices used in the analysis, together with introducing the data. Section 4.5 presents the results of the model's steady-state values, current practices vs. optimal decision rules, and sensitivity analyses. Section 4.6 concludes the paper.

3.2 Value of soil resources in agricultural production

A number of qualitative studies focusing on the implications of rural environmental degradation have shed light on how the incomes of rural communities are affected by resource degradation. Yet, there is limited empirical work demonstrating the quantitative importance of natural resources as factors of production (Lopez 1997). Valuing the local natural resource base in the developing world is a challenging task. The subsistence nature of smallholder agriculture means that farmers make production, consumption, and resource allocation decisions subject to considerable temporal uncertainty, both in terms of the biophysical environment (soil quality, rainfall, adverse weather conditions, pests, etc.) and the economic environment (output and input prices, input availability, etc.). Hence, farming systems in developing countries are very complex; they include a large number of interlinked activities, outcomes of which frequently depend directly on the conditions of local natural resources rather than on external input use. Since natural resources affect farming activities through complex biophysical processes, their effects may not be entirely understood and are difficult to quantify. In addition, natural resource management in developing countries has environmental implications that often go beyond farm boundaries, both temporally and geographically, and volatility in markets and prices complicate the analysis (Barbier and Bergeron 2001).

Interest in the impacts of soil resource management on agricultural output dates back to at least the Dust Bowl era of the 1930s in the American Midwest (Thampapillai and Anderson 1994). Recognizing the effects of land use practices and agricultural technologies on agricultural productivity, a rich body of literature in agricultural economics addresses these issues in a static production framework. Specifically for Sub-Saharan Africa, numerous studies address crop responses to fertilizer use, hybrid seeds, and other external inputs or reasons for their limited applications (see, for example, recent studies in Kenya by Marenya and Barrett (2009a), Suri (2011), Duflo, Kremer, and Robinson (2011), and Sheahan, Black, and Jayne (2013)).

At the same time, relatively few studies explicitly recognize the direct impacts of management practices on soil fertility beyond including indicators for farmers' perception of soil quality. Several studies consider the effects of decreasing common pools of biomass or leaving land fallow. Lopez (1997) examines the common village-level stock of biomass and its decline due to reductions in the fallow periods in Ghana. By incorporating village-level biomass as an input in agricultural production, he finds that it is an important factor of production and is often exploited beyond the socially optimal level. Goldstein and Udry (2008) demonstrate the importance of fallows for on-farm soil quality, and hence, profits from agricultural plots left fallow, also in Ghana. As applications of animal manure deliver not only nutrients necessary for plant growth but also help maintain long-term soil fertility, Gavian and Fafchamps (1996) and Sheahan, Black, and Jayne (2013), for example, include indicator variables for manure use, while Marenya and Barrett (2009b) consider the value of livestock as a proxy for manure applications. Only two papers from SSA, to our knowledge, include quantities of animal manure as inputs in crop response models (Teklewold 2012; Matsumoto and Yamano 2011), and only one considers the quantities of crop residues (Chapter 2).

Soil degradation in the current period imposes a reduction in net benefits on the future generation (i.e., user cost); therefore, it ideally needs to be evaluated within an intertemporal framework. Some of the earlier work treating soil as a renewable resource comes from the U.S. For example, Burt (1981) employs a dynamic programming framework to model soil conservation in the U.S. Northwest, using depth of topsoil and the percentage of organic matter therein as the state variables and cropping practices as the control variables. McConnell (1983) uses soil loss as the state variable in a theoretical model of soil conservation to argue that the private and social rates of soil erosion are the same under most institutional arrangements.

Yet, the paucity of detailed information available to economists, such as technical data on rates of soil fertility loss, as well as the inherent complexity of farming systems, has limited the dynamic analysis of soils in developing countries. Some past studies focus on qualitative analysis (see, for example, French (1986)), while others include biophysical variables such as soil nutrients (carbon, nitrogen, phosphorus), organic matter depletion and soil erosion and simulate the effects of land degradation by incorporating parameters estimated in a separate biophysical model into a model of economic behavior. Barbier (1998), for example, combines a linear programming model of economic behavior with agricultural production parameters obtained from the results of the Erosion Productivity Impact Calculator (EPIC) model to study land degradation in Burkina Faso. Wise and Cacho (2011) use the Soil Changes Under Agriculture, Agroforestry, and Forestry (SCUAF) model to derive soil-carbon changes, crop-yield dynamics and tree-biomass accumulation as functions of management variables in a dynamic simulation model to assess the financial viability of agroforestry systems as carbon sinks in Indonesia.

Specifically for western Kenya, two simulation models examine the links between biophysical and economic processes at the farm scale. Shepherd and Soule (1998) develop a simulation model to predict the long-term effects of farming systems on nutrient cycling, plant production and farm income, while Stephens et al. (2012) use a system dynamics model to examine the interactions between natural resource-based poverty traps and food security for small farms in Kenya. Both of these models, however, are descriptive or predictive (not optimization problems), and do not allow for changes in management practices in response to physical changes in soil.

Only when detailed biophysical data from the research area are available and allow for estimation of crop productivity responses and soil condition changes, however, can bioeconomic models truly internalize the effects of land degradation on household intertemporal decisions. In one such example, using plot-level data from field experiments in the Ethiopian highlands, Holden, Shiferaw, and Pender (2005) assess the impacts of land degradation, population growth, market imperfections, and increased risk of drought on household production, food security, and welfare.

Our paper contributes to both static and dynamic strands of the literature. Our dynamic bioeconomic model treats soil fertility as an input in agricultural production and a renewable resource, while the rich agronomic and socio-economic datasets we use allow for the model's precise estimation. We explicitly recognize that agricultural outcomes depend on the conditions of local natural resources and consider soil fertility as a factor of agricultural production. At the same time, we model farm household intertemporal management practices and their effects on current and future agricultural productivity. By doing so, we are also able to assign monetary value to soil fertility and specifically soil carbon, thus quantitatively demonstrating the importance of natural resources as primary factors of production in smallholder agriculture.

3.3 Focus on soil carbon

We focus on soil carbon as the interface between the social and biophysical processes. There are several compelling reasons for doing so. First, there is a strong relation between soil organic carbon (SOC) and soil fertility, on the one hand, and crop productivity and soil fertility, on the other. Although SOC is not essential to plant growth *per se* and its benefits can be to a degree substituted by applying external inputs, the SOC pool is related to the amount of soil organic matter (SOM) with multiple benefits to soil productivity, such as nutrient availability, water-holding capacity, and soil biota, and therefore, on agronomic/biomass productivity (Lal 2006; Blanco-Canqui et al. 2013). Increases in SOC, in addition, not only increase average yields, but also decrease the susceptibility of yields to weather shocks (Graff-Zivin and Lipper 2008).

Land use decisions, such as the conversion of forests to agricultural land, have a major influence on the level of the SOC pool. By removing the bulk of aboveground biomass, conversion to agricultural land breaks the carbon movement cycle in the ecosystem as soil carbon is not replenished fast enough to keep up with decomposition. A large fraction of the accumulated carbon and soil nutrients thus become lost; this generally happens most rapidly in the years immediately after agricultural conversion (Murty et al. 2002). Current agricultural practices in resource-poor economies also deplete the SOC and SOM pools, and by doing so degrade soil quality and have an adverse effect on agronomic productivity. At the same time, agricultural management practices that alter the inputs of organic matter or the decomposition rate of SOM can build up the stock of soil organic carbon. Such practices include leaving land fallow, no-till farming, residue retention, manuring, composting, N fertilization, mulching, incorporation of grass and legumes in the rotation cycle, and the use of agroforestry systems (Lal 2006; WB 2012).

The second reason for our focus on soil carbon is found in the potential of carbon sequestration to simultaneously achieve two sustainability goals: the improvement of agricultural productivity and climate change mitigation (Antle and Stoorvogel 2008). Land use changes and agricultural practices can transfer atmospheric carbon dioxide (CO_2) to soil. With the continuing use of these practices over 20-50 years, observed rates of SOC sequestration can range from 0 to 150 kg C/ha per year in dry and warm regions, and up to 100-1,000 kg C/ha per year in humid and cool climates, depending on soil texture, characteristics and climate (Lal 2004). As a result, it is estimated that soil carbon sequestration from sustainable land use and agriculture could potentially offset the emissions from fossil fuels by 0.4-1.2 Gt C per year, or 5 to 15 percent of the global fossil fuel emissions (Lal 2004).

The third reason for focusing on soil carbon, as Antle and Stoorvogel (2008) note, is the fact that despite great interest in the international community and among national policy-makers, there is little available information about the potential for and impacts of payments for agricultural carbon sequestration from actual projects. By estimating the potential for carbon sequestration and valuing carbon on the western Kenyan farms, we provide such empirical evidence.

3.4 Study area: western Kenyan highlands

The western Kenyan highlands provide our case study. Surrounding Lake Victoria on the Kenyan side, this is one of the most densely populated regions of the country, with over 55 percent of the population living below the national rural poverty line (about US$0.59 per day) (WRI 2007). The complexity of smallholder farming systems in developing countries, as discussed above, also characterizes this research area. Rural households engage in a range of agricultural activities. While their main objective is increasing food supplies (Waithaka et al. 2006), subsistence farmers also strive to earn income and satisfy household energy needs.

Average farms are about 0.5-2 hectares in size and originally formed part of the Guineo-Congolese forest system that became converted to agricultural land in the 20th century. Farms have medium to high agricultural potential (WRI 2007), but suffer from severe soil degradation. The incorporation of crop residues at plowing, crop rotations and short fallows were some of the main means of maintaining soil fertility in crop fields in western Kenya until the 1960s (Crowley and Carter 2000). As population increased and farm areas declined, however, crop rotations and fallowing periods were reduced and most farmers have stopped planting woodlots, making cereal residues the principal on-farm source of fuel. Only wealthier households with larger land holdings have continued fallowing and/or using crop rotations (Crowley and Carter 2000). As a result, the amount of organic material returned to the soil after harvest has significantly declined in the area and maize monoculture has hastened soil deterioration (Solomon et al. 2007).

We examine one of the main agricultural activities of households in rural western Kenya—production of a subsistence crop, maize (*Zea mays* L.). Maize is the most commonly grown and consumed grain in the area, having established itself as a dominant food crop in Kenya at the beginning of the 20th century (Crowley and Carter 2000). Despite its significant contribution to satisfying household food needs and cultivation by most smallholders on the largest proportion of farm area, maize production often results in low yields. Farmer-reported average maize yields are in the range of 1.65 and 2.7 Mg/ha[1] (Sheahan, Black, and Jayne 2013). The potential yields in response to water and nutrient availability for this environmental range, however, are found to be much higher, between 10.8 and 11.4 Mg/ha (Tittonell and Giller 2013).

Low yields correspond to current agricultural practices—no fallowing, limited use of hybrid seeds and mineral fertilizer, as well as organic resources, such as crop residues, animal manures, compost, etc. In fact, the use of maize residues as soil organic amendments is traded off against other applications. Less than half of all residues is left on the field for soil fertility management; the other half is roughly equally split between household energy and animal feed (Chapter 2). Soil carbon stocks, as a result, are heavily depleted (Solomon et al. 2007).

Data from several sources are used to build the bioeconomic model described below. Plot-level maize yields and carbon stocks come from a long-term agronomic experiment in Vihiga and Nandi districts of western Kenya in 2005-2012, while socio-economic household-level data and prices are from the household and market surveys in the districts surrounding the agronomic sites in 2011-2013. The data sources are shown in Figure A.1.2 and further discussed in the sections that follow. Our soil analysis reported the total stocks of soil carbon, which are equivalent to total organic carbon since the soils in the research site are acidic and

[1] 1 megagram (Mg) = 1,000 kilogram (kg) = 1 metric tonne. 1 hectare (ha) = 10,000 square meters.

do not contain carbonates.

3.5 Economic model

Our model is similar to that of Burt (1981): the farmer's objective is to maximize the discounted present value of net returns from the land resource over an infinite planning horizon. Instead of focusing on the depth of topsoil and percentage of soil organic matter to capture soil fertility, however, we use soil carbon as a state variable that influences agronomic productivity, and its flow depends on the choice of farming practices. Adopting the model to a developing-country setting requires some additional considerations. When markets for agricultural outputs or inputs are missing, or when transaction costs are excessive, rural households respond by linking their production and consumption decisions to satisfy multiple objectives of food security, income generation, and risk reduction (de Janvry, Fafchamps, and Sadoulet 1991). This nonseparability in consumption and production also implies that consumption needs and asset distribution have significant impacts on production decisions and thus the management of natural resources (Holden and Binswanger 1998). While small-scale farmers in our study area may face large transaction costs, similar to Wise and Cacho (2011), we argue that profit is an important part of the farmers' objectives. Moreover, we explicitly account for opportunity cost of household labor, land, and organic resources. In addition, we use farmer-reported prices that reflect potential transaction costs and availability constraints and perform price sensitivity analysis. We also only focus on production of maize, the staple cereal, and the practices to manage soil fertility and increase maize yields, abstracting from the farmer's decisions in terms of the amount of land and the choice of crops to cultivate.

Assuming away the variation in farm size (and thus imposing constant returns to scale), suppose a representative farmer cultivates a hectare of land of homogenous quality with maize. Let c_t represent the state of farmer's land in year t, defined by a single soil-quality indicator—soil carbon content. The farmer grows maize by employing a range of land use and management decisions: let f_t be the quantity of mineral nitrogen applied and $\alpha_t \in [0, 1]$ be the share of maize residues left on the field for soil fertility at the end of year t that influences the stock of soil carbon in $t + 1$. Maize production (Mg/ha) is then a function of soil carbon and nitrogen fertilizer: $y_t = y(c_t, f_t)$. The change in soil carbon content depends not only on the carbon content in the previous period, but also on the farmer's management decisions: $c_{t+1} - c_t = g(c_t, f_t, \alpha_t)$, where $g(\cdot)$ is a function describing soil carbon dynamics. The initial level of soil carbon, $c_0 = a > 0$, is given. The farmer earns profit from growing maize and also derives value from having maize residues to be used as cooking fuel, animal feed, or soil organic amendment. Let $\pi_t = \pi(c_t, f_t, \alpha_t) = py(c_t, f_t) + qr_t - nf_t - qr_t\alpha_t - m$ be the annual profit obtained from a hectare planted with maize, where p is the price of maize (\$/Mg), q is the per unit value of crop residues in highest household use (\$/Mg), r_t is the total quantity of maize residues produced in year t (Mg/ha), n is the price of nitrogen (\$/Mg), and m is the per-hectare cost of preparing the land, planting, and harvesting maize (\$/ha).

3.5.1 Farmer's objective

The farmer's objective is then to maximize the discounted present value of annual profits by growing maize on a hectare of land over an infinite horizon, with a discount factor $\rho =$

$1/(1+\delta)$ for the discount rate δ:

$$\max_{\{f_t,\alpha_t\}} \pi = \sum_{t=0}^{\infty} \rho^t [py(c_t, f_t) + qr_t - nf_t - qr_t\alpha_t - m]$$

$$\text{subject to}$$

$$c_{t+1} - c_t = g(c_t, f_t, \alpha_t),$$

$$c_0 = a > 0, \text{given.} \tag{3.1}$$

We assume that total crop residues produced in period t are a fraction of maize yield in period t, so that $r_t = ky_t$, where k is the time-independent conversion parameter (maize residue to grain ratio).[2] Then assuming that f_t, α_t, c_t and λ_t, the multiplier on the soil carbon constraint, are restricted to being nonnegative, the discrete-time current value Hamiltonian can be written as

$$H = py(c_t, f_t) + qky(c_t, f_t) - nf_t - qky(c_t, f_t)\alpha_t - m + \rho\lambda_{t+1}g(c_t, f_t, \alpha_t) \tag{3.2}$$

$$= (p + qk(1-\alpha_t))y(c_t, f_t) - nf_t - m + \rho\lambda_{t+1}g(c_t, f_t, \alpha_t), \tag{3.3}$$

where the multiplier λ_{t+1} can be interpreted as the current-value shadow price of the soil

[2]Residue or straw to grain ratio is a standard conversion parameter to estimate the production of crop residues (Smil 1999).

carbon stock at time $t+1$. The first order conditions require that

$$\frac{\partial H}{\partial f_t} = (p + qk(1-\alpha_t))\frac{\partial y(\cdot)}{\partial f_t} - n + \rho\lambda_{t+1}\frac{\partial g(\cdot)}{\partial f_t} = 0, \tag{3.4}$$

$$\frac{\partial H}{\partial \alpha_t} = -qky(\cdot) + \rho\lambda_{t+1}\frac{\partial g(\cdot)}{\partial \alpha_t} = 0, \tag{3.5}$$

$$\rho\lambda_{t+1} - \lambda_t = -\frac{\partial H}{\partial c_t} = -\left[(p + qk(1-\alpha_t))\frac{\partial y(\cdot)}{\partial c_t} + \rho\lambda_{t+1}\frac{\partial g(\cdot)}{\partial c_t}\right], \tag{3.6}$$

$$c_{t+1} - c_t = \frac{\partial H}{\partial[\rho\lambda_{t+1}]} = g(c_t, f_t, \alpha_t). \tag{3.7}$$

Re-writing the first order conditions, we have the following results:

$$(p + qk(1-\alpha_t))\frac{\partial y(\cdot)}{\partial f_t} + \rho\lambda_{t+1}\frac{\partial g(\cdot)}{\partial f_t} = n, \tag{3.8}$$

$$\rho\lambda_{t+1}\frac{\partial g(\cdot)}{\partial \alpha_t} = qky(\cdot), \tag{3.9}$$

$$\lambda_t = \rho\lambda_{t+1}\left[1 + \frac{\partial g(\cdot)}{\partial c_t}\right] + (p + qk(1-\alpha_t))\frac{\partial y(\cdot)}{\partial c_t}, \tag{3.10}$$

$$c_{t+1} - c_t = g(c_t, f_t, \alpha_t). \tag{3.11}$$

Equations 3.8 and 3.9 equate "full marginal value" to marginal cost for the two management variables, f and α. Full marginal value is the marginal value product in current production plus the marginal value based on the discounted shadow price for carbon in $t+1$. Equation 3.10 is a form of the co-state equation relating the shadow price on carbon in period t to its discounted future marginal value in $t+1$ plus the marginal value product of carbon in production in period t. Equation 3.11 is a restatement of the state equation.

3.6 Empirical model

The construction of the empirical model used to estimate the farmer's maximization problem (Equation 3.1) consists of several steps. We first specify and econometrically estimate the maize yield equation ($y(\cdot)$) as a function of soil carbon stock (to a depth of 0.1 m) (c) and nitrogen fertilizer (f). We then specify and calibrate the soil carbon equation ($g(\cdot)$) to approximate the annual change in soil carbon stock from maize residues left on the field and carbon loss from mineralization. Two management variables of interest are, then, the application rates of nitrogen fertilizer (f) and the share of maize residues left on the field as soil amendments to replenish soil carbon (α). The two equations interactively describe crop-yield dynamics and soil-carbon changes and provide parameters for our biophysical model. As a last step, we describe the economic variables used in the empirical model and their sources before proceeding to the discussion of our results.

3.6.1 Maize yield function

The biophysical data used to estimate the maize yield function come from agronomic experimental sites in Vihiga and Nandi districts of western Kenya. The sites were established in 2005 and maintained until 2012 as a part of a chronosequence experiment designed to analyze the long-term effects of land conversion from primary forest to continuous agriculture (Ngoze et al. 2008; Kinyangi 2008; Kimetu et al. 2008; Guerena 2014). A chronosequence—a set of sites that share similar attributes but are of different ages—was established on twenty-eight farms of different age since conversion from forest to agricultural land.[3] Prior to the establishment of the experimental sites, soils had received very little or no mineral fertilizer since forest clearing, no animal manure, and had been cropped with maize for 5, 20, 35, 80,

[3]A chronosequence is an important tool for studying temporal dynamics of soil development across multiple time-scales (Stevens and Walker 1970).

and 105 years (Kinyangi 2008).

Each year experimental plots received nitrogen mineral fertilizer at a rate of 0 and 120 kg per hectare, and in 2011 and 2012 the nitrogen (N) application rate varied at 0, 80, 120, 160, 200, and 240 kg per hectare. In addition, organic inputs (*Tithonia diversifolia* leaves, wood charcoal, and sawdust) were applied at a rate of 18 Mg of carbon per hectare over three seasons in 2005 and 2006 (6 Mg/ha per season). All other management variables (e.g., type of maize hybrid seed, timing of weeding and harvesting, etc.) were maintained the same across the sites. The four treatments include control (with and without N input), *Tithonia diversifolia* (with and without N input), charcoal (with and without N input), and sawdust (with and without N input). Maize grain yield data (oven-dry measurements) are available for each farm, treatment and year from 2005 to 2012. While the soil samples were collected at 0.1 m depth from experimental plots each year, not all were analyzed for soil carbon stock given the large number of samples involved and therefore the high time and financial cost of soil chemical analysis. A sub-sample, representing three major age groups, each treatment and year (177 samples), was analyzed for total soil carbon after ball milling using a Dumas combustion analyzer. Bulk density was measured using three rings per plot in order to calculate carbon stocks. Following Kinyangi (2008), the resulting data were fitted using a three-parameter exponential decay model, $y = y_0 + ae^{-bx}$, where y_0 is the final carbon equilibrium level, a is the amount of carbon lost (Mg/ha), b is the rate of loss, and x is years since conversion from forest, for each of treatment-fertilizer sub-samples. The established relationships were then used to predict plot-specific soil carbon stocks.[4]

The heterogeneity of soil fertility and the differing impacts of inputs on individual plants on otherwise homogenous farms have been shown to imply a smooth aggregate production function (Berck and Helfand 1990). We use a quadratic specification to approximate the

[4]Soil samples were collected at harvest of the long rains season, so that in the final predictions a lagged variable is used: e.g., a soil carbon stock measured during the harvest of 2005 is used as $c_{t=2006}$, a soil carbon stock relevant for maize production in 2006. The sampling procedure and the construction of soil carbon stock variable are described in Appendix 3.A.

unknown true relationship between maize yields, soil carbon stocks and nitrogen applications, and to capture the interactions between soil fertility and nitrogen inputs. The same functional form is also used in recent studies focusing on maize production and soils across Sub-Saharan Africa (see, for example, Sheahan, Black, and Jayne (2013) and Harou et al. (2014)). We estimate

$$y_{kit} = \gamma_0 + \gamma_c c_{kit} + \gamma_{cc} c_{kit}^2 + \gamma_f f_{kit} + \gamma_{ff} f_{kit}^2 + \gamma_{cf} c_{kit} f_{kit} + \eta_k + \zeta_i + \theta_t + \xi_{kt} + \epsilon_{kit}, \quad (3.12)$$

where y_{kit} is maize yield (Mg/ha) for treatment k on farm i at time t, c_{kit} is the soil carbon stock (Mg/ha), f_{kit} is the nitrogen fertilizer input (Mg/ha), γ_0, γ_c, γ_{cc}, γ_f, γ_{ff} and γ_{cf} are coefficients to be estimated, η_k is a treatment fixed effect, ζ_i is a farm-level fixed effect, θ_t is a year fixed effect, ξ_{kt} is a treatment-year interaction fixed effect, and ϵ_{kit} is the i.i.d., mean zero, normally distributed regression error.

Pooling observations across the eight years, twenty-eight farms, and four treatments, there are 1,450 observations.[5] Table 3.1 shows summary statistics for the variables used.[6] Similarly to Harou et al. (2014), our data and, therefore, estimations focus on locally attainable yield levels, which are defined as the yields from researcher-managed plots or the maximum yields achievable by resource-endowed farmers in their most productive fields (95^{th}-percentile yields in a farmer field survey) (Tittonell and Giller 2013). The average maize yields from the chronosequence experiment are 4.5 Mg/ha, while they are 4.38 Mg/ha for the 95^{th}-percentile of farmers in the household survey conducted in the same area. Our detailed dataset spanning eight years allows us to make credible estimates of the yield re-

[5]The number of observations differs by farm. Several farms exited the chronosequence experiment because of their change in land ownership or farmers decided to discontinue working with the researchers. Some other observations are missing due to outlier status in grain yield measurements or other recording issues. We omit observations with the values of maize yield in the top and bottom one percent of the distribution.

[6]Nitrogen content of maize roots and residues is very low; it averages around 1 percent (for example, 0.7 percent in Gentile et al. (2011), 1.06 percent in Kinyangi (2008), or 1.27 percent in Latshaw and Miller (1924)). We do not add nitrogen in maize residues to nitrogen from mineral fertilizer.

sponse rates to the additions of mineral fertilizer and soil carbon stocks. It does not allow, however, for the incorporation of legume intercropping and additions of animal manure as soil amendments that are also characteristic of the western Kenyan highlands.

Table 3.2 shows the estimated coefficients of the maize yield function, as well as the average marginal productivities for carbon stock and nitrogen fertilizer. The estimation includes farm, year and treatment fixed effects, which control for initial conditions and time-invariant farm heterogeneity (i.e., slope, drainage, etc.), annual changes in rainfall and other weather effects, and the treatments, respectively. Since rainfall may have differential impacts on plots with different treatments, we also include the year-treatment interaction. Column (1) shows the standard errors clustered at the farm level, while column (2) shows bootstrapped standard errors.

The quadratic specification seems to fit the data quite well; the R-squared of the estimated model is 0.50, and we cannot reject the joint significance of the second order terms (a Wald test statistic of 8.16 and a P-value of zero against the $\chi^2(3)$ distribution). For every additional Mg of soil carbon stock, maize yield increases by 0.06 Mg,[7] while an addition of 100 kg of nitrogen fertilizer results in the yield increase of 1,039 kg. Figure 3.2 shows the distribution of the estimated returns to soil carbon and nitrogen application, with the estimated returns to nitrogen being shown for observations with $f > 0$. Of particular interest is the negative coefficient on the interaction term between carbon stock and nitrogen fertilizer. The negative sign suggests substitutability between the two inputs, which is similar to the findings of a comprehensive meta analysis of Chivenge, Vanlauwe, and Six (2011). Synthesizing the results from the 57 agronomic studies of maize yields on smallholder farms across Sub-Saharan Africa, the authors find that overall, the combined addition of organic resources and nitrogen fertilizer results in negative interactive effects on maize yields (about 445 kg/ha as compared to 218 kg/ha in our sample). They argue that the negative interaction effects

[7] Diaz-Zorita, Duarte, and Grove (2002) find a similar relationship: a 1 Mg/ha decrease in SOC is associated with a 0.04 Mg/ha yield loss across 134 farmers' wheat fields in Argentina.

can be explained by an excess amount of nitrogen added: over 70 percent of the studies included in their meta analysis applied at least 100 kg of nitrogen per hectare, which can reduce the agronomic N use efficiency and conceal the possible positive interactions.[8] The N application rate in our sample is 120 kg N/ha for most observations and we find similar agronomic N use efficiency: 12.3 kg of maize grain per 1 kg of nitrogen added, similar to the 13.6 kg of maize grain estimated by Chivenge, Vanlauwe, and Six (2011).[9] Our data and estimation also support the finding of Chivenge et al. (2007) and Chivenge, Vanlauwe, and Six (2011) that the combined applications of organic resources and nitrogen results in lower soil organic carbon than the addition of organic resources alone. This may be attributed to enhanced decomposition of the added organic resources (Knorr, Frey, and Curtis 2005; Khan et al. 2007; Kimetu et al. 2009).[10]

3.6.2 Soil carbon equation

Annual changes in soil carbon stock reflect the balance between carbon outflows and inflows. Outflows are losses through gas fluxes associated with microbial and plant respiration, water and wind erosion, and deep leaching. Inflows include carbon in crop residues, animal manure, compost, and other organic resources (Blanco-Canqui et al. 2013). As a first-step approximation, we model the annual change in soil carbon, $\Delta c = c_{t+1} - c_t$, as a sum of carbon losses in the form of carbon mineralization and carbon additions in the form of maize

[8]Marenya and Barrett (2009b), in contrast, find complementaries between soil carbon and nitrogen fertilizer in the same research area as ours. N applications in their study are much lower—average of 5.21 kg for an average plot size of 0.33 ha (about 16 kg N/ha, similar to farmer-reported application rates in our household survey), while soil carbon is measured as percent by weight as determined by lab analyses.

[9]Agronomic N use efficiency is calculated for the sample averages according to the following formula: N use efficiency = (maize yield on treatment plots—maize yield on control plots)/total N applied.

[10]Our data corroborate this finding. The average maize yield following the addition of organic resources and nitrogen fertilizer is 4.52 Mg/ha as opposed to 3.33 Mg/ha following the addition of organic resources alone; while average total soil carbon stock is lower: 43.69 Mg/ha vs. 48.68 Mg/ha. These differences are also statistically significant (with the p-value=0.0000).

residues left on the field for soil fertility:

$$c_{t+1} - c_t = -Dc_t + A(\alpha_t Fky(c_t, f_t))^B, \tag{3.13}$$

where D is rate of annual soil carbon loss, A and B are parameters calibrated using the Rothamsted Carbon Model for turnover of carbon in soil (Coleman and Jenkinson 1999), F is carbon content of maize residues, and k is maize residue to grain ratio.

According to the Intergovernmental Panel on Climate Change (IPCC) guidelines, the relative soil carbon stock change factor is 0.91 ($\pm$4%) for tropical wet soils with low residue return due to their removal, which implies an average 10 percent annual decrease in soil carbon stock (IPCC 2003). The main loss of soil carbon is carbon dioxide (CO_2) release from the soil surface, referred to as carbon mineralization. This process is mainly a result of microbial decomposition of soil organic matter. While soil organic matter (SOM) is crucial for maintaining overall soil fertility, higher levels of SOM induce greater microbial decomposition rates, leading to higher rates of carbon loss through carbon dioxide mineralization. Using a laboratory experiment to study the impacts of pre-existing SOM on soil mineralization after addition of organic matter in soils from the chronosequence farms, Kimetu et al. (2009) show that carbon losses are greater in the carbon-rich soils than in carbon-poor soils regardless of the quality of the applied organic resource. Total CO_2-C annual mineralization (C loss to C stock ratio) is found to depend on the time in continuous cultivation: it is between 8 and 12 percent over the course of one year. D is assumed to be 0.11.

