Agricultural Productivity and Soil Carbon Dynamics: A Bioeconomic Model

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We examine the dynamic management of a soil resource—the issue at the core of both environmental and development challenges in developing countries. Our theoretical framework extends the traditional bioeconomic model of renewable resources to soil carbon management and investigates the effects of changes in agricultural practices on farmers' natural resource base and livelihoods. We parameterize the model using an eight-year panel data set from an agronomic experiment and data from household and market surveys in the western Kenyan highlands. The optimal maize yields and soil carbon stocks are higher than those observed in the region. This divergence is partly explained by farmers' heterogeneous time preferences (with the implied discount rates of 5% to 25%), information barriers, and market imperfections. The steady-state shadow price for soil carbon ranges from \$95/Mg to \$168/Mg, indicating a significant opportunity cost for soil mismanagement.

Key words: Agricultural productivity, bioeconomic model, environmental degradation, Kenya, natural resource management, soil carbon dynamics.

JEL codes: O13, Q12, Q24, Q57.

Depletion of soil fertility is considered to be one of the major biophysical causes of low per capita food production in Sub-Saharan Africa (SSA; Sanchez 2002). 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% of land across SSA suffer from nutrient depletion, making it the primary source of soil degradation across the continent (Tully et al. 2015). Degraded soils are less responsive to changing climate, and more and more resources are needed to maintain food production. As a result, about 414 million people in SSA—up from 290 million people in 1990—live in extreme poverty, and SSA remains the region with the highest prevalence of undernourishment (UN 2014). Soil resources also play a major role in the global carbon cycle and contain about 2,500 billion metric tons of carbon, making soils the largest terrestrial pool of carbon (Woodward et al. 2009). And while agriculture accounts for 20% to 30% of total global greenhouse gas emissions, agricultural soils and biomass

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also sequester carbon out of the atmosphere (WB 2012). "Climate-smart" farming practices—retention of crop residues, reduced tillage, mulching, use of manures, agroforestry, and many others—can take advantage of the soil role as a carbon sink and a carbon store and simultaneously reduce emissions.

In this article, we examine the management of a soil resource in smallholder agriculture in the tropics and ask to what extent agricultural practices can enhance soil fertility, thus simultaneously increasing yields and sequestering carbon. We develop a theoretical framework that extends the traditional bioeconomic model of renewable resources to soil carbon management and investigates the effects of changes in practices on farmers' natural resource base and livelihoods. We calibrate the model to the western Kenyan highlands to examine the management of a soil resource in one particular setting. This investigation has considerable data requirements. Since soil degradation in the current period imposes a reduction in net benefits on the future generation, it needs to be evaluated within an intertemporal framework. Yet, the paucity of detailed information available to economists, such as technical data on soil fertility change and corresponding rates of yield response, 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 (e.g., French 1986), while others simulate the effects of land degradation by incorporating parameters estimated in a separate biophysical model into a model of economic behavior (e.g., Barbier 1998). In contrast, we have both detailed biophysical and socio-economic data to parametrize one bioeconomic model. Using an eight-year panel data set from an agronomic chronosequence experiment in Vihiga and Nandi counties, and data from household and market surveys in the same area, our empirical model combines an econometrically estimated production function and a calibrated soil carbon flow equation in a maximum principle framework. The unique nature of our chronosequence data set, comparable to a quasi-natural experiment, allows for detailed estimation of site-specific dynamic relationships between land use management, agronomic productivity, and soil fertility.

We use the bioeconomic model to determine the optimal management of the farming system over time in terms of one "climate-smart" farming practice—the combined application of mineral fertilizer and crop residues. The application of both mineral and organic resources is required to overcome soil fertility depletion (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, which are 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 one 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).

Given the prevailing price levels, we find that the optimal management strategies lead to maize yields that are far higher (3.53–4.17 Mg/ha) than those currently observed in the region. More depleted soils require higher application rates of mineral fertilizer and crop residues at the outset, thus decreasing the net value of maize production on farms with worse initial resource endowments. Moreover, our focus on soil carbon allows us to estimate the potential for soil carbon sequestration in the research area, and to assess its value. Similar to other studies in Sub-Saharan Africa, annual soil carbon sequestration rates of 440 kg/ha and 240 kg/ha can be achieved in western Kenya on depleted and medium-fertility soils, respectively. The steady-state shadow price for soil carbon ranges from \$95/Mg to \$168/Mg (or \$27 to \$47/Mg of CO_2 equivalent), indicating a significant opportunity cost to soil mismanagement. In addition, we provide evidence on the reasons for divergence between the optimal management practices (as shown by our model) and the current practices observed in western Kenya. The equilibrium levels of soil carbon and maize yield are highly dependent on the discount rate used, carbon content of crop residues, and prices, suggesting the role of farmers' time and risk preferences, information-related barriers, and imperfect markets in agricultural production and natural resource management.

This article is broadly related to a body of research in economics that examines human-environment interactions. In particular, it shares with a smaller set of articles an explicit recognition of the direct impact of agricultural practices on natural resource base and rural livelihoods. Most existing studies examine the impact in a static framework. For example, some consider the effects of decreasing common pools of biomass or leaving land fallow on agricultural production and profits (Lopez 1997; Goldstein and Udry 2008), while others examine the impacts of applying animal manure or crop residues on agricultural livelihoods (Gavian and Fafchamps 1996; Marenya and Barrett 2009; Matsumoto and Yamano 2011; Teklewold 2012; Sheahan, Black, and Jayne 2013; Berazneva et al. 2018a). Recognizing that many natural resources are renewable, another set of articles examines natural resources in a dynamic setting. Some of the earlier work treating soil as a renewable resource comes from the United States (see, e.g., Burt 1981 and McConnell 1983); more recently, Barbier (1998) and Holden, Shiferaw, and Pender (2005), for example, analyze land degradation in a developing country setting. Specifically for western Kenya, two simulation models investigate 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.

Our article contributes to both static and dynamic strands of the literature. Our dynamic bioeconomic (optimization) model treats soil as an input in agricultural production and a renewable resource, while the rich agronomic and socio-economic data sets we use allow for the model's precise estimation. We explicitly recognize that agricultural outcomes depend on the conditions of local natural resources and model farmers' intertemporal management practices and their effects on current and future agricultural productivity. Therefore, we offer a method to demonstrate the potential for increasing yields and sequestering carbon and to estimate the monetary value of soil carbon that can be applied in other settings; we also present a detailed case study relevant for improved resource allocation at the farm level and for national agricultural policy in Kenya.

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, the SOC pool is related to the amount of soil organic matter (SOM), which contains soil nitrogen, phosphorus, and other important soil macro- and micro-nutrients. Soil organic matter has multiple benefits to soil productivity (such as nutrient availability, water-holding capacity, and soil biota) and to agronomic productivity, with the impact on the quantity of external inputs required to achieve a given yield (Lal 2006; Blanco-Canqui et al. 2013). Additionally, increases in SOC and SOM not only increase average yields, but also decrease the susceptibility of yields to weather shocks (Graff-Zivin and Lipper 2008).

Land use decisions have a major influence on the level of the SOC pool. A large fraction of the accumulated carbon and soil nutrients is lost following land conversion from natural environments (e.g., forests) to agricultural land (Murty et al. 2002). Current agricultural technologies and practices in resource-poor economies also deplete the SOC and SOM pools, and by doing so degrade soil fertility with an adverse effect on agronomic productivity. At the same time, agricultural 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 residue retention, nitrogen fertilization, fallowing, no-till farming, manuring, composting, 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). 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). Land use changes and agricultural practices can transfer the CO_2 in the atmosphere to soil organic carbon. While the potential soil carbon sequestration capacity is not well known, some estimates suggest that sustainable land use and agriculture could sequester 0.4–1.2 Pg of carbon per year (Lal 2004). This amount is equivalent to 5% to 15% of global emissions from fossil fuels. The rate of carbon sequestration of no-tillage and residue management, adjusted for emissions associated with these technologies, for example, ranges from 240 kg C/ha to 950 kg C/ha per year (or 0.88–3.48 Mg CO_2 equivalent/ha) across Latin America, Asia, and Africa (WB 2012).[1]

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.

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 about 40% to 50% of the population living in poverty (KIPPRA 2013). 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 twentieth century. Households engage in a range of agricultural activities: they cultivate food and cash crops (both annual and perennial), keep chickens and livestock, and grow trees on woodlots for timber and fuel. While their main objective is increasing food supplies, smallholder farmers also strive to earn income and make a profit (Waithaka et al. 2006). Land is privately owned, with most parcels either inherited or purchased.

