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Technology Adoption and Climate-Related Policy Evaluation among East African Smallholders:
A Bioeconomic Model of the Trade-offs between Trees and Subsistence

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I. Introduction and Research Objectives

Small-scale farmers have been identified as crucial players in the mitigation of global climate change (Verchot, et al., 2007) and are sometimes blamed for their contribution to the problem via land degradation. They are also among the most vulnerable to land degradation and perhaps to the effects of climate change due to their dependence on agriculture (Reardon and Vosti, 1995). Building on studies of the potential for carbon markets to reduce deforestation in the Amazon, there is growing support for agroforestry as a way to mitigate the carbon footprint of agriculture on the intensive margin as well (Vosti, et al., 2001). While agroforestry has less carbon density than natural forests, it represents a huge potential carbon sink due the large area devoted to agriculture across the globe (Franzel and Scherr, 2002).

Last year, the World Bank announced The Kenya Agricultural Carbon Project, located in the Nyaza and Western provinces in Kenya (World Bank, 2010).[1] Intended as a catalyst for formal carbon market operations in the area, the project is also expected to improve food security and increase incomes. These goals may be achieved through a variety of means: planting trees on plot borders can reduce soil erosion and thus sustain or possibly increase crop productivity (Liniger, 1992), integrating trees into fields can provide access to nutrients released by their composting leaves (Garrity, et al., 2010), planting coppicing trees can provide erosion protection and green manure as well as regular flows of fuelwood (Kaschula, et al., 2005), and introducing rotations of leguminous trees has been shown to increase maize yields (Verchot, et al, 2007). Trees may also support smallholder adaptation to climate change. Tree root systems can be more successful than other land uses at finding water and nutrients in soils (Verchot, et al, 2007), and thus are more likely to survive during droughts; trees promote water infiltration and retention in the soils, perhaps enhancing annual crop productivity beneath or near them (Malmer, et al., 2009); and the presence of trees may increase evapotranspiration rates, which helps keep soils aerated after heavy rains (Burgess, et al., 2001).

Unfortunately, our scientific understanding of the likely total benefits of agroforestry in adaptation to climate change, and to whom those benefits would accrue, and when, “is rudimentary at best” (Verchot, et al., 2007, p. 916). Much of our ignorance derives from uncertainty about the trajectory of climate change itself, especially at the level of the farm, though there is also still much work to be done on the physiology of trees in agriculture (Ong and Huxley, 1996). The core hopes for carbon markets in the developing world is that profit-maximizing behavior on the part of smallholders will shift land use towards woody perennials (thereby increasing on-farm carbon stocks) and simultaneously increase incomes. Supporters of the Kenya Agricultural Carbon Project, the first of its kind on the continent, have lofty “triple win” expectations; increased local incomes, improved local environmental quality, and mitigated global carbon emissions (World Bank, 2010). The likelihood of such a win-win-win outcome remains an empirical question, and policy options for cost-effectively promoting such outcomes are not known.

[1] The project is organized through the WB’s Carbon Finance Unit, which purchases emissions reductions from the Swedish organization Vi Agroforestry which is overseeing project-related land use changes in the region. Revenues to purchase the carbon credits come from the BioCarbon Fund, with both public and private contributors (World Bank, 2011).

This paper presents and demonstrates the potential usefulness of a model designed to address these issues at farm level. Our spatial and socioeconomic unit of observation is an archetypical small-scale operational holding in east Africa and the household that manages it. Our geographic focus will be the ICRAF study sites in the Lake Victoria river basin in the Siaya District, Nyaza Province, Kenya. Our analysis is informed by site visits, interviews with key informants, and the Western Kenya Integrated Ecological Management Project dataset. The model can be used for three related purposes: characterizing current and future land use choices under current and projected future baseline policy and climate scenarios, describing the effects on farmer behavior of selected new policy initiatives and technological options, and identifying the synergies and trade-offs between increased carbon sequestration and farm-level outcomes brought about by policy/technology changes.