The main source of soil carbon inputs is maize residues left on the field from previous seasons. Parameters A and B are chosen to fit the equilibrium levels of soil carbon, shown by the Rothamsted Carbon Model for turnover of carbon in soil (Coleman and Jenkinson 1999), calibrated for the geographic location of the chronosequence farms, as well as the equilibrium levels of maize yields.[11] Parameter k is the median value of maize residue to grain ratio in the chronosequence data, while F, carbon content of maize residues, is the weighted carbon content of leaves, stems, and cobs from Latshaw and Miller (1924).

3.6.3 Prices

Economic variables used in the empirical model are prices of maize grain (p) and nitrogen (n), the per-hectare cost of preparing the land, planting, and harvesting maize (m), opportunity cost of maize residues (q), and the discount rate (δ). Socio-economic farm-level data to derive the economic variables come from the detailed household and production survey in the Nyando and Yala river basins of western Kenya in 2011-2012. Price, cost and market data were collected from public sources and interviews with farmers, as well as market sellers and buyers in 2011, 2012, and 2013.

The empirical distributions of prices reported in the household survey are summarized in Table 3.3. They reflect small quantity premiums, travel costs, local availability, and other potential transaction costs. The median price of maize grain (p) is 331 \$/Mg, while the average maize price reported in market surveys is slightly higher, 410 \$/Mg. The main sources of nitrogen in western Kenya are found in the fertilizer mixes: Di-ammonium phosphate (DAP) with a nitrogen content of 18 percent is commonly applied during planting, while urea (N content 46 percent) and calcium ammonium nitrate (CAN) (N content 26 percent) are applied as top dressing. The cheapest source of nitrogen is urea fertilizer (2,070 \$/Mg); all three fertilizer types, however, are commonly applied. To represent local availability and preferences, similar to Sheahan, Ariga, and Jayne (2013), we construct a composite price of nitrogen from the prices of the main fertilizer types, using their relative shares in the

[11] The procedure used to calibrate the Rothamsted Carbon Model and estimate the equilibrium levels of soil carbon in the research area is developed by Dominic Woolf. This procedure and our choice of A and B are described in Appendix 3.B.

household survey as weights.[12] The composite median price of nitrogen (n) is 4,434 \$/Mg (its equivalent from the market surveys is 4,390 \$/Mg).

The per-hectare cost of preparing the land, planting, and harvesting maize (m) includes the additional monetary and opportunity costs incurred during maize production—the cost of seeds, transportation, equipment, sacks for storage, etc. as well as paid and household labor and land rental value. The opportunity cost of household labor is calculated by multiplying the number of days worked by household members and an average agricultural daily wage of 100 Kenyan shillings. To account for the opportunity cost of land, we run a hedonic analysis of land characteristics using the reported land rental value for the households that rented in or rented out parcels during the household survey. Parcel characteristics include perceived soil type and quality, as well as measured soil carbon content and parcel altitude. We then use the estimated coefficients to calculate the average land rental value in the entire sample of surveyed households.[13]

The use of maize residues for soil fertility management among western Kenyan farmers is traded off against two other competing uses of biomass: household energy and livestock feed. The household survey shows that currently about a quarter of maize residues is used as fuel, another quarter is allocated for feeding animals, and the remaining half is left on the field, mulched, or collected to apply as organic soil amendments. Chapter 2 estimates the value of maize residues left on the fields for soil fertility management, using the same household survey. The median value (q) is 58 \$/Mg and it is similar to the value of crop residues in other household uses. While very few households in the survey purchased livestock feed, many bought fuelwood. Specific energy, energy per unit mass that is often used for

[12] The formula used is the following: n=price of DAP/0.18 $\times$ 0.69 + price of urea/0.46 $\times$ 0.16 + price of CAN /0.26 $\times$ 0.15. The weights (0.69 for DAP, 0.16 for urea and 0.15 for CAN) are derived from the household survey.

[13] The hedonic regression and the distribution of all prices used in the analysis are reported in Appendix 3.C. While we recognize the difference between land rental value and the longer-term value of owned land, as well as other limitations of the hedonic analysis (Palmquist 2005), it is not the primary focus of our analysis. We use this strategy to approximate average opportunity cost of land in the area.

comparing fuels, of mixed fuel and maize stover and cobs in western Kenya is very similar (Torres-Rojas et al. 2011).[14] The mean (median) price of fuelwood in the household survey is 77 (61) $/Mg.

Another critical factor affecting farmers' investment in soil resource conservation is the extent to which they discount the future. Higher discount rates lead to lower than optimal steady-state stocks of renewable resources and faster depletion rates of non-renewable resources (Hotelling 1931; Clark 1990). Previous empirical research suggests that the discount rates implied by behavior in field studies or in experimental settings exceed market interest rates, yet they show significant variability in the estimates and suffer from numerous challenges that tend to bias the estimates upward (Frederick, Loewenstein, and O'Donoghue 2002). While there are fewer studies in developing countries, the ones that exist point to additional challenges of constrained credit markets and their implications for discounting and borrowing (Pender 1996). To approximate smallholders' discount rates in western Kenya we surveyed lending institutions—banks, micro-finance institutions, market traders, etc.—in the research area. The survey also showed significant variability: the annual interest rate ranges from 3 to 24 percent, depending on the type of loan, amount, and lending institution. We use the discount rate of ten percent and check the results for the discount rates of five and fifteen percent.

All prices are quoted in US dollars using the 2011-2012 average exchange rate of 84 Kenyan Shillings (KES) per 1 US dollar (USD). Values for the agronomic and economic variables and prices used in the model together with their sources are summarized in Table 3.4.

[14]It is 17.2 MJ/kg for mixed wood, 17.3 MJ/kg for maize stover and 16.9 MJ/kg for maize cobs.

3.6.4 Difference in resource endowments: three soil fertility levels

The wealth of a household can also be measured by its natural resource endowment. Farms with better soil fertility enjoy higher maize yields that may translate to higher profits and assets. Moreover, richer households are found to be more patient (implying lower discount rates) (Pender 1996; Tanaka, Camerer, and Nguyen 2010). To account for the difference in resource endowments, we vary the initial soil carbon stock: $c_0 = 14.00$, 19.12, and 36.13 Mg/ha. The values correspond to farms with depleted, medium-fertility, and fertile soils. They are the 5^{th}, 50^{th}, and 99^{th}-percentile of the distribution of soil carbon stocks on maize plots in the three household survey villages closest to the chronosequence sites.

3.7 Results and discussion

The empirical implementation of the model described in Section 3.5 and parametrized in Section 3.6 maximizes the discounted net present value of maize production over a 50-year horizon, which is defined as the sum of the discounted net revenue from maize production over the interval $t = 0, 1, ..., T-1$ and a final function in period $t = T$. We assume that the infinite-horizon problem asymptotically converges to the full steady-state values. We approximate this convergence in a finite-horizon problem with the final function $\Psi(c_T) = -\frac{1+\delta}{\delta}(c_{ss} - c_T)^2$. The final function penalizes any actions that would deplete soil carbon as t gets closer to T.

The solution of our bioeconomic model results in the optimal decision rules for the two management variables—nitrogen input (f_t) and share of residues (α_t)—and the associated values of soil carbon (c_t) and maize yield (y_t). Prior to solving the finite-horizon problem, with final function, we determine the steady state of the infinite-horizon problem which can be compared to the terminal carbon stock in the finite-horizon problem, c_T. We then discuss the sensitivity of the infinite-horizon steady state to discount rate and prices.

3.7.1 Steady-state analysis

We first look at the steady-state equilibrium to answer the question whether the optimal management strategies would ever be sustainable *ad infinitum*. For the steady-state equilibrium to exist, we need $f_t = f > 0$ and $\alpha_t = \alpha > 0$. The functional forms in Equations 3.12 and 3.13 and $c_{t+1} = c_t = c$ imply the following first order conditions:

$$\lambda ABF(\alpha Fky(c,f))^{B-1} - (1+\delta)q = 0, \tag{3.14}$$

$$[p + qk(1-\alpha) + \rho\lambda AB(\alpha Fky(c,f))^{B-1}\alpha Fk][\gamma_f + 2\gamma_{ff}f + \gamma_{cf}c] - n = 0, \tag{3.15}$$

$$[p + qk(1-\alpha) + \rho\lambda AB(\alpha Fky(c,f))^{B-1}\alpha Fk][\gamma_c + 2\gamma_{cc}c + \gamma_{cf}f] - (\delta + D)\rho\lambda = 0, \tag{3.16}$$

$$A(\alpha Fky(c,f))^{B} - Dc = 0. \tag{3.17}$$

It can be shown that c_{ss} will be locally stable if and only if $|\theta'(c_{ss})| < 1$, where $\theta(c_t; f_t, \alpha_t) \equiv (1-D)c_t + A(\alpha_t Fky(c_t, f_t))^B$ (Conrad 2010). Given the parameters in Table 3.4, we can simultaneously solve Equations 3.14, 3.15, 3.16, and 3.17 to get the endogenously determined equilibrium values for share of maize residues to leave on the field for soil fertility, rate of nitrogen application, and soil carbon stock (Table 3.5). For δ = 10%, α_{ss} = 0.54, f_{ss} = 0.13 Mg/ha, c_{ss} = 25.63 Mg/ha, and the corresponding y_{ss} = 3.91 Mg/ha. The equilibrium value of soil carbon stock, c_{ss} = 25.63 Mg/ha, is the same as the long-term equilibrium value of soil carbon obtained with the Rothamsted Carbon Model. Both α_{ss} = 0.54 and f_{ss} = 0.13 Mg/ha are higher than the current farming practices in western Kenya. The average application rates in the household survey are 0.47 for maize residues and 0.018 Mg/ha for nitrogen fertilizer. Higher steady-state α_{ss} also corresponds to higher maize grain and residue yield. The equilibrium maize yield (y_{ss}) is 3.91 Mg/ha, which is almost double the average yield reported in the household survey.

The steady-state analysis suggests that the optimal management strategies can be achieved and will be sustainable, leading to high levels of soil carbon stock and associated increases in maize production. These levels of soil carbon and maize yield are, however, dependent on the discount rate (Table 3.5). A lower discount rate ($\delta = 5\%$) results in a higher steady-state stock of soil carbon and maize yield ($c_{ss} = 33.28$ Mg/ha and $y_{ss} = 4.17$ Mg/ha, respectively). This is consistent with other empirical studies that demonstrate the inverse relationship between discount rates and household profits and assets (Pender 1996; Tanaka, Camerer, and Nguyen 2010).

The price of maize grain, nitrogen and maize residues used are the median values of the respective empirical distributions of prices reported in the household survey and estimated in Chapter 2. They are subject to small quantity premiums, travel costs, local availability, and other potential transaction costs. To explore the sensitivity of the steady-state results to the changes in prices, we use additional information from the empirical distributions. Assuming $\delta = 10\%$, the top panel of Table 3.6 shows the steady-state values of α_{ss}, f_{ss}, c_{ss}, y_{ss}, and λ_{ss} when we simultaneously change the values of p, n and q: use either median or mean value, as well as decrease the average values by subtracting or adding 50 or 25 percent of the respective standard deviations ($\mu - 0.5\sigma$, $\mu - 0.25\sigma$, $\mu + 0.25\sigma$, $\mu + 0.5\sigma$). Our results hold up to the price values in the range of $\mu - 0.5\sigma$ to $\mu + 0.5\sigma$. As all prices go up, the steady-state share of maize residues (α_{ss}) decreases, and so do the value of carbon stock (c_{ss}) and maize yield (y_{ss}). In the bottom panel, we alter one prices at a time. We keep the price of maize (p) at its median value, and increase or decrease either price of nitrogen (n) or value of crop residues (q) (by 25 percent from its median value). There is a clear trade-off between nitrogen fertilizer and maize residues. As the price of nitrogen increases, the steady-state value of f_{ss} goes down and the steady-state value of α_{ss} goes up (and the other way around). Higher values of α_{ss} also correspond to the higher carbon stock (c_{ss}) and the corresponding yield (y_{ss}). They can be achieved either with a lower price of crop residues or a higher price of nitrogen.

3.7.2 Value of carbon

In steady state the shadow price of soil carbon is given by Equation 3.16. When $\delta = 10\%$ and with median prices, Equation 3.16 implies $\lambda_{ss} = 137.93$ \$/Mg (Table 3.5). The shadow price of soil carbon is the present value of one Mg of soil carbon when maintained for the rest of time. And it is considerably higher than the net marginal benefit of an additional unit of soil carbon in maize production, $p(\gamma_c + 2\gamma_{cc}c_{ss} + \gamma_{cf}f_{ss}) = 21$ \$/Mg, thus confirming the benefit of the dynamic analysis.

Our steady-state shadow price of soil carbon, 138 \$/Mg of carbon or 38 \$/Mg of carbon dioxide equivalent (CO_2e),[15] is substantially higher than the majority of the existing national and sub-national carbon pricing instruments. Carbon dioxide prices in the European Union Emissions Trading System remained in the range of 5-9 \$/Mg of CO_2e in 2013 (WB 2014), and the average price for forestry offsets in 2012 was 7.8 \$/Mg of CO_2e (Peters-Stanley, Gonzalez, and Yin 2013). At the same time, our price is closer to the global shadow cost of carbon based on the estimates of future climate change damages. Two recent estimates of the social cost of carbon are 35.8 \$/Mg of CO_2e for the preferred 3 percent constant discount rate (IWG 2010, 2013) and 18.6 \$/Mg of CO_2e for declining discount rates (Nordhaus 2014). It is also similar to 35 \$/Mg of CO_2e, the inherent value of soil organic carbon, estimated as the "hidden cost" of soil carbon restoration though biochemical transformation of biomass carbon in Lal (2014).

Our estimates of soil carbon value highlight the considerable local private benefits of carbon sequestration in the form of soil fertility improvements and increased maize yields. They also suggest a lower bound on the societal value of soil carbon, which should also include the monetary equivalent of all ecosystem services provisioned by a unit of soil carbon (Lal 2014).

[15] Conversion from carbon to carbon dioxide is done by multiplying the amount of carbon by 3.667 (WB 2012).

3.7.3 Current practices vs. optimal decision rules

We start by running the model with the average values for f and α from the household survey to approximate the current practices of farmers in western Kenya. This simulation is instructive for the calibration of the model and to observe the change in soil carbon if current practices are preserved. Not surprisingly the soil carbon stock rapidly declines from the initial levels to the steady state of 11-14 Mg/ha and the corresponding maize yield of 0.78-1.11 Mg/ha (see Figure 3.3). Similar carbon stocks and maize yields are observed in the household survey. Soil carbon stocks are lower than 19 Mg/ha and maize yields are lower than 1.26 Mg/ha for half of the households in the three villages closest to the chronosequence farms.

We then allow the model to maximize the discounted profit over 50 years with $\delta = 10\%$. Soil carbon stocks reach the steady-state level ($c_{ss} = 26$ Mg/ha) for the three farm types in 35 years (Table 3.7, Figure 3.5 shows the time paths for the first 35 years). For farms with depleted and medium-fertility soils, soil carbon stock increases; for farms with fertile soils, however, it declines from $c_0 = 36$ Mg/ha to $c_{ss} = 26$ Mg/ha, with the largest decrease in the first ten years. This is consistent with the results of Kinyangi (2008) from the same sites. Following land conversion from forests to agricultural land, Kinyangi (2008) finds significant loss of soil carbon pool during the first 11 years of continuous maize cultivation even with additions of mineral fertilizer. On a global scale, Davidson and Ackerman (1993) find that between 20 and 40 percent of soil carbon is lost following conversion to agriculture in various ecosystems worldwide, with most of this loss occurring within the first few years following conversion.

The World Bank Report "Carbon Sequestration in Agricultural Soils" finds that soil carbon sequestration reaches saturation for most of the land management technologies in the first 25 years (WB 2012). This is true in our analysis. Over first 25 years, the soil carbon stock on farms with depleted soils increases by 11 Mg/ha, with an average annual increase of 440 kg/ha of carbon. And for farms with medium soil fertility the average annual increase is 240 kg/ha. These two rates are similar to 375 kg/ha of annual soil carbon sequestration found from the use of crop residues for soil fertility management across the 46 studies in Sub-Saharan Africa (WB 2012).[16] And this average rate is similar to the rates from applying mulches, planting cover crops, and practicing no-tillage.

Reaching and sustaining the steady-state values of soil carbon and corresponding maize yields requires different initial management strategies for the farms with different soil fertility (Figure 3.4). For farms with depleted and medium-fertility soils, the optimal rate of nitrogen input and share of residues are high from the beginning: $f_0 = 0.16$ Mg/ha and $\alpha_0 = 0.64$ for farms with depleted soils and $f_0 = 0.15$ and $\alpha_0 = 0.59$ for farms with medium-soil fertility. Maintaining high maize yields on farms with fertile soils is, however, initially possible with much lower rates: $f_0 = 0.10$ Mg/ha and $\alpha_0 = 0.47$. As soil carbon stock declines, higher applications rates are required (see Table 3.7).

The equilibrium maize yield due to the optimal decision rules in our model is similar to the average yields from the researcher-managed chronosequence plots. Using the data from the nearby Vihiga, Kakamega, and Teso districts and simulations of the soil-crop dynamic model of nutrient balances (DYNBAL), Tittonell et al. (2006, 2007) also find that maize grain yields increase with increasing contents of soil carbon and nitrogen, with the potential maize grain yields varying between 10.8 and 11.4 Mg/ha. Their yields are much higher than the yields shown by our model. In addition to the soil-crop interactions, we also consider the socio-economic constraints, such as high prices of external inputs, competing uses for maize residues, and farmers' time preferences. Our results, hence, are more reflective of both biophysical and socio-economic constraints on production.

[16] The report's calculation of the average carbon sequestration rate is based on estimating the cost-effectiveness of the land management practices, assuming the discount rate of 9 percent and the adoption period of 25 years (WB 2012).

The difference in the present value of profit from a representative hectare of land is also observed between the farms with different initial soil fertility (Table 3.7). The profit is greatest for the farms with the best initial conditions (6,870 $/ha)—farms with high starting values of soil carbon stock. This finding highlights the importance of initial natural resource base for maize yields and consequent farmer livelihoods: high initial carbon stocks allow for maintaining soil fertility over time with lower initial rates of costly external inputs, while low initial carbon stocks require substantial fertilizer applications from the start, in the range of 150-160 kg/ha, and in their absence may give rise to "soil degradation poverty traps" (Marenya and Barrett 2009b; Stephens et al. 2012).

3.8 Conclusion

We examine the link between natural resources and agricultural production in smallholder systems of western Kenya. Our findings show that regardless of the initial soil fertility levels it is agronomically possible to double maize yields and increase and maintain large stocks of soil carbon. The optimal management strategies lead to maize yields of 3.74-4.17 Mg/ha and carbon stocks of 20.76-33.28 Mg/ha (in the top 0.1 m), with discount rates of five to fifteen percent and given the prevailing price levels. Reaching and sustaining these high maize yields and soil carbon stocks, however, requires considerable application rates of mineral fertilizer and organic resources. Combining applications of both mineral fertilizer and organic resources takes advantage of the positive effects on soil quality, and this has future benefits in the form of increased productivity. The process of transformation of crop residues into soil carbon also requires additional nutrients such as nitrogen (Lal 2014). Application rates also depend on the initial condition of soil fertility. For farms with depleted and medium-fertility soils, the optimal rates of nitrogen input and share of residues are high from the beginning (0.15-0.16 Mg/ha and 0.47-0.59, respectively), while fertile soils permit lower applications rates initially. Better initial natural resource endowment (more fertile soils) also translates to higher profits: the discounted net present value of agricultural profits from a representative hectare of land is US$6,870 for farms with fertile soils, and reduces to $4,537 and $3,814 for farms with medium-fertility and degraded soils, respectively.

The question remains why the optimal practices as shown by our model diverge from the current practices of western Kenyan farmers. We believe there are several explanations. Farmers' investment in long-term soil resource conservation is necessarily influenced by their time and risk preferences. High rates of time preference, for example, can lead to lower than optimal steady-state stocks of renewable resources and faster depletion rates of non-renewable resources (Hotelling 1931; Clark 1990). In our model, the equilibrium value of soil carbon stock is the lowest with the highest discount rate (20.76 Mg/ha for the discount rate of 15 percent). High rates of time preference lead to lower application rates of organic resources and mineral fertilizer, lower yields, and agricultural profits, thus perpetuating soil degradation and poverty. Uninsured risk has also been shown to be a binding constraint on farmer investment (Shively 2001; Karlan et al. 2012).

Another explanation is in imperfect capital markets and farmers' liquidity constraints. Our model does not impose any constraints on capital—it assumes that farmers can purchase nitrogen fertilizer in required quantities. There are reasons to believe, however, that financial market imperfections can hinder optimal agricultural investments by smallholder farmers (Beaman et al. 2014). Moreover, cash liquidity constraints and poverty in assets can also be correlated with higher rates of time preference (Holden, Shiferaw, and Wik 1998). In our household survey, richer farmers[17] apply, on average, 23 Kg/ha of nitrogen fertilizer, with some plots receiving 100-130 kg/ha, similar to the optimal rate. The richer farmers, therefore, are more likely to invest in soil conservation.

[17] Richer farmers are those with the asset index, derived from a factor analysis on household durables and housing quality (Sahn and Stifel 2003), in the top quartile of the distribution.

Yet, another explanation can be due to information-related barriers (Foster and Rosenzweig 1995). Some recent evidence suggests that farmers across Sub-Saharan Africa do not significantly vary input application rates according to perceived soil quality (Sheahan and Barrett 2014). Smallholder farmers may not possess the information about sustainable soil fertility management. Public agricultural extension programs, one of the main sources of agricultural information in Kenya, have been found to have limited impact on agricultural technology adoption and have also been criticized for their poor quality (Aker 2011). Since information is rarely costless and symmetric in developing countries, information constraints can be an important barrier to adopting soil fertility management practices.

Moreover, high application rates of maize residues can be achieved in smallholder systems only if alternative sources for competing uses are identified and made available. Removing crop residues for fodder and fuel are prevailing practices throughout the developing world in the tropics and subtropics (Lal 2006). In the absence of readily available and affordable substitutes, removing crop residues from agricultural fields contributes to depletion of soil fertility, thus decreasing agronomic productivity and reducing fertilizer efficiency. Sustainable management of soil resources that are fundamental in agrarian societies, therefore, needs to become part of any government policy or program aimed at improving agricultural productivity, achieving food security, and eliminating poverty. Such strategies could include fertilizer subsidies, extension services, establishment of biofuel plantations on degraded and marginal lands, and improving access to credit.

Our analysis also has implications for global climate policy debates in terms of understanding the potential of soil carbon sequestration in mitigating climate change. Our findings show that in the western Kenyan highlands considerable amounts of carbon can be sequestered over 25 years. The soil carbon stock changes for depleted and medium-fertility soils equate to an average annual increase in soil carbon of 440 and 240 kg C/ha, respectively. Our findings also show high equilibrium on-farm value of soil carbon: it ranges between 119 and 168 US$/Mg of carbon or 32 and 46 US$/Mg of carbon dioxide equivalent, depending on the discount rate used. These estimates highlight the considerable local private benefits of carbon in the form of soil fertility improvements and increased maize yields and suggest a lower bound on the societal value of soil carbon.

In this paper we consider profit maximization as the only objective of farming households and soil carbon as the state variable. To account for other objectives of farming households and the existing socio-economic and biophysical constraints, the objective function could be further extended to incorporate, for example, the objective of food security; additional constraints and farming practices can also be included. The model set-up also allows us to introduce participation in a Clean Development Mechanism project to receive payments for carbon sequestration services, as in Wise and Cacho (2011). The income provided by carbon payments could partially counteract the effects of high discount rates and we expect in this scenario it would be possible to achieve even higher soil carbon stocks and corresponding maize yields.

Figure 3.1: Map of the research farms and villages.

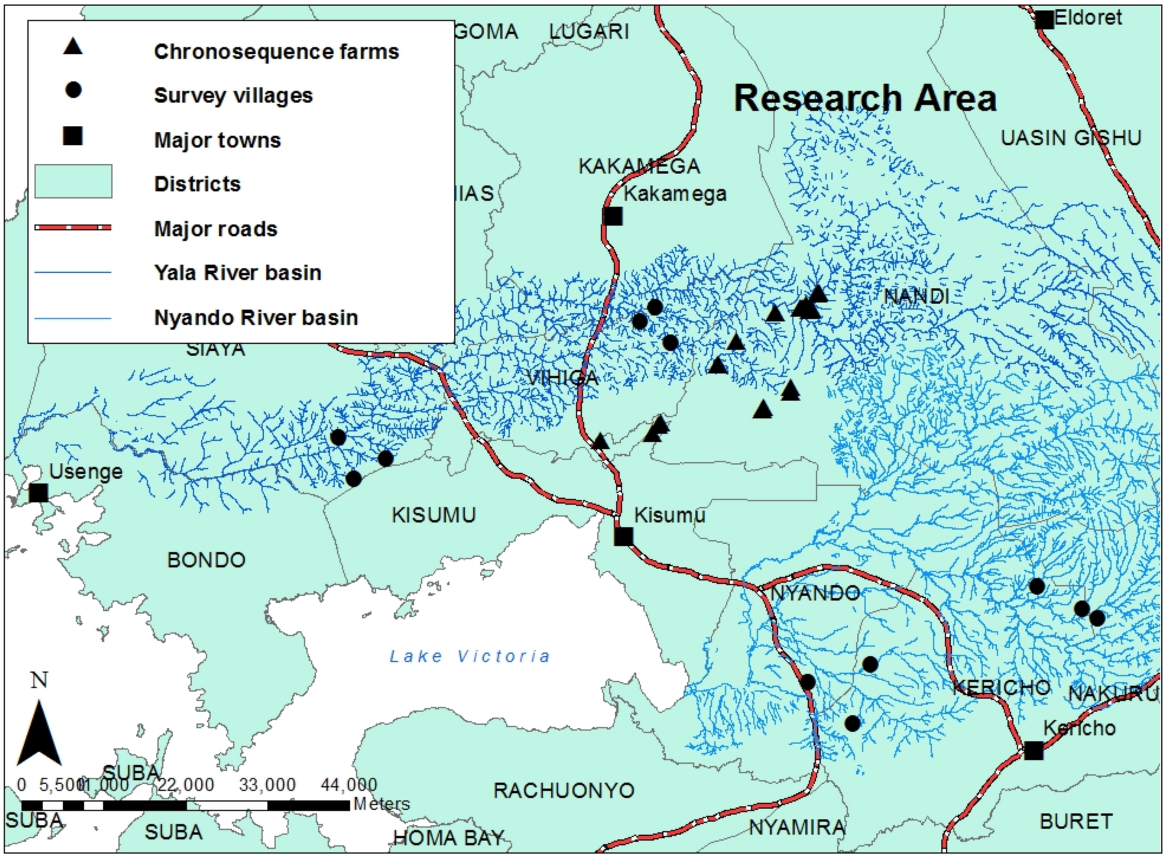

Figure 3.2: Estimated returns to soil carbon, dYdC, (N=1,450) and nitrogen fertilizer, dYdF, (N=882 observations with $f > 0$).

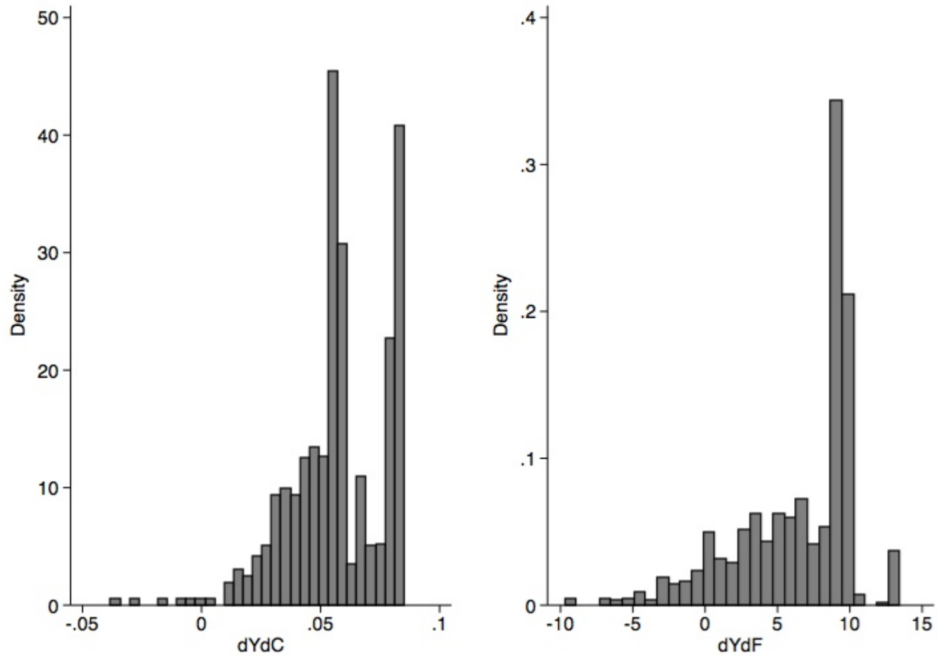

Figure 3.3: Current practices: f=0.018 Mg/ha and α=0.47 for depleted, medium-fertility, and fertile soils.