Farms have medium to high agricultural potential (WRI 2007), but suffer from severe soil degradation. Dominant soil types are acrisols, ferralsols, and nitisols (Jaetzold and Schmidt 1982), with many characterized by soil acidity and phosphorus deficiency (Kisinyo et al. 2014). Soil erosion due to rain is also common. The incorporation of crop residues at plowing, crop rotations, and short fallows were some of the means of maintaining soil fertility 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 stopped planting woodlots, making cereal residues main sources of fuel and animal feed. In this area, less than half of all residues are left on the field, mulched, or collected to apply as organic amendments for soil fertility management; the other half are roughly equally split between household energy and animal feed (Berazneva et al. 2018a).[2] As a result, the amount of organic material returned to the soil after harvest has significantly declined 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 staple crop, maize (*Zea mays* L.). Maize is the most commonly grown and consumed grain in the area, having been established as a dominant food crop in Kenya at the beginning of the twentieth century (Crowley and Carter 2000). Farmers in the area believe that a successful farm must produce the staple maize for home consumption, while the surplus maize is to be sold to neighbors or the local market (Waithaka et al. 2006).[3] Despite its significance (the cereal is also cultivated on the largest proportion of farm area), maize production often results in low yields. Farmer-reported average annual maize yield in western Kenya is 1.65 Mg/ha

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

[2] The household survey, described below, shows that over 80% of farmers currently use maize residues for soil fertility management. The top three additional conservation investments are intercropping (78% of plots), building of terraces (27% of plots), and using rotations (16% of plots).

[3] About 40% of households in our survey sell maize, and among those who do, only about 5% sell more than 63% of their annual yield.

(Berazneva et al. 2018a; average yield is 2.71 Mg/ha in the nationwide Tegemeo Rural Household Survey as reported in Sheahan, Black, and Jayne 2013).[4] These yields correspond to current agricultural practices—no fallowing, limited use of hybrid seeds and low application rates of mineral fertilizer and organic resources, and conventional (hand, oxen, or tractor) tilling.

Over the last several decades, however, Kenya has experienced expanding markets for agricultural inputs and outputs. Sheahan, Black, and Jayne (2013), for example, document the consistent increase in risk-adjusted economically optimal rates of fertilizer application since the mid-1990s. Holden, Otsuka, and Place (2009) show that land rental markets in densely-populated areas of SSA are active, where land is scarce and land holdings are fragmented. And using data from the Siaya Lands Office of the ministry of lands in Kenya, Michelson and Tully (2018) provide evidence of vibrant and well-functioning land markets in western Kenya.

Data from several sources are used to build our bioeconomic model. Plot-level maize yields and carbon stocks come from a long-term agronomic experiment in the Vihiga and Nandi counties of western Kenya from 2005 to 2012, while socio-economic household-level data and prices are from the household and market surveys in the counties surrounding the agronomic sites from 2011 to 2013. The survey and agronomic experiment locations are shown in figure 1 and further discussed in the sections that follow.

Economic Model

Our model is similar to that of Burt (1981): we assume that the farmer's objective is to maximize the discounted present value of net returns from land over an infinite planning horizon. Instead of focusing on the depth of top soil 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 several additional considerations. In response to incomplete or missing markets, rural households may link their production and consumption decisions to satisfy multiple objectives of income generation, food security, and risk reduction with potential impacts on the management of natural resources (de Janvry, Fafchamps, and Sadoulet 1991; Holden and Binswanger 1998). As a result of ambiguous or insecure property tenure rights, households may also adjust their agricultural practices and underinvest in long-term soil resource management (Goldstein and Udry 2008). In addition, the inherent uncertainty of agricultural activities may be amplified in the context of low-resource rain-fed agriculture that is more susceptible to weather fluctuations and volatility of agricultural markets or policy environments (Rosenzweig and Binswanger 1993).

As discussed above, the assumption of functioning markets may be reasonable in the context of western Kenya, where property rights are also secure.[5] Similar to Wise and Cacho (2011) and Pagiola (1999), we argue that net returns to agricultural production is an important part of the farmers' objectives and a necessary condition to adopt conservation practices, and following Burt (1981), assume an infinite planning horizon. Net returns represent the amount of profits the household could earn if both maize grain and residue were marketable outputs. To allow for some market imperfections, however, we explicitly account for the opportunity cost of household labor, land, and organic resources, use farmer-reported prices that reflect potential transaction costs, and availability constraints, and perform sensitivity analysis. Introducing farmers' risk aversion via a concave utility function, as is a common practice (Moschini and Hennessy 2001), does not alter the derivation of the steady-state results. Following Conrad and Leard (2013), we establish the equivalence of the steady-state results when maximizing the present value of net returns or when maximizing the present value of utility for a risk-averse farmer in an online supplementary appendix (A.1).

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

[5] In the sample of households used in the empirical estimation, 84% of households engage in off-farm employment, 62% hire agricultural laborers, 60% purchase fertilizer, and about 15% participate in land markets, either renting in or renting out parcels of land for cultivation. Almost all households own at least one parcel of land with over 90% of households having a document to certify land right (usually a title deed with land registration certificate) and about 94% do not report ever having conflict over land ownership.

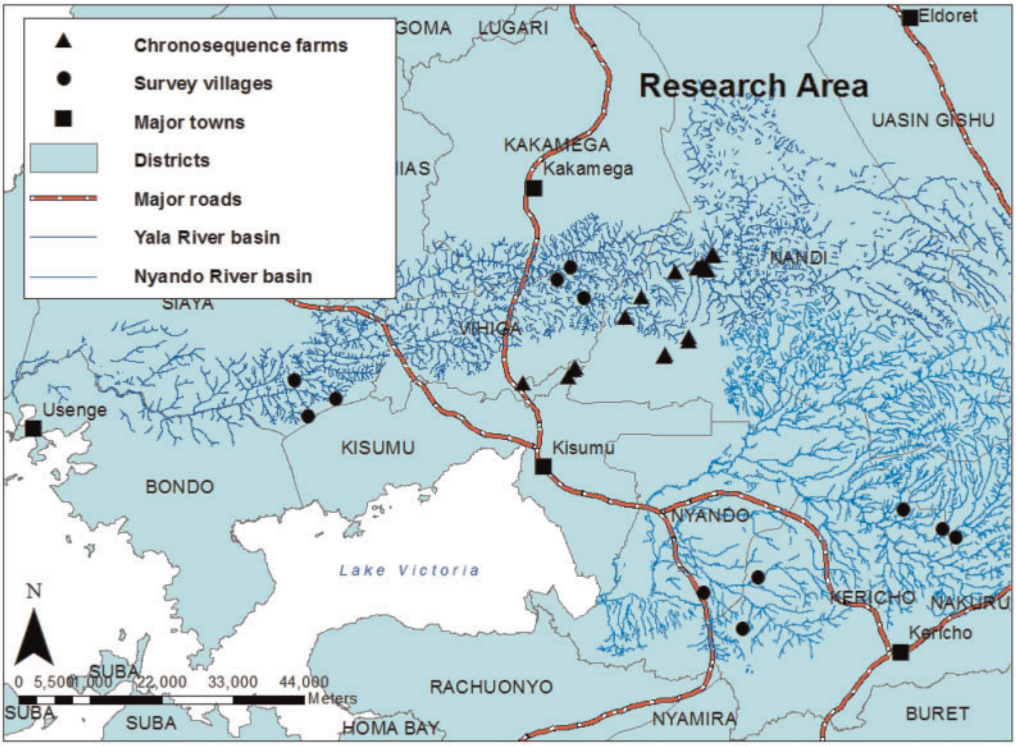

Figure 1. Research sites

Note: The map shows the location of farms in the chronosequence experiment and survey villages in the household survey.

We note, however, that our model has its limitations. We focus only on the production of one crop during the main agricultural season and one "climate-smart" farming practice. We thus abstract from other farming decisions, such as choice of crops or allocation of resources to food or cash crops, livestock rearing, or cultivation of trees. We also assume away the variation in farm size and thus impose constant returns to scale. While our model is necessarily a simplification of complex smallholder systems, however, our assumptions allow for the estimation of exact relationships in maize production, make our model fully bioeconomic, and offer important insights for agricultural policy and climate mitigation.