The bioeconomic model introduced here is an important contribution to research describing the potential links between trees in agricultural landscapes and climate change.[2] While there are many inviting research avenues, from the purely agronomic to the purely sociological, in this project we answer Morton's (2007) call for a conceptual framework that recognizes and makes concrete "the complexity and high location-specificity of [smallholder] production systems" (p. 19,682). We focus attention on the trade-offs between the direct benefits of planting trees (fuel, fruit, and potentially carbon payments) and the forgone benefits of other land and household labor uses.

The next section introduces the farm household model and provides some details regarding its specification. Section III presents selected results of the baseline simulation and those of key sensitivity analyses to test the model's robustness. Section IV present the results of a pair of policy experiments – the first examines the effects the effects of climate change and the second reports the effects of paying farmers to sequester and retain above-ground carbon stocks. Section V provides conclusions and discusses selected policy implications. A list of references appears at the end of the paper.

II. The Farm Household Bioeconomic Model[3]

The model is a multi-period bioeconomic optimization model drawing on work done in a variety of settings, from purely agricultural to forest-based (Vosti, et al., 2002; Börner, 2005). Taking the former approach, Börner, Mendoza, and Vosti (2007) focus on the use and management of secondary fallow to replenish soils. Their research site in the Amazon was nearing the end of the transition from forest to agriculture. Börner, Mburu, Guthiga, and Wambua (2009) develop a similar model to identify the opportunity costs of maintaining forest cover and restricting access to non-timber forest products among households in the Kakamega Forest, Kenya. In another recent study in Kenya at the other end of the agriculture-forest spectrum, Peralta and Swinton (2009) address the trade-offs between subsistence food and commercial fuelwood production. Like them, we base our fuelwood technologies on *Eucalyptus*

[2] For a review of this literature, see Kandji, et al., 2006.
[3] For details, see Call et al., 2012.

grandis, but we also focus on household fuel needs and explore food security issues with greater detail.

Mathematical programming models like these simulate household income-maximizing behavior subject to predetermined resource, market, and production constraints, as well as to so-called “non-economic objectives” such as food security (Bhagwati and Srinivasan, 1969). The basic linear programming tools are essentially the same as those developed by Hazell and Norton (1986); the contribution here is the identification and categorization of archetypical production technologies and their associated input bundles for the chosen setting. Operationalizing this type of model requires a combination of household survey data and interviews with farmers and field experts to generate the required technical coefficients and initial conditions. This approach is typically more feasible than estimating the required coefficients via econometric studies, which have significantly larger data requirements and higher costs.[4] Once established for an archetypical household, the technical coefficients serve as model inputs. The outputs consist of household choices of land and labor use and production technologies that maximize the discounted stream of disposable income subject to the constraints laid out below.

The model's comparative advantage for analysis of the chosen setting lies in its ability to capture two crucial factors underlying household decision-making: the dynamics of intertemporal trade-offs and the multiplicity of household objectives. The term “intertemporal” refers to both the ongoing future implications of a single decision as well as the many opportunities for decision-making over time that affect household welfare at a given moment. For example, the decision to plant mango trees right now takes labor out of annual cropping, thus reducing current-year income and perhaps increasing the cost of food for the household. Simultaneously, it adds new activities to the household's future choice set—harvesting and marketing mangoes—thus increasing the potential for future cash income and altering future sources of nutrition. Investing in perennials is not, however, a discrete decision. A certain amount of cash income earned from mangoes in a given year could be satisfied through multiple paths, including regular investment in a few trees each previous year, a one-time investment in a large orchard, or any combination of the two extremes. The model is well-designed to expose the dynamics underlying all these decisions for mangoes as well as other multi-year activities.

The second contribution of the model to our understanding of smallholders’ trade-offs is its ability to capture multiple household objectives. Individuals have many goals; households are the setting for negotiation over the multiple goals of multiple individuals (Carter and Katz, 1997; Udry, 1996).[5] Our bioeconomic model provides a tractable analysis of household decision-making by distinguishing three key objectives: the maximization of farm profit, the satisfaction of household nutrition, and the achievement of a minimum acreage of maize and beans. By restricting our analysis to these objectives, we implicitly assume that the household is operating under the following rules-of thumb: 1) family health will be maintained as long as a known minimum quantity of several nutrients is satisfied, but no increase in nutrient consumption beyond this minimum provides any benefit; 2) the household must plant a certain minimum