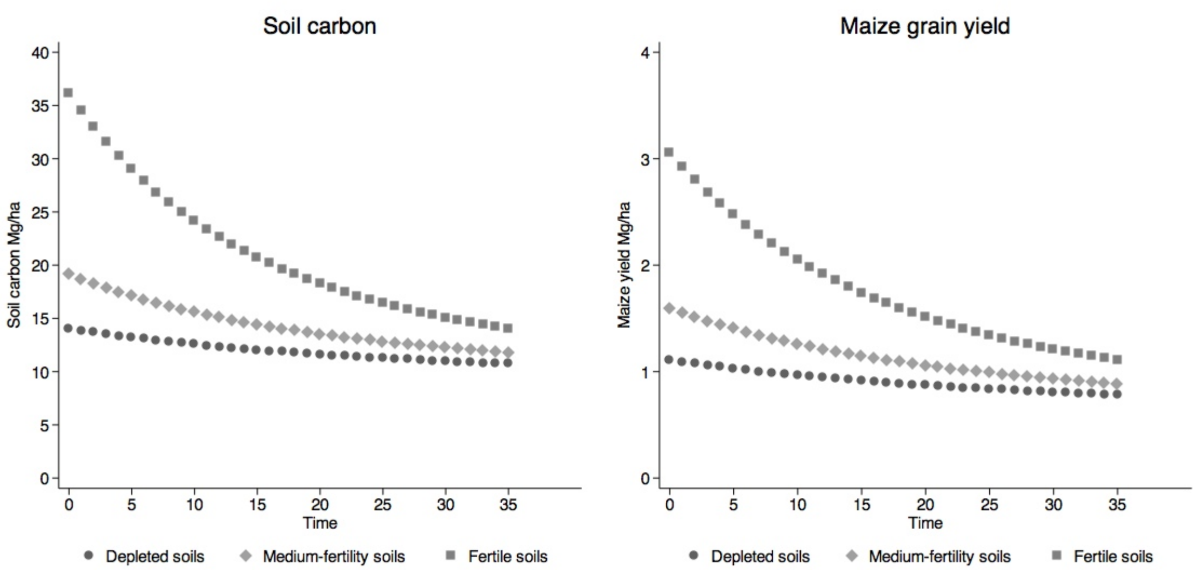

Figure 3.4: Optimal decision rules: time paths for nitrogen input, f_t, and share of residues for soil fertility management, α_t (δ=10%).

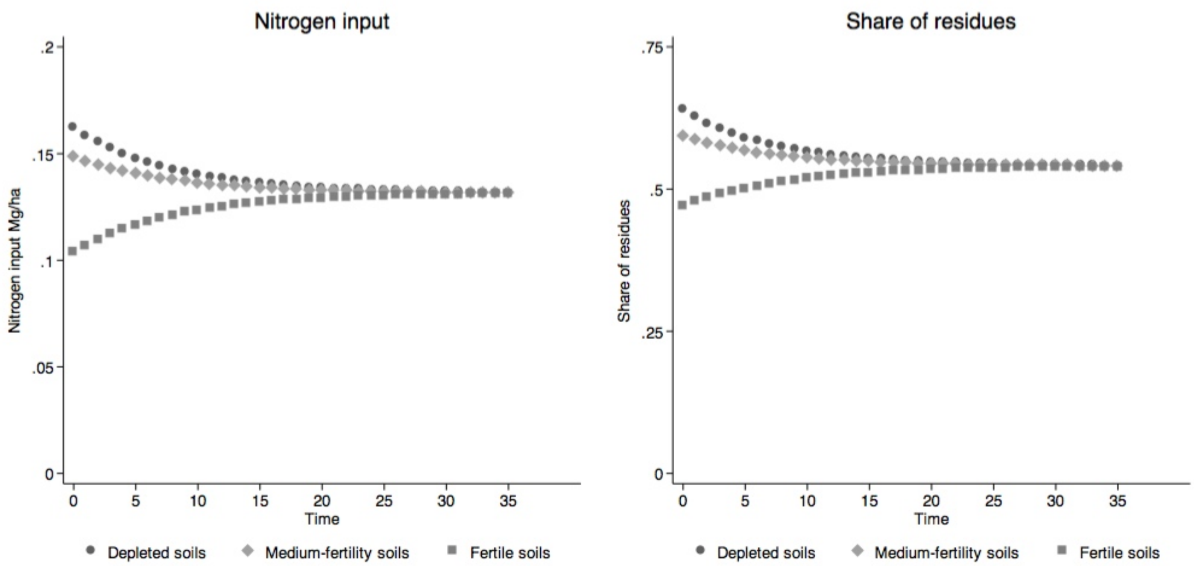

Figure 3.5: Optimal decision rules: time paths for soil carbon stock, c_t, and maize yield, y_t (δ=10%).

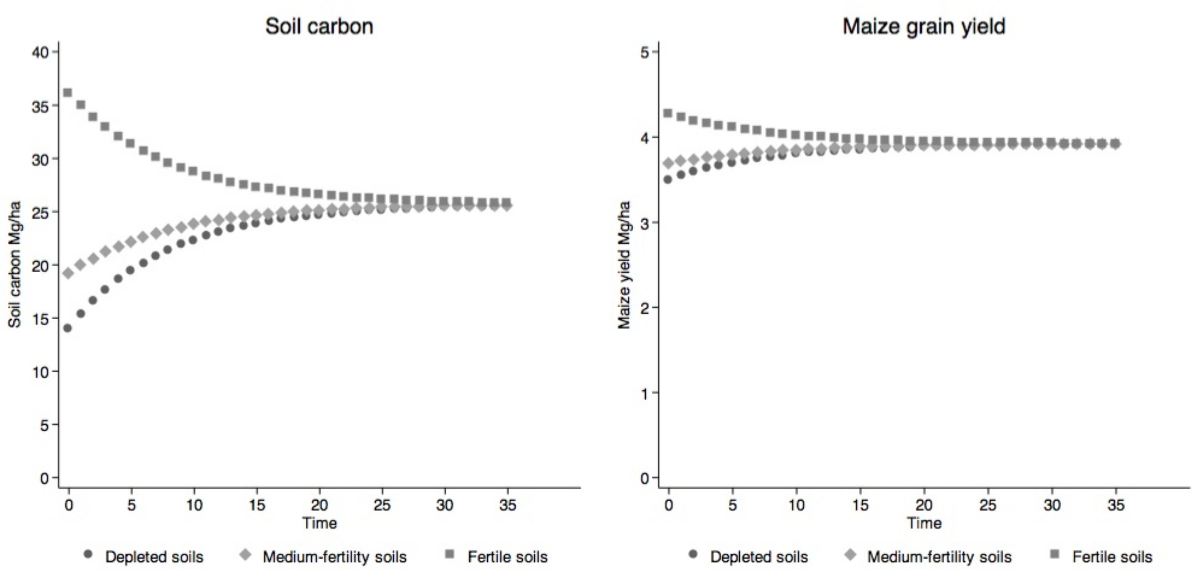

Table 3.1: Summary statistics for maize production function (N=1,450).

Variable	Unit	Mean	St. deviation	Min	Max
Grain yield	Mg/ha	4.05	2.47	0.16	12.14
Carbon stock	Mg/ha	45.64	18.53	31.79	182.49
Nitrogen fertilizer	Mg/ha	0.08	0.07	0	0.24

Table 3.2: Maize yield as a function of soil carbon stock and nitrogen fertilizer.

Maize yield (Mg/ha)	(1) Clustered	(2) Bootstrapped
Soil carbon stock (Mg/ha)	0.113***	0.113***
	(0.0354)	(0.0264)
Squared: Soil carbon stock (Mg/ha)	-0.000413**	-0.000413***
	(0.000157)	(0.000126)
Nitrogen fertilizer (Mg/ha)	27.04***	27.04***
	(4.704)	(3.119)
Squared: Nitrogen fertilizer (Mg/ha)	-41.30***	-41.30***
	(10.12)	(10.46)
Interaction: Carbon stock and Nitrogen fertilizer (Mg/ha)	-0.218***	-0.218***
	(0.0632)	(0.0564)
Constant	-1.461	-1.461
	(1.215)	(0.910)
Observations	1,450	1,450
R-squared	0.500	0.500
Farmer, Year, Treatment Fixed Effects	YES	YES
Year-Treatment Interaction	YES	YES
Return to soil carbon stock mean (st.dev.)	0.06 (0.02)	0.06 (0.02)
Return to nitrogen fertilizer mean (st.dev.)	10.39 (6.58)	10.39 (6.58)

*** p<0.01, ** p<0.05, * p<0.1. **Column (1)** shows standard errors clustered at farm level (28 farms). **Column (2)** shows bootstrapped standard errors (1,000 replications).

Table 3.3: Summary statistics: price of maize, p, nitrogen, n, value of residues, q, and per-hectare production cost, m.

Price	Unit	Mean μ	Median 50%	St. dev. σ	25%	75%	N
p	\$/Mg	349	331	95	265	397	120
n	\$/Mg	4,346	4,434	1,737	3,251	5,291	190
q	\$/Mg	65	58	52	24	94	144
m	\$/ha	445	375	283	290	516	309

Table 3.4: Baseline parameter values for economic and agronomic variables.

Variable	Description	Value	Unit	Source
Maize yield function				
γ_0	Constant	-0.810*	–	Chronosequence data
γ_c	Coefficient on c_t	0.113	–	Chronosequence data
γ_{cc}	Coefficient on c_t^2	-0.000413	–	Chronosequence data
γ_f	Coefficient on f_t	27.038	–	Chronosequence data
γ_{ff}	Coefficient on f_t^2	-41.295	–	Chronosequence data
γ_{cf}	Coefficient on $c_t f_t$	-0.218	–	Chronosequence data
Soil carbon equation				
D	Rate of soil carbon loss	0.11	–	IPCC (2003); Kimetu et al. (2009)
A	Carbon plant input parameter	2.4	–	Chronosequence data, ROTHC-26.3
B	Carbon plant input parameter	0.52	–	Chronosequence data, ROTHC-26.3
k	Maize residues to grain ratio	1.5	–	Chronosequence data
F	Carbon content of maize residues	0.43	–	Latshaw and Miller (1924)
Prices				
p	Price of maize	331	\$/Mg	Market and household surveys
n	Price of nitrogen fertilizer	4,434	\$/Mg	Market and household surveys
q	Value of crop residues	58	\$/Mg	Household survey
m	Maize production cost	375	\$/ha	Household survey
δ	Discount rate	5, 10, 15	%	Market survey
Initial conditions				
c_0	C stock in depleted soils	14.00	Mg/ha	Household survey
	C stock in medium-fertility soils	19.12	Mg/ha	Household survey
	C stock in fertile soils	36.13	Mg/ha	Household survey

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*To account for fixed effects in the estimation of the production function, we add the average of coefficients for each of the fixed effects category (farm, year, treatment, year-treatment) to the coefficient on the constant term: $-1.461 + 0.651 = -0.810$

Table 3.5: Steady-state values: changing discount rate.

Variable	Unit	$\delta = 5\%$	$\delta = 10\%$	$\delta = 15\%$
Share of residues, α_{ss}	$0 - 1$	0.84	0.54	0.38
Nitrogen input, f_{ss}	Mg/ha	0.11	0.13	0.14
Carbon stock, c_{ss}	Mg/ha	33.28	25.63	20.76
Maize yield, y_{ss}	Mg/ha	4.17	3.91	3.74
Value of carbon, λ_{ss}	\$/Mg	167.55	137.93	118.71

Table 3.6: Steady-state values: changing prices ($\delta = 10\%$).

Variable	$\mu - 0.5\sigma$	$\mu - 0.25\sigma$	median	μ	$\mu + 0.25\sigma$	$\mu + 0.50\sigma$
Price of maize, p	302	325	331	349	373	397
Price of nitrogen, n	3,478	3,912	4,434	4,346	4,780	5,215
Value of crop residues, q	39	52	58	65	78	91
Share of residues, α_{ss}	0.73	0.56	0.54	0.46	0.39	0.35
Nitrogen input, f_{ss}	0.13	0.14	0.13	0.15	0.15	0.16
Carbon stock, c_{ss}	31.28	26.49	25.63	23.58	21.61	20.20
Maize yield, y_{ss}	4.24	4.05	3.91	3.97	3.85	3.86
Value of carbon, λ_{ss}	111.49	127.50	137.93	143.13	158.48	173.69

Variable	$n \uparrow 25\%$	$n \downarrow 25\%$	median	$q \uparrow 25\%$	$q \downarrow 25\%$
Price of maize, p	331	331	331	331	331
Price of nitrogen, n	5,543	3,326	4,434	4,434	4,434
Value of crop residues, q	58	58	58	73	44
Share of residues, α_{ss}	0.71	0.41	0.54	0.38	0.82
Nitrogen input, f_{ss}	0.09	0.17	0.13	0.15	0.11
Carbon stock, c_{ss}	28.42	22.86	25.63	21.04	32.55
Maize yield, y_{ss}	3.60	4.11	3.91	3.82	4.12
Value of carbon, λ_{ss}	151.74	124.11	137.93	144.69	130.48

Mean (μ), median, and standard deviation (σ) of prices are from their empirical distributions.

Table 3.7: Time paths for share of residues, α_t, nitrogen input, f_t, soil carbon stock, c_t, maize yield, y_t, and discounted annual profit, $\rho^t\pi_t$, over 35 cycles for the farms with different resource endowments (δ=10%, median prices).

	Depleted soils					**Medium-fertility soils**					**Fertile soils**				
t	α_t	f_t	c_t	y_t	$\rho^t\pi_t$	α_t	f_t	c_t	y_t	$\rho^t\pi_t$	α_t	f_t	c_t	y_t	$\rho^t\pi_t$
0	0.64	0.16	14.00	3.49	170.74	0.59	0.15	19.12	3.68	315.10	0.47	0.10	36.13	4.27	774.62
1	0.63	0.16	15.36	3.54	190.38	0.59	0.15	19.88	3.71	305.78	0.48	0.11	34.90	4.23	674.92
2	0.62	0.16	16.56	3.58	201.16	0.58	0.14	20.56	3.73	293.45	0.48	0.11	33.81	4.19	589.96
3	0.61	0.15	17.63	3.62	205.32	0.58	0.14	21.15	3.75	279.15	0.49	0.11	32.85	4.16	517.30
4	0.60	0.15	18.56	3.66	204.60	0.57	0.14	21.67	3.77	263.69	0.50	0.11	32.01	4.13	454.95
5	0.59	0.15	19.39	3.69	200.36	0.57	0.14	22.14	3.79	247.66	0.50	0.12	31.26	4.11	401.25
6	0.58	0.15	20.12	3.72	193.63	0.56	0.14	22.55	3.80	231.51	0.50	0.12	30.60	4.08	354.84
7	0.58	0.14	20.77	3.74	185.22	0.56	0.14	22.91	3.82	215.57	0.51	0.12	30.02	4.06	314.59
8	0.57	0.14	21.34	3.76	175.74	0.56	0.14	23.23	3.83	200.06	0.51	0.12	29.50	4.05	279.57
9	0.57	0.14	21.84	3.78	165.66	0.56	0.14	23.51	3.84	185.15	0.52	0.12	29.05	4.03	248.98
10	0.57	0.14	22.28	3.79	155.33	0.55	0.14	23.76	3.85	170.94	0.52	0.12	28.65	4.02	222.19
11	0.56	0.14	22.67	3.81	144.99	0.55	0.14	23.97	3.85	157.51	0.52	0.12	28.29	4.00	198.65
12	0.56	0.14	23.02	3.82	134.84	0.55	0.14	24.17	3.86	144.88	0.52	0.13	27.98	3.99	177.91
13	0.56	0.14	23.33	3.83	125.02	0.55	0.13	24.34	3.87	133.07	0.52	0.13	27.71	3.98	159.58
14	0.56	0.14	23.60	3.84	115.60	0.55	0.13	24.49	3.87	122.06	0.53	0.13	27.46	3.98	143.34
15	0.55	0.14	23.83	3.85	106.66	0.55	0.13	24.62	3.88	111.83	0.53	0.13	27.25	3.97	128.92
16	0.55	0.14	24.04	3.86	98.21	0.55	0.13	24.74	3.88	102.37	0.53	0.13	27.06	3.96	116.08
17	0.55	0.13	24.23	3.86	90.29	0.55	0.13	24.84	3.88	93.62	0.53	0.13	26.89	3.96	104.63
18	0.55	0.13	24.39	3.87	82.89	0.55	0.13	24.94	3.89	85.56	0.53	0.13	26.74	3.95	94.40
19	0.55	0.13	24.54	3.87	76.00	0.54	0.13	25.02	3.89	78.14	0.53	0.13	26.61	3.95	85.24
20	0.55	0.13	24.67	3.88	69.61	0.54	0.13	25.09	3.89	71.33	0.53	0.13	26.50	3.94	77.02
21	0.55	0.13	24.78	3.88	63.70	0.54	0.13	25.15	3.90	65.08	0.53	0.13	26.39	3.94	69.65
22	0.55	0.13	24.88	3.89	58.24	0.54	0.13	25.21	3.90	59.35	0.53	0.13	26.30	3.94	63.01
23	0.54	0.13	24.97	3.89	53.21	0.54	0.13	25.26	3.90	54.10	0.54	0.13	26.23	3.93	57.05
24	0.54	0.13	25.04	3.89	48.59	0.54	0.13	25.30	3.90	49.30	0.54	0.13	26.15	3.93	51.67
25	0.54	0.13	25.11	3.89	44.35	0.54	0.13	25.34	3.90	44.92	0.54	0.13	26.09	3.93	46.81
26	0.54	0.13	25.17	3.90	40.45	0.54	0.13	25.37	3.90	40.91	0.54	0.13	26.04	3.93	42.43
27	0.54	0.13	25.22	3.90	36.89	0.54	0.13	25.40	3.90	37.25	0.54	0.13	25.99	3.92	38.48
28	0.54	0.13	25.27	3.90	33.62	0.54	0.13	25.43	3.91	33.92	0.54	0.13	25.95	3.92	34.90
29	0.54	0.13	25.31	3.90	30.64	0.54	0.13	25.45	3.91	30.87	0.54	0.13	25.91	3.92	31.66
30	0.54	0.13	25.35	3.90	27.91	0.54	0.13	25.47	3.91	28.10	0.54	0.13	25.88	3.92	28.73
31	0.54	0.13	25.38	3.90	25.42	0.54	0.13	25.49	3.91	25.57	0.54	0.13	25.85	3.92	26.08
32	0.54	0.13	25.41	3.90	23.14	0.54	0.13	25.51	3.91	23.27	0.54	0.13	25.82	3.92	23.67
33	0.54	0.13	25.44	3.91	21.07	0.54	0.13	25.52	3.91	21.17	0.54	0.13	25.80	3.92	21.50
34	0.54	0.13	25.46	3.91	19.18	0.54	0.13	25.53	3.91	19.26	0.54	0.13	25.78	3.92	19.52
35	0.54	0.13	25.48	3.91	17.45	0.54	0.13	25.54	3.91	17.52	0.54	0.13	25.76	3.92	17.73
	Total net revenue				$3,814.09	**Total net revenue**				$4,536.93	**Total net revenue**				$6,869.55

Total net revenue is calculated as the sum of the discounted net revenue from $t = 0$ to $t = 34$ and $\rho^{34}\pi_{ss}/\delta$, the present value of net revenue if the steady state is maintained from $t = 35$ to infinity.

APPENDIX

3.A Soil carbon stock value

The chronosequence dataset contains 1,450 observations across 28 farms, eight years (2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012) and four treatments, each with and without nitrogen fertilizer (control with and without N, *Tithonia diversifolia* leaves with and without N, wood charcoal with and without N, and sawdust with and without N). In addition, for 2011 and 2012 we have varied rates of N application on control plots—0, 0.08, 0.12, 0.16, 0.20 and 0.24 N Mg/ha. Since the soil analysis of all observations was cost- and time-prohibitive, we used the following sampling design to select a sub-sample for detailed soil chemistry analysis. Three farms at each conversion group—old, medium-age, young—were chosen for their close geographic proximity.[18] Prior to analysis we mixed soil of the three farms at each conversion group for each year and treatment to create representative soil samples at each conversion group for the total number of 177 soil samples.

The soil samples were analyzed at the Cornell Nutrient Analysis Laboratory (CNAL) in May 2014 for total nitrogen and carbon as percentage by dry weight. To calculate soil carbon stocks on an equal mass basis, we follow the procedure described in Betemariam et al. (2011). Soil carbon stock is calculated by multiplying the carbon concentration of an oven-dry weight with bulk density and soil depth:

$$SC = \frac{C}{100} \times \rho \times D \times (1 - frag) \times 100, \tag{3.18}$$

where SC is soil carbon stock (Mg C/ha), C is soil carbon concentration of soil fines determined in the laboratory (%), ρ is soil bulk density (g/cm^3), D is depth of the sampled soil

[18] Three farms in Kechire converted in 1950, three farms in Kereri/Bonjoge converted in 1986, and three farms in Sik Sik converted in 2000.

layer (cm), $frag$ is % mass fraction of coarse fragments/100, and 100 is used to convert the unit to Mg C/ha. We assume $frag$ to equal 5%. Soil bulk density was measured for all chronosequence farms in 2009 as described in Guerena (2014). We use the average (across three farms at each conversion group) bulk density for each treatment with and without fertilizer. Table 3.A.1 shows the average bulk densities used.[19]

Table 3.A.1: Soil bulk density (g/cm^3).

Treatment	(1) Old farm	(2) Medium-age farm	(3) Young farm
Control=1, Fertilizer=0	1.2246	1.2187	1.2246
Control=1, Fertilizer=1	1.1300	1.2246	1.1297
Charcoal=1, Fertilizer=0	1.2246	1.1918	1.2246
Charcoal=1, Fertilizer=1	1.1244	1.1616	1.0903
Sawdust=1, Fertilizer=0	1.2246	1.1837	1.2246
Sawdust=1, Fertilizer=1	1.1153	1.1943	1.0279
Tithonia=1, Fertilizer=0	1.2246	1.1474	1.2246
Tithonia=1, Fertilizer=1	1.1433	1.1806	1.0495
Average by age	1.1491	1.1878	1.0980

Bulk density measured in 2009. **Full sample bulk density, 1.1450,** is the average of 72 observations. Average by age bulk density is the average of 24 observations in each age group with 8 treatments and 3 farms.

Following Kinyangi (2008), we establish long-term carbon degradation equilibria of tropical soil (of 10 cm depth) as a function of time under long-term cropping. The soil analysis data are fitted using a three parameter single exponential decay model, $y = y_0 + ae^{-bx}$, where y_0 is the final soil carbon equilibrium level, a is C degradation (Mg/ha), b is rate of loss, and x is years since conversion from forest. We first fit the model using the full dataset (177 soil samples), then fit the model for each of the treatment-fertilizer group separately.[20] The results are shown in Table 3.A.2 and Figures 3.A.1, 3.A.2, 3.A.3, 3.A.4, and 3.A.5.

[19]Using average conversion group bulk density or average full sample bulk density does not significantly alter the results.

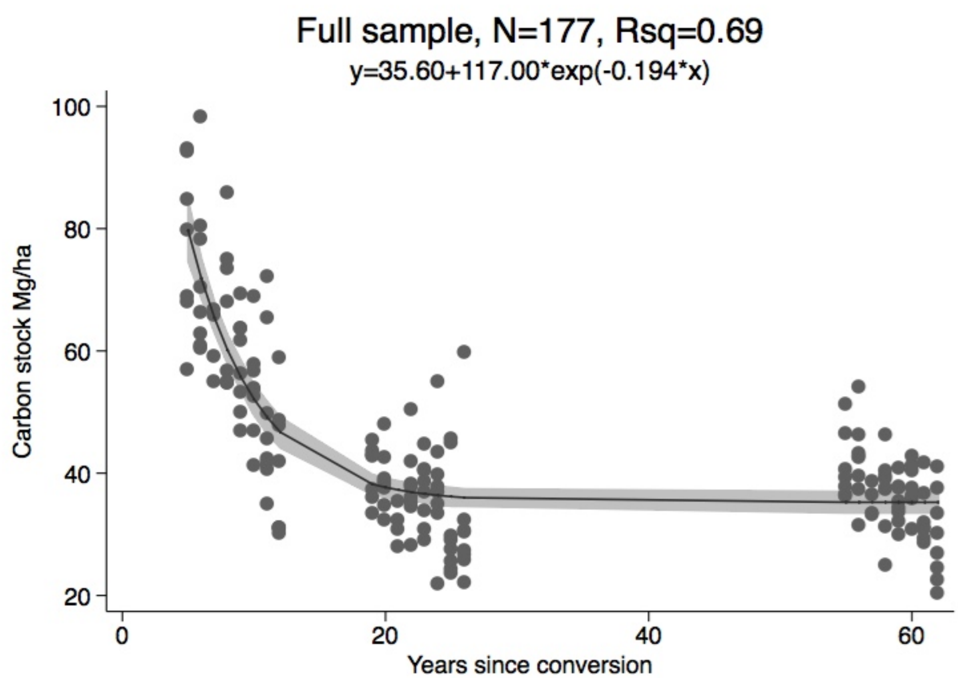
[20]We also tried fitting OLS to the data, with soil carbon stock as a dependent variable and indicator variables for treatment, year and farm age as independent variables, both for the full sample and for the three farm age groups separately. The exponential model provided, however, a better fit and out-of-sample predictions.

Table 3.A.2: Exponential fit for full sample vs. for each treatment-fertilizer group.

Treatment	(1) y_0	(2) a	(3) b	(4) N	(5) R^2
Full sample	35.60	117.00	0.194	177	0.69
Control=1, Fertilizer=0	33.26	85.21	0.149	21	0.78
Control=1, Fertilizer=1	31.79	76.69	0.128	21	0.79
Charcoal=1, Fertilizer=0	40.20	262.93	0.307	21	0.75
Charcoal=1, Fertilizer=1	35.58	117.56	0.149	24	0.83
Sawdust=1, Fertilizer=0	36.08	230.11	0.275	21	0.82
Sawdust=1, Fertilizer=1	34.34	69.52	0.136	24	0.78
Tithonia=1, Fertilizer=0	37.61	106.26	0.178	21	0.64
Tithonia=1, Fertilizer=1	35.75	64.65	0.177	24	0.59

Based on $y = y_0 + a \times e^{-bx}$, where y is soil carbon stock (Mg/ha), y_0 is the equilibrium soil carbon level, a is carbon degradation, b is rate of loss, and x is years since conversion from forest.

Figure 3.A.1: Exponential fit for full sample.



Using parameters of the exponential decay model summarized in Table 3.A.2, we predict soil carbon stocks for the entire sample of 1,450 observations. The density of predicted soil

Figure 3.A.2: Exponential fit for control with and without N fertilizer.

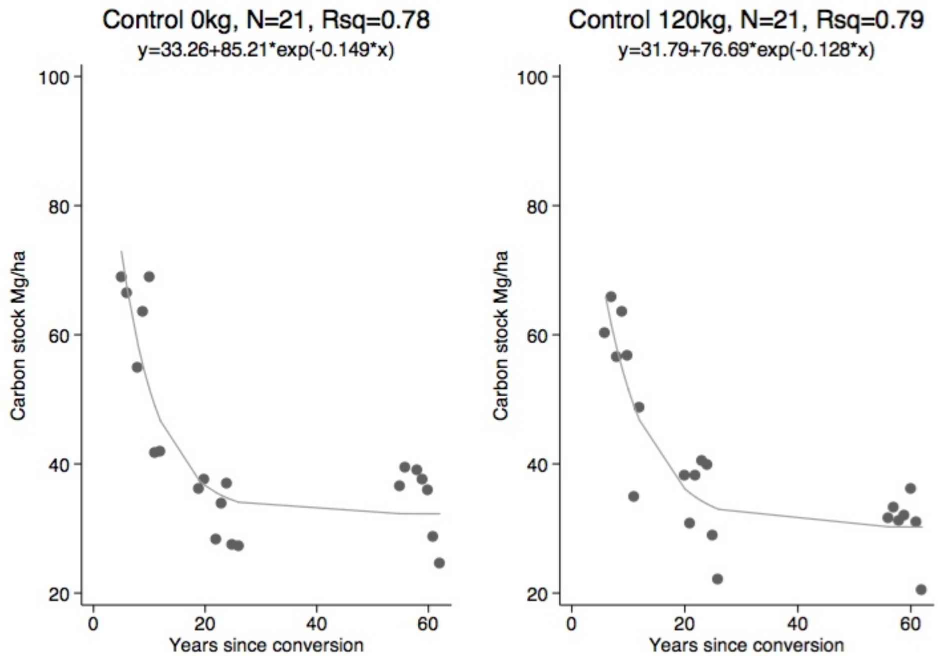


Figure 3.A.3: Exponential fit for charcoal with and without N fertilizer.

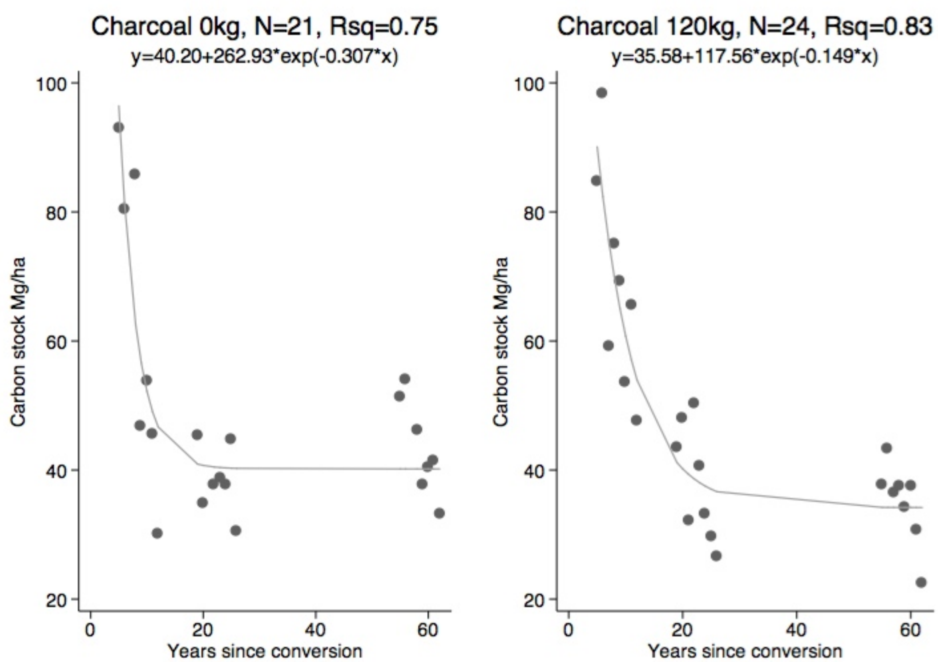


Figure 3.A.4: Exponential fit for sawdust with and without N fertilizer.