Farmer's Objective

Suppose a representative farmer cultivates a hectare of land of homogenous quality with maize during the main agricultural season. Let c_t represent the state of farmer's land in year t, defined by a single soil-fertility indicator—soil carbon content. The farmer grows maize by making two 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 net revenue 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 net returns 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).

The farmer's objective is then to maximize the discounted present value of annual net returns 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:

$$(1) \quad \max_{\{f_t,\alpha_t\}} \pi = \sum_{t=0}^{\infty} \rho^t [py(c_t, f_t) + qr_t - nf_t - qr_t\alpha_t - m]$$

subject to

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

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

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).[6] Restricting f_t, α_t, c_t and λ_t, the multiplier on the soil carbon constraint, to being nonnegative, the discrete-time current value Hamiltonian can be written as

$$(2) \quad H = py(c_t, f_t) + qky(c_t, f_t) - nf_t - qky(c_t, f_t)\alpha_t - m + \rho\lambda_{t+1} g(c_t, f_t, \alpha_t)$$
$$= (p + qk(1-\alpha_t))y(c_t, f_t) - nf_t - m + \rho\lambda_{t+1} g(c_t, f_t, \alpha_t)$$

where the multiplier λ_{t+1} can be interpreted as the current-value shadow price of the soil carbon stock at time $t+1$. The first order conditions require that

$$(3) \quad \frac{\partial H}{\partial f_t} = (p + qk(1-\alpha_t)) \frac{\partial y(\cdot)}{\partial f_t} - n + \rho\lambda_{t+1} \frac{\partial g(\cdot)}{\partial f_t} = 0,$$

$$(4) \quad \frac{\partial H}{\partial \alpha_t} = -qky(\cdot) + \rho\lambda_{t+1} \frac{\partial g(\cdot)}{\partial \alpha_t} = 0,$$

$$(5) \quad \rho\lambda_{t+1} - \lambda_t = -\frac{\partial H}{\partial c_t} = -[(p + qk(1-\alpha_t)) \frac{\partial y(\cdot)}{\partial c_t} + \rho\lambda_{t+1} \frac{\partial g(\cdot)}{\partial c_t}],$$

$$(6) \quad c_{t+1} - c_t = \frac{\partial H}{\partial[\rho\lambda_{t+1}]} = g(c_t, f_t, \alpha_t).$$

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

$$(7) \quad (p + qk(1-\alpha_t)) \frac{\partial y(\cdot)}{\partial f_t} + \rho\lambda_{t+1} \frac{\partial g(\cdot)}{\partial f_t} = n,$$

$$(8) \quad \rho\lambda_{t+1} \frac{\partial g(\cdot)}{\partial \alpha_t} = qky(\cdot),$$

$$(9) \quad \lambda_t = \rho\lambda_{t+1} \left[1 + \frac{\partial g(\cdot)}{\partial c_t}\right] + (p + qk(1-\alpha_t)) \frac{\partial y(\cdot)}{\partial c_t},$$

$$(10) \quad c_{t+1} - c_t = g(c_t, f_t, \alpha_t).$$

Equations (7) and (8) 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 (9) 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 (10) is a restatement of the state equation.

Empirical Model

The construction of the empirical model used to estimate the farmer's maximization problem (equation 1) consists of several steps. We first specify and econometrically estimate the maize yield equation ($y(\cdot)$) as a function of soil organic carbon stock (to a depth of 0.1 meter) (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. The two equations interactively describe crop-yield dynamics and soil-carbon changes and provide parameters for our bioeconomic model. As a last step, we describe the economic variables and their sources before proceeding to the discussion of our results.

Maize Yield Function

The biophysical data used to estimate the maize yield function come from agronomic experimental sites in Vihiga and Nandi

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

counties in 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 (Kimetu et al. 2008; Kinyangi 2008; Ngoze et al. 2008; Güereña et al. 2016). A chronosequence—a set of sites that share similar attributes but are of different ages—was established on 28 farms of different ages since conversion from forest to agricultural land.[7] 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 five, twenty, thirty-five, eighty, and 105 years (Kinyangi 2008).

Each year experimental plots received nitrogen mineral fertilizer at a rate of 0 or 120 kg per hectare, and in 2011 and 2012 the nitrogen (N) application rate varied at 0, 80, 120, 160, 200, or 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), *Tithonia diversifolia* (with and without N), charcoal (with and without N), and sawdust (with and without N). Maize grain yield data (oven-dry measurements) are available for each farm, treatment, and year. A subsample representing three major age groups, each treatment, and year (177 samples), was analyzed for total soil carbon.[8] Following Kinyangi (2008), the resulting data were fitted using a three-parameter exponential decay model for each of treatment-fertilizer sub-samples and the established relationships were then used to predict plot-specific soil carbon stocks (the sampling procedure and the construction of soil carbon stock variable are described in the online appendix A.2.).[9]

Table 1. Maize Production During the Long Rains Season, 2005–2012

Variable	Mean	St.dev.	Min.	Max.
Maize grain yield (Mg/ha)	4.05	2.47	0.16	12.14
Soil carbon stock (to a depth of 0.1 m) (Mg/ha)	45.64	18.53	31.79	182.49
Nitrogen fertilizer application (Mg/ha)	0.08	0.07	0	0.24

Note: $N = 1,450$. Data from the chronosequence experiment for estimation of equation (11).

In the research sites, soils are acidic and do not contain carbonates, so the reported total soil carbon is equivalent to organic soil carbon. Since over 90% of phosphorus is held in organic form, soil carbon also indirectly controls for phosphorus and other soil nutrients that may be limiting in the context of western Kenya. Pooling observations across eight years, 28 farms, and four treatments, there are 1,450 observations.[10] Table 1 shows summary statistics for the variables used.[11]

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 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 SSA (see, e.g., Sheahan, Black, and Jayne (2013) and Harou et al. (2017)). We estimate

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

[8] The soil analysis for total soil carbon was done after ball milling using a Dumas combustion analyzer (NC 2100 Analyzer, ThemoQuest Italia S.p.A., Rodano-Milan, Italy). Bulk density was sampled in three locations per plot at harvest and the average was taken.

[9] Soil samples were collected at harvest of the long rains season, so that in the final predictions a lagged variable is used: for example, 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.

[10] 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 1% of the distribution.

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

$$(11)\quad y_{kit} = \gamma_0 + \gamma_c c_{kit} + \gamma_{cc} c_{kit}^2 + \gamma_f f_{kit} + \gamma_{ff} f_{kit}^2 + \gamma_{cf} c_{kit} f_{kit} + \eta_k + \zeta_i + \theta_t + \xi_{kt} + \epsilon_{kit}$$

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. Farm, year, and treatment fixed effects 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.

Similarly to Harou et al. (2017), our data and, therefore, estimations focus on locally attainable yields, 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 4.05 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. The chronosequence data set allows us to make credible estimates of the yield response rates to soil carbon and the additions of mineral fertilizer. It does not allow, however, to incorporate legume intercropping, additions of animal manure as soil amendments, or other common agricultural practices of the western Kenyan highlands.

Table 2 displays the estimated coefficients of the maize yield function. Column (1) shows the standard errors clustered at the farm level, while column (2) shows bootstrapped standard errors. The quadratic specification fits the data with an R-squared of 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, the mean increase in maize yields is 60 kg, while an addition of 100 kg of nitrogen fertilizer results in the mean yield increase of 1,039 kg (the distributions of the estimated returns are shown in figure 2).[12] The negative coefficient on the interaction term between carbon stock and nitrogen fertilizer suggests some substitutability between the two inputs, consistent with the findings of a comprehensive meta analysis from the 57 agronomic studies of maize yields on smallholder farms across SSA of Chivenge, Vanlauwe, and Six (2011). These authors find that the combined addition of organic resources and nitrogen fertilizer results in negative interactive effects on maize yields, which can be explained by an excess amount of nitrogen added.[13] Our data

Table 2. Maize Grain Yield as a Function of Soil Carbon Stock and Nitrogen Fertilizer

Maize grain yield (Mg/ha)	(1) Clustered st.errors	(2) Bootstrapped st.errors
Soil carbon stock (Mg/ha)	0.113***	0.113***
	(0.0354)	(0.0264)
Squared: Soil carbon stock	−0.000413**	−0.000413***
	(0.000157)	(0.000126)
Nitrogen fertilizer (Mg/ha)	27.04***	27.04***
	(4.704)	(3.119)
Squared: Nitrogen fertilizer	−41.30***	−41.30***
	(10.12)	(10.46)
Interaction: Soil carbon stock and nitrogen fertilizer	−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

Note: Estimation of equation (11). Data from the chronosequence experiment. Asterisks indicate the following: *** = p < 0.01, ** = p < 0.05, and * = p < 0.1. Column (1) shows standard errors (values in brackets) clustered at farm level (28 farms). Column (2) shows bootstrapped standard errors (1, 000 replications). Estimation includes farm, year, and treatment fixed effects, as well as year-treatment interaction.