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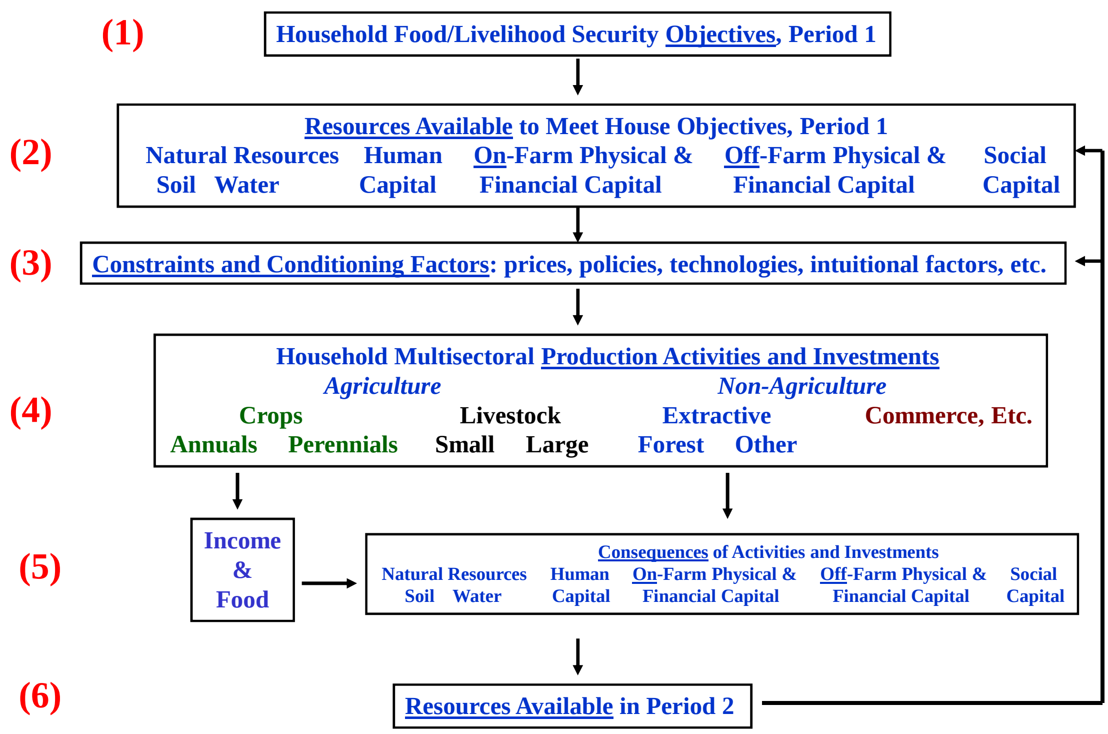
[4] Hazell and Norton (1986) cite two problems with econometric models: data limitations, especially in developing countries where production time series are usually unavailable (as they are in our study area); and difficulty accounting for all relevant structural changes such as price changes and policy reform (pp. 4-5).

[5] An exhaustive account of these goals would include health (both regular nutrition as well as emergency medical care), physical comfort and aesthetic satisfaction, companionship and fellowship with others, and autonomy to pursue various opportunities for personal growth.

number of acres of maize and beans for psychological or cultural reasons, regardless of the relative profitability of alternatives; and 3) all other amenities that improve household welfare cannot be provided at home and therefore must be accessed through markets. While these decision-rules may appear simplistic, they still unearth a great deal of interesting behavior that would be impossible without such a starting point. Furthermore, their relative influence on household outcomes can be examined through extensive sensitivity analyses around the minimum maize and bean acreage and alternative specifications incorporating revenue risk into profit-maximization and yield risk into nutrition-satisfaction.

Figure 1 depicts the logical sequence of 'decisions' taken within the model. The model begins by establishing an objective (1) and then takes stock of the human, natural and other resources available to meet this objective (2). Relative prices, available technologies, etc. (3) affect the potential contributions of available resources to meeting the established objective. The model then decides (for a given time period) which agricultural and non-agricultural activities and investments to pursue (4), choosing those that contribute most (at the margin) to the objective. The activities and investments provide food and income, and also change the stocks of resources (some positively, some negatively) available for the next period's decision making (5). The loop begins again (6) with updated stocks. The model searches over all production and employment options and years to discover the single combination of activities and investments (running from the baseline to the terminal year, identified by the analyst) that best meet the household's objective.