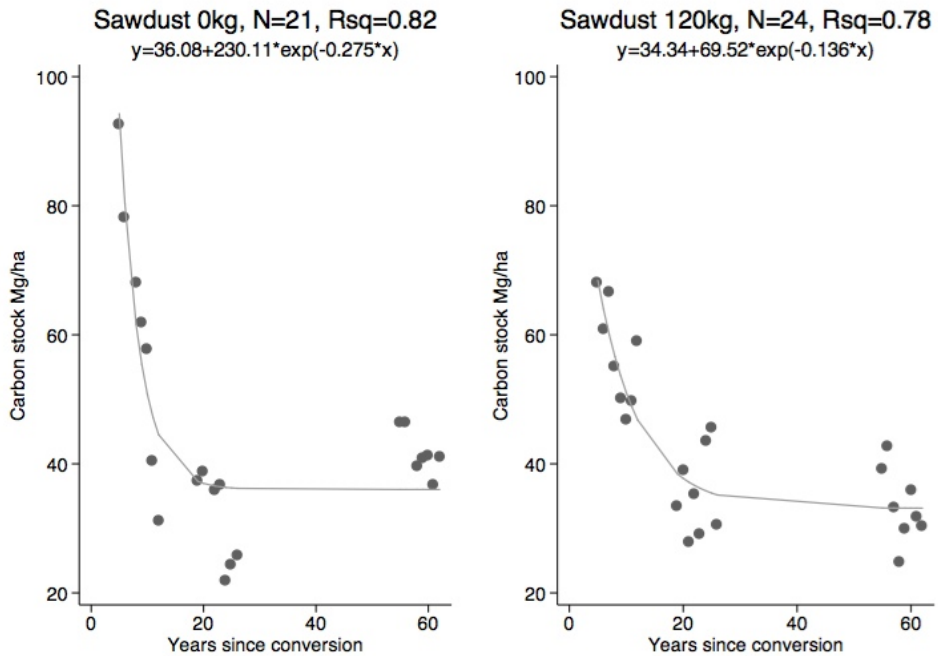
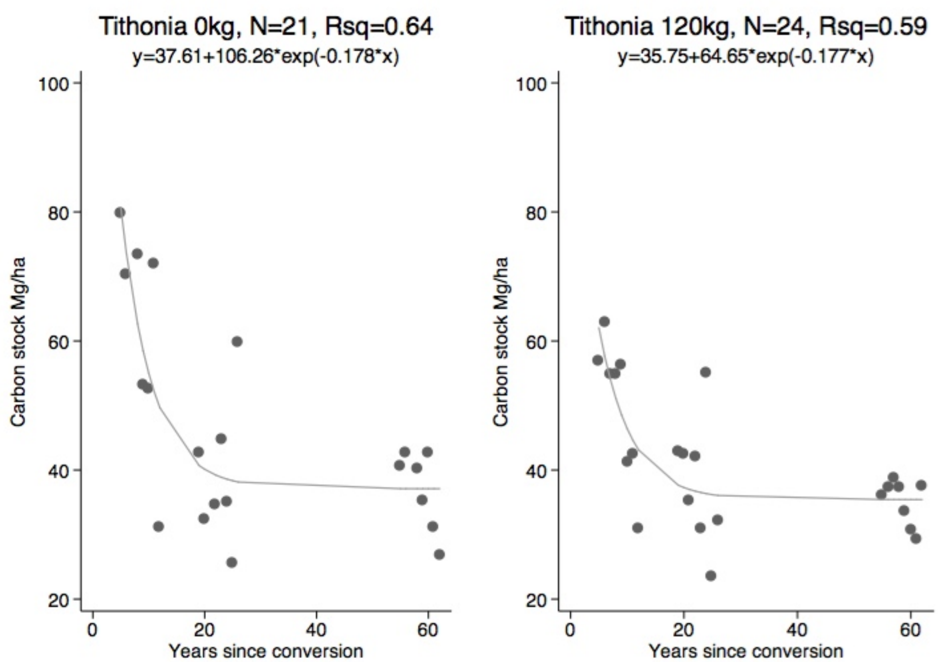
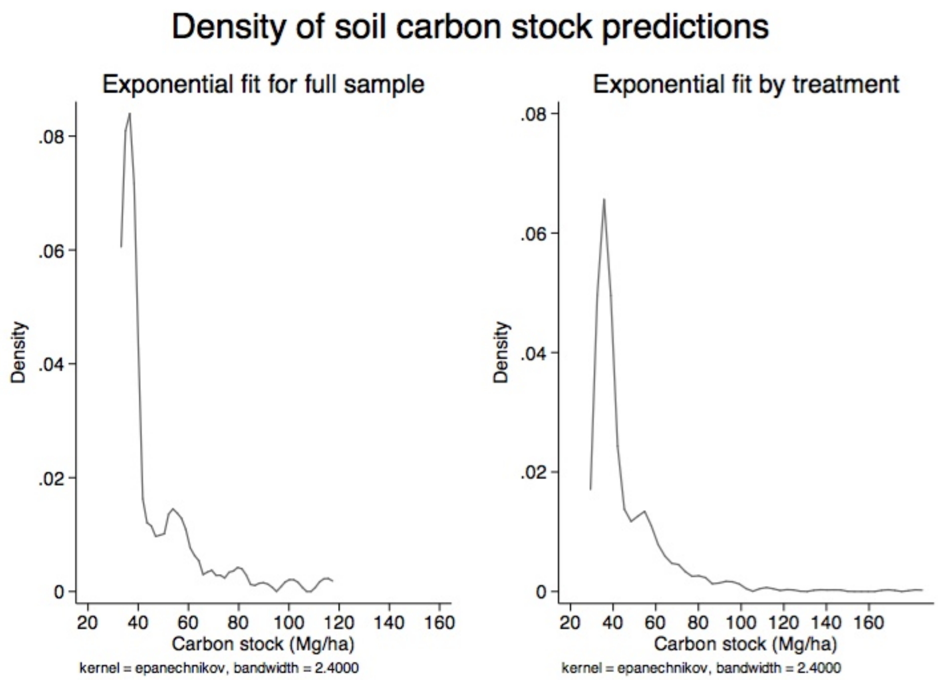


Figure 3.A.5: Exponential fit for *Tithonia* with and without N fertilizer.



carbon stocks (Mg/ha) is shown in Figure 3.A.6, with the correlation coefficient of the two predictions being 0.93. Given a slightly better fit of the model for each treatment-fertilizer group, we use the predictions shown on the right-hand side panel of Figure 3.A.6 in our estimation of the production function.

Figure 3.A.6: Density of predicted soil carbon stocks (Mg/ha).



3.B Calibrating soil carbon equation

The Rothamsted Carbon Model (ROTHC-26.3) is one of the most widely used models to study the turnover of soil organic carbon. The model estimates the carbon dynamics for decades or centuries under different management and requires few inputs that are easily available for the chronosequence farms: the carbon inputs into the soil, as well as soil clay content and monthly weather conditions (rainfall, temperature, and open pan evaporation) (Coleman and Jenkinson 1999). The data requirements, their values and sources used for calibration of the Rothamsted carbon model are described in Table 3.B.1.[21]

Table 3.B.1: Data requirements for the ROTHC-26.3 model.

Variable	Data	Source
Average monthly mean air temperature (°C)*	18.2 (J), 18.2 (F), 18.5 (M), 19.6 (A), 19.7 (M), 19.5 (J), 20 (J), 20.2 (A), 20.3 (S), 20.2 (O), 18.8 (N), 18.6 (D)	New_locClim, FAO (2005)
Monthly precipitation (mm)*	129 (J), 201 (F), 170 (M), 150 (A), 97 (M), 80 (J), 58 (J), 117 (A), 127 (S), 243 (O), 207 (N), 150 (D)	New_locClim, FAO (2005)
Monthly evaporation (mm)*	132 (J), 144 (F), 146.13 (M), 158 (A), 145.07 (M), 160.27 (J), 163.73 (J), 154.80 (A), 172.53 (S), 144.13 (O), 138.27 (N), 130.27 (D)	New_locClim, FAO (2005)
Soil depth (cm)	10	
Clay content of the soil (%)	47	Kimetu et al. (2009)
DPM/RPM ratio for maize**	1.44	Coleman and Jenkinson (1999)
Soil cover	Fallow only in July and August	
Monthly input of plant residues	In February and June	
Amount of inert organic matter	Unknown, obtained as described in the modeling section	

*The weather data are displaced by six months so that the soil is at field capacity at the start of the model run, as suggested by Coleman and Jenkinson (1999). **Ratio of decomposable plant material to resistant plant material. Value suggested by Coleman and Jenkinson (1999).

The weather data come from New_LocClim: Local Climate Estimator, an FAO software program and database, which provides estimates of average climatic conditions at locations for which no observations are available (FAO 2005). The monthly long-term mean temperature, precipitation and evaporation are interpolated for the chronosequence farms—00° 09' 34"N, 34° 57' 37"E, 1,780 m altitude (Kinyangi 2008).

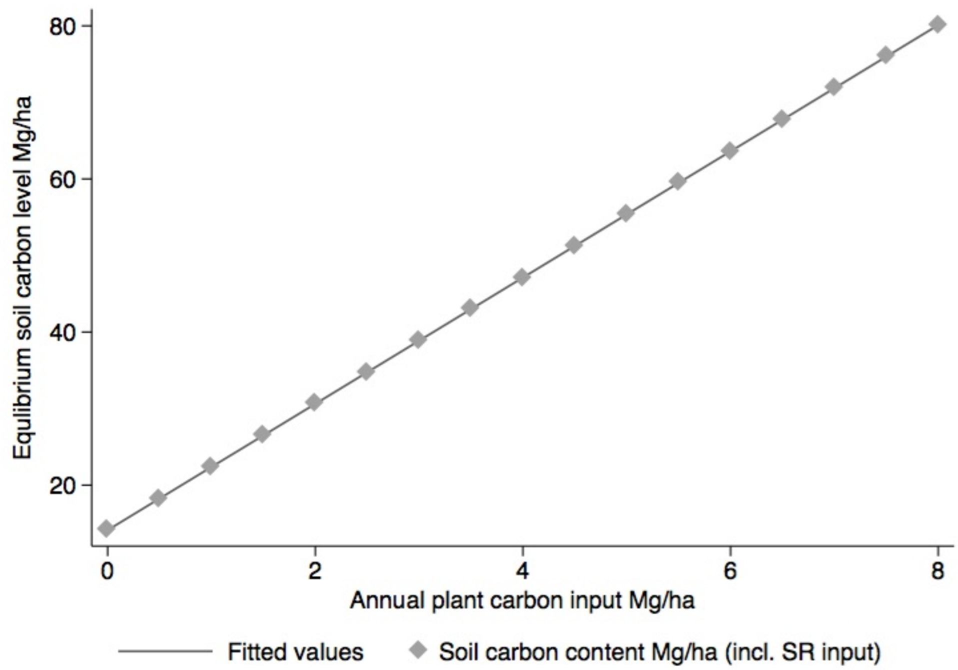
[21] The procedure used to calibrate the Rothamsted Carbon Model and estimate the equilibrium levels of soil carbon in the research area is developed by Dominic Woolf.

ROTHC-26.3 is first run to estimate the equilibrium values for tropical forest with the climate data and soil clay content described in Table 3.B.1, and assuming annual inputs to the tropical forest soil equal to the mean net primary production of carbon for broadleaf evergreen forest specified in Potter (1999)—1,075.4 g/m^2/year which translates to 0.896 Mg/ha/month. The initial level of measured total soil carbon is 65 Mg C/ha (Kinyangi 2008) and the DPM/RPM ratio, ratio of decomposable plant material to resistant plant material, is 0.25, the default for deciduous and tropical woodland (Coleman and Jenkinson 1999). Running the model in "inverse," when inputs are calculated from known changes in soil organic matter, we obtain the amount of inert organic matter (IOM), 5.6899 Mg/ha, and monthly input of plant residues, 0.4996 Mg C/ha. Now running the model "forward," we obtain the starting values in Mg/ha for decomposable plant material (DPM)—0.1410, resistant plant material (RPM)—13.9892, microbial biomass (BIO)—1.1866, humidified organic matter (HUM)—43.9959, and inert organic matter (IOM)—5.6899, to be used in the model simulations for different management scenarios.

To simulate the soil carbon equilibrium levels under different management scenarios, we run ROTHC-26.3 "forward" for different levels of plant carbon inputs (0, 0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5, 5.5, 6, 6.5, 7, 7.5, 8 Mg C/ha) applied in February, the end of the main Long Rains season, and assuming the constant rate of plant carbon inputs, 1 Mg C/ha, in June to reflect the crop residues left on the field in the end of the Short Rains season. The resulting equilibrium levels of soil carbon (after 10,000 years) for different levels of plant carbon inputs are shown in Figure 3.B.1 that suggests a linear relationship: equilibrium soil carbon = 14.12431 + 8.247451 * plant carbon input.

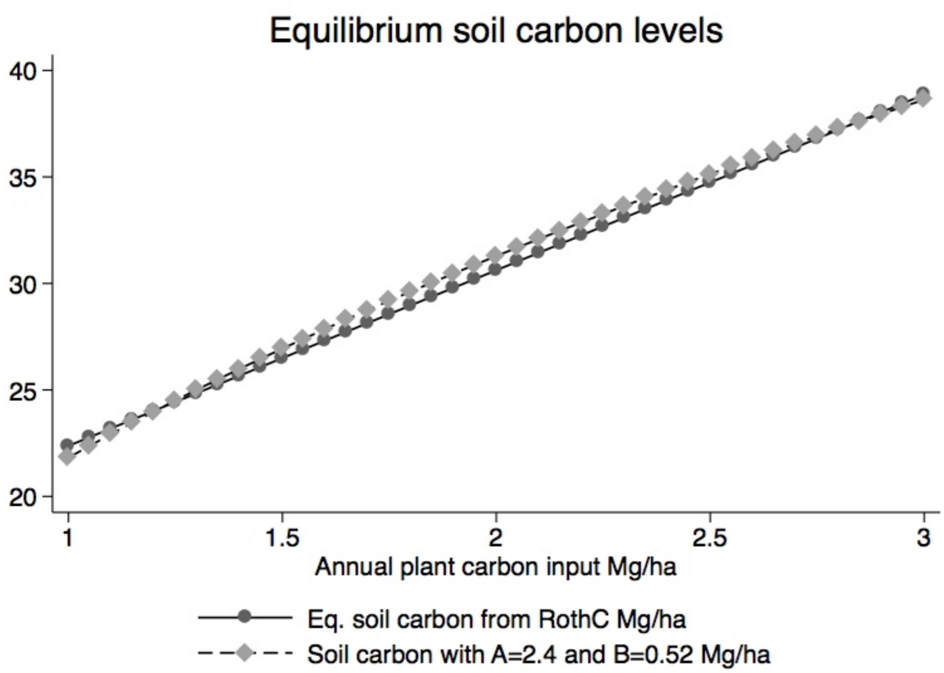
To find values for the parameters A and B in the soil carbon equation, $g(\cdot) = c_{t+1} - c_t = -Dc_t + A(\alpha_t Fky(c_t, f_t))^B$, we use the data predicted by the RothC model. In equilibrium, equation 3.17 implies that $A(\alpha Fky(c, f))^B = Dc$, or $\ln(c) = \ln(A) - \ln(D) + B\ln(\alpha kFy(\cdot))$ in logs, where D, soil carbon mineralization rate, F, carbon content of maize residues, and

Figure 3.B.1: Equilibrium levels of soil carbon from ROTHC-26.3 as a function of plant carbon inputs.



k, maize residue to grain ratio, are given. The data predicted by RothC suggest a linear relationship between the equilibrium soil carbon content (c) and plant carbon input (x) (Figure 3.B.1) such that $\ln(c) = 3.08 + 0.52\ln(x)$. Since x is also equal to $\alpha kFy(\cdot)$ in equation 3.17, we assume that $3.08 = \ln(A) - \ln(D)$ and $0.52 = B$, giving values for $A = 2.4$ and $B = 0.52$. Although equation 3.17 is non-linear, for $x \in (1, 3]$ that is a reasonable range of plant carbon input in maize systems in western Kenya, equation 3.17 closely mirrors the data predicted by the RothC model as can be seen in Figure 3.B.2.

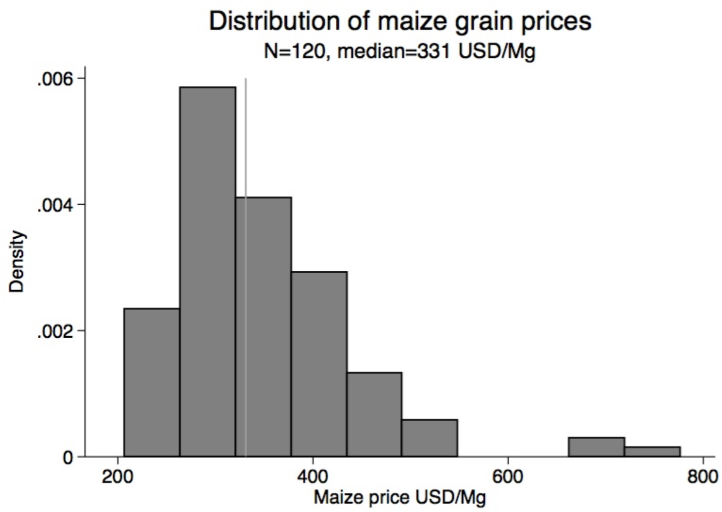
Figure 3.B.2: Calibrating the soil carbon function.



3.C Prices

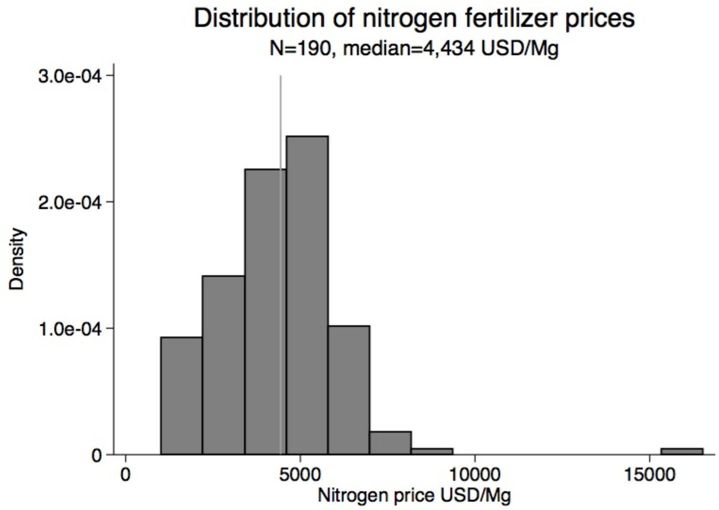
The following figures show the empirical distributions of prices as reported in the household survey or estimated in Chapter 2, using the same household survey data. Table 3.C.1 shows the estimation of the hedonic price function used to approximate land rental values in the research area.

Figure 3.C.1: Maize grain price in the household survey.



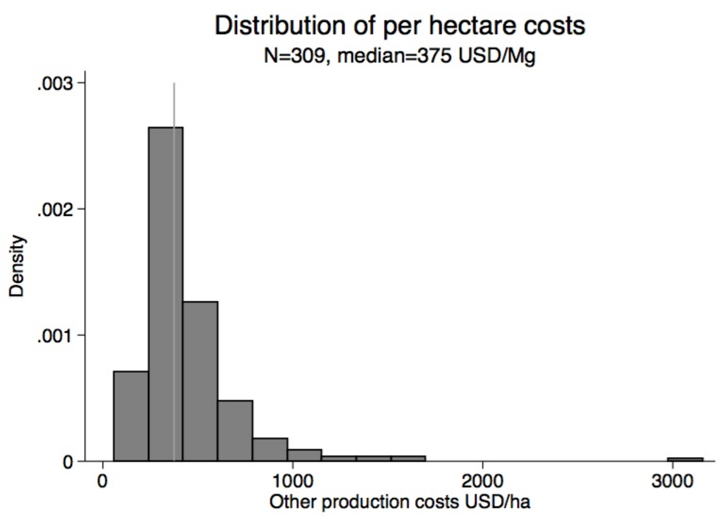
Note: N=120, households that sold maize. The average market price in 2011-2012 is 410 \$/Mg.

Figure 3.C.2: Composite nitrogen price in the household survey.



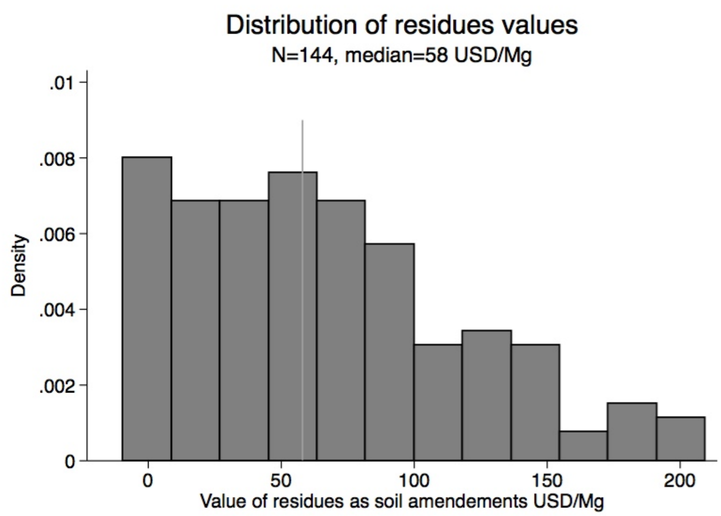
Note: N=190, households that bought DAP, urea, and/or CAN. 2,070 \$/Mg is the price of nitrogen in urea, 4,390 \$/Mg is the composite price of nitrogen from the market surveys. n = price of DAP/0.18 $\times$ 0.69 + price of urea/0.46 $\times$ 0.16 + price of CAN/0.26 $\times$ 0.15.

Figure 3.C.3: Per-hectare maize production costs in the household survey.



Note: N=309. Production costs include the cost of preparing the land, planting, and harvesting maize, including household and paid labor and land rental value.

Figure 3.C.4: Value of maize residues left on the fields for soil fertility management.



Note: N=144. Estimated in Chapter 2.

Table 3.C.1: Hedonic regression of land rental value.

Rent (USD/ha)	(1)	(2)
Indicator for loam soil	-19.66	-10.30
	(13.92)	(8.585)
Indicator for clay soil	-19.58	-22.98*
	(16.87)	(12.09)
Indicator for murram soil	-42.52***	-28.19***
	(15.08)	(9.694)
Indicator for moderate or fertile soil	26.83**	29.90***
	(11.42)	(8.502)
Organic soil carbon (% by weight)		1.543
		(4.843)
Plot GIS altitude (m)		0.0637***
		(0.0172)
Constant	62.12***	-42.20
	(15.08)	(29.71)
Observations	53	45
R-squared	0.170	0.481
Mean predicted value (st.dev.)	64.70 (17.18)	65.06 (24.66)
Median predicted value	69.29	59.19

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Indicator for sandy soil omitted.

CHAPTER 4

SMALL-SCALE BIOENERGY PRODUCTION IN SUB-SAHARAN AFRICA: THE ROLE OF FEEDSTOCK PROVISION IN ECONOMIC VIABILITY

4.1 Introduction

Renewable energy from materials derived from biological sources—bioenergy—accounts for about ten percent of global primary energy demand, and some recent estimates suggest a considerable potential for expansion (IEA 2014). Most existing traditional bioenergy use is in developing countries in the form of burning solid biomass for residential cooking. Fuelwood and charcoal, for example, account for more than 60 percent of total energy use in Sub-Saharan Africa (SSA) (Eisentraut 2010). Access to modern energy in developing countries, however, remains limited. More than 620 million people in SSA are without access to electricity, with nearly 80 percent of those lacking access living in rural areas. Two-thirds of total energy consumption in SSA is in the residential sector (mostly for cooking), while transport accounts for only 11 percent of final energy consumption, and industry, agriculture, and service sectors together account only for 21 percent (IEA 2014).

Modern, reliable and high quality energy, however, is necessary to provide lighting, heating, communication, transport, and mechanical power to support education, better health, and higher household incomes. Not surprisingly, there is growing interest in SSA, as elsewhere in the developing world, to establish modern bioenergy sectors to supplement existing traditional energy reserves. While for many industrial countries the main drivers for developing the bioenergy sector are reducing greenhouse gas (GHG) emissions and diversifying energy sources, developing countries have additional objectives. Bioenergy sector expansion is also viewed as a means of stimulating economic development—providing biofuel for powering agricultural machinery, transporting goods to markets, accessing medical services, and creating jobs (Kojima and Johnson 2005; Jumbe, Msiska, and Madjera 2009; Lynd and Woods 2011).

Expansion of the modern bioenergy sector, in general, and biofuels, in particular, is, however, not without tradeoffs. Many of the challenges are centered on the provisioning of raw materials, or feedstocks, for biofuel production. These include competition with food production for land resources, environmental concerns, and increasing GHG emissions (see, for example, Fargione et al. (2008) and Tilman et al. (2011)). Second-generation biofuels, however, offer potential solutions for some of the sustainability issues often associated with biofuels from food crops (Hammond and Seth 2013). They use cellulosic biomass from non-edible feedstocks that do not compete with food production and can be produced with lower life-cycle GHG emissions than traditional fossil fuels. Such feedstocks include agricultural residues, sustainably harvested wood and forest residues, perennial plants grown on degraded lands, double cropped and mixed cropping systems, and municipal and industrial wastes (Tilman et al. 2009).

Crop residues (cereal and legume straws, leaves, stalks, tops of vegetables, sugar, and oil crops, etc.), in particular, are of great potential interest as biofuel feedstocks, because they do not require additional land cultivation, do not compete with food production, and are already found in considerable quantities (Eisentraut 2010). There are, however, several important competing uses for crop residues. Crop residues are used as animal fodder, especially in developing countries. They are also essential for maintaining many soil properties and processes, such as storing and recycling nutrients, stabilizing soil structure, reducing risks of soil erosion, improving water retention, and enhancing agronomic productivity, among many others (Lal 2005). So the removal of crop residues from fields can lead to a decline in soil fertility with long-term adverse impacts on the environment.

The existing studies that assess bioenergy expansion potential in SSA mostly focus on the technical feedstock provision potential of entire countries or they make assumptions about the percentage of residues that is "safe" to use for bioenergy (see, for example, Senelwa and Hall (1993) in Kenya, Jingura and Matengaifa (2008) in Zimbabwe, Milbrandt (2009) in Liberia, Duku, Gu, and Hagan (2011) in Ghana, and Ackom et al. (2013) in Cameroon). It is, however, important to understand the true economic cost of using crop residues as bioenergy feedstocks. There are major economic and environmental tradeoffs associated with alternative uses of crop residues. And in many places, markets for crop residues do not exist, complicating the assessment of the true costs of residues to smallholder farmers. It is also important to recognize the challenges in scaling up bioenergy infrastructure (Richard 2010). Overall, understanding the security of biomass supply in developing countries and accounting for its various challenges (sourcing from small farms, seasonality of availability, etc.) is essential to correctly estimate the feasibility of bioenergy production and profitability (Eisentraut 2010).[1]

In this paper, we analyze the *ex ante* economic viability of small-scale bioenergy production in rural SSA, specifically focusing on one challenge—feedstock provision costs. We consider the availability and cost of purchasing maize residues from smallholder farmers, as well as the cost of transporting them to a small-scale pyrolysis-biochar plant in rural western Kenya. We account for maize residue yield risk and its effect on feedstock prices, and the pyrolysis-biochar plant's potential power to exercise monopsony prices. We offer the first detailed estimates of feedstock provision costs for SSA, and assess whether producing bioenergy is economically viable or whether initial government subsidies would be necessary to account for the social and environmental benefits of rural bioenergy production.

A pyrolysis-biochar plant producing ethanol and biochar, a soil amendment, is chosen for several reasons. Ethanol is one of the most promising biofuels. In principle, it can be derived from any lignocellulosic biomass and then blended with gasoline for transportation fuels, thus

[1] Other challenges associated with bioenergy development in poor and remote regions, such as technical know-how, capital availability, lack of private sector capacity, market development, land tenure security, poor infrastructure, lack of skilled labor, and limited financing possibilities are described elsewhere (see, for example, Ewing and Msangi (2009), Eisentraut (2010)).

allowing the countries to retain the existing transportation infrastructure (e.g., refueling stations). In western Kenya, for example, Kisumu already has facilities for ethanol-gasoline blending, and similar facilities are being completed in Eldoret and Nakuru (MOE 2015). Biochar also offers several benefits. Once incorporated in soils, biochar has been shown to increase crop yields and reduce fertilizer requirements, and its high carbon content and stability offer soil carbon sequestration and climate change mitigation potential (Lehmann 2007b; Stavi and Lal 2013).

Our focus on small-scale production with the end goal of local bioethanol and biochar use is an opportunity to consider an alternative model to large-scale, monoculture-oriented production, and the benefits it can bring to smallholder farmers. There is growing evidence that smallholder farmers can benefit from small-scale bioenergy production if production, marketing, and distribution networks are designed with the view to help the poor (e.g., Woods (2006), Ewing and Msangi (2009), von Maltitz and Staffor (2011)). The evidence from existing small-scale bioenergy projects is, however, scarce and points to the challenges to their economic feasibility without considerable donor support (von Maltitz and Staffor 2011).

Using detailed household-level and market data from the western Kenyan highlands, we provide a detailed *ex ante* assessment of one particular case and draw implications for the small-scale bioenergy development in other rural settings. We demonstrate that feedstock provision costs strongly depend on regionally specific agro-ecological and socio-economic conditions. Crop yields, planting density, and value of crop residues to farmers exhibit a high degree of heterogeneity even in the limited geographic area considered. They result in highly varying feedstock purchase and transportation costs, depending on the location of the pyrolysis-biochar system. Only under the best-case scenario (that with the lowest provision costs), do we find that a pyrolysis-biochar plant with 15 Mg of feedstock per hour capacity has a positive estimated net present value (NPV). Initial capital investment, feedstock cost, final product prices, and interest rates have the greatest impacts on NPV estimates. To help promote small-scale bioenergy production, initial government support may be required to account for the social and environmental benefits of rural bioenergy production.

In the following section, we discuss the available technologies for bioenergy production in Sub-Saharan Africa, focusing on one in particular—a pyrolysis-biochar system to produce bioethanol and biochar. In section 4.3 we discuss the implications of sourcing feedstock from small-scale farmers. We describe the study area, and explain our methods to derive feedstock availability, price, and transport costs. In section 4.4 we present the metrics to assess the economic viability of the pyrolysis-biochar system, while in section 4.5 we discuss our results. Section 4.6 concludes the paper and discusses the implications of our findings for the small-scale bioenergy development in other rural settings.