[12] 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.

[13] Over 70% of the studies included in the 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. The N application rate in our sample is 120 kg N/ha for most observations and we find similar agronomic N use efficiency: 12 kg of maize grain per 1 kg of nitrogen added, similar to the 14 kg of maize grain estimated by Chivenge, Vanlauwe, and Six (2011). 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. Marenya and Barrett (2009), 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 kg for an average plot size of 0.33 ha (about 16 kg N/ha, similar to farmer-reported application rates in

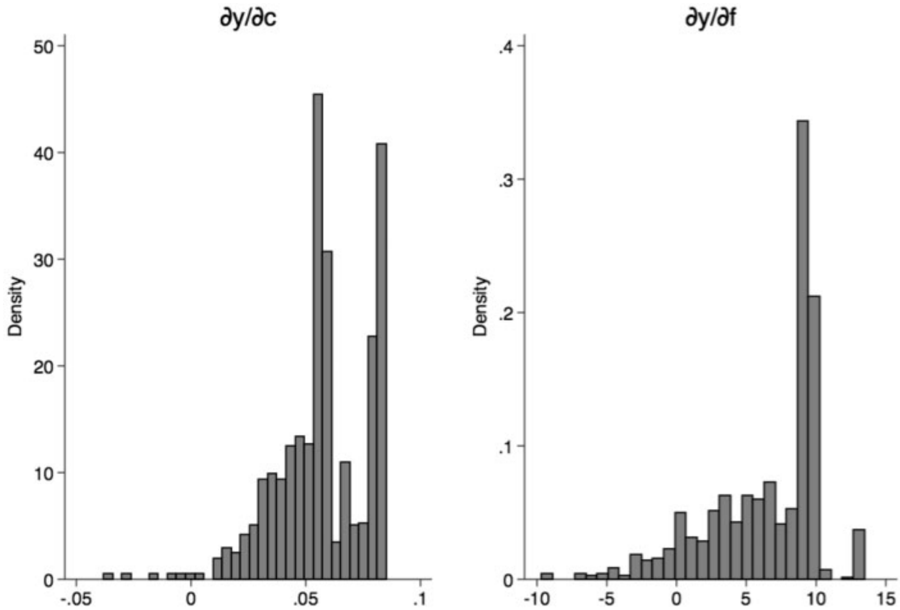

Figure 2. Distributions of estimated returns to soil carbon and nitrogen fertilizer (Mg/ha)

Note: The distribution of estimated returns to soil carbon, $\partial y/\partial c = \gamma_c + 2\gamma_{cc}c + \gamma_{cf}f$, is on the left panel (N=1,450) and to nitrogen fertilizer, $\partial y/\partial f = \gamma_f + 2\gamma_{ff}f + \gamma_{cf}c$, is on the right panel (N=882 observations with $f > 0$), following equation (11) and table 2.

and estimation also support the findings of Chivenge et al. (2007) and Chivenge, Vanlauwe, and Six (2011), namely 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).[14]

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 residues left on the field for soil fertility:

$$(12) \quad c_{t+1} - c_t = -Dc_t + A(\alpha_t Fky(c_t, f_t))^B$$

where D is rate of annual soil carbon loss with conventional tillage, A and B are parameters calibrated using the Rothamsted Carbon Model for turnover of carbon in soil (Coleman and Jenkinson 1996), F is carbon content of maize residues, and k is maize residue to grain ratio.

According to the Intergovernmental Panel on Climate Change (IPCC) Tier 1 guidelines, the relative soil carbon stock change factor is 0.91 (±4%) for tropical wet soils with conventional tillage and low residue return, which implies an average 10% annual decrease in soil carbon stock (IPCC 2003). The main loss of soil carbon is CO_2 release from the soil surface, referred to as carbon mineralization, mainly as a result of microbial decomposition of soil organic matter (SOM). While SOM is crucial for maintaining overall soil fertility, its higher levels induce greater microbial decomposition, leading to higher

our household survey), while soil carbon is measured as percent by weight as determined by lab analyses.

[14] 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).

rates of carbon loss through CO_2 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% over the course of one year; D is assumed to be 0.11.

The main source of soil carbon inflows in the study area 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, calibrated for the geographic location of the chronosequence farms and the equilibrium levels of maize yields (details of the calibration are in the online supplementary appendix A.3). 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).

Prices

The data used to derive the economic variables come from the detailed household survey in the Nyando and Yala river basins of western Kenya in 2011/12. The survey included over 300 randomly selected farming households in 15 villages in Kakamega, Kericho, Kisumu, Siaya, Uasin Gishu, and Vihiga counties and a wide range of topics covering agricultural activities, socio-economic status, and natural resource use.[15] Sampling, design, and implementation of the survey are described in Berazneva (2015). In addition, price and market data were collected from public sources and interviews with farmers, as well as market sellers and buyers, in the same villages and town centers in close proximity to the survey villages in 2011, 2012, and 2013. 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).

The empirical distributions of prices reported in the household survey are summarized in table 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% is commonly applied during planting, while urea (N content 46%) and calcium ammonium nitrate (CAN; N content 26%) 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 (2016), we construct a composite price of nitrogen from the prices of the main fertilizer types using their relative shares in the household survey as weights.[16] 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 altitude. We then use the estimated coefficients to calculate the

[15] Three villages were randomly selected from each of the five 10-kilometer blocks that were part of the original geographic coverage of the Western Kenya Integrated Ecosystem Management Project, which was implemented from 2005 to 2010 by the Kenya Agricultural Research Institute and the World Agroforestry Center.

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

Table 3. Empirical Distribution of Prices

Variable	Mean μ	Median *med*	St. Dev. σ	25%	75%	N
Price of maize, p ($/Mg)	349	331	95	265	397	120
Price of nitrogen fertilizer, n ($/Mg)	4,346	4,434	1,737	3,251	5,291	190
Value of crop residues, q ($/Mg)	65	58	52	24	94	144
Maize production cost, m ($/ha)	445	375	283	290	516	309

Note: Data from the household survey.

average land rental value in the entire sample of surveyed households. The results of the hedonic regression and the distribution of all prices used in the analysis are reported in the online supplementary appendix A.4.[17]

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. Berazneva et al. (2018a) estimate 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.[18] 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 nonrenewable 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, microfinance institutions, market traders, etc.—in the research area. The survey also showed significant variability: the annual interest rate ranges from 3% to 24%, depending on the type of loan, amount, and lending institution. Similar to Pagiola (1996), who studies the effects of price policy changes on farmers' incentives to adopt soil conservation measures in Kenya, we use the discount rate of 10%; however, we also check our results for the discount rates of 5% to 25%.

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. These are the 5th, 50th, and 99th-percentile of the distribution of soil carbon stocks on maize plots in the three survey villages closest to the chronosequence sites.

All prices are quoted in U.S. dollars using the 2011/12 average exchange rate of 84 Kenyan Shillings (KES) per 1 U.S. dollar (USD). Values for the agronomic and economic variables together with their sources are summarized in table 4.

[17] 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). We use this strategy to approximate average opportunity cost of land in the area.

[18] Specific energy, energy per unit mass that is often used for comparing fuels, of mixed fuel and maize stover and cobs in western Kenya is very similar (Torres-Rojas et al. 2011). It is 17.2 MJ/kg for mixed wood, 17.3 MJ/kg for maize stover and 16.9 MJ/kg for maize cobs.