Figure 1: Sequence of household decisions taken within the model[6]



[6] This figure is adapted from Reardon and Vosti (1995).

It should be noted that the model is not spatial, i.e., we cannot track the exact location on the farm of specific agricultural activities. The model's spatial resolution (the geographic unit of analysis) and its spatial extent (the comprehensive spatial unit contemplated by the model) are one and the same—the operational holding of the farm household. Depending on the issue being addressed using the model, the analyst can be more (or less) confident regarding locating on the farm where specific land use choices might play out, or regarding the extrapolation of farm-level results to a broader geographic area. The spatial resolution/extent cannot be easily changed: going 'below' the farm level required making production activities site-specific and going 'above' the farm requires identifying and modeling inter-farm and other linkages. Neither of these options is examined in this paper.

Key model components

Household and farm characteristics

The model is structured around a representative household and farm, which is described by both fixed characteristics and initial conditions that can be updated through decision-making over time. In the former category are land and labor endowments and the full set of technical parameters associated with the production, marketing, and storage options available to the household. These are held constant throughout the model simulation time horizon. Another fixed characteristic is the level of remittances received from family members working elsewhere; in all simulations reported here these are fixed at zero. Initial conditions include cash-on-hand, tool and livestock ownership, inventories of food and fuel, and extent of in-process cropping activities that will produce yields in the first season of the simulation. While fixed for the first month of the simulation, each of these initial conditions is altered through household decisions in subsequent months or years.

Initial conditions constrain the outcomes in early years of the model simulations, but within a few years their influence wears off and household land and labor allocation decisions stabilize around a steady state. For this reason, our lack of good data to inform selection of some of the initial conditions is not very problematic. However, our choice of other fixed characteristics, especially land and labor endowments, bears importantly on model output for all simulations. We assume that the household owns two acres and is comprised of six members—a man and woman and four teenage children—in all simulations. The household is not allowed to buy, sell, or rent land, though limited amounts of adult labor may flow onto and off of the farm. Members of the household do not age in the current version of the model.[7]

It is useful to compare the household characteristics chosen for the model to data from the WKIEMP sample, which is comprised of 1272 smallholder farm families in the Nzoia, Yala, and Nyando river basins in western Kenya (Verchot, no date). These households were interviewed between 2005 and 2007. Average landholdings were 6.15 acres with a large standard deviation of 22.63. Two acres corresponded to the 35th percentile for that sample; the median was 3. Average family size was 3.59, with a median of 6 and a standard deviation of 6.82.

[7] This is a technical simplification that would be fairly straightforward to address.

Annual products and their production technologies

Maize and beans have two seasons, "long" (January through August) and "short" (August through January).[8] Monthly tasks are summarized in Table 1. Colored cells indicate months of full-time land use, while white cells indicate months when labor for a given crop for non-production activities. Groundnuts can only be grown in the long season. Sorghum is planted at the beginning of the long season and yields grain in August; with minimal upkeep the same plants can be induced to produce even higher yields in December. Sweet potatoes and cassava follow a different schedule from other annuals, running from April to November and then December to February. They may be planted repeatedly in the same plots, thus cutting down on land preparation labor requirements. For simplicity, we assume that the major land preparation work is done in April, and that the household will evaluate whether to replant in December.[9]

Table 1: Annual crop schedule

Crop	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar
Local long season maize	slash	manure	plant	weed	weed		harvest	harvest, post							
Hybrid long season maize with typical fertilizer use	slash		plant	weed	weed		harvest	harvest, post							
Hybrid long season maize with optimal fertilizer use	slash		plant	weed	weed		harvest	harvest, post							
Groundnuts	prep		plant	weed		weed		harvest	post						
Sorghum	prep		plant	weed	weed			harvest	prep, weed			harvest			
Local short season maize								prep	manure, plant	weed	weed	harvest	post		
Hybrid short season maize with typical fertilizer use								prep	plant	weed	weed	harvest	post		
Hybrid short season maize with optimal fertilizer use								prep	plant	weed	weed	harvest	post		
Cassava & sweet potatoes				major prep	plant	weed					harvest, prep	plant	weed		harvest