4.2 Bioenergy production technologies in SSA and pyrolysis-biochar system

The available technologies for bioenergy production in Sub-Saharan Africa are numerous. They are applicable at different scales, for diverse purposes, under various climatic conditions, and with multiple feedstock sources (Rutz and Janssen 2012). Bioenergy technologies range from small-scale household cookstoves to village-level medium-enterprise applications to large-scale industrial plants. For all scales, different conversion technologies (biological, mechanical, thermal, chemical processes) produce liquid, gaseous, and solid bioenergy, which can be converted into electricity, heat, cooking and lighting energy, and transportation fuels.

The most common traditional technology for biomass conversion into bioenergy is a three-stone fire or "open fire" cookstove, with wood fuels (charcoal and firewood) as the dominant biomass feedstock. Smoke from burning of solid biomass fuels on open fire stoves is responsible for high concentrations of health-damaging pollutants such as particulate matter and carbon monoxide, while incomplete combustion of fuels releases black carbon (soot), contributing to poor health outcomes and climate change (Rehfuess, Mehta, and Pruss-Ustun 2006; Adkins et al. 2010). Where on-farm biomass is scarce, the off-farm fuelwood collection burden often falls on women and children, while the cutting down of trees for firewood or to make charcoal contributes to deforestation (Arnold, Kohlin, and Persson 2006; Hosonuma et al. 2012).

Another common technology for biomass conversion into bioenergy is a farm-size biogas digester. Their use has been rapidly increasing since the 1970s; there are now more than 30 million household digesters in China, about 3.8 million in India, and tens of thousands in both Nepal and Bangladesh (Rajendran, Aslanzadeh, and Taherzadeh 2012). The use of farm biogas digesters in Sub-Saharan Africa is, however, still limited, and among those that exist many do not function due to often high capital costs and laborious maintenance and repair requirements (Bond and Templeton 2011; Austin et al. 2012).

Modern energy technologies that utilize numerous biomass feedstocks to produce electricity and heat, however, are also in use, albeit much less widespread. Most of the existing ones form part of large-scale plants (e.g., use of bagasse to provide heat energy for a sugar mill), while technologies for stand-alone production of biofuels for transport in SSA are still in nascent stages. The government of Kenya, for example, lists inadequate research and development on alternative biofuel feedstocks and technologies as one of the main challenges confronting its national biofuel policy (MOE 2015). It also recognizes that producing energy crops for biofuel production carries the threat of competing with production of food.

One of the promising technologies for the sustainable production of renewable energy is pyrolysis—a process that involves thermal decomposition of biomass at elevated temperatures with a limited supply of oxygen (Lehmann and Joseph 2009). Pyrolysis can generate liquid and gaseous energy sources from a large diversity of biomass feedstocks, including woody and herbaceous materials, agricultural and food processing residues, municipal waste, as well as other waste products (Yaman 2004; Lehmann 2007a). During pyrolysis, biomass is converted into a liquid product (i.e., bio-oil), a solid char (i.e., biochar), and non-condensable gases such as carbon monoxide, carbon dioxide, hydrogen, methane and higher hydrocarbons (i.e., "syngas" or "pyrolysis gas") (Brown 2009). While pyrolysis gas is mostly suitable for process heat and power generation and unsuitable for long-distance distribution or residential applications, bio-oil can be refined into drop-in "green" transportation fuels—fuels that can substitute for petroleum gasoline and can be distributed in the same fueling infrastructure (Brown, Wright, and Brown 2011).

Biochar, a major product of pyrolysis, has many appealing properties. It can be sold as charcoal briquettes, used to pre-dry biomass, or employed in water purification and gas cleaning; its novel value, however, has been found in its application as a soil amendment (Lehmann 2007b). Biochar has high carbon content and may contain up to half of the total carbon of the original organic matter. Biochar is also highly stable against decay and retains nutrients better than other forms of soil organic matter (Lehmann 2007a). As a result, once incorporated into soils, biochar can enhance soil fertility, resulting in improved crop yields, and reduce applications of energy-intensive agricultural inputs like nitrogen fertilizer. Furthermore, it can reduce environmental pollution by retaining nutrients such as nitrogen and phosphorus in the soil and reducing the leaching of nutrients into groundwater or their erosion into surface waters (Lehmann 2007b). In contrast to crop residues and other organic resource applications, biochar's stability in terms of carbon storage over a long timescale allows for removing carbon dioxide from the atmosphere. Once assimilated by plant growth, carbon dioxide can be stored in a stable soil-carbon form rather than returned to the atmosphere through decomposition (Roberts et al. 2010).

While the engineering studies of pyrolysis and biochar production are many, economic feasibility analysis is rare and, to our knowledge, exists only for industrial-scale systems and in a developed-country setting. Several studies in the US carefully consider both fast and slow pyrolysis technologies using maize residues as a feedstock (see, for example, McCarl et al. (2009), Roberts et al. (2010), and Brown, Wright, and Brown (2011)). While the existing technologies are found unprofitable, the authors point to many assumptions relying on highly uncertain data and show that their results are most sensitive to feedstock costs, biochar benefits, and plant costs, as well as policies on GHGs and energy prices. To our knowledge, there are no studies analyzing the profitability of a pyrolysis-biochar project in Sub-Saharan Africa.

While still hypothetical, the pyrolysis-biochar system can become an attractive technology for the production of bioenergy. Since biomass is the feedstock that people in developing countries already know how to grow, its use in the pyrolysis-biochar system could be a key ingredient in generating additional incomes and improving agricultural productivity through biochar applications. Unlike cookstoves and biogas digesters, the system can use any non-edible lignocellulosic biomass. Its robust nature allows for considerable flexibility in the quality and type of the biomass feedstock. The system's larger scale will also require substantial capital investment and maintenance and operating costs. It can, however, tap into private domestic and foreign investment and potential government subsidies. Moreover, with soil carbon sequestration through biochar applications and the displacement of fossil fuels in the production of inorganic fertilizer and associated emissions, pyrolysis-biochar systems may offer a way forward for participation in international offset mechanisms or voluntary emissions offset markets (Whitman and Lehmann 2009). Thus, the technology deserves careful consideration for a developing-country setting.

4.3 Feedstock provision (biomass supply) costs

There are several categories of direct economic costs associated with the adoption of pyrolysis-biochar systems: feedstock provision costs, capital costs, and operating and maintenance costs of the system. The most uncertain and geographically varied of these are feedstock provision, or biomass supply, costs. These include both feedstock purchase and transportation costs. Not surprisingly, the costs depend heavily on regionally specific conditions such as feedstock availability, its price, and available infrastructure with respect to transport networks and their use (Eisentraut 2010).

To assess the availability of biomass for energy production, both existing and future, a number of studies focus on global, regional, and country-level estimates. Most of these studies analyze either geographic or technical potential. The geographic potential refers to the theoretical potential of growing biomass in a given area that is considered available and suitable for biomass production. Technical potential also includes losses during the harvesting process (Eisentraut 2010). Many of the existing estimates, however, ignore economic constraints to biomass availability and accordingly demonstrate higher available amounts of biomass that could be produced cost-competitively in practice. Moreover, regional and country-level estimates inevitably mask a high degree of geographic variation in biomass production. Both of these factors contribute to considerable uncertainty in estimating feedstock provision costs.

The other challenge lies in calculating the purchase price of feedstocks. Markets for many agricultural residues do not exist since processing technologies have not yet emerged. As a result, there are often no reliable data for the purchase price of feedstock. When data do exist, the available estimates vary significantly between different types and locations.[2] At the same time, since bioenergy sector expansion in developing countries is also meant to

[2] Eisentraut (2010), for example, reports the following price ranges for freshly harvested sugar cane tops and leaves: 3-8 \$/Mg in Brazil, 8-15 \$/Mg in Thailand, and 20-30 \$/Mg in India.

stimulate rural development (Kojima and Johnson 2005), the purchase price of feedstock needs to internalize social costs (Gallagher et al. 2003). Ideally, residue prices should reflect the opportunity costs for the private benefits of leaving crop residues on the fields, thus imitating a government policy of sustainable land use.

Typically, biomass transportation costs increase with larger plant sizes that exhibit higher feedstock demands and, consequently, increased transport distances and more complex logistics associated with storage and handling (Eisentraut 2010). Moreover, agricultural residues (even when naturally air-dried) have low bulk density (e.g., 0.1 Mg/m^3 for straw) that contributes to higher costs of moving biomass and requires significant investments in transportation. While the local sourcing of feedstock can help overcome the diseconomies of scale associated with long-distance transportation of biomass (Richard 2010), infrastructure and road maintenance especially in rural areas of developing countries is often precarious, further increasing feedstock provision costs. Reflecting these considerations, Eisentraut (2010) suggests that feedstock transport costs are approximately 10-25 percent of total biomass costs, but can be as high as 65 percent under unfavorable conditions. This wide range of estimates makes the general determination of the economic feasibility of bioenergy systems problematic and reinforces the importance of focusing on the specific biophysical and economic circumstances characterizing local areas. For these reasons, having access to micro-level data and doing a meticulous assessment of a specific case can reduce the uncertainty of accurately estimating feedstock provision costs.

4.3.1 Study area

We focus on one geographic area—the western Kenyan highlands (Western, Nyanza, and Uasin Gishu provinces)—to estimate the availability and provision costs as one particular example. The research area is one of the most densely populated regions of Kenya (100-

300 people per square kilometer), with over 55 percent of the population living below the national rural poverty line (WRI 2007). Our estimates are based on several micro-level datasets collected between 2011 and 2013 in the Yala and Nyando river basins, two of the major seven influent rivers feeding Lake Victoria in Kenya. The five research sites (Lower Yala, Mid Yala, Upper Yala, Lower Nyando, and Mid Nyando) are similar in terms of agricultural practices, but vary in altitude, rainfall, soils, and socio-economic characteristics, and thus represent the diversity of the East African highlands (Figure A.1.2).[3]

A household-level survey collected information on biomass availability and uses, as well as agricultural production over the 2011 calendar year. It covered 21 randomly sampled households in three villages in each of the research sites, comprising a total sample of about 315 households. Average farms are about 1-2 hectare in size and originally formed part of the tropical forest that became converted to agricultural land. Farmers practice subsistence agriculture with maize being the main food commodity. Plot-level data included farmer-reported annual and perennial crop harvest, chemical and organic inputs, seeds, household and hired labor, as well as GPS-measured plot size and farmers perceptions of soil quality. Access to electricity (about 11 percent of the sample population) and use of transportation fuels (12 percent) is slightly higher than Kenya averages (WB 2015).

In addition, a survey of 56 commercial centers in April-June 2012 described the demand and supply patterns of available energy and transportation in rural western Kenya (Cadogan and O'Sullivan 2012; Lane 2013). This survey collected market price data from energy sellers and buyers, as well as estimated the demand for modern energy services from small businesses in each of the commercial centers.

[3]The sites formed part of the original geographic coverage of the Western Kenya Integrated Ecosystem Management Project, implemented between 2005-2010 by the Kenya Agricultural Research Institute and the World Agroforestry Center and funded from the Global Environmental Facility of the World Bank. The 10x10 km sites were chosen to satisfy the GEF criteria of carbon sequestration and biodiversity increment potential, severity of land degradation, and the proximity to reserves with significant degradation because of external pressure.

4.3.2 Crop residue availability

The standard procedure to estimate the technical potential of cereal crop residues for energy production consists of multiplying country-level average cereal grain yields by a product-to-residue ratio (see, for example, Jingura and Matengaifa (2008), Milbrandt (2009), and Duku, Gu, and Hagan (2011)). Some of the studies also consider selected economic constraints on technical availability, and assume fixed percentages of residues that can be safely removed from the fields (e.g., Ackom et al. (2013)). Without having access to micro-level data, these country-level studies and the estimates they produce, however, may underestimate or, more likely, overestimate both the technical and economic potential of biomass for local bioenergy production.

In rural western Kenya, maize residues are one of the main on-farm biomass sources (Torres-Rojas et al. 2011). We use maize grain yields (Mg/ha/year)[4] data from the household survey. To convert maize grain yields to maize residue yields, we use the product-to-residue ratio observed in the research area. Crop residues in the study area, as elsewhere in Sub-Saharan Africa, are used for different purposes: about a quarter of maize residues is fed to domestic animals, another quarter is used as household fuel, and the remaining residues are left on the fields for soil fertility management (Chapter 2). Therefore, we use 50 percent as the estimated proportion of economically available residues for bioenergy production.

4.3.3 Feedstock cost

As discussed above, there are several challenges surrounding the estimation of feedstock cost. The cost of maize residues and their delivery to the plant is likely to be influenced by residue production density that is in turn determined by maize yields, their volatility across space

[4] 1 megagram (Mg) = 1,000 kilogram (kg) = 1 metric tonne. 1 hectare (ha) = 10,000 square meters = 2.47 acres.

and time, and the land area around the plant under maize cultivation. Moreover, there are reasons to expect that the pyrolysis-biochar plant will be able to exercise monopsony power when it comes to purchasing residues from smallholder farmers.

Similar to Gallagher et al. (2003), Caputo et al. (2005), and Sesmero and Sun (2015), we assume that maize residues feeding the pyrolysis-biochar plant are collected over a circular geographic area centered on the plant with uniform yield and harvest practices. Therefore, additional residues can only be procured from an expanding circle around the plant, from the extensive margin only. In contrast to previous literature, however, we combine both the effects of yield volatility on residue price and partial spatial price discrimination on transportation cost.

Let p be the farm-gate price of residues ($/Mg). Since markets for agricultural residues in western Kenya do not exist, we can estimate their value using either a production or a substitution approach. As applied to non-marketed sources of biomass, the production approach demonstrates the value of residues by calculating changes in farm profits or production output by including residues as a production input (see for example, Lopez (1997) and Klemick (2011)), while the substitution approach derives the value of residues from the observed prices for marketed substitutes (Teklewold 2012; Magnan, Larson, and Taylor 2012).

Given the focus on sourcing from smallholders, we rely on household-level data to estimate the farm-gate feedstock price. The value of maize residues is assessed on the basis of monetary worth of the equivalent amount of fertilizer required to compensate for the loss of crop residues, as estimated in Chapter 2. It reflects the private benefit of leaving crop residues on the fields and should be similar to the social value of sustainable land use.

This farm-gate price is, however, can also be influenced by yield volatility. Adverse weather and other production shocks can lead to lower residue yields, thus increasing the value of residues harvested. The higher value can be a result of harvesting cost that is fixed per unit of area or due to increased risk of soil erosion. On the other hand, high residue yields may increase the prevalence of pests and disease, thus potentially lowering the value of residues to the farmer. Following Sesmero and Sun (2015), we allow for the link between residue price and yield by a linear relationship:

$$p = \alpha - \beta y, \tag{4.1}$$

where p is the farm-gate price of residues (\$/Mg) and y is the maize residue yield (Mg/ha).

The parameter β captures the effect of changes in residue yield on price. We calibrate β, following Sesmero and Sun (2015), so that the elasticity of residue price with respect to yield is equal to one at the median yield and residue values in the data.[5] It is calculated as $\frac{dp}{dy}\frac{y}{p} = -\beta\frac{y}{p} = 1$, which implies $\beta = -\frac{p}{y} = -\frac{58.24}{2.99} = -19.48$, meaning that a reduction in residue yield of one Mg per ha is associated with a decrease of value of maize residues to farmers of 19.48 \$/Mg. Then, α is calculated from the equation above and it is equal to 116.49 \$/Mg.[6]

Feedstock transport cost is determined to account for intrinsic feedstock characteristics such as scattered geographic distribution. The procurement area and, therefore, the transport distance from the point of feedstock production to a bioenergy plant depend on several factors. These include the capacity of the plant and the quantity of feedstock required, as well as local crop yields, and planting density around the bioenergy plant.

[5] As suggested by some estimates, a ten percent reduction in residue yield can lead to a seven percent increase in on-farm per unit harvest cost of maize residues, due to existing cost factors that are fixed per unit of area. Sesmero and Sun (2015) argue that a value of 0.7 is, therefore, a lower bound on the elasticity of residue price with respect to yield and it is probably higher once soil erosion risk is taken into consideration.

[6] The farm-gate value of maize residues is also spatially and temporally heterogeneous. In fact, the value is different across households in our dataset and, controlling for natural capital, is higher for poorer households (Chapter 2). In this paper we use the median value of maize residues and focus our attention on the effect of yield volatility on feedstock prices.

The transportation component of residue cost increases with the distance traveled (r) and the amount of feedstock procured (Q). It can be approximated by $Q = \pi r^2 \Delta y$, which is the product of the circular area around the plant and the density of residues (Gallagher et al. 2003; Caputo et al. 2005; Sesmero and Sun 2015). Inside this collection area, the actual plots with maize cultivation are only a fraction of total land area and may be unevenly distributed. Therefore we measure Δ, the density of planted maize in the total area, as the share of total farm size assuming a uniform biomass distribution density over the entire area of the collection basin. Since Q represents the capacity of the biochar-pyrolysis plant, the maximum distance to procure the required feedstock is, therefore, $r = \sqrt{\frac{Q}{\pi \Delta y}}$. As shown by Gallagher et al. (2003), the average transport cost can then be derived as $\frac{2}{3}tr$, where t is the freight rate in \$/Mg/km, the unit cost of trucking feedstock from farms to the biochar-pyrolysis plant. Hence, the transportation cost increases with the freight rate and the maximum distance traveled, while the supply radius increases with plant capacity and decreases with residue density.

Given the geographic distribution and a large number of small farms producing maize residues, the biochar-pyrolysis plant is likely to have monopsony power in the maize residue market. Agricultural and natural resource markets are often characterized by spatially distributed supply and significant transport costs, so that the processing facilities can exercise price discrimination in the form of partial or complete absorption of freight charges (Lofgren 1985; Graubner, Balmann, and Sexton 2011). To account for this possibility and similar to Lofgren (1985), let $\gamma \in [0, 1]$ measure the degree of spatial price discrimination. Then, when $\gamma = 1$, the plant bears the entire transportation cost and the producers of maize residues receive the same price irrespective of their location relative to the plant (uniform delivered pricing). But when $\gamma < 1$, the plant can pass along some of the transportation cost to producers (partial freight absorption).

Putting these elements together, the per-unit feedstock cost (c) can then be calculated as

$$c = p + \gamma\frac{2}{3}tr = \alpha - \beta y + \gamma\frac{2}{3}t\sqrt{\frac{Q}{\pi\Delta y}}, \tag{4.2}$$

where c depends on the maize residue yield (y), freight rate (t), plant capacity (Q), residue density (Δ), and the market power of the biochar-pyrolysis plant (γ).

4.4 Economic viability of small-scale bioenergy production

In order to assess the economic viability of small-scale bioenergy production in rural Sub-Saharan Africa and the relative magnitude of the feedstock provision costs and their variability, we focus on a hypothetical pyrolysis-biochar plant in western Kenya. The plant operates on the thermochemical conversion platform and uses maize residues from the surrounding farms as feedstock. The feedstock is gasified to produce syngas that is then converted into ethanol by a biological reaction (fermentation) using microbial catalysts (the process is described in Piccolo and Bezzo (2009)). In addition to ethanol, the plant coproduces biochar. While there is a trade-off between ethanol and biochar yields (Woolf et al. 2014), both products are valuable and need to be considered to take full advantage of environmental and social benefits of the pyrolysis-biochar system.

Given our focus on small-scale bioenergy production in a rural setting, we analyze a plant that can process 15 Mg of dry feedstock per hour and operates at 75 percent capacity,[7] so that the annual biomass required is 98,550 Mg. As common in other techno-economic analyses of bioenergy projects, we also assume the life of plant of 20 years and interest rate of 10

[7] 85 percent is often assumed as a *levelized* capacity factor, an average capacity over the life of a plant, while historic data show that the annual average capacity factor for a coal-fired plant in the US varies between 65 and 75 percent (Rubin 2012). Given the developing country setting, we assume a lower capacity factor of 75 percent.

percent. To approximate total capital and operating costs, we use the recent estimates from the literature. The pyrolysis capital cost comes from McCarl et al. (2009) who analyze the costs and benefits of fast and slow pyrolysis technologies using maize residues as a feedstock. The biofuel conversion capital cost is from Piccolo and Bezzo (2009) who present the first comprehensive analysis of the gasification and fermentation process. Annual operating and maintenance costs are assumed to be four percent of total capital costs as in Shabangu et al. (2014).

The direct economic benefits of the pyrolysis-biochar plant are bioethanol and biochar sales. Given the infant nature of the pyrolysis bioethanol markets, we assign the value to pyrolysis ethanol as an equivalent to a conventional product. Brazil is one of the worlds largest producers of ethanol, with a substantial domestic market and considerable exports. Since Brazil's sugarcane-based ethanol is cheaper to produce than the US corn-based ethanol, we use the five-year average of Brazil's producer prices—0.55 US$ per liter (OECD/FAO 2015).[8]

The price of biochar is often estimated in comparison to a conventional fertilizer price, its value in terms of increased yields, or its combustion value (McCarl et al. 2009; Galinato, Yoder, and Granatstein 2011). In Kenya, conventional charcoal is the primary energy source for 82 percent of urban and 34 percent of rural households. The producer price of charcoal is estimated at 85 US$/Mg, with market prices ranging between 306 US$/Mg (wholesale) to 952 US$/Mg (consumer retail) (KFS 2013). We assume biochar's combustion value (the producer price of charcoal, 85 US$/Mg) as the lowest price. Its total value, however, comes from soil improvements and associated agricultural productivity increases, and climate change mitigation (Lehmann and Joseph 2009). Thus, our base value is higher—115 US$/Mg. These and other assumptions used, as well as their assumed variability, are summarized in

[8] `http://www.agri-outlook.org` [Accessed 07/05/2015]. For comparison, the five-year average of ethanol wholesale free on board price in Omaha, Nebraska is 0.62 US$ per liter (`http://www.neo.ne.gov/statshtml/66.html`).

Table 4.1.

We then derive three economic decision criteria used in the analysis of investments economic viability—net present value (NPV), payback period (PBP), and internal rate of return (IRR). Net present value (NPV) compares the value of money now with the value of money in the future. Assuming that total annual economic benefits (TAB) and total annual operating costs (TOC) do not change over the projects lifetime (t), we calculate the NPV ($) from the expression:

$$NPV = \sum_{t=1}^{T} \frac{(TAB - TOC)_t}{(1+\delta)^t} - TCIC, \tag{4.3}$$

where δ is the annual interest rate and TCIC is the total overnight capital and installation costs (the sum of pyrolysis capital cost and the biofuel conversion capital cost).

Payback period (PBP) refers to the number of years required to return the project's original investment. Assuming that initial investment is the total capital and installation costs (TCIC) and that annual net profits are constant over time, we calculate the undiscounted UPBP ($) as follows:

$$UPBP = \frac{TCIC}{(TAB - TOC)}. \tag{4.4}$$

Internal rate of return (IRR) estimates the interest rate needed to make the present value of a stream of net revenues equal to zero. It is calculated as IRR that solves the following equation:

$$NPV = \sum_{t=1}^{T} \frac{(TAB - TOC)_t}{(1+IRR)^t} \Big/ TCIC. \tag{4.5}$$

If IRR is higher than the discount rate, investment is considered profitable. For a high risk project such a pyrolysis-biochar system, the suggested IRR is usually 15 percent (Piccolo and Bezzo 2009).

4.5 Results

We first present the estimates of feedstock availability and provision costs using the micro-level data from the research area and focusing on a high degree of variability between the five research sites. We use the median values; however, report the empirical distributions of maize residue yield that proxy for spatial and temporal variability. The site-level estimates of maize residue yields, maize planting density, and residue cost suggest a range of purchasing and transportation costs that can be expected now if a pyrolysis-biochar plant was placed in one of the research sites. We then calculate the economic decision criteria (net present value, internal rate of return, and payback period), using the lowest estimate of the feedstock provision costs, and perform sensitivity analysis of this net present value to several economic variables. Then, to account for yield volatility and following Sesmero and Sun (2015), we estimate the probability distributions of maize residue yield in five research sites and model the cost of feedstock as a function of that distribution.

4.5.1 Maize residues availability in western Kenya

Following the standard procedure to estimate the technical potential of maize crop residues for energy production, we first present country-level and province-level average cereal grain yields (Table 4.2). For country-level estimates (second row) we use the 2000-2011 average maize production from FAOSTAT, while for province-level estimates (third row) we use the data from the Kenya Agricultural Sector Data Compendium reported in Sheahan, Ariga, and Jayne (2013). Estimates in the last row are based on the household-level data from western Kenya. Grain yield averages (Mg/ha) vary across the three data sources. The three province averages are higher than the country-level average, which is not surprising given that Nyanza, Western, and Rift Valley provinces have some of the most favorable agro-climatic conditions in Kenya. The province averages, however, are higher than average yields reported by farmers in the household survey. Yet, even averages from the household survey hide a great degree of variation in both technical and economic availability of residues. Figure 4.2 shows the distribution of maize residue yields in the five research sites, as well as for the whole sample.[9] The median harvest is the highest in Upper Yala (4.15 Mg/ha) and the lowest is in Lower Yala (2.25 Mg/ha).

Despite the low technical potential for feedstock from maize residues in the research area, its economic potential is even lower. Crop residues are an important resource in smallholder agriculture, providing feed for domestic animals and used as household fuel. Leaving crop residues on the fields as a soil amendment is also essential to enhancing, maintaining, and sustaining long-term soil fertility and agricultural productivity. Their removal for other uses has led to the depletion of the soil organic pool in the tropics and subtropics, accelerating soil degradation, severe erosion, and water pollution (Lal 2006). It is difficult to imagine the removal of all residues for bioenergy production since such a move, together with its environmental implications, would require a major change in farming and biomass utilization systems (Senelwa and Hall 1993). As the household survey reported, we use 50 percent of maize residues as the amount of residues available for bioenergy production.

[9]For the 186 households (out of 309) that cultivated maize twice in 2011, the sum of yields from both seasons (long rains and short rains) is shown.

4.5.2 Feedstock provision costs: price and transport

The estimates for non-marketed maize residue value are from Chapter 2. Using the same household data, the household-specific shadow value of maize residues used for soil fertility management is estimated using coefficients from a maize production function and household-specific fertilizer prices. For the sustainable bioenergy production, the social cost included in the supply analysis must involve opportunity costs associated with alternative residue uses (Gallagher et al. 2003). And since we assume that only 50 percent of maize residues can be included in supply to avoid soil degradation, our estimates approximate farmers' decisions under a policy of sustainable land use.

The median value for the whole sample is 58.24 $/Mg. This is close to the value of cereal stubble in Morocco estimated by Magnan, Larson, and Taylor (2012). Similar to maize residue yields, however, there is a high degree of variability in the value of maize residues to western Kenyan farmers (Table 4.3). The lowest median residue value is observed in Upper Yala (27.09 $/Mg), the site with the highest yields. For Mid Yala, the site with the second highest median residue yield (3.95$/Mg), however, the median residue value is very high: 101.72 $/Mg. A very high population density and small sized farms characterize this research site, placing a greater demand on residues from alternative uses.

To calculate the cost of transporting maize residues to a pyrolysis-biochar plant, we also need to know the distribution of maize residues over the entire area of the collection basin. Assuming that households in our survey are representative of the research area, we scale maize residue yields available for bioenergy by the share of land under maize cultivation in each of the research sites in total farm area (maize planting density).[10] This means that our feedstock planting density is not the residue yield of the maize-producing plots, but the

[10]For households that planted maize twice in 2011, we estimate the feedstock distribution density as follows: maize residues yield in long rains multiplied by the share of land planted with maize in long rains in total farm area + maize residues yield in short rains multiplied by the share of land planted with maize in short rains in total farm area.

average equivalent yield of the entire geographic area around the plant to define the average feedstock transport distance.

The estimate of the freight rate (\$/Mg/km), the unit cost of trucking feedstock from farms to the biochar-pyrolysis plant, is the average freight rate reported in the commercial center survey (\$/Mg/km average for 5, 7, 10, and 12 Mg capacity trucks, including the minimum charge). Some other estimates from Kenya suggest that the operational cost for semi-trailers is 1 \$/Mg/km (similar to the costs in Europe), while the trucking businesses charge 1.20 \$/Mg/km to the client (WB 2005). The degree of freight cost absorption is assumed to be 80 percent, i.e., the pyrolysis-biochar plant bears 80 percent of the transportation cost and passes 20 percent to the farmers. Similar practices are observed in the sugarcane and tea growing industries in the research area. Sugarcane mills, for example, pick up cane at the farms and then deduct a portion of the transportation costs from the final payments to farmers.

Table 4.3 summarizes the variables used for the calculation of the feedstock cost for the five research sites and for the whole sample. Given the difference in maize planting density (maize residue yield times maize land as a share of total land) and value, both feedstock purchase and transport cost significantly vary between the sites. The highest feedstock unit cost is observed in the Mid Yala region (101.72 \$/Mg), while the transportation unit cost in this region is one of the lowest (13.43 \$/Mg) because of the relatively high density of maize residues. The transportation cost as a share of feedstock purchase cost also varies between 13 and 40 percent, similar to the shares suggested by Eisentraut (2010). The geographically varied agro-ecological and socio-economic conditions are reflected in the highly variable feedstock provision costs among the five research sites and can only be seen with the micro-level data. The sample averages necessary mask this heterogeneity, and suggest the average total provision costs almost double than the costs estimated for Upper Yala.

The highest maize residue yield and maize land share, and the lowest residue unit price are observed in Upper Yala (4.15 Mg/ha/year, 0.55, and 29.97 \$/Mg at the median, respectively). As a result, the Upper Yala site has the smallest radius of the catchment area necessary to provide feedstock to the pyrolysis-biochar plant. For a plant with 15 Mg of feedstock per hour capacity, such a radius is 16.57 km. The total feedstock provision cost (both feedstock cost and transport cost) is also, therefore, the lowest—3,654,000 \$/year. It is this value that we use in the economic viability estimations.