Table 4. Parameter Values in the Bioeconomic Model

Variable	Description	Value	Unit	Source
Maize yield function[a]				
γ_0	Constant	−0.810	–	Chronosequence experiment
γ_c	Coefficient on c_t	0.113	–	Chronosequence experiment
γ_{cc}	Coefficient on c_t^2	−0.000413	–	Chronosequence experiment
γ_f	Coefficient on f_t	27.038	–	Chronosequence experiment
γ_{ff}	Coefficient on f_t^2	−41.295	–	Chronosequence experiment
γ_{cf}	Coefficient on $c_t f_t$	−0.218	–	Chronosequence experiment
Soil carbon equation				
D	Rate of soil carbon loss	0.11	–	IPCC (2003); Kimetu et al. (2009)
A	Carbon plant input parameter	2.40	–	Chronosequence, ROTHC-26.3
B	Carbon plant input parameter	0.52	–	Chronosequence, ROTHC-26.3
k	Maize residues to grain ratio	1.50	–	Chronosequence experiment
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, 20, 25	%	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

Note: Superscript [a]denotes the following: to account for fixed effects in the estimation of the production function following equation (11), 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.

Results and Discussion

The empirical implementation of the bioeconomic model maximizes the discounted net present value of maize production over a fifty-year horizon, which is defined as the sum of the discounted net revenue from maize production over the interval $t = 0, 1, \ldots, T - 1$ 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 $\Psi(c_T) = -\frac{1+\delta}{\delta}(c_{ss} - c_T)^2$, which 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). We first 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 run the model with the average values for f and α from the household survey to approximate the current practices of farmers in western Kenya and compare the results to the optimal decision rules when the model maximizes the discounted net revenue over 50 years. We examine the sensitivity of the infinite-horizon steady state values to discount rate, carbon content of maize residues, and prices to suggest why the current practices of farmers in Kenya diverge from the optimal practices. Finally, we discuss the value of soil carbon.

Steady-State Analysis

Looking at the steady-state equilibrium answers 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 11 and 12 and $c_{t+1} = c_t = c$ imply the following first order conditions:

$$(13) \quad [p + qk(1-\alpha) + \rho\lambda AB(\alpha Fky(c,f))^{B-1} \alpha Fk][\gamma_f + 2\gamma_{ff} f + \gamma_{cf} c] - n = 0,$$

Table 5. Steady-State Values: Changing Discount Rate δ

Variable	$\delta = 5\%$	$\delta = 10\%$	$\delta = 15\%$	$\delta = 20\%$	$\delta = 25\%$
Share of residues, α_{ss} (0–1)	0.84	0.54	0.38	0.28	0.21
Nitrogen input, f_{ss} (Mg/ha)	0.11	0.13	0.14	0.15	0.16
Carbon stock, c_{ss} (Mg/ha)	33.28	25.63	20.76	17.40	14.95
Maize yield, y_{ss} (Mg/ha)	4.17	3.91	3.74	3.58	3.53
Value of carbon, λ_{ss} (\$/Mg)	168	138	119	105	95

Note: Steady-state values are from a simultaneous solution of equations (14), (13), (15), and (16), given the parameters in table 4. We vary the discount rate: $\delta = 5, 10, 15, 20, 25\%$.

$$(14)\quad \lambda ABF(\alpha Fky(c,f))^{B-1} - (1+\delta)q = 0,$$

$$(15)\quad [p + qk(1-\alpha) + \rho\lambda AB(\alpha Fky(c,f))^{B-1} \alpha Fk][\gamma_c + 2\gamma_{cc}c + \gamma_{cf}f] - (\delta + D)\rho\lambda = 0,$$

$$(16)\quad A(\alpha Fky(c,f))^{B} - Dc = 0.$$

It can be shown that the steady-state stock of soil carbon, 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 4, we can simultaneously solve equations (13), (14), (15), and (16) to get the endogenously determined equilibrium values for rate of nitrogen application, share of maize residues, and soil carbon stock (see table 5). For $\delta = 10\%$, the steady-state values are $f_{ss} = 0.13$ Mg/ha, $\alpha_{ss} = 0.54$, $c_{ss} = 25.63$ 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 $f_{ss} = 0.13$ Mg/ha and $\alpha_{ss} = 0.54$ are higher than the current farming practices in western Kenya, and the equilibrium maize yield $y_{ss} = 3.91$ Mg/ha is more than double the average yield reported in the household survey.

Current Practices vs. Optimal Decision Rules

Running the model with the average values for $f = 0.018$ Mg/ha and $\alpha = 0.47$ from the household survey 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 10.70-14.00 Mg/ha after thirty-five years and corresponds to maize yields of 0.78–1.11 Mg/ha (figure 3). Similar carbon stocks and maize yields are observed in the household survey. Soil carbon stocks are lower than 19.12 Mg/ha for half of the households in the three villages closest to the chronosequence farms, where farmers reported the median maize yield of 1.31 Mg/ha on plots where we collected soil samples in the long rains of 2011 (the household-level annual average maize yield is 1.65 Mg/ha as described in Berazneva et al. 2018a). As a result, smallholder farmers in Kenya "cultivate marginal soils with marginal inputs, produce marginal yields, and perpetuate marginal living and poverty" (Lal 2004, p. 1626).

We then allow the model to maximize the discounted net revenue over fifty years with $\delta = 10\%$. For farms with different resource endowments, the values for soil carbon, nitrogen input, and share of residues in this finite-horizon problem converge to the steady-state values of the infinite-horizon problem within the first thirty-five years (tables 5 and 6). Figure 4 shows the time paths for soil carbon stock and their convergence to the steady state of 25.63 Mg/ha. For farms with depleted and medium-fertility soils, soil carbon stock increases; for farms with fertile soils, however, it declines from $c_0 = 36.13$ Mg/ha to $c_t = 35 = 25.76$ Mg/ha, with the largest decrease in the first ten years. This is consistent with previous research. Following land conversion from forests to agricultural land in the same sites, Kinyangi (2008) finds significant loss of soil carbon stock during the first eleven 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% of soil carbon is lost following conversion to agriculture in various ecosystems worldwide, with most of this loss occurring within the first few years after conversion. On the other hand, soil carbon sequestration reaches saturation for most of the land management technologies in the first twenty-five years (WB 2012). This is true in our analysis. Over first twenty-five years,

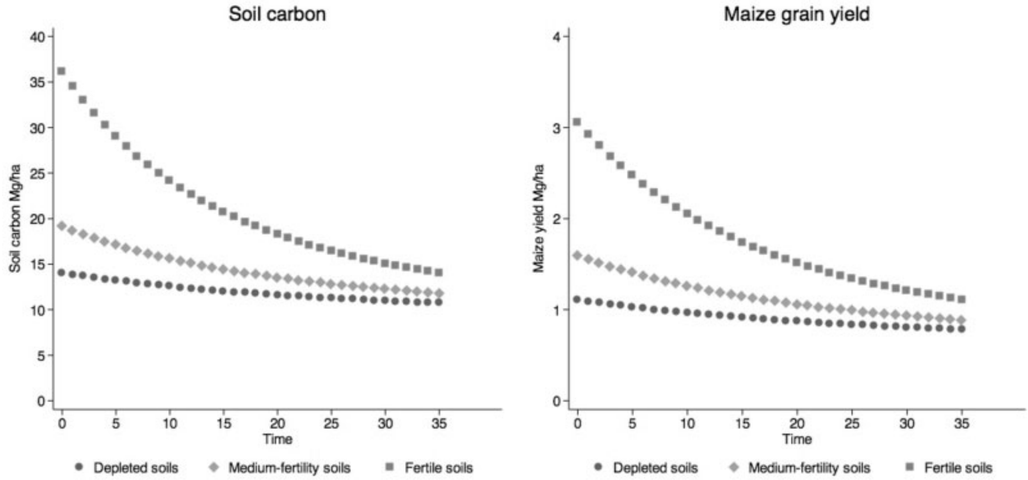

Figure 3. Time paths for soil carbon stock c_t (Mg/ha) and maize grain yield y_t (Mg/ha) corresponding to current farming practices on farms with different initial resource endowments

Note: Time paths are from the model simulation. Current farming practices are the average values for nitrogen fertilizer ($f = 0.018$ Mg/ha) and share of residues ($\alpha = 0.47$) observed in the household survey. Depleted, medium-fertility, and fertile soils correspond to the initial stock of carbon c_0=14.00, 19.12, 36.13 Mg/ha, respectively.

the soil carbon stock on farms with depleted soils increases by 11.11 Mg/ha, with an average annual increase of 444 kg/ha of carbon. And for farms with medium soil fertility, the average annual increase is 249 kg/ha. These two rates are similar to 374 kg/ha, the average annual soil carbon sequestration rate from the use of crop residues for soil fertility management across the 46 studies in Sub-Saharan Africa (WB 2012).[19]

Figure 4 also shows the time paths for maize yields and their convergence to the steady-state level of 3.91 Mg/ha. This equilibrium maize yield is similar to the average yields from the researcher-managed chronosequence plots (table 1). 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. Hence, our results are more reflective of both biophysical and socio-economic constraints on production, and offer *economic* potential for improvements in yields. We note, however, that even this higher equilibrium yield may not be sufficient to feed a large family with land holdings less than one hectare.