4.5.3 Economic viability and sensitivity analysis

Using the feedstock cost from the Upper Yala research site, Table 4.4 summarizes the costs and benefits of the 15 Mg/hr pyrolysis-biochar system, and shows the three economic viability indicators: net present values (NPV), internal rate of return (IRR), and undiscounted payback period (UPBP). At the assumed discount rate of 10 percent, NPV is positive (\$1,643,513), and the initial capital investment can be paid off in 8.25 years. And although IRR exceeds the assumed interest rate, it is, however, below the recommended 15 percent value for high-risk investments.

The key variables with the most significant impact on the profitability of the pyrolysis-biochar plant are similar to other studies: initial capital investment, feedstock cost, final product prices, and interest rates (the variables, as well as their baseline, low, and high values are summarized in Table 4.5). Figure 4.3 shows the impact of varying the baseline values on the economic viability of the pyrolysis-biochar plant indicated by the net present value (NPV).

Ethanol and biochar prices have the highest impact on profitability. Brazil's sugarcane-based ethanol was, on average, 0.38 \$/liter in 2009 and 0.69 \$/liter in 2011 (OECD/FAO 2015). The ethanol unit price of 0.35 to 0.75 Mg/liter varies the net present value from -\$22,436,187 to \$25,723,084. Given the absence of biochar markets in Eastern Africa, we also assume a high spread in the biochar unit price: from 85 \$/Mg to 230 \$/Mg, with consequent changes to net present value (from -\$7,662,030 to \$37,314,451). This high degree of ethanol price volatility and uncertainty in the value of biochar may require initial private or government support (in the form of guaranteed ethanol or biochar prices).

When feedstock purchase cost is increased to 65 \$/Mg (similar to the second highest value of maize residues in the five research sites), the net present value of the plant becomes negative: -\$30,163,485. The ability of the plant to pass some of the transportation cost to the farmers is also important: when the plant takes the full responsibility for transportation, the net present value falls to -\$451,486. Similar to other techno-economic studies of the bioenergy production, the baseline value for interest rate is assumed to be 10 percent. Given the developing-country additional objectives for bioenergy development, however, a lower interest rate may be more appropriate. The interest rate of five percent changes the net present value to \$26,326,339, suggesting considerable benefits of the pyrolysis-biochar plant in Upper Yala.

4.5.4 Varying yields and residue cost

To explicitly model both geographic and temporal yield volatility and its effect on residue prices, we follow the procedure outlined in Sesmero and Sun (2015). We first fit empirical yield distributions for the whole sample and five research sites (blue lines over distributions in Figure 4.2). Yields are best approximated by the gamma distribution, Γ, with shape and rate parameters differing for each site.[11] We now also allow for the link between residue price and yield by a linear relationship: $p = \alpha - \beta y$, where p is the farm-gate price of residues (\$/Mg) and y is the maize residue yield (Mg/ha). Parameters α and β are calibrated as discussed above using the site-specific median yield and residue values, so that α and β are

[11] Whole sample $\Gamma(2.104,0.591)$, Lower Nyando $\Gamma(1.502,0.492)$, Mid Nyando $\Gamma(2.668,0.867)$, Lower Yala $\Gamma(3.181,1.235)$, Mid Yala $\Gamma(2.342,0.477)$, Upper Yala $\Gamma(2.955,0.707)$.

different for each site (Table 4.3). Therefore, randomness in yields has two effects on the feedstock provision costs and the calculations of the net present value. First, it introduces risk in maize harvest density and thus influences the transportation cost. Second, it adds risk to the farm-gate price of residues.

We then calculate net present values (10,000 iterations for each location) based on fitted yield distributions. These simulations result in a probability distribution of NPVs for each of the five research sites and for the whole sample. Figure 4.4 shows the cumulative density functions (CDFs) and the first two moments of the distributions are reported in Table 4.6. Similarly to the deterministic analysis, the mean of the net present value is positive only for one research site—Upper Yala ($740,924), with all other sites and the whole sample showing the average negative net present values. Placing a pyrolysis-biochar plant in Upper Yala is also a less risky investment. Upper Yala is preferred to all other locations by both risk-neutral and risk-averse investors. Its NPV distribution displays higher mean and lower standard deviation than other sites, and simple visual inspection of Figure 4.4 confirms that the Upper Yala CDF dominates all other CDFs in a second-order stochastic sense (both high and low values are less likely, but the reduction in the probability of low values is large enough to offset the reduction in probability of high values).

4.5.5 Non-monetary benefits

Production of both bioethanol and biochar can result in net greenhouse gas (GHG) offsets that we do not consider in this paper. Biofuels are considered potentially "carbon neutral" since biomass feedstock absorbs the carbon dioxide which is released when biofuels are burnt. The extent of the GHG reductions, however, depends on land use changes associated with biomass production, conversion technologies, and often on methodological assumptions. The GHG savings estimates range from about +85 percent to -30 percent (Hammond and Seth

2013), and for ethanol from sugarcane, for example, they are +70-100 percent (Bringezu et al. 2009). Moreover, while credits for renewable energy calculated from the displacement of fossil fuel energy are common in emissions trading schemes, the production of biochar can also offer additional emissions credits.

Soil carbon is primarily derived from plant matter. In the tropics, however, biomass decomposes quickly, and about 80 to 90 percent of carbon from biomass added to soil can be lost after 5-10 years (Jenkinson and Ayanaba 1977). In contrast, pyrolysis stabilizes carbon in biochar in a form that is resistant to further decomposition and the stored carbon in soil is not susceptible to release due to changes in management practices (Lehmann 2007b). In addition, biochar applications can enhance agronomic efficiency and even substitute directly for fertilizer and other agricultural inputs, thus decreasing fertilizer applications and increasing yields (Gaunt and Cowie 2009).

Several studies include a complete life-cycle analysis of the GHG emissions from a pyrolysis-biochar system. McCarl et al. (2009), for example, estimate the net GHG offset for slow pyrolysis with maize residue feedstock to be 1.112 Mg of carbon dioxide equivalent (CO_2e) for each Mg of feedstock. Their analysis of GHG offsets includes both GHG emissions (fossil fuels used during residue harvest, transportation, and processing, plant operations, carbon consequences of biomass removal and nutrient replacement, and biochar transportation and application) and GHG emissions avoided (fossil fuel offset, reduction in inputs, and sequestration enhancement). Although the existing carbon pricing instruments are below 10 \$/Mg of CO_2e,[12] even a modest payment for the GHG offsets can increase the pyrolysis-biochar system's profitability.

We also do not account for other potential environmental benefits of the pyrolysis-biochar system (e.g., changes in water and air quality) and for the dynamic nature of the crop-

[12] Carbon dioxide prices in the European Union Emissions Trading System remained in the range of 5-9 \$/Mg of CO_2e in 2013 (WB 2014), and the average price for forestry offsets in 2012 was 7.8 \$/Mg of CO_2e (Peters-Stanley, Gonzalez, and Yin 2013).

biochar production relationship. Biochar applications on farms that supply feedstock to the pyrolysis-biochar plant can enhance maize yields and thus availability and cost of feedstock. Since bioenergy production in developing countries is also viewed as a means of stimulating economic development (Kojima and Johnson 2005), other non-monetary benefits may include increased access to markets, educational and medical facilities, agricultural machinery, and new jobs.

4.6 Conclusion

Conversion technologies for most second-generation biofuels are still at early stages of development, with multiple technological and economic challenges impeding their commercial deployment (Hammond and Seth 2013). In this paper, we consider one of these challenges—feedstock supply. We analyze the cost of purchasing maize residues from smallholder farmers and the cost of transporting them to a small-scale pyrolysis-biochar plant in rural western Kenya. Using micro-level data from five research sites, we show how the differences in maize residue yields, maize planting density, and value of residues to farmers drive a great degree of variability in feedstock provision costs even in the limited geographic area considered. The pyrolysis-biochar plant with the 15 Mg of feedstock per hour capacity is found to have positive net present value only in one research site—Upper Yala, with the lowest feedstock provision costs. At the assumed discount rate of 10 percent, NPV is $1,643,513, and the initial capital investment can be paid off in 8.25 years. And although the internal rate of return index exceeds the assumed interest rate, it is, however, below the recommended 15 percent value for high-risk investments. We also show that, in addition, Upper Yala research site with the highest maize yield and maize planting density, as well as the lowest value of maize residues to farmers, would be preferred to all other locations by both risk-neutral and risk-averse investors.

Our results also suggest a range of purchasing and transportation costs of maize residues that can be expected now if a pyrolysis-biochar plant were to be placed in western Kenya. We would, however, expect significant adjustments in feedstock availability and provision costs, as well as the associated spillovers to local biomass and fuel markets, with an actual placement of such a pyrolysis-biochar plant. If biochar were to be used on the farms supplying feedstock for the plant, for example, higher maize yields could result both in greater availability and lower cost of feedstock, thus lowering the feedstock provision costs for the plant. Pyrolysis-based fuel production could also influence the household demand for residential fuel by offering new fuel alternatives and changing the current allocation shares of maize residues to different uses. Moreover, we use 50 percent of maize residues as the amount of residues available for bioenergy production to approximate farmers' current practices. A private market for residues as feedstocks for bioenergy production could, however, alter these practices, inducing higher supply of residues for bioenergy production and potentially higher social costs if not enough residues were to be left on the fields for soil fertility management. Such general equilibrium effects are of great interest and deserve careful analysis in future research.

There are several implications of our results for small-scale bioenergy production in other rural settings. First, the country-level statistics that are so common to the past literature hide a great degree of heterogeneity in terms of both the agro-ecological environment and socio-economic conditions. Even if we were to analyze the economic viability of the bioenergy plant using the average values from our dataset, we would not capture all the variability that exists. Therefore, having access to micro-level data helps resolve some of the uncertainty in terms of the feedstock provision costs and to locate areas where small-scale bioenergy production can be profitable. Second, given the high sensitivity of net present value estimates to final product prices and feedstock provision costs, initial government support—in the form of guaranteed ethanol or biochar prices, subsidies for feedstock purchase, etc.—would likely be required to assure economic viability (but that dependence itself would be a drawback).

To help promote small-scale bioenergy development, national biofuel policies should focus on raising financial resources for infrastructure development, investing in research and development, and establishing regulatory and institutional frameworks (Jumbe, Msiska, and Madjera 2009). Finally, since for many developing countries bioenergy carries multiple development objectives, including non-monetary benefits as well as using a lower discount rate in the analysis may be more appropriate. Accounting for diversity of agro-ecological and socio-economic constraints is necessary to match the global enthusiasm about bioenergy and its potential to deliver access to modern energy services, spur economic growth, and mitigate climate change.

Figure 4.1: Five research sites: Lower Nyando, Mid Nyando, Lower Yala, Mid Yala, and Upper Yala.

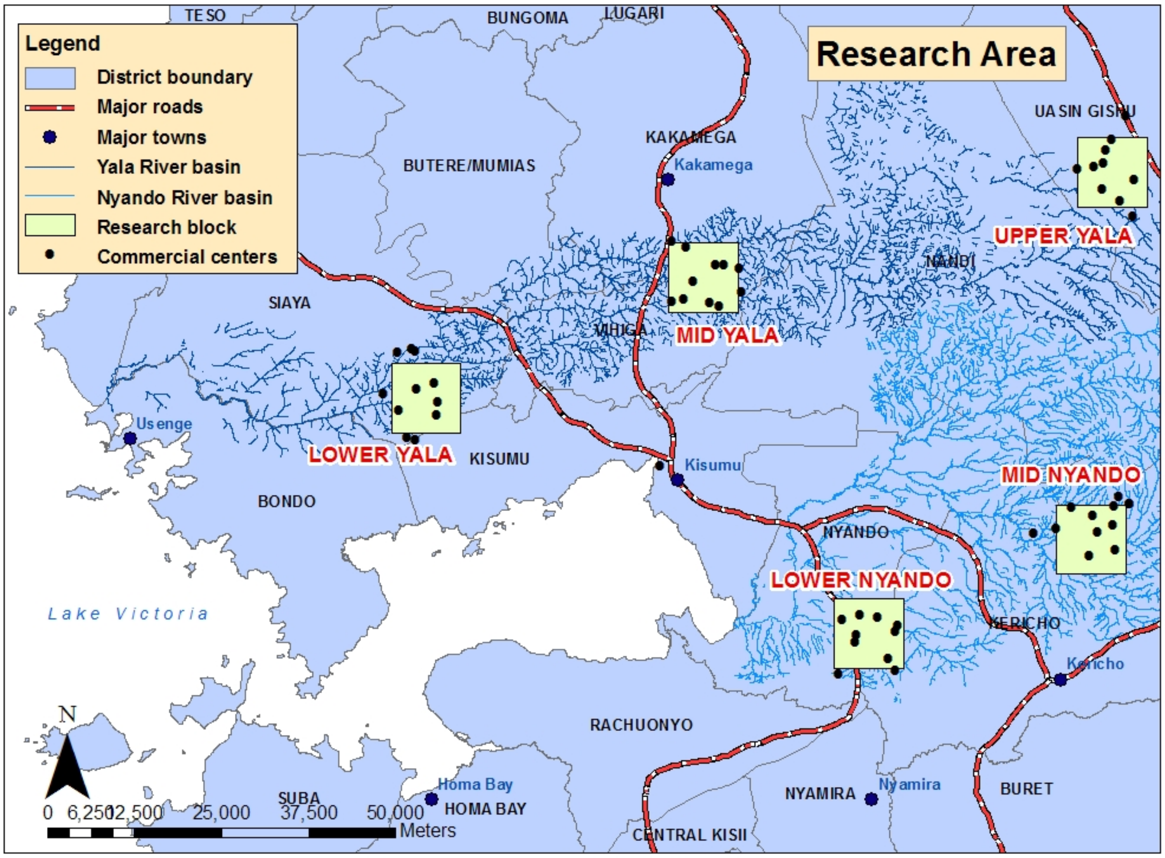
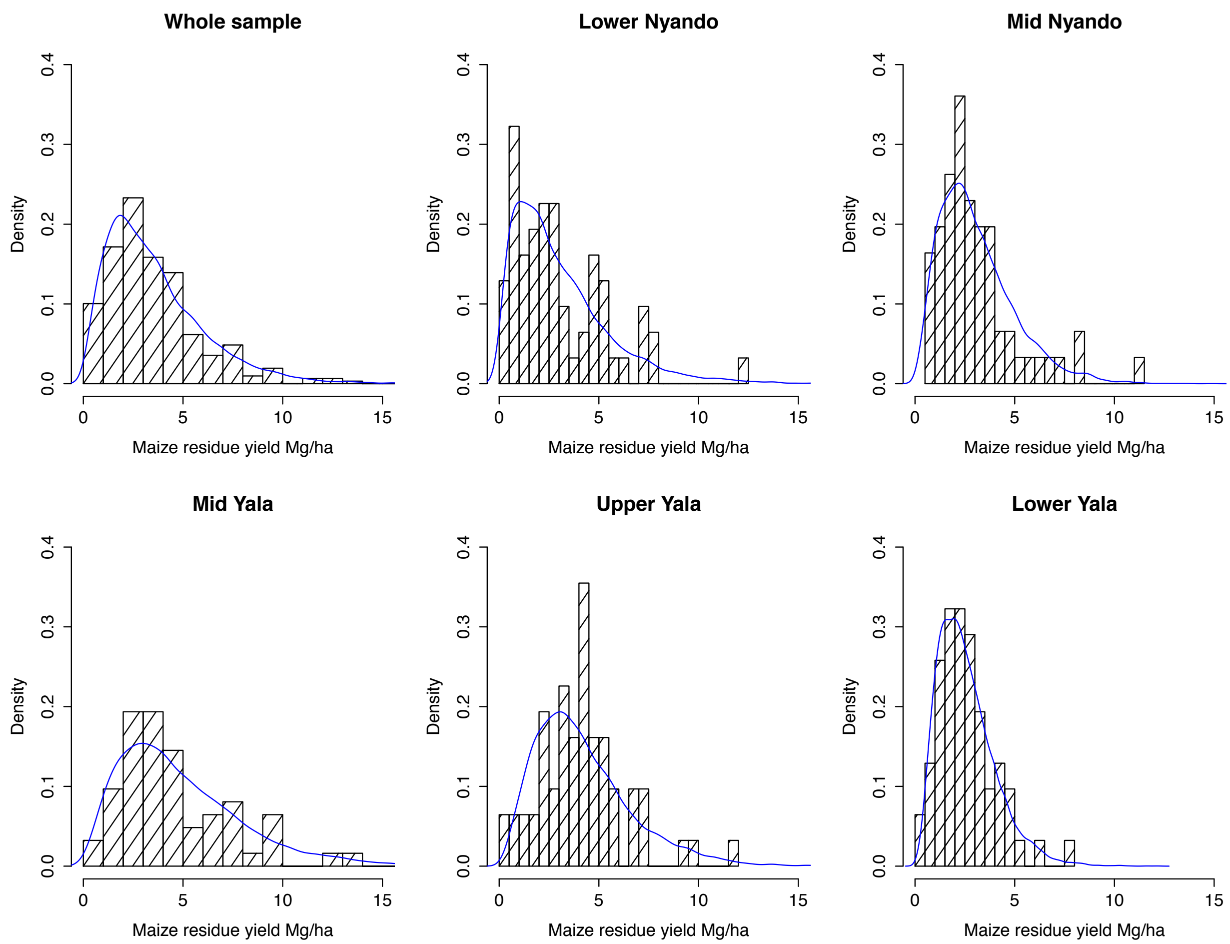
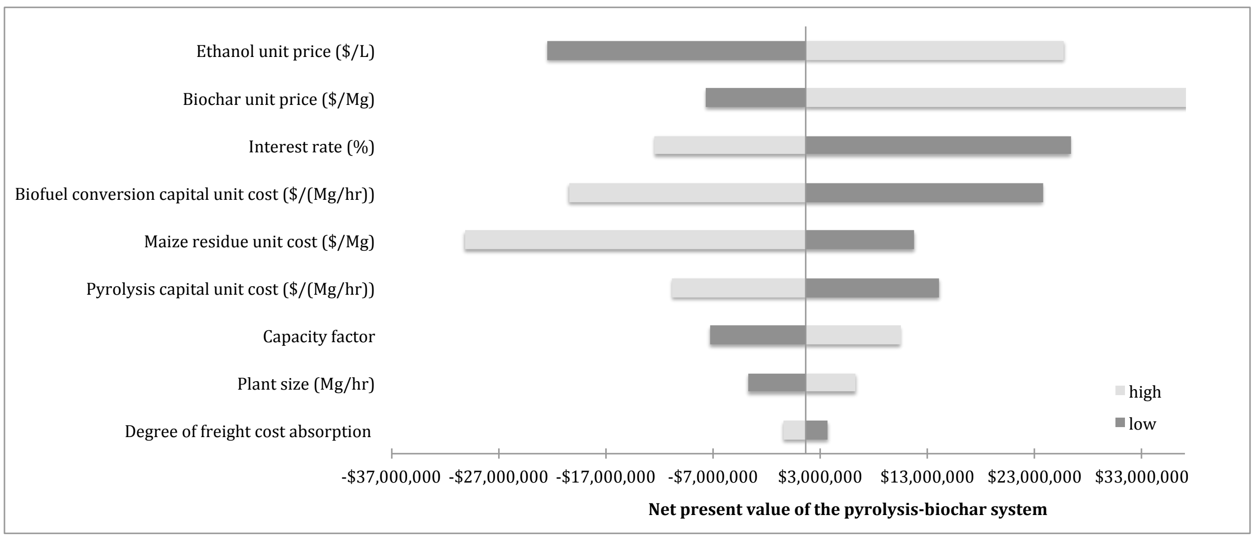


Figure 4.2: Maize residue yields in western Kenya: distributions of maize residue yields from the household survey data, by research site and for the whole sample.



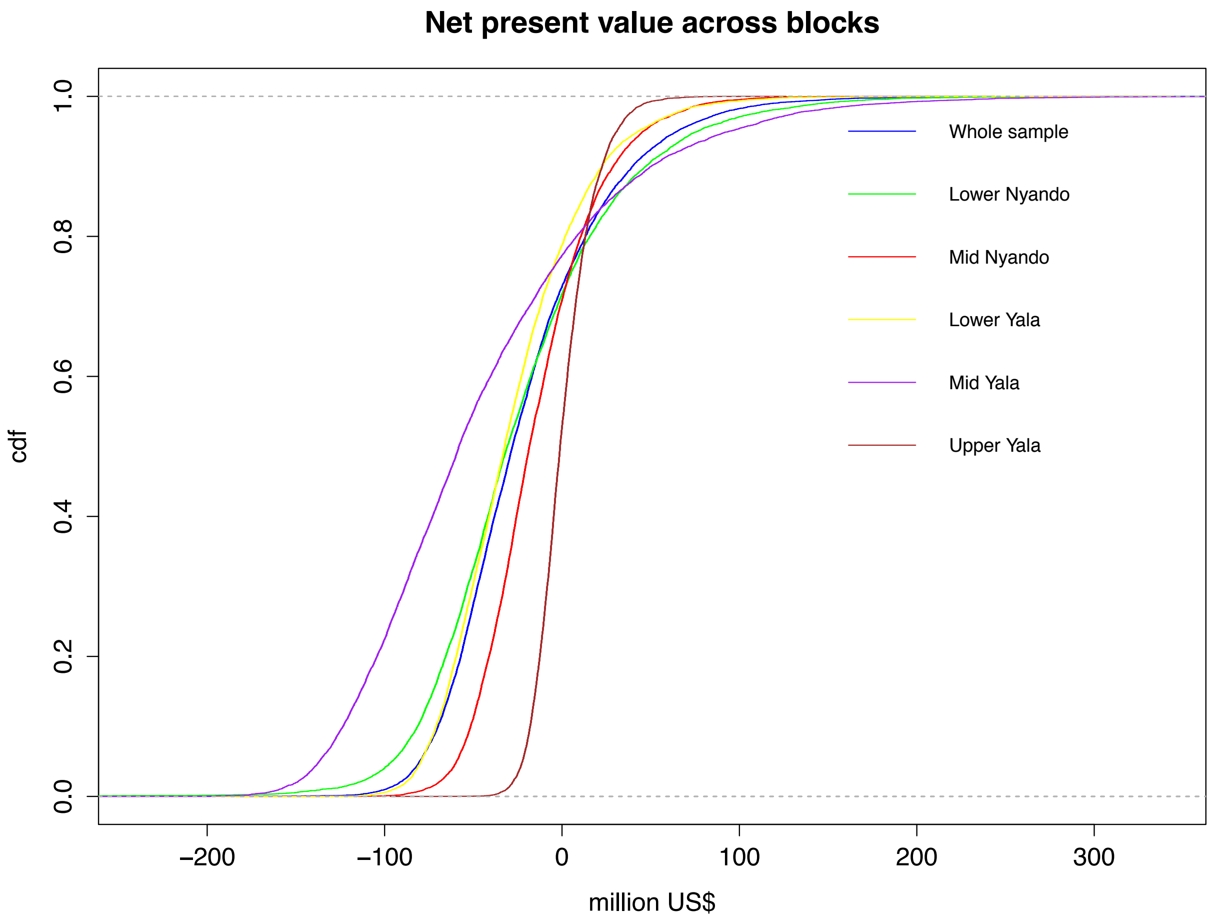
Note: The blue line shows fitted Gamma distributions.

Figure 4.3: Sensitivity analysis for a pyrolysis-biochar plant size of 15 Mg/hr.



Note: Net present value at the baseline is $1,643,513, for the parameters in Table 4.4. Table 4.5 shows the low, baseline, and high values for each of the sensitivity variables used in the calculations.

Figure 4.4: Cumulative density functions of the net present value simulations.



Note: CDFs are based on fitted maize residue yields (10,000 iterations for each location), site-specific residue value and share of maize land in total land. All other parameters are at the baseline values as appear in Table 4.1 and 4.3.

Table 4.1: Values of main economic parameters.

Variable	Unit	Value
Pyrolysis-biochar plant		
Plant size	Mg DM/hr	15
Capacity factor	%	75
Interest rate	%	10
Life of plant	Years	20
Capital and operating costs		
Pyrolysis capital unit cost	\$/(Mg DM/hr)	1,240,000
Biofuel conversion capital unit cost	\$/(Mg DM/hr)	2,198,309
Operating and maintenance (4% of capital costs)	\$/year	2,062,985
Annual revenue		
Biochar yield, including ash	Mg/Mg feedstock	0.3697
Biochar price	\$/Mg	115
Biochar produced	Mg/year	36,434
Biochar revenue	\$/year	4,189,910
Biofuel yield, in L	L/Mg feedstock	143.50
Biofuel price, in L	\$/L	0.55
Biofuel produced, in L	L/year	14,141,925
Biofuel revenue, in L	\$/year	7,778,059
Total annual revenue	\$/year	11,967,969

Data sources: Shabangu et al. (2014), McCarl et al. (2009), Piccolo and Bezzo (2009), authors' estimates.

Table 4.2: Maize grain yields (Mg/ha).

Data source	Country	Nyanza Province	Western Province	Rift Valley Province
FAO, 2000-2011 average	1.61			
KASDC, 2000, 2004, 2007, 2010 average	1.74	2.16	2.50	2.42
Household survey, 2011		1.13	1.68	2.23

For household survey data, average estimates are based on 6 villages in Nyanza province, 3 villages in Western province, and 6 villages in Rift Valley province. Data sources: FAOSTAT, Kenya Agricultural Sector Data Compendium (as reported in Sheahan et al. (2013)), authors' household survey.

Table 4.3: Feedstock provision costs by research site.

Variable	Unit	All N=309	Lower Nyando N=62	Mid Nyando N=61	Lower Yala N=62	Mid Yala N=62	Upper Yala N=62
Plant capacity (Q)	Mg/year	98,550	98,550	98,550	98,550	98,550	98,550
Freight cost (t)	$/Mg/km	1.13	1.13	1.13	1.13	1.13	1.13
Maize residue yield	Mg/ha/year	2.99	2.45	2.61	2.25	3.95	4.15
Maize residue for bioenergy (y)	Mg/ha/year	1.49	1.23	1.31	1.12	1.97	2.08
Maize land as share of total land (d)	0-1	0.35	0.20	0.31	0.40	0.32	0.55
Transportation radius (r)	km	24.50	35.76	27.84	26.42	22.28	16.57
Maize residue unit cost (p)	$/Mg	58.24	53.43	46	63.49	101.72	27.09
α		116.48	106.86	92.00	126.98	203.44	54.18
β		19.51	21.79	17.61	28.27	25.76	6.52
Degree of freight cost absorption (γ)	0-1	0.8	0.8	0.8	0.8	0.8	0.8
Feedstock cost	$/Mg	58.24	53.43	46.00	63.49	101.72	27.09
Transportation cost	$/Mg	14.77	21.55	16.78	15.93	13.43	9.99
Transportation cost/feedstock cost		0.25	0.40	0.36	0.25	0.13	0.37
Total provision cost	$/year	7,194,851	7,389,621	6,186,536	7,826,391	11,347,967	3,654,000

We use site-specific median values for maize residue yield, maize land as share of total land, and maize residue unit cost. We assume that half of maize residue yield is available for bioenergy production. Data sources: Authors' household survey and estimates.

Table 4.4: Net present value, internal rate of return, and payback period with the lowest total provision cost (Upper Yala estimates).

Variable	Unit	Baseline
Plant size	Mg DM/hr	15
Capacity factor	0-1	0.75
Interest rate	%	10
Life of plant	Years	20
Operating and maintenance (4% of capital costs)	$/year	2,062,985
Total provision cost	$/year	3,654,000
Total annual cost	$/year	5,716,986
Biochar price	$/Mg	115
Biochar produced	Mg/year	36,434
Biochar revenue	$/year	4,189,910
Biofuel price	$/L	0.55
Biofuel produced	L/year	14,141,925
Biofuel revenue	$/year	7,778,059
Total annual revenue	$/year	11,967,969
Total capital cost	$	51,574,635
Total annual profit	$/year	6,250,984
Net present value	$	1,643,513
Internal rate of return	%	10.46
Payback period	Years	8.25

Table 4.5: Sensitivity analysis inputs.

Variable	Unit	Low	Baseline	High
Plant size	Mg DM/hr	10	15	20
Capacity factor	0-1	0.65	0.75	0.85
Interest rate	%	5	10	15
Pyrolysis capital unit cost	$/(Mg DM/hr)	620,000	1,240,000	1,860,000
Biofuel conversion capital unit cost	$/(Mg DM/hr)	1,099,155	2,198,309	3,297,464
Maize residue unit cost	$/Mg	15	27.09	65
Degree of freight cost absorption	0-1	0.6	0.8	1
Biochar unit price	$/Mg	85	115	230
Biofuel unit price	$/L	0.35	0.55	0.75

Table 4.6: Mean and standard deviation of the net present value distributions to account for maize residue yield volatility.

Location	Unit	Mean	St.dev.
Whole sample	$	-20,512,774	45,808,233
Lower Nyando	$	-23,049,850	55,590,411
Mid Nyando	$	-14,158,779	32,889,395
Lower Yala	$	-27,391,758	38,418,434
Mid Yala	$	-44,615,208	72,404,285
Upper Yala	$	740,924	16,374,118

CHAPTER 5

CONCLUSIONS

5.1 Overview

Understanding the link between natural resources, poverty, and environment, and reconciling the potential tradeoffs among them, is necessary to meet the competing demands of poverty alleviation, energy sufficiency, and environmental conservation in Africa. Biological resources and crop residues, in particular, play a significant role in smallholder agriculture and, together with land and labor, constitute much of farmers' productive resources. Their management not only satisfies immediate objectives such as providing livestock feed or residential fuel, but these resources can also enhance longer-term agricultural productivity, support a range of ecosystem services, and mitigate climate change through carbon sequestration. Each of the three foregoing essays on the economics of biomass management in western Kenya suggests conclusions and policy recommendations that might lead to more effective management of natural resources, both in Kenya and in other rural developing regions. Some of the broader lessons learned regarding natural resource management and future research directions are discussed below.