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 5). 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 lower rates: $f_0 = 0.10$ Mg/ha and $\alpha_0 = 0.47$. As soil carbon stock declines, higher applications rates are required (table 6). Table 6 also shows that in order to achieve higher carbon stocks and maize yields on farms with depleted and medium-fertility soils, substantial quantities of both resources (fertilizer and maize residues) are required annually. If the annual applications were to end, soil carbon and maize yields would eventually decline. Using

[19] 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% and the adoption period of twenty-five years (WB 2012).

Table 6. Time Paths for Optimal Share of Residues α_t (0–1), Nitrogen Input f_t (Mg/ha), Soil Carbon Stock c_t (Mg/ha), Maize Yield y_t (Mg/ha), and Discounted Annual Net Revenue $\rho^t\pi_t$ ($/ha) over 35 Years on Farms with Different Initial Resource Endowments

	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	171	0.59	0.15	19.12	3.68	315	0.47	0.10	36.13	4.27	775
1	0.63	0.16	15.36	3.54	190	0.59	0.15	19.88	3.71	306	0.48	0.11	34.90	4.23	675
2	0.62	0.16	16.56	3.58	201	0.58	0.14	20.56	3.73	293	0.48	0.11	33.81	4.19	590
3	0.61	0.15	17.63	3.62	205	0.58	0.14	21.15	3.75	279	0.49	0.11	32.85	4.16	517
4	0.60	0.15	18.56	3.66	205	0.57	0.14	21.67	3.77	264	0.50	0.11	32.01	4.13	455
5	0.59	0.15	19.39	3.69	200	0.57	0.14	22.14	3.79	248	0.50	0.12	31.26	4.11	401
6	0.58	0.15	20.12	3.72	194	0.56	0.14	22.55	3.80	232	0.50	0.12	30.60	4.08	355
7	0.58	0.14	20.77	3.74	185	0.56	0.14	22.91	3.82	216	0.51	0.12	30.02	4.06	315
8	0.57	0.14	21.34	3.76	176	0.56	0.14	23.23	3.83	200	0.51	0.12	29.50	4.05	280
9	0.57	0.14	21.84	3.78	166	0.56	0.14	23.51	3.84	185	0.52	0.12	29.05	4.03	249
10	0.57	0.14	22.28	3.79	155	0.55	0.14	23.76	3.85	171	0.52	0.12	28.65	4.02	222
11	0.56	0.14	22.67	3.81	145	0.55	0.14	23.97	3.85	158	0.52	0.12	28.29	4.00	199
12	0.56	0.14	23.02	3.82	135	0.55	0.14	24.17	3.86	145	0.52	0.13	27.98	3.99	178
13	0.56	0.14	23.33	3.83	125	0.55	0.13	24.34	3.87	133	0.52	0.13	27.71	3.98	160
14	0.56	0.14	23.60	3.84	116	0.55	0.13	24.49	3.87	122	0.53	0.13	27.46	3.98	143
15	0.55	0.14	23.83	3.85	107	0.55	0.13	24.62	3.88	112	0.53	0.13	27.25	3.97	129
16	0.55	0.14	24.04	3.86	98	0.55	0.13	24.74	3.88	102	0.53	0.13	27.06	3.96	116
17	0.55	0.13	24.23	3.86	90	0.55	0.13	24.84	3.88	94	0.53	0.13	26.89	3.96	105
18	0.55	0.13	24.39	3.87	83	0.55	0.13	24.94	3.89	86	0.53	0.13	26.74	3.95	94
19	0.55	0.13	24.54	3.87	76	0.54	0.13	25.02	3.89	78	0.53	0.13	26.61	3.95	85
20	0.55	0.13	24.67	3.88	70	0.54	0.13	25.09	3.89	71	0.53	0.13	26.50	3.94	77
21	0.55	0.13	24.78	3.88	64	0.54	0.13	25.15	3.90	65	0.53	0.13	26.39	3.94	70
22	0.55	0.13	24.88	3.89	58	0.54	0.13	25.21	3.90	59	0.53	0.13	26.30	3.94	63
23	0.54	0.13	24.97	3.89	53	0.54	0.13	25.26	3.90	54	0.54	0.13	26.23	3.93	57
24	0.54	0.13	25.04	3.89	49	0.54	0.13	25.30	3.90	49	0.54	0.13	26.15	3.93	52
25	0.54	0.13	25.11	3.89	44	0.54	0.13	25.34	3.90	45	0.54	0.13	26.09	3.93	47
26	0.54	0.13	25.17	3.90	40	0.54	0.13	25.37	3.90	41	0.54	0.13	26.04	3.93	42
27	0.54	0.13	25.22	3.90	37	0.54	0.13	25.40	3.90	37	0.54	0.13	25.99	3.92	38
28	0.54	0.13	25.27	3.90	34	0.54	0.13	25.43	3.91	34	0.54	0.13	25.95	3.92	35
29	0.54	0.13	25.31	3.90	31	0.54	0.13	25.45	3.91	31	0.54	0.13	25.91	3.92	32
30	0.54	0.13	25.35	3.90	28	0.54	0.13	25.47	3.91	28	0.54	0.13	25.88	3.92	29
31	0.54	0.13	25.38	3.90	25	0.54	0.13	25.49	3.91	26	0.54	0.13	25.85	3.92	26

Continued

Table 6. continued

	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	$\rho^t\pi_t$
32	0.54	0.13	25.41	3.90	23	0.54	0.13	25.51	3.91	23	0.54	0.13	25.82	3.92	24
33	0.54	0.13	25.44	3.91	21	0.54	0.13	25.52	3.91	21	0.54	0.13	25.80	3.92	22
34	0.54	0.13	25.46	3.91	19	0.54	0.13	25.53	3.91	19	0.54	0.13	25.78	3.92	20
35	0.54	0.13	25.48	3.91	17	0.54	0.13	25.54	3.91	18	0.54	0.13	25.76	3.92	18
	Total net revenue				\$3,814	Total net revenue				\$4,537	Total net revenue				\$6,870

Note: Time paths are from the model optimization, using $\delta = 10\%$ and median prices. Depleted, medium-fertility, and fertile soils correspond to the initial stock of carbon c_0=14.00, 19.12, 36.13 Mg/ha, respectively. 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.

the chronosequence data, Güereña et al. (2016) show increases in maize yields with significant applications of organic resources. The residual effects of organic amendments, however, disappear after several years with no applications, suggesting that high input levels of organic matter must be sustained to maintain yields and to prevent soil fertility decline. This is true for many sustainable agricultural practices: storage of carbon in soils is volatile and leads to re-emission into the atmosphere if land management practices are changed (WB 2012). The risk of nonpermanence, however, is lower if such practices result in more profitable farming systems overall.

We also observe a difference in the present value of net revenue from a representative hectare of land between the farms with different initial soil fertility (table 6). The net revenue is greatest for farms with the best initial conditions (6,870 \$/ha)—farms with high starting values of soil carbon stock. This highlights the importance of an 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. Without annual applications of fertilizer and organic resources, however, farmers may find themselves in self-reinforcing "soil degradation poverty traps" (Marenya and Barrett 2009; Stephens et al. 2012; Barrett and Bevis 2015). The finding also underscores the importance of considering an initial natural resource base when designing cost-effective policies and programs and offering targeted solutions to farmers with heterogeneous resource endowments.

Reasons for Divergence

The question is then "Why do the optimal practices, as shown in our model, diverge from the current practices of farmers in western Kenya?" There are at least three possible explanations: high discount rates, information barriers, and imperfect markets, which we explore via the sensitivity analysis contained in tables 5, 7, and 8.