5.2 Lessons learned

In the western Kenyan highlands, an average farm produces 3.2 Mg of maize residues annually (or 5.06 Mg per hectare). Maize residues constitute critical productive resources, and few of them are wasted. Nearly half (47 percent) of maize residues on the farms in the household survey are allocated to soil fertility management, about 25 percent are used for animal feed, and 22 percent are used for household fuel. A minor amount of the remaining residues are allocated to miscellaneous uses, such as building materials, livestock bedding, etc. Furthermore, over 60 percent of households use animal manure as organic fertilizer—an additional outcome of feeding crop residues to cattle—with positive impacts on soil quality and crop yields. As a result, the total value of maize residues to smallholder farmers is substantial. While the economic literature has devoted significant attention to the values of other critical resources in smallholder agriculture such as land, labor, and external inputs, there have been few attempts to value non-marketed residues. The first essay (Chapter 2) estimates the shadow value of maize residues left on the fields for soil fertility management. The resulting value of annual maize residue production per farm is estimated at US$208 (22 percent of the median income). Put it differently, maize residues constitute about 37 percent of the total value of cereal production (both grain and residues) in western Kenya. While the estimated value (the most conservative of which is 5.49 Kenyan shillings or $0.06 per kilogram) is high, it is surprisingly close to the price of fuelwood in the area—which is substitutable for residues when used as a fuel for cooking in the household—and to estimates of the value of agricultural residues from Ethiopia and Morocco (Teklewold 2012; Magnan, Larson, and Taylor 2012).

The amounts of crop residues produced, their allocation to different uses, and their values, however, differ among households. Average maize residue yields, for example, range from 2.15 Mg/ha to 9.12 Mg/ha between the 15 villages in the household survey. This difference in yields, as well as in maize planting density (the area devoted to maize as a share of total area), consequently determines residue availability for bioenergy production and helps determine where to locate a bioenergy producing plant (Chapter 4). Richer households with more livestock allocate more residues as animal feed, while poorer households with the lowest quantities of purchased fertilizer allocate the largest share of maize residues for soil fertility management. The value of maize residues (per kilogram) is also higher for poorer households (Chapter 2). As a result, the promotion of agricultural technologies and bioenergy alternatives centering on crop residues cannot presume their wide availability and no or low cost across all households.

As suggested by both the theoretical and empirical results in the first essay (Chapter 2), the value of maize residues used for soil fertility management extends beyond fertilizer substitution and likely includes the longer-term benefits of leaving crop residues on the fields. This is consistent with a meta-analysis from 57 studies across Sub-Saharan Africa by Chivenge, Vanlauwe, and Six (2011) who demonstrate that the addition of organic resources in one season also have residual effects in the subsequent seasons. Similarly, the second essay (Chapter 3) demonstrates the longer-term benefits of leaving crop residues on the fields through their contribution to soil carbon. The shadow price of soil carbon is the private benefit of carbon sequestration to the farmer in the form of soil fertility improvements and increased maize yields and is estimated at 138 \$/Mg. This price is more than six times higher than the value of one unit of soil carbon in maize production during one year, thus confirming the benefit of evaluating natural resources in an intertemporal framework.

The second essay (Chapter 3) also evaluates the potential ability to increase yields and sequester carbon in the research area, once the agro-ecological environment and socio-economic conditions are taken into consideration. The results show that regardless of the initial soil fertility levels the optimal management strategies (mineral fertilizer and maize residue application rates) lead to maize yields of 3.74-4.17 Mg/ha—more than double the yields observed in the household survey—and carbon stocks of 20.76-33.28 Mg/ha (in the top 0.1 m), with discount rates of five to fifteen percent and given the prevailing price levels. These optimal application rates, however, are significantly higher than those observed in the household survey.

The question why the optimal practices as predicted by the model in the second essay (Chapter 3) diverge from the current practices of western Kenyan farmers deserves special attention. The potential explanations suggested in Chapter 3—farmers' time and risk preferences, imperfect markets and liquidity constraints, and information-related barriers—have important implications both for policy and future research. First, investments in any sustainable agricultural practice with long-term benefits are necessarily influenced by farmers' time and risk preferences. High rates of time preference, for example, can lead to lower or incomplete adoption of such practices; uninsured risk has also been shown to be a binding constraint on long-term investments (Shively 2001; Karlan et al. 2012). Second, financial market imperfections can delay optimal agricultural investments by smallholder farmers (Beaman et al. 2014), while cash liquidity constraints and poverty in assets can also be correlated with higher rates of time preference (Holden, Shiferaw, and Wik 1998). Third, information constraints also play a role; smallholder farmers may simply not possess adequate information about sustainable agricultural practices. Since the traditional sources of information such as public agricultural extension programs have been found to have limited impacts on agricultural technology adoption (Aker 2011), other means to provide farmers access to and higher quality of information in the form of technical assistance from NGOs, electronic communications, and other mechanisms can help surmount obstacles to the adoption and practice of sustainable agricultural practices.

The current socio-economic and policy environments of Kenya and most other nations do not fully support the adoption of sustainable agricultural practices such as the retention of crop residues, use of manure and compost, no-till farming, agroforestry, and other practices that enhance soil fertility. To improve agricultural productivity, achieve food security and address rural poverty, it is imperative that, going forward, climate-smart agricultural practices that focus on soil resource management become an integral component of national policies and practical actions (Powlson et al. 2011). These practices and interventions must guarantee that farmers have reliable access to agricultural inputs and develop institutional environments that support rural communities (Vanlauwe et al. 2015). They could include a combination of agricultural extension, information provision, economic incentives, fertilizer subsidies, improved access to credit, development of rural infrastructure and output markets, and government regulations. Finding alternative sources for animal feed and household fuel is also important (Lal 2005).

The second essay (Chapter 3) also finds a considerable scope for agricultural carbon sequestration in the research area. The bioeconomic model shows that over the first 25 years the average rate of annual carbon sequestration is 440 kg/ha of carbon on farms with depleted soils and 240 kg/ha of carbon on farms with medium soil fertility. These sequestration rates are close to 375 kg/ha, the average rate from the use of crop residues for soil fertility management, found across 46 studies in Sub-Saharan Africa (WB 2012). In general, sustainable agricultural practices have the potential to sequester 0.4-1.2 Pg of carbon per year on the world's agricultural and degraded soils, an amount equivalent to 5-15 percent of global emissions from fossil fuels (Lal 2004). This is an additional incentive for national policies and programs to promote sustainable agricultural practices. Payments for agricultural carbon sequestration, for example, can stimulate adoption of sustainable practices and increase rural incomes (Antle and Stoorvogel 2008). By tapping into international carbon markets, such policies can also partially counteract the other challenges associated with the adoption of climate-smart practices discussed above.

Participation in the international and national carbon mechanisms can also be used for promotion of second-generation bioenergy and biochar production. Production of both bioethanol and biochar can result in net greenhouse gas (GHG) offsets, as the third essay (Chapter 4) suggests. While conversion technologies for most second-generation biofuels are still at early stages of development, there is increasing interest in SSA, as elsewhere in the developing world, in establishing modern bioenergy sectors to supplement existing traditional energy reserves and stimulate rural economic growth. Numerous technological and economic challenges, however, remain. One of the challenges has to do with accounting for the true economic availability of crop residues as a feedstock for bioenergy production. The third essay (Chapter 4) explores how the differences in maize residue yields, maize planting density, and crop residue values to farmers drive a great degree of variability in feedstock provision costs in western Kenya, even in the limited geographic area examined. The pyrolysis-biochar plant with a 15 Mg of feedstock per hour capacity is found to have positive net present value only in one location (Upper Yala research site), with the lowest feedstock provision costs.

The heterogeneity of feedstock provision costs, as well as the high sensitivity of net present value estimates to final product prices, offer several lessons for second-generation bioenergy projects, both in Kenya and other developing countries. To promote small-scale bioenergy production that can benefit the rural areas and farmers supplying feedstock, such projects need to account for multiple development objectives, include non-monetary benefits, and take advantage of net GHG offsets. They may also require initial government support in the form of guaranteed product prices, subsidies, or tax breaks. In general, national biofuel policies should focus on raising financial resources for infrastructure development, investing in research and development, and establishing regulatory and institutional frameworks (Jumbe, Msiska, and Madjera 2009).

5.3 Future research

The findings of the three essays suggest several directions for future research. Due to data constraints the first essay (Chapter 2), for example, assumes time invariance in the use of crop residues. Farming practices and the values of natural resources, however, can change in response to outside shocks and changes in market and environmental conditions. Magnan, Larson, and Taylor (2012), for instance, find different values for cereal stubble in normal rainfall and drought years. Therefore, this assumption, while plausible in the research area, needs to be rigorously tested. Understanding how farmers form perceptions about the quality of their natural resources is also important for promotion of sustainable agricultural practices. Some recent evidence, for example, suggests that farmers across Sub-Saharan Africa do not significantly vary input application rates according to perceived soil quality (Sheahan and Barrett 2014). The household survey used in the three essays supports this finding. And similar to farmers in Ethiopia (Karltun, Lemenih, and Tolera 2013), farmers in western Kenya instead use crop yields to judge the fertility of their soils. Whether these perceptions translate into improved management practices, and whether existing data collection methods accurately capture them, are still questions to be answered. Finally, time and risk preferences can dictate farmers' choices of agricultural practices and their management of natural resources. These preferences, however, are difficult to measure. While many studies in developing countries have traditionally relied on simple choice experiments to elicit preferences, some recent work in Vietnam, for example, uses more sophisticated techniques (Tanaka, Camerer, and Nguyen 2010).

More and better data are required to answer these and other research questions. The fieldwork for this project involved several innovative methods: we collected biophysical data such as soil samples and tree measurements, used hand-held GPS devices to accurately calculate farm and plot area, and used audio recordings to ensure data quality (Berazneva 2014). Going forward, panel and experimental data, best suited to the question at hand, may be required. Moreover, collaborations with soil scientists, agronomists, and engineers have allowed me to explore questions about human-environment interactions. These collaborations, both in research and implementation, will be important to improve agricultural productivity and assure environmental sustainability and resilience to climate change, and thereby help address food security in Sub-Saharan Africa.

APPENDIX A

FIELDWORK DESCRIPTION

A.1 Research area

The research sites are in the Nyando and Yala river basins, two of the major seven influent rivers feeding Lake Victoria in the Kenya sector (Figures A.1.1 and A.1.2). The five research sites—Lower Nyando, Mid Nyando, Lower Yala, Mid Yala, and Upper Yala—formed part of the original geographic coverage of the Western Kenya Integrated Ecosystem Management Project (WKIEMP), implemented between 2005-2010 by the Kenya Agricultural Research Institute (KARI) and the World Agroforestry Center (ICRAF) and funded from the Global Environmental Facility (GEF) of the World Bank. In 2005 the 10x10 km sites were chosen to satisfy the GEF criteria of carbon sequestration and biodiversity increment potential, severity of land degradation, and the proximity to reserves with significant degradation because of external pressure (WB 2010).

Within each 10x10 km site, three sub-locations (Kenyan lowest administrative units at the time of the household survey) were chosen at random to ensure geographic coverage. A list of villages in each chosen sub-location was gathered in consultation with the local authorities from which three villages in each sub-location were chosen at random. A list of households for each chosen village (as well as the village boundary) was determined with the help of the village elders and twenty-one households in each village were then randomly chosen for an interview. In total, the sample comprises of about 315 households—twenty-one households in most of the fifteen villages in the sample (three villages in each of the five research sites).[1]

Table A.1.1 lists the villages, their administrative locations, and the dates of visits. The

[1]In one of the villages, Nyangera B, we surveyed two additional households; two households refused to allow soil sampling.

Figure A.1.1: East Africa.

Note: Research provinces are highlighted in purple.

changed order of village visits during the second round reflects seasonal constraints (e.g., timing of planting, start of short rains, road conditions, etc.).

Figure A.1.2: Map of the research area.

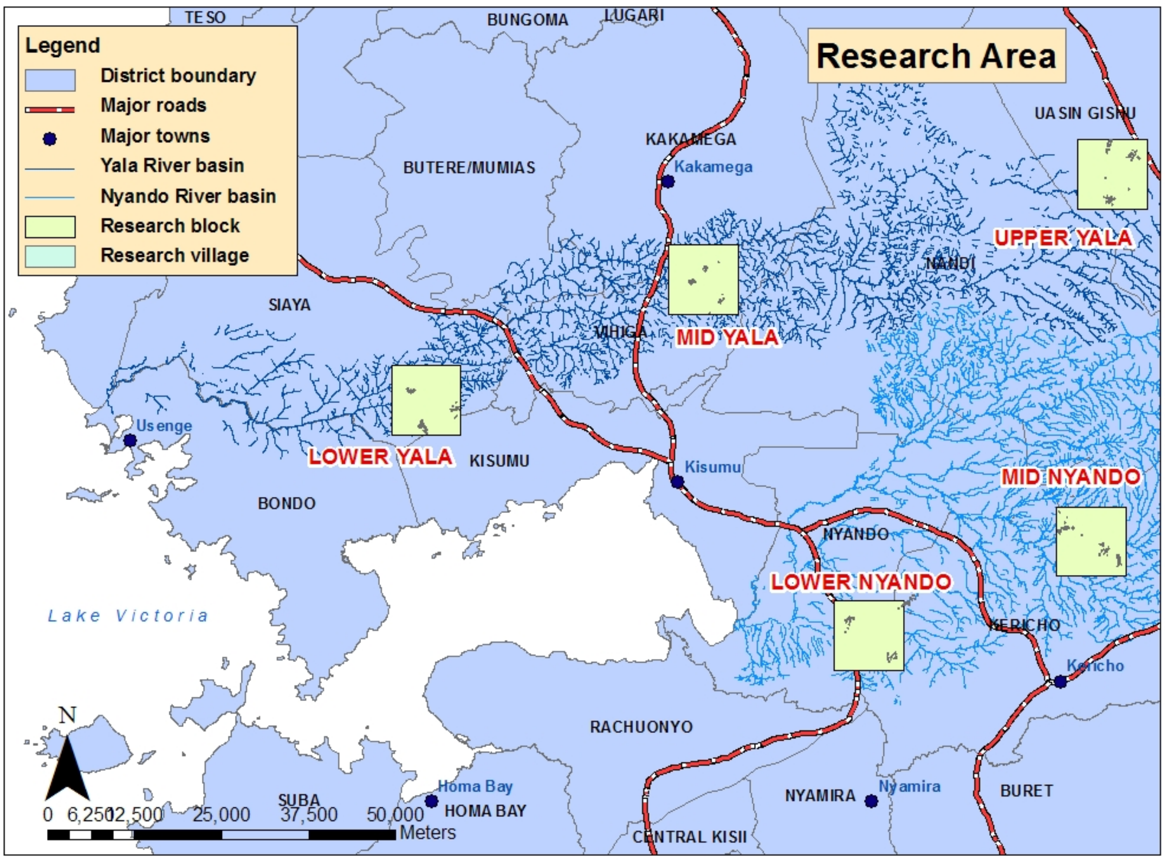


Table A.1.1: Villages in the sample.

Village	Sub-location	Location	District	Province	Date of first visit	Date of second visit
Lower-Nyando						
Kanyibana A	Awach	North-East Nyakach	Kisumu	Nyanza	11-14 Oct 2011	23-24, 27-28 Feb 2012
Tabet B	Kaplelartet	Kaplelartet	Kericho	Rift Valley	19, 24-26 Oct 2011	29 Feb, 1-2, 5 Mar 2012
Ratunwet	Lekwenyi	Kapsorok	Kericho	Rift Valley	17-18, 20-21 Oct 2011	6, 8-9 Mar 2012
Mid-Nyando						
Ogwedhi B	Koru Central	Koru	Kisumu	Nyanza	27, 29, 31 Oct, 1 Nov 2011	29-31 Mar 2012
Kagai	Kandege	Fort Tenan	Kisumu	Nyanza	2-4, 7 Nov 2011	12-14 Mar 2012
Kures	Siwot	Chilchila	Kericho	Rift Valley	8-11 Nov 2011	26-28 March 2012
Mid-Yala						
Chamakanga	Chamakanga	Busali West	Vihiga	Western	16-18, 21 Nov 2011	17-20 Apr 2012
Jeveleli	Shiveye	Iguhu	Kakamega	Western	22-25 Nov 2011	13-14, 16 Apr 2012
Bumira B	Jivololi	Shamakhokho	Vihiga	Western	28-30 Nov, 1 Dec 2011	10-12 Apr 2012
Lower-Yala						
Kanyilaji B	Nguge	West Gem	Siaya	Nyanza	2, 5-7 Dec 2011	2-4 Apr 2012
Nyangera B	Onyinyore	South Gem	Siaya	Nyanza	8-9, 12-13 Dec 2011	30 Apr, 1-3 May 2012
Kasagoma B	Ndori	South Gem	Siaya	Nyanza	14-15, 19-20 Dec 2011	23-26 Apr 2012
Upper-Yala						
Tulwet West	Tulwet	Tulwet	Uasin Gishu	Rift Valley	4-6, 9 Jan 2012	21-23 Mar, 5 May 2012
Lelmolok A	Kesses	Kesses	Uasin Gishu	Rift Valley	9-12 Jan 2012	15-17 Mar 2012
Chepkitin B	Tarakwa	Tarakwa	Uasin Gishu	Rift Valley	16-18 Jan 2012	19-21 Mar 2012

A.2 Data collection

The fieldwork focused on collecting both socio-economic and biophysical data. The survey instrument was developed in consultation with scientists at Cornell University and the World Agroforestry Center, and also reflected input from qualitative interviews and field testing, both of which facilitated the incorporation of knowledge and opinions of local farm households. Once the survey instrument was finalized, it was reviewed and approved by the Institutional Review Board of Cornell's Office of Research Integrity and Assurance (Protocol ID number 1107002353 was found to be exempt from a full IRB review on 08/12/2011).

The research team included three interviewers to administer the questionnaire to sample farmers, three field technicians to collect biophysical and geo-referenced data, three office staff members at ICRAF's field office in Kisumu to check, clean, and input the collected data into a program specifically designed for data entry, and a driver to transport the team to the survey villages and assist with the project implementation. Figure A.2.1 shows the timeline of the project's activities.

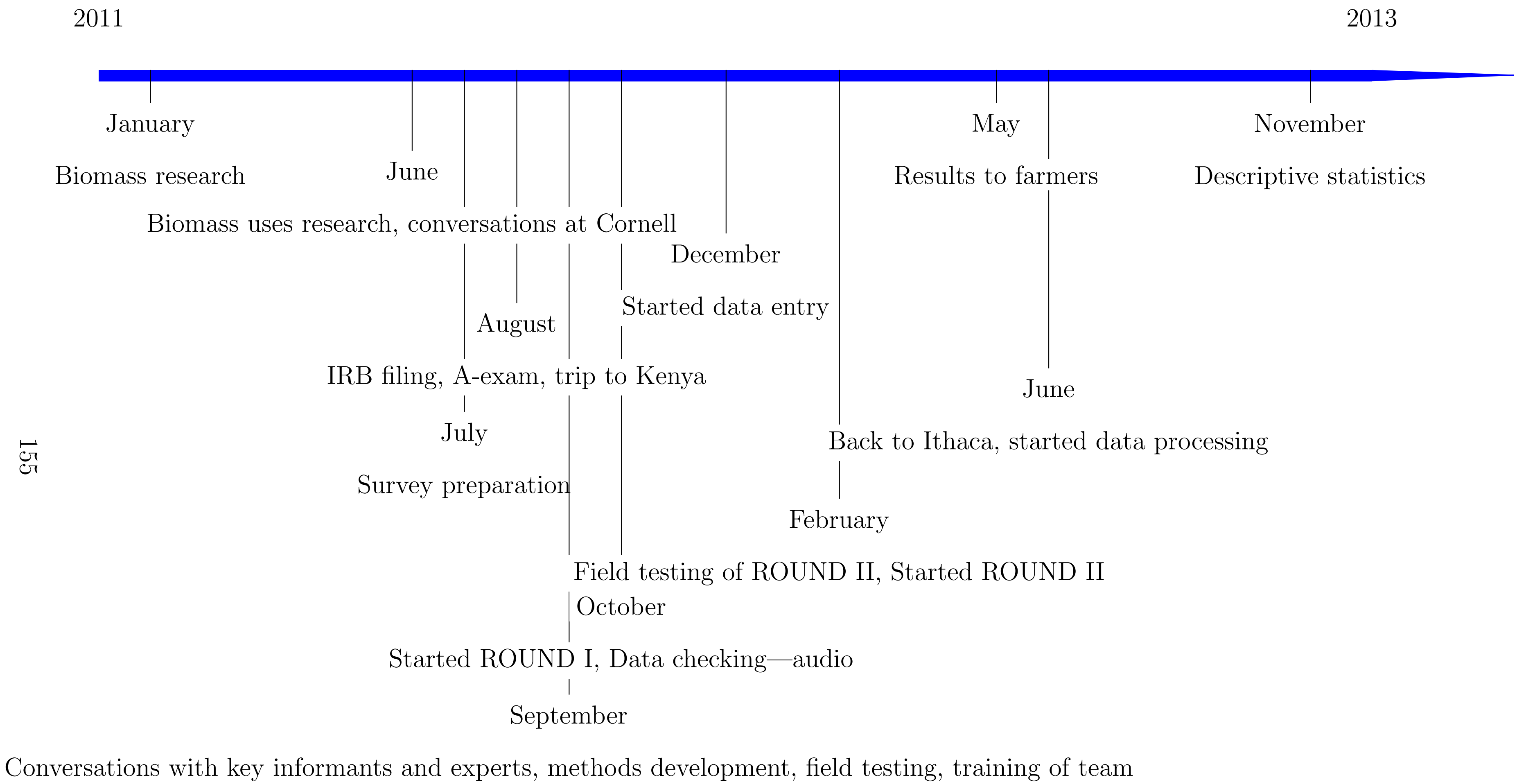
The data collection efforts consisted of (i) an agricultural and socio-economic household survey, (ii) biophysical measurements, (iii) spatial (geo-referenced) data, and (iv) village and market surveys.

A.2.1 Household survey

To account for the bi-modal rain pattern and consequent two distinct cropping seasons in several of the research sites, the household survey was split into two rounds and covered a wide range of standard World Bank Living Standards Measurement Survey topics. The first round of the survey (October 2011—January 2012) collected the following data: household production activities of the first completed cropping season of 2011 (long rains), income sources, household resource endowments in terms of land, labor, and biomass, and socio-economic characteristics such as household composition, educational background, and labor market participation. The second round (February 2012—May 2012) re-visited the same households to collect information on household production activities of the second cropping season of 2011 (short rains), residential energy use, access to information, household assets, recent shocks, and attitudes towards changing climate.[2]

[2]The first round included 317 households and the second round included 313 households. Three households that had taken part in the first round moved before our second visit (to Nairobi or Mombasa), and one household refused to take part in the second round.

Figure A.2.1: Timeline.



A typical interview took 2–2.5 hours to complete and the data were recorded by enumerators on the field sheets provided. The interviews were also audio recorded using Olympus VN-8100PC Digital Voice Recorders with consent from participants to check accuracy of the written information and for training purposes. The data were first checked by an enumerator at the end of each household visit, then checked again in the field office. When questions came up, the data were checked against the audio recording. The data were then double-entered using the Census and Survey Processing System (CSPro), a public domain software package developed and supported by the U.S. Census Bureau.

A.2.2 Biophysical measurements

Since one of the project's goals was to accurately measure on-farm biomass availability, we supplemented the data collected via household surveys with our own measurements. A list of trees and shrubs present in the area was developed in September 2011, based on Maundu and Tengnas (2005) and Kindt et al. (2011), as well as conversations with ICRAF scientists. The list included about 100 species and contained their scientific names, as well as names in English, Kiswahili, and, when available, names in the local languages (Luo, Luhya, Nandi, or Kipsigis). During farm visits, field technicians identified and counted the trees and shrubs, and measured diameter at breast height (DBH) for all trees with DBH over 10 centimeters (31.5 centimeters in circumference).

Tree diameter is an easy to record proxy for many tree structural properties, including above-ground tree biomass (Dietz and Kuyah 2011). It is often used as a key component in allometric equations for tree biomass assessment, which were developed and extensively field tested by ICRAF in western Kenya (Kuyah et al. 2012). To determine DBH, the circumference of the tree about 1.3 meter above the ground was measured using a regular metric tape. Where the trunk or large branches were divided, we measured the circumference of all sub-sections. Assuming a circular cross-section, measurements of tree circumference can be transformed into diameter (DBH = circumference/π).

Stand-alone (scattered) trees around the homestead, agricultural plots, as well as trees in windrows or hedgerows along plot boundaries, were identified and their count was recorded by species. The recording was divided into trees with DBH less than 5 cm, trees with DBH between 5 and 10 cm, and trees with DBH over 10 cm, for which the exact DBH was recorded. The number of scattered shrubs was recorded by species, and for shrubs along boundaries we recorded the number of shrubs along a 4 m long sample, up to three species found, and the exact length of the boundary in meters (measured using GPS). Trees on woodlots most often belonged to one species (e.g., *Eucalyptus saligna* or Sydney blue gum) and were counted based on the area of each woodlot (measured using GPS) and the number of trees in a 2x2 m random sample. If woodlot trees had DBH greater than 10 cm, then DBH was recorded for all the trees found in a 2x2 m random sample.

Soil samples were taken from the largest maize plot on each farm. Only several households did not cultivate maize during the long rains season of 2011. For these farms, soil samples were taken from the largest cultivated plot. Topsoil (0–20 cm) was collected from four randomly chosen positions within the maize plot using a soil auger. The depth of any restricted layer while augering, as well as a GPS reading of the center point of the plot (coordinates, elevation, and accuracy of GPS) were recorded in the field sheet. The four samples were thoroughly mixed, then air dried at the ICRAF field office in Kisumu, and passed through a 2-mm sieve. The samples were taken to the ICRAF Nairobi Soil-Plant Spectral Diagnostics Laboratory in January 2012 and analyzed using near infrared (NIR) spectroscopy, a rapid nondestructive technique for analyzing the chemical composition of materials. The analysis predicted some key soil properties such as organic carbon (C), nitrogen content (N), extractable phosphorous (P) and potassium (K), and soil pH, which were later used for a three-tiered soil fertility classification scheme. The three tiers used were "good," "low," and "very low," and were created based on thresholds and recommendations for soils in the area from the Kenya Agricultural Research Institute (Mukhwana and Odera 2009) and from the Cornell Soil Health Test (Moebius-Clune et al. 2011).

A.2.3 Spatial data

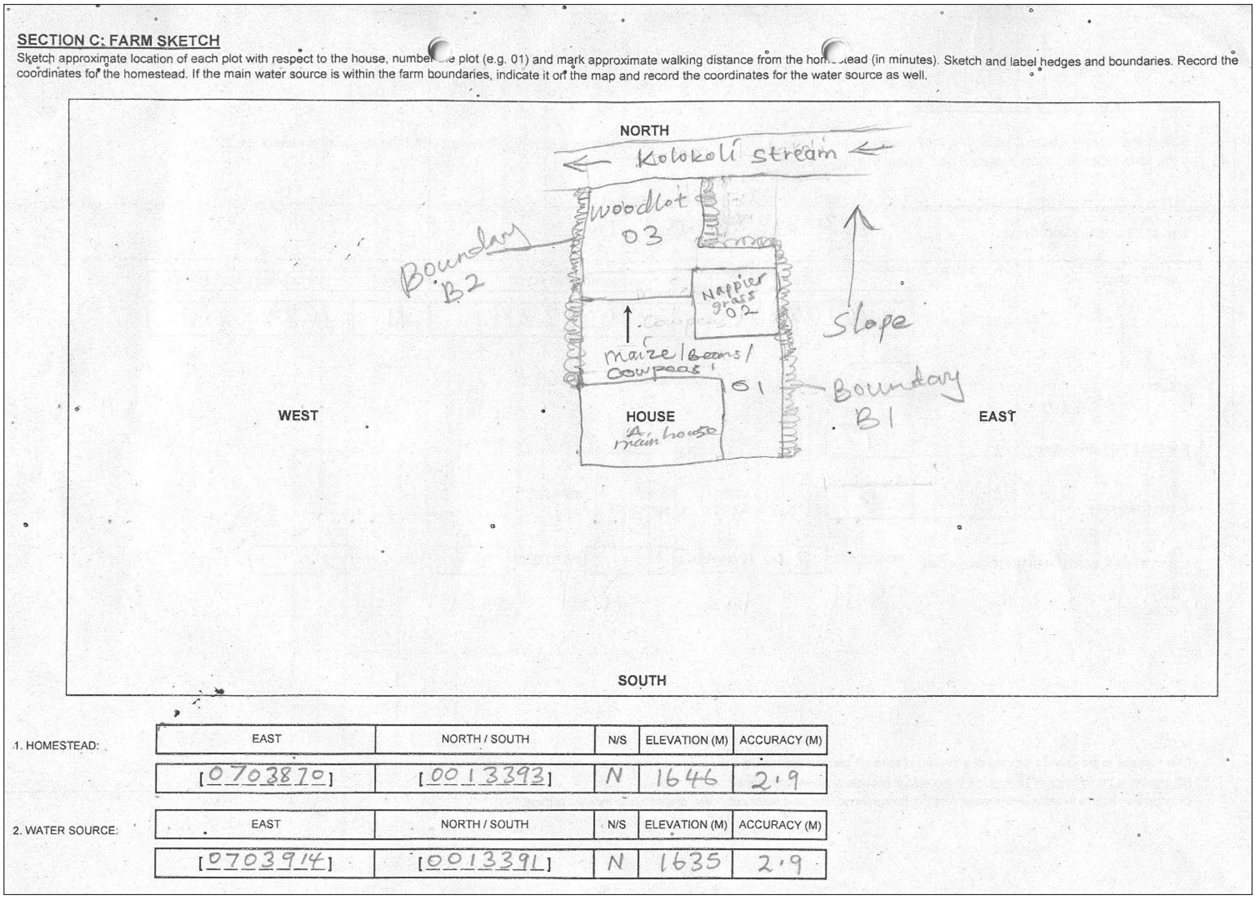
The spatial data were collected using GPSMAP 60 CSX (one unit) and eTrex Vista HCx (two units) during the first round of the survey, October 2011–January 2012. The following waypoints were taken during each household visit: location of homestead, location of water source (if available), location of soil sample taken from the largest maize plot, corner of each plot and parcel,[3] and hedge/boundary tracked. We also tracked the perimeter of each parcel, the perimeter of each plot, and the length of each hedge (shrubs along boundaries). All parcels and plots were identified by the primary farmer (who often accompanied a field technician during tracking).