Farmers' investments 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

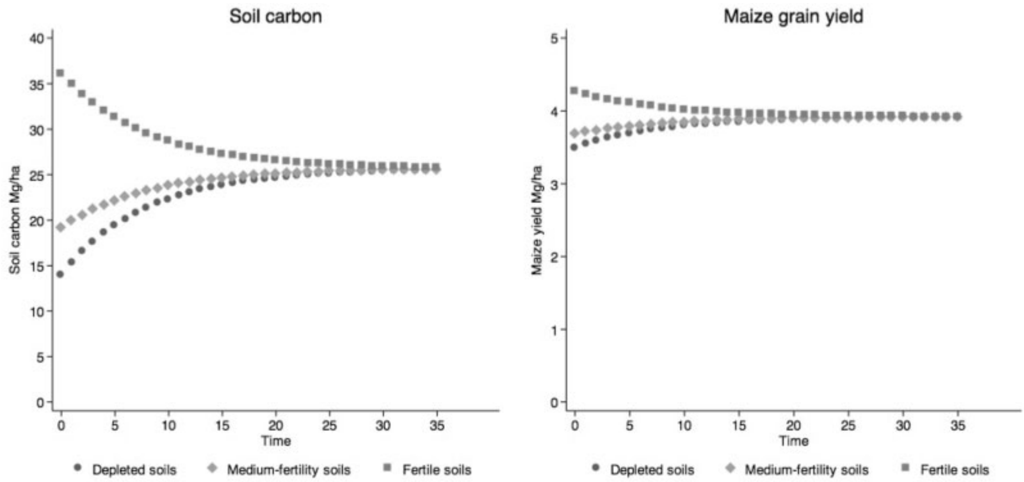

Figure 4. Time paths for optimal soil carbon stock c_t (Mg/ha) and maize grain yield y_t (Mg/ha) on farms with different initial resource endowments

Note: Time paths are from the model optimization, using $\delta = 10\%$ and median prices. Depleted, medium-fertility, and fertile soils correspond to the initial stock of carbon c_0=14.00, 19.12, 36.13 Mg/ha, respectively.

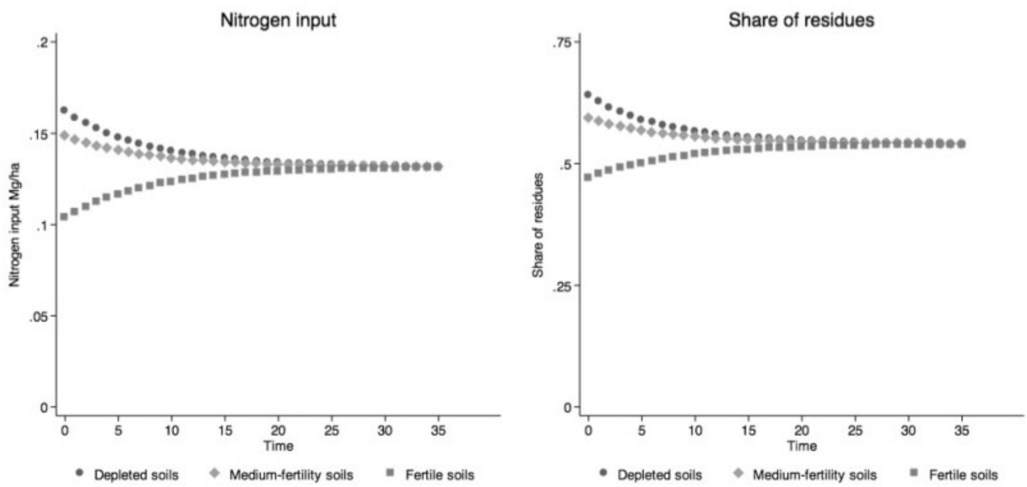

Figure 5. Time paths for optimal rates of nitrogen fertilizer f_t (Mg/ha) and share of residues α_t (0–1) on farms with different initial resource endowments

Note: Time paths are from the model optimization, using $\delta = 10\%$ and median prices. Depleted, medium-fertility, and fertile soils correspond to the initial stock of carbon c_0=14.00, 19.12, 36.13 Mg/ha, respectively.

lower than optimal steady-state stocks of renewable resources and faster depletion rates of non-renewable resources (Hotelling 1931; Clark 1990). Uninsured risk has also been shown to be a binding constraint on farmer investment (Shively 2001; Karlan et al. 2014). Table 5 shows the steady-state values of soil carbon stocks for the discount rate of 5%, 10%, 15%, 20%, and 25%. As expected, the equilibrium value of soil carbon stock is the highest with the lowest discount rate (c_{ss} = 33.28 Mg/ha with $\delta = 5\%$) and decreases as the discount rate increases (c_{ss} =14.95 Mg/ha with $\delta = 25\%$). Similar values for the soil carbon stock are observed in the household survey. The initial soil carbon stock levels (c_0 = 14.00, 19.12, and 36.13 Mg/ha) in the optimization model correspond to the 5th, 50th, and 99th-percentile of the distribution of soil carbon stocks on maize plots in the survey. If farmers are indeed dynamic optimizers, then our results suggest that the implied discount

Table 7. Steady-State Values: Changing Carbon Content of Maize Residues F for $\delta = 10$ and 20%

Variable	$\delta = 10\%$			$\delta = 20\%$		
	$F=0.43$	$F=0.38$	$F=0.33$	$F=0.43$	$F=0.38$	$F=0.33$
Share of residues, α_{ss} (0–1)	0.54	0.50	0.45	0.28	0.25	0.22
Nitrogen input, f_{ss} (Mg/ha)	0.13	0.14	0.15	0.15	0.16	0.16
Carbon stock, c_{ss} (Mg/ha)	25.63	22.70	19.73	17.40	15.35	13.29
Maize yield, y_{ss} (Mg/ha)	3.91	3.81	3.73	3.58	3.56	3.42
Value of carbon, λ_{ss} (\$/Mg)	138	140	141	105	106	107

Note: Steady-state values are from a simultaneous solution of equations (14), (13), (15), and (16), given the parameters in table 4. We vary carbon content of maize residues: $F = 0.43, 0.38, 0.33$.

Table 8. Steady-State Values: Changing Price of Maize p, Price of Nitrogen n, and Value of Crop Residues q for δ=10%

Variable	$p,n,q = \mu - 0.5\sigma$	$p,n,q = \mu - 0.25\sigma$	$p,n,q = med$	$p,n,q = \mu$	$p,n,q = \mu + 0.25\sigma$	$p,n,q = \mu + 0.50\sigma$
Share of residues, α_{ss} (0–1)	0.73	0.56	0.54	0.46	0.39	0.35
Nitrogen input, f_{ss} (Mg/ha)	0.13	0.14	0.13	0.15	0.15	0.16
Carbon stock, c_{ss} (Mg/ha)	31.28	26.49	25.63	23.58	21.61	20.20
Maize yield, y_{ss} (Mg/ha)	4.24	4.05	3.91	3.97	3.85	3.86
Value of carbon, λ_{ss} (\$/Mg)	111	128	138	143	158	174

Variable	$p,q = med$ $n = 1.25med$	$p,q = med$ $n = 0.75med$	$p,n,q =$ med	$p,n = med$ $q = 1.25med$	$p,n = med$ $q = 0.75med$
Share of residues, α_{ss} (0–1)	0.71	0.41	0.54	0.38	0.82
Nitrogen input, f_{ss} (Mg/ha)	0.09	0.17	0.13	0.15	0.11
Carbon stock, c_{ss} (Mg/ha)	28.42	22.86	25.63	21.04	32.55
Maize yield, y_{ss} (Mg/ha)	3.60	4.11	3.91	3.82	4.12
Value of carbon, λ_{ss} (\$/Mg)	152	124	138	145	130

Note: Steady-state values are from a simultaneous solution of equations (14), (13), (15), and (16), given the parameters in table 4 and assuming $\delta = 10\%$. In the top panel, we show the steady-state values of $\alpha_{ss}, f_{ss}, c_{ss}, y_{ss}$, and λ_{ss} when we use either median (*med*) or mean (μ) values for p, n, and q, or decrease/increase prices by subtracting/adding 50% or 25% of the respective standard deviation (σ) from the mean values of p, n, and q. For each price, μ, *med*, and σ are from their empirical distributions as observed in the household survey (table 3, online supplementary appendix A.4). p (\$/Mg): $med = 331$, $\mu = 349$, $\sigma = 95$. n (\$/Mg): $med = 4{,}434$, $\mu = 4{,}366$, $\sigma = 1{,}737$. q (\$/Mg): $med = 58$, $\mu = 65$, $\sigma = 52$. In the bottom panel, 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% from its median value.

rates that correspond to the observed (field) soil carbon levels are in the range of 5% to 25%. It is likely that farmers in western Kenya are heterogeneous with respect to their rate of time preferences so that their agricultural practices result in different stocks of the natural resources. 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). Moreover, if land tenure were insecure and, following Goldstein and Udry (2008), we modeled the likelihood of losing land as a Poisson process, the hazard rate would need to be added to the rate of time preference, increasing the effective discount rate.

Another explanation is in information-related barriers (Foster and Rosenzweig 1995). Some recent evidence suggests that farmers across SSA do not significantly vary input application rates according to perceived soil quality (Sheahan and Barrett 2017; Berazneva et al. 2018b). Smallholder farmers may not have adequate information about sustainable soil fertility management and therefore underestimate the benefits of leaving organic resources on the fields. Suppose farmers underestimate the importance of maize residues so that F, carbon content of residues, is believed to be lower than measured. Table 7 shows the steady-state values of soil carbon for three different values of F for the discount rates of 10% and 20%. The equilibrium value of soil carbon stock with $F = 0.33$ (0.10 lower than measured) is 19.73 Mg/ha for $\delta = 10\%$ and 13.29 Mg/ha for $\delta = 20\%$. Similar values of soil carbon stock are also observed in the household survey. This information-barrier explanation is plausible as 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 conservation practices.

Another explanation for the divergence between current and optimal management practices lies in imperfect capital markets and farmers' liquidity constraints. Financial market imperfections can hinder optimal agricultural investments by smallholder farmers (Beaman et al. 2014), and cash liquidity constraints and poverty in assets can also be correlated with higher rates of time preference (Holden, Shiferaw, and Wik 1998). While our model does not explicitly consider imperfect markets or impose any constraints on capital, the prices used in our analysis reflect some market imperfections (small quantity premiums, travel costs, local availability, and other potential transaction costs that influence current practices). We can also use additional information from the empirical distributions of prices in the market and household surveys. Assuming $\delta = 10\%$, the top panel of table 8 shows the steady-state values of α_{ss}, f_{ss}, c_{ss}, y_{ss}, and λ_{ss} when we use either median (*med*) or mean (μ) values for p, n, and q, or decrease/increase prices by subtracting/adding 50% or 25% of the respective standard deviation (σ) from the mean values of p, n, and q ($\mu - 0.5\sigma$, $\mu + 0.5\sigma$, $\mu - 0.25\sigma$, or $\mu + 0.25\sigma$). As all prices go up, the steady-state soil carbon level decreases as expected (to 21.61 when all prices increase by 25% of their standard deviations and to 20.20 Mg/ha if all prices increase by 50% of their standard deviations, similar to the levels of soil carbon observed in the household survey). To highlight a trade-off between the use of nitrogen fertilizer and maize residues, in the bottom panel of table 8, 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% from its median value). 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). In our household survey, richer farmers, who may be less liquidity constrained, apply more nitrogen fertilizer but less crop residues to achieve higher yields as compared to poorer farmers.[20]

Value of Carbon

Our model also allows us to assign monetary value to soil carbon thus quantitatively demonstrating the importance of natural resources as primary factors of production in smallholder agriculture. In steady state the shadow price of soil carbon is given by equation (15). With median prices, equation (15) implies λ_{ss} between \$95 and \$168/Mg, depending on the discount rate (table 5). The shadow price of soil carbon is the present value of one metric ton (Mg) of soil carbon when maintained for the rest of time. 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, showing the residual effects of increases in soil fertility and confirming the benefit of the dynamic analysis.

Our steady-state shadow price of soil carbon, \$95 to \$168/Mg of carbon or \$27 to \$47/Mg of carbon dioxide equivalent (CO_2e), is also 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 to \$9/Mg of CO_2e in 2013 (WB 2014), and the average price for forestry offsets in 2012 was \$8/Mg of CO_2e (Peters-Stanley, Gonzalez, and Yin 2013). 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).

[20] Richer farmers are those in the three villages closest to the chronosequence farms 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. These farmers apply, on average, 57 kg/ha of nitrogen fertilizer, with some plots receiving 100–154 kg/ha.

Conclusion

Sustainable management of soil resources is one of the main environmental and development challenges in many developing countries. We examine this challenge in the context of smallholder maize systems of western Kenya and one "climate-smart" agricultural practice—the combined application of mineral fertilizer and organic resources—by estimating the economic potential for maize yields and soil carbon sequestration. Our findings show that regardless of the initial soil fertility levels it is possible to considerably increase maize yields and achieve 3.53–4.17 Mg/ha, while increasing or maintaining stocks of soil carbon. Farms with better initial resource endowments (more fertile soils) require smaller application rates of fertilizer and residues at the outset and, as a result, enjoy higher profits. Achieving high application rates of fertilizer and maize residues in smallholder systems, however, requires some additional support and investments. While fertilizer use in Kenya, and elsewhere in SSA, is greater and more widespread than is often acknowledged, application rates are highest in countries with input subsidy programs (Sheahan and Barrett 2017). Maize residues (and other organic resources more generally) can be used for soil fertility management only when 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 the depletion of soil fertility, thus decreasing agronomic productivity and reducing fertilizer efficiency.

We also find that the long-term equilibrium levels of soil carbon are highly dependent on the discount rate used (with the implied discount rates of 5% to 25%), carbon content of crop residues (if farmers underestimate the importance of leaving organic resources for long-term soil fertility), and prices that proxy for potential market imperfections and management costs. These different equilibrium levels of soil carbon point to the role of farmers' time and risk preferences, information-related barriers, and imperfect markets in agricultural production and natural resource management, and can explain the divergence between the optimal management practices and the current practices observed in the household survey. Our results show that profitability alone is not a sufficient condition for farmers to adopt and maintain profitable sustainable practices. The reasons for divergence between the optimal and current practices, therefore, offer guidance for the design, implementation, and targeting of government policies and programs to increase yields and optimally manage soil resources in Kenya. Such policies and programs need to focus on relieving existing financial and information constraints and correcting market failures, and, given the existing heterogeneity in soil resource endowments, target specific groups of farmers. They could, for example, include fertilizer subsidies, extension services, the establishment of biofuel plantations on degraded and marginal lands, improving access to credit, and reducing demand for fuels by increasing fuel use efficiency with improved cookstoves. Particular attention also needs to be paid to policy-induced changes in farmers' incentives to adopt sustainable practices (Pagiola 1996).

Moreover, our analysis has implications for global climate policy debates in terms of understanding the potential of soil carbon sequestration in mitigating climate change. We show that in the western Kenyan highlands considerable amounts of carbon can be sequestered over twenty-five 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. The equilibrium value of soil carbon is also high: it ranges between \$95 and \$168/Mg of carbon or \$27 and \$47/Mg of carbon dioxide equivalent, depending on the discount rate used. These estimates highlight the significant local private benefits of carbon sequestration in the form of soil fertility improvements and increased maize yields (or a significant opportunity cost to soil mismanagement) and 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). We note, however, the risk of nonpermanence of many sustainable agricultural practices: soil carbon gets released into the atmosphere if land management practices change. Making sustainable agricultural practices more profitable is, therefore, imperative to help farmers not only adopt but also maintain such practices.

Smallholder systems in western Kenya and elsewhere are inherently complex: farmers grow multiple crops, rear livestock, often hold off-farm jobs, and pursue other livelihood strategies. Our research, however, considers only maize cropping in western Kenya during the main agricultural season and one "climate-smart" agricultural practice; thus, our results should be interpreted within this context. Leaving crop residues on the fields and incorporating them with conventional tillage is the most common soil conservation practice in the research area; however, it may not be the one with the highest potential to sequester carbon. Reviewing existing research on conservation tillage, Busari et al. (2015), for example, note that zero tillage has the highest carbon sequestration potential among different tillage practices. And Stavi and Lal (2013) identify agroforestry and biochar applications as the most promising options to sequester large amounts of carbon over the long run. Conservation practices, however, are context-specific and may not be applicable under all circumstances. Therefore, more empirical estimates of the potential for carbon sequestration, improvements in yields, and the value of carbon are needed using other conservation practices and from different settings. In this article, we also consider net revenue maximization as the 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 goal of food security; additional constraints and farming practices can also be included. Moreover, the model set-up allows to introduce participation in carbon offset markets 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.

Supplementary Material

Supplementary material are available at *American Journal of Agricultural Economics* online.

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