Some additional spatial data were collected during the second household visit (February–May 2012). The GPS measurements were taken from parcels/plots located farther than a 10 minute walk from a household (they were not measured during our first visit). On several occasions, we had to drive to reach additional land parcels/plots. Some parcel/plots measurements were still missing. Those were the land units either located farther than a 30 minute drive away from a household or impenetrable due to thick vegetation (e.g., thick forest). The new GPS measurements were also taken from plots that were split from previously recorded plots for cultivation during the short rains season. In addition, some GPS measurements were confirmed during the second visit if the previous measurements

[3] A "parcel" was defined as a unit of land defined by its acquisition as a single contiguous unit, so that it is under a single title (ownership or lease). A parcel often included several plots. A "plot" was defined as a contiguous piece of land on which a unique crop or a mixture of crops is grown, under a uniform, consistent crop management system. It must be continuous and should not be split by a path of more than one meter in width. Plot boundaries are defined according to the crops grown and the operator.

were deemed unclear or inaccurate due to the GPS unit malfunctioning or poor satellite connection.

Figure A.2.2: Example of farm sketches.

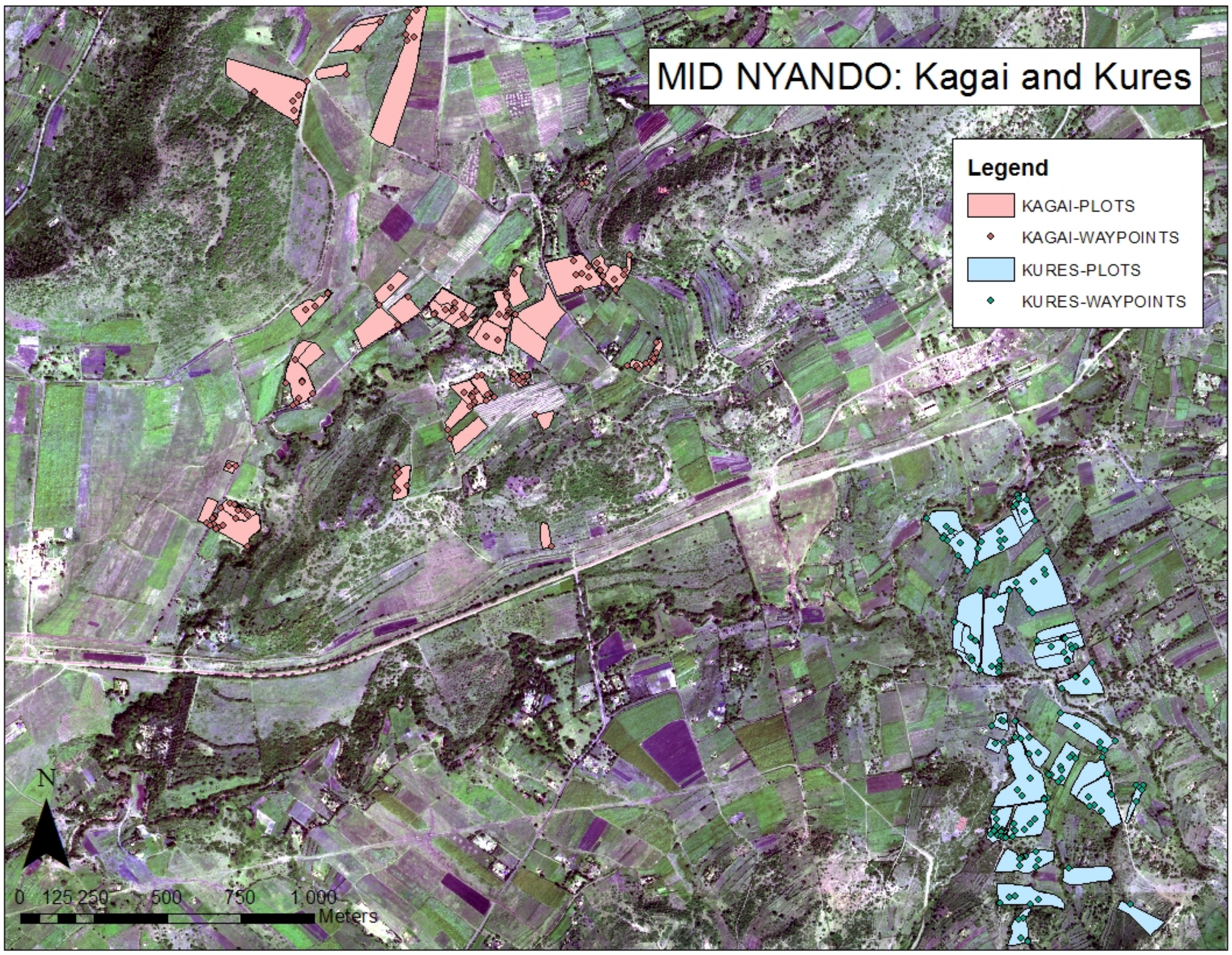

SECTION C: FARM SKETCH

Sketch approximate location of each plot with respect to the house, number ... plot (e.g. 01) and mark approximate walking distance from the hom...tead (in minutes). Sketch and label hedges and boundaries. Record the coordinates for the homestead. If the main water source is within the farm boundaries, indicate it on the map and record the coordinates for the water source as well.

	EAST	NORTH / SOUTH	N/S	ELEVATION (M)	ACCURACY (M)
1. HOMESTEAD:	[0703870]	[0013393]	N	1646	2.9
2. WATER SOURCE:	[0703914]	[0013391]	N	1635	2.9

The spatial data were saved on the GPS units and downloaded from the units to a PC on a daily basis (in .txt, .xls, and .shp formats) using DNR Garmin Version 5.4.1 software (copyright of the Minnesota Department of Natural Resources). In addition, the data were recorded by hand in household survey/biophysical measurement field sheets: area of parcels and plots, length of hedges, and waypoints of parcel/plot corners. For a homestead, water source, and soil sample waypoints, we additionally recorded elevation and accuracy (in meters). The primary use of each plot during the last completed cropping season was recorded and was categorized into food crops, cash crops, kitchen garden, grazing/pasture land, woodlot, forest, fallow land, cover crop, or uncultivated. These data were recorded in an Excel spreadsheet. We also sketched each farm/homestead: location of the homestead and water source (if available) within the farm, approximate location of each plot with respect to the house, its perimeter, label, and location of hedges (farm sketches were scanned) (see, for example, Figure A.2.2).

Figure A.2.3: Example of spatial data collected: Kagai and Kures.



All the spatial data were confirmed against the farm sketches and the QuickBird images of the research sites. Five high-resolution multispectral images (2.44–2.88 meter pixel resolution) were taken from the QuickBird earth observation satellite (owned by DigitalGlobe) in the early 2010 and acquired by the World Agroforestry Center. Lower Nyando and Mid Nyando images are dated 27 January 2010, Upper Yala—9 February 2010, Mid

Yala—18 February 2010, and Lower Yala—12 March 2010. The data collected in the field were transferred to ArcGIS, a geographic information system (GIS) for working with maps and geographic information, overlaid the QuickBird images and, having confirmed with each farm's sketch, adjusted (e.g., plot polygon) when necessary. Figure A.2.3 shows waypoints and tracks in two sample villages—Kagai and Kures—overlaid the Mid Nyando QuickBird remote sensing image.

A.2.4 Village and market surveys

Village-level data were collected during both rounds. Village elders were interviewed to gather information about village infrastructure and access to basic services: distance from roads and nearest towns; availability of markets, post office, banking facility, cell phone coverage, electricity, piped water access, agricultural extension services; etc. We visited local primary and secondary schools to get reliable estimates of the cost of sending a child to school (school fees, books and materials, extra tuition, uniforms, meals, etc.).

In addition, during each round we collected price data on locally available agricultural commodities (including measurements of local units).

A.3 Households and their resources

A typical household in the sample has about 6 household members (Table A.3.1), with a dependency ratio, defined as the number of household members aged less than 15 or over 65 divided by the number of household members aged between 15 and 65, of 1.13.[4] The head of household, the main income earner and decision maker, is on average 51 years old, and,

[4] A "household" was defined as a person or a group of people living in the same compound, answerable to the same head and sharing a common source of food and/or income.

for over 80 percent households in the sample, is male. However, for 8 percent of households the male household head lives and/or works away (e.g., as a factory laborer in Nairobi or a shop keeper in Mombasa), leaving his spouse to run their rural home and make agricultural decisions on their farm. On average, the household head has about 7 years of schooling, which corresponds to incomplete primary school (in Kenya, primary school is currently 8 years). However, for 16 percent of households in the sample the head has no formal education, and for nine percent the head has more than secondary education (college or university). Most households (85 percent) are engaged in off-farm employment, with two household members working off-farm per household on average. Most off-farm jobs are still in agriculture (33 percent of all jobs in the sample)—preparing land, planting, weeding and harvesting on other farms, or local trade (19 percent) and services (ten percent).

Table A.3.1: Sample summary statistics—demographics.

Variable	Mean	St. Dev.	Min	Max	N
Household size	6.03	2.46	1	13	317
Dependency ratio	1.13	0.94	0	6	311
Head age	51.06	15.44	20	90	317
Head is male, with a wife or wives (%)	68.45	–	–	–	317
Head is male, divorced, single or widowed (%)	3.79	–	–	–	317
Head is female, divorced, single or widowed (%)	19.56	–	–	–	317
Head is female, husband lives/works away (%)	8.20	–	–	–	317
Head years of education	6.86	4.59	0	20	317
Head has no education (%)	16.40	–	–	–	317
Head has more than secondary education (%)	9.46	–	–	–	317
Household with off-farm employment (%)	85.49	–	–	–	317
Household members with off-farm jobs	1.93	1.03	1	6	271

Virtually all dwellings in the sample are owned by households. A two- or three-room house (2.85 is the average number of rooms in the sample) is typically built with mud and poles or mud and stones (81 percent of main dwellings in the sample), and has sturdy sheets of corrugated iron (*mabati*) for the roof (74 percent of houses) (Table A.3.2). Mud used for walls is often mixed with cow dung and requires periodic re-plastering. Other popular materials include cement and baked or burnt bricks (8 percent and 5 percent, respectively).

While most households build traditional pit toilets, about 19 percent of households in the sample have no toilet facility. When it comes to household assets, households on average have 14 pieces of furniture and one radio. About 40 percent of households in the sample own a bicycle, and only 7 percent and 4 percent own a motorcycle and a car, respectively. However, the majority of households owns at least one mobile phone (1.7 is the sample average). The prevailing agricultural assets include hand hoes and pangas, large knifes used for cutting vegetation (an East African variant of the machete). Households in the sample own three hand hoes and two pangas, on average, suggesting widespread use of hoe-farming. Ownership of ploughs—either ox/donkey or tractor ploughs—is not as common: only 58 households in the sample own ox ploughs and six households own tractor ploughs. However, a greater percentage of households rent these tools: 51 percent of households either owned or rented an ox plough and 23 percent of households either owned or rented a tractor plough for the agricultural seasons of 2011.

Table A.3.2: Sample summary statistics—household assets.

Variable	Mean	St. Dev.	Min	Max	N
House walls made of mud and poles (% households)	81.47	–	–	–	313
House roof made of corrugated iron (% households)	74.12	–	–	–	313
No toilet facility (% households)	18.53	–	–	–	313
Radio	1.18	0.93	0	10	313
Mobile phone	1.70	1.34	0	10	313
Furniture/furnishings	14.21	8.96	0	51	313
Bicycle	0.49	0.61	0	2	313
Motorcycle	0.07	0.27	0	2	313
Car	0.06	0.31	0	3	313
Hand hoe	3.39	1.86	0	10	313
Panga	1.68	0.88	0	6	313
Ox/donkey plough	0.21	0.48	0	3	313
Tractor plough	0.02	0.14	0	1	313

The most common source of agricultural information in the area appears to be radio—74 percent of households reported receiving information/advice for their agricultural activities in 2011 from radio. Only 74 households (24 percent of the 313 households surveyed) reported receiving information from the government agricultural extension service, and 45 households (14 percent) reported receiving information from an NGO or a research organization. This last source of agricultural information is not surprising given a considerable presence of large agricultural NGOs and research organizations in western Kenya. Thirty-one households in the sample (almost 10 percent) also reported taking part in an agricultural project run by an NGO and/or a research organization. Most of these projects happened in the last ten years, were often run by CARE Kenya, ICRAF, Kenya Agricultural Research Institute (KARI), and VI-Agroforestry, or their partnerships, and focused on tree planting, agroforestry and its benefits, as well as in some cases on horticulture and livestock-rearing activities. Agricultural information sharing also appears to be widespread among farmers in each of the surveyed villages. About 20 percent of households reported receiving advice from lead farmers in their village and 41 percent of households reported receiving advice from peer farmers—neighbors, relatives, and friends. Forty households (13 percent of the 313 households asked) also participated in farmer groups (for the total of 44 groups). These farmer groups had 41 members in each, on average, and focused on savings and/or credit (19 groups), marketing of agricultural products (11 groups), animal husbandry (11 groups), tree nursery and tree planting (10 groups), and/or productivity enhancement (10 groups), as reported by our respondents. When asked about the main benefits of farmer group participation, households mostly mentioned access to loans, free agricultural inputs (e.g., seeds or seedlings), and labor sharing.

A typical farm in western Kenya is about 2.5-5 acres in size (Tittonell et al. 2005), with our sample average being 3.64 acres (Figure A.3.3).[5] A household often owns and/or cultivates several parcels of land (with 1.51 parcels being the sample average). Most land is inherited or received as gift from parents (63 percent of 482 parcels in the sample), while

[5]Farm area size is based on farmers's estimates and is the average from 310 farms. Several farms are not counted as their owners did not know the size of their land holding; and 3 farms are excluded due to their outlier status. 1 acre = 4,047 square meters = 0.405 hectares.

smaller percentages are purchased (23 percent) or rented in (9 percent). For 43 percent of parcels (of 482 in the sample), households have a document to certify their land rights (mostly a title deed with land registration certificate), and for 76 percent of those the document is in the husband's name. For 40 percent of parcels a document to certify land rights is with other family members—most often with the husband's parents (83 percent). Farmers in the sample are also secure about their land rights. Most have never had a conflict over land rights and would feel comfortable leaving their parcels fallow.

Table A.3.3: Sample summary statistics—land holding and cultivation.

Variable	Mean	St.Dev.	Min	Max	N
Land holding size (acres) (farmer estimates)	3.64	4.00	0.05	33.50	310
Number of parcels owned and/or cultivated	1.51	0.69	1	4	317
Long rains cultivation					
Number of plots cultivated	2.45	1.32	1	9	315
Cultivated plot size (acres) (farmer estimates)	0.78	0.98	0.01	10	695
Cultivated plot size (acres) (GPS)	0.68	1.02	0.02	12.09	756
Cultivated plot altitude (m)	1622.91	338.64	1207.07	2261.15	756
Distance from homestead (m)	186.48	535.70	5.45	7378.05	756
Soil quality (1.very fertile—5.not productive)	2.17	1.08	1	5	771
Slope (1.flat—3. steep)	1.53	0.55	1	3	771
Plots—chemical fertilizer applied (%)	44.88	–	–	–	771
Households applying chemical fertilizer (%)	66.25	–	–	–	317
Plots—organic fertilizer applied (%)	62.78	–	–	–	771
Households using organic fertilizer (%)	78.55	–	–	–	317
Plots—hired labor (%)	42.80	–	–	–	771
Households hiring agricultural labor (%)	56.47	–	–	–	317
Short rains cultivation—261 households					
Number of plots cultivated	2.07	1.20	1	6	261
Cultivated plot size (acres) (farmer estimates)	0.55	0.78	0.01	12	502
Cultivated plot size (acres) (GPS)	0.43	0.61	0.02	8.66	537
Cultivated plot altitude (m)	1537.69	272.47	1204.66	2265.48	537
Distance from homestead (m)	125.82	288.35	5.45	4392.21	537
Plots—chemical fertilizer applied (%)	29.87	–	–	–	539
Households applying chemical fertilizer (%)	39.46	–	–	–	261
Plots—organic fertilizer applied (%)	49.91	–	–	–	539
Households using organic fertilizer (%)	62.45	–	–	–	261
Plots—hired labor (%)	45.08	–	–	–	539
Households hiring agricultural labor (%)	54.79	–	–	–	261

The homestead on a typical farm is usually located upslope near a road and is surrounded by scattered trees and living fences to define the housing compound (Tittonell et al. 2005). Agricultural plots are most often located around the homestead (as close as 5.45 m), however, some parcels are further away from the homestead (at times more than 7 km away). An average distance of a cultivated plot from the homestead during the long rains was 186.48 m[6] (Table A.3.3). On average, a household cultivated 2.45 plots during the long rains season and 2.07 plots during the short rains season of 2011. While all households in the sample cultivated their land during the long rains, only 261 households did so in the short rains. The diversity of agroecosystems across the 15 villages dictates some differences in rainfall availability, altitude, and the possibility of two cropping seasons and their length. An average plot size during the long rains was 0.78 acre according to farmers' estimates, or 0.68 acre according to the GPS measurement. Cultivated plots during the short rains are smaller on average—0.55 acre according to farmers' estimates, or 0.43 acre according to the GPS measurement.

All plots in the sample are rainfed. Even in those areas where two cropping seasons are possible, since the short rains are shorter in length and the amount of rainfall is less predictable, most households opt to reduce their cultivation efforts. This explains a smaller average number of plots cultivated and a reduced plot size during the second cropping season, as well as decreased input application. Thirty nine percent of households applied some chemical fertilizer (e.g., di-ammonium phosphate and urea) and 62 percent applied organic fertilizer (mostly animal manure or compost) in the short rains, as opposed to 66 percent and 79 percent, respectively, during the long rains. Although most farmers in the sample are subsistence farmers and cultivate their own land, more than half of the households also

[6] The distance between the center point of each plot and the corresponding homestead was calculated based on the GPS data collected during household visits (geographic coordinates) using an accurate ellipsoidal model of the Earth and assuming elevation above the ellipsoid is zero. The distance was calculated only for plots for which geographic coordinates were available. Several plots were not measured as they were located more than 30 minutes drive from homesteads. Twenty-four plots among those measured were located further than one km away from the homestead. If we were to exclude these 24 plots, the average distance would decrease to 110.52 m.

hired agricultural labor for planting, weeding, or harvesting (56 percent in the long rains and 55 percent in the short rains).

Along the Yala and Nyando river basins, the dominant soil types are acrisols, ferralsols and nitisols (Jaetzold and Schmidt 1982). While nitisols can be of high fertility, acrisols and ferralsols are strongly leached or weathered. Farmers in the sample identified their soil fertility as mostly moderate. Table A.3.4 summarizes the results from the near infrared (NIR) spectroscopy soil analysis. Organic carbon content is an indicator of soil organic matter that is readily available as a carbon and energy source for the soil microbial community (i.e., food for the soil food web) and averages 2.45 percent (by volume) in the sample. Nitrogen, phosphorus, and potassium are critical nutrients for plant growth and yield; nitrogen content seems to be very low across the sample. Soil pH measures the degree of soil acidity or alkalinity (from 0 to 14); neutral pH is 7 and optimum pH for plant growth is 6.5. Average pH in the sample is 5.82, which is lower than optimal.

Table A.3.4: Sample soils data by key indicator (N=315).

Indicator	Mean (Ranking)	St. Dev.	Min	Max
Organic carbon content (% by volume)	2.45 (Good)	1.30	0.81	9.45
Total nitrogen content (% by volume)	0.16 (Very Low)	0.09	0.06	0.87
Extractable P (g/kg)	0.0134 (Good)	0.0153	0.0006	0.1321
Extractable K (g/kg)	0.36 (Good)	0.22	0.05	1.34
Soil pH	5.82 (Low)	0.52	4.35	7.13

Farms in the sample are often very diversified: households grow annual crops for home consumption, perennial cash crops for sale, and trees to satisfy residential energy needs. Over 80 percent of all cultivated plots during both seasons were occupied by food crops—grains and tubers (maize, maize and beans, cassava, sorghum, sweet potatoes, millet), with two annual crops grown on each farm on average (Table A.3.5). Maize is the most popular grain in the area, having quickly established itself as a dominant food crop in the beginning of the 20th century due to its relatively higher yields per unit of land and two crops per calendar year in many villages (Crowley and Carter 2000). Most sample households (312 households) grew maize during the long rains and 187 households grew maize during the short rains season as well. Annual crops are often intercropped (e.g., maize and beans) to maximize land use. Many households also devote small plots around the homestead to growing vegetables, such as collard greens, cowpea, pumpkin leaves, and indigenous vegetable plants, among others. The farthest plots are found on the slopes towards the waterways and are often dedicated to cash crops and woodlots, or left for pasture. Almost 40 percent of households grow perennial cash crops such as tea and sugarcane, as well as the increasingly market-oriented crops of bananas and Napier grass. Requiring inputs and relatively high investments, cash crops are predominantly grown for sale and in most cases are not consumed by the household. Most households in the Mid Yala villages also have a banana plot to provide food, a storage area for cattle fodder, as well as, at various times, a protected place for childbearing and other household rituals (Crowley and Carter 2000).

Table A.3.5: Sample summary statistics—production.

Variable	Mean	St. Dev.	Min	Max	N
Number of annual crops grown in LR	2.19	0.78	1	5	317
Number of annual crops grown in SR	2.19	1.02	1	5	247
Households with perennial crops (%)	38.80	–	–	–	317
Households with woodlots (%)	15.77	–	–	–	317
Households with trees (%)	97.79	–	–	–	317
Number of farm trees (farmer estimates)	324.56	1,312.10	0	11,020	317
Number of farm trees (measured)	128.93	127.69	0	976	317
Number of farm tree species	9.79	4.67	0	23	317
Households own animals (%)	93.38	–	–	–	317
Number of local cows	1.89	2.86	0	19	297
Number of improved cows	1.04	2.42	0	20	297
Number of chickens	11.25	25.51	0	300	297

Trees from woodlots—small plantations of cultivated trees—play an important role on many farms, serving as on-farm sources of fuel and/or construction wood and, at times, households sell wood in the market. About 16 percent of households in the sample have woodlots, with an average woodlot size of 0.17 acres (693 m^2). But almost all households

(98 percent) have trees on their farms. Linear tree formations or windrows are largely mono-specific, with three species dominating their composition: *Cupressus lusitanica*, *Eucalyptus salinga*, and *Pinus patula* (Bradley 1988). Hedgerows are deliberately planted homogenous bushes, trees, and other vegetation types along the edge of various plots. They are often dominated by one or two species, chosen for specific purposes, such as the demarcation of plot boundaries, provision of firewood, fruits or livestock feed, use as soil amendments, ornamental purposes, etc. For example, sturdy hedges of *Tithonia diversifolia* or *Lantana camara* are planted due to their rapid growth and impenetrability to livestock (Bradley 1988). Moreover, a wide variety of isolated trees is found on each farm. A typical farm in the sample has about 129 trees (or 325 according to farmers' estimates).[7] Some are planted specifically for their fruit or wood, for shade, or medicinal or ornamental purposes; while others are left from land clearing or grow naturally. On average, farms have 10 different tree species, with *Eucalyptus saligna* and *Markhamia lutea* being the most popular species. More than half (212) of households in the sample grow *Eucalyptus saligna* and 168 households grow *Markhamia lutea*. Other popular tree species are *Psidium guajava* or guava, *Cupressus lusitanica* or Mexican cypress, and *Grevillea robusta* or silky oak, among others. Over 93 percent of households keep farm animals. Each household has, on average, two local cows (Zebu breeds), one improved dairy cow, and eleven chickens.

A.4 On-farm biological resources in western Kenya

Following Bari et al. (1998), on-farm non-edible biomass can be broadly categorized into four major types according to its source: crop residues and other plant materials, trees and hedgerows, animal and household waste. These major categories loosely correspond to the different land use types: crop residues are collected from growing annual food crops and

[7] We did not count trees on several farms that had large areas of thick forests. This could explain a large divergence in the estimates.

perennial cash crops, while trees and bushes are found on woodlots and throughout the farm as windrows, hedgerows and isolated trees. Table A.4.1 shows the main biomass sources in western Kenya. For each source of biomass, Table A.4.1 also shows percentage of households in the sample producing it, the month the biomass source is most abundant, and the main three uses (with the percentage of households dedicating the biomass source to each use). Most biomass is used for several different purposes, leaving none wasted. The main three uses are feeding domestic animals (either collecting biomass or grazing animals on the fields after harvest), kitchen or household fuel, and for soil fertility management (leaving crop residues in the fields, mulching or collecting biomass to apply as organic amendment later on).

More than 93 percent of households in the sample own domestic animals, but only 36 households purchased feed for their cows as a supplement, stating that their cattle primary grazed on their land. Twenty-seven percent of households, for example, left some maize stover in the fields for grazing cattle, while 33 percent collected maize stover as animal feed.[8] Crop residues from other annual (e.g., sorghum) and perennial (e.g., sugarcane and banana) crops are also used as cattle feed, while some households (7 percent in the sample) specifically grow fodder grasses (*Pennisetum purpureum*, or Elephant or Napier grass). Woody biomass (defined as biomass from woody or ligneous plants, including shrubs), on the other hand, satisfies most of domestic cooking energy needs. Only a small portion of woody biomass (as charcoal) is dedicated to heating an iron or other household chores. Most households cook on traditional open fire stoves and use twigs and branches (71 percent of households) and/or wood (42 percent) from their own farms. Almost all households, after shelling their maize, use maize cobs as fuel (96 percent). Some others supplement their cooking needs with cereal straw (30 percent of households that produce it) or tea prunings (31 percent). Different sources of biomass are also widely used for soil fertility management (leaving crop residues on the fields as organic soil amendment, mulching, applying animal manure, or ash

[8]Biomass uses are not exclusive. We asked about three main uses for each biomass source.

from burning biomass for kitchen fuel, etc.)—most households in the sample reported using all different sources of crop residues for soil improvement measures.

Several uses of source-specific biomass are also widespread. For example, ash from burning the bean plants in an outside fire is collected and stored to be used in cooking to make vegetable dishes more palatable (25 percent of households reported doing so). Cow dung—mixed with ash and soil or by itself—is used to re-plaster the outside walls of homes or other mud structures (63 percent of households). Apart from being collected as firewood, woody biomass is also used in construction and furniture making, as well as to demarcate land use units and farms (18 percent of households use twigs and brunches and 35 percent of households use wood from their farms as building materials). Moreover, medicinal, ornamental uses, and shade provision are also common uses of tree biomass (Kindt, Simons, and Van Damme 2004). Eighty-nine households (29 percent of the sample) reported making charcoal mostly from their own trees, with about 206 kg of charcoal made in 2011 per household on average. Fifty-eight households reported selling their charcoal.

It is worth noting that biomass production and utilization patterns vary according to agricultural season, farm size, land use practices, soil fertility, as well as household size and socio-economic characteristics, and prevailing cultural practices. Annual crop residue availability follows the agricultural season. For example, legume residues are most abundant in June and maize stover in August—the respective harvesting months of the long rains agricultural season. The higher productivity of maize crops on more fertile soils or on farms more recently converted from forest leads to higher productivity (per acre) of maize residues (Torres-Rojas et al. 2011). Wealthy households use inorganic fertilizers, practice fallowing on a portion of their farm and incorporate maize stover for soil management to achieve higher crop yields, while poor households get higher returns from using maize residues as fuel (Crowley and Carter 2000).

Only several biomass sources (twigs/branches, wood, timber offcuts) are commonly traded in local markets. However, although markets for other sources of biomass do not exist, households engage in the collection or barter of biomass to satisfy their needs. For example, 34 households in the sample reported acquiring additional maize stover, with 24 households getting stover from their neighbors for feeding livestock. Forty households acquired maize cobs from their neighbors to supplement their energy sources (of those, 34 households collected maize cobs for free). One hundred thirty-eight households acquired twigs and branches, while 4 households sold some twigs and branches from their farm. Of those who acquired woody biomass, 81 households collected it on community areas or a neighboring farm for free, and 32 purchased it mostly at local markets.

Table A.4.1: Primary sources of biomass and its uses.

Biomass source	% Households	Most abundant	Maine uses (% producing households)
Primary Source: Crop residues and other plant materials			
Maize stover	99.05%	Aug	Left in the field (77%)
			Collected for feeding own animals (33%)
			Left in the field for grazing own animals (27%)
Maize cobs	98.74%	Aug	Collected for own fuel (96%)
			Left in the field (12%)
			Collected for own fertilizer (4%)
Cereal straw/husks	14.83%	Aug	Left in the field (81%)
			Collected for own fuel (30%)
			Left in the field for grazing own animals (13%)
Tubers/roots residues	6.94%	Dec	Left in the field (60%)
			Collected for planting (27%)
			Collected for feeding own animals (23%)
Legume residues	77.92%	Jun	Left in the field (44%)
			Collected for own food (25%)
			Collected for feeding own animals (19%)
Vegetable residues	17.67%	All	Left in the field (79%)
			Collected for own food (11%)
			Collected for own fertilizer (4%)
Tea/coffee prunings	4.10%	Apr	Left in the field (92%)
			Collected for own fuel (31%)
			Collected for own building materials (8%)
Sugarcane straw	7.57%	Dec	Left in the field (63%)
			Collected for feeding own animals (46%)
Banana residues	20.19%	All	Left in the field (83%)
			Collected for feeding own animals (36%)
Fodder grasses	7.26%	All	Collected for feeding own animals (78%)
			Collected for sale (13%)
			Collected for own fertilizer (9%)
Primary Source: Animal waste			
Cow dung	72.24%	All	Collected for own fertilizer (89%)
			Collected for own building materials (63%)
			Left in the field (10%)
Poultry excreta	81.70%	All	Collected for own fertilizer (93%)
			Left in the field (7%)
Primary Source: Trees and bushes			
Leaves, twigs, branches	70.98%	All	Collected for own fuel (92%)
			Collected for own building materials (18%)
			Left in the field (7%)
Wood	41.96%	Apr/Aug	Collected for own fuel (81%)
			Collected for own building materials (35%)
			Collected to make charcoal for sale (11%)
Timber offcuts	7.26%	Jun	Collected for own building materials (61%)
			Collected for own fuel (39%)
Sawdust	8.52%	Sep	Left in the field (48%)
			Collected for own fuel (30%)
			Collected for poultry bedding (11%)

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