We allow farmers to choose among three production technologies for maize, which can be grown with different amounts of fertilizer and using different types of seeds: "local," which requires manure generated on-farm and maize seed produced and purchased locally;[10] "hybrid typical," which uses hybrid seed and a typical, less-than-recommended, amount of chemical fertilizer; and "hybrid optimal," where hybrid seeds and chemical fertilizer are used following the instructions of local extension agents.[11] The more fertilizer is used, the less labor is required. Labor and non-labor inputs for an acre cultivated under each technology are laid out in Table 2 below, along with net revenues associated with each. Net revenues capture the variation of input

[8] We assume that maize is always intercropped with beans, a common practice in western Kenya (Nyoro, et al., 2004), so any reference to maize production should be taken to mean joint maize and bean production. The sequential nature of intercropping is captured in the spread of planting labor over two months and the staggering of crop harvests.

[9] A more exhaustive treatment would reduce the labor requirement for tubers planted in April on land previously allocated to tubers. Our arbitrary choice of April as the month of major labor investment should capture the importance of labor trade-offs, if not their exact timing.

[10] We assume free access to locally-produced manure and ignore access to home-produced seed.

[11] These classifications were informed by interviews with Luka Anjeho, who provided suggestions for the ratios of fertilizer, labor, and maize and bean outputs under each of the three. Hybrid typical technologies use 70 kg of DAP per season per acre while hybrid optimal technologies use 120 kg. Note that both of these technologies fall the 40kg cut-off between low-input and high-input users adopted by some researchers (Nyoro, et al., 2004).

and output prices by month, but the value of labor used to calculate the entries in Table 2 is assumed fixed (thus ignoring possible seasonal changes in the shadow value of household labor). In these calculations, the hybrid *optimal* technology is the most profitable choice. The hybrid *typical* technology uses less labor than the *local* technology, and produces higher revenues in the short season (but not the long season). We include all three options in the model to allow for the possibilities that liquidity constraints may prevent the up-front purchase of fertilizer, or that labor constraints may prevent optimal fertilizer use associated with both higher yields and increased labor requirements for harvesting.

Table 2: Maize and beans activities summary, per acre

Crop	Per-acre inputs, outputs, and values	January	February	March	April	May	June	July	August	September	October	November	December	Total
Local maize and beans, long season	Total labor requirement (days)	16	6	10	20	20		4	9					85 days
	Value of non-labor inputs ($)			335										$335
	Output (kg maize)								90					90 kg
	Output (kg beans)								45					45 kg
	Value of output ($)								623					$623
	Net revenue ($)*	**-17**	**-6**	**-346**	**-21**	**-21**		**-4**	**613**					**$200**
Local maize and beans, short season	Total labor requirement (days)	7							16	16	20	20	6	85 days
	Value of non-labor inputs ($)									258				$258
	Output (kg maize)	90												90 kg
	Output (kg beans)	45												45 kg
	Value of output ($)	545												$545
	Net revenue ($)*	**538**							**-7**	**-265**	**-7**	**-7**	**-7**	**$245**
Hybrid typical maize and beans, long season	Total labor requirement (days)	16		13	12	12		4	9					66 days
	Value of non-labor inputs ($)			442	133	133								$708
	Output (kg maize)								90					90 kg
	Output (kg beans)								45					45 kg
	Value of output ($)								929					$929
	Net revenue ($)*	**-17**		**-455**	**-146**	**-146**		**-4**	**920**					**$153**
Hybrid typical maize and beans, short season	Total labor requirement (days)	7							16	13	12	12	6	66 days
	Value of non-labor inputs ($)									364	133	133		$631
	Output (kg maize)	90												90 kg
	Output (kg beans)	45												45 kg
	Value of output ($)	919												$919
	Net revenue ($)*	**919**								**-364**	**-135**	**-135**		**$284**
Hybrid optimal maize and beans, long season	Total labor requirement (days)	16		13	12	12		6	68					127 days
	Value of non-labor inputs ($)			602	200	200								$1001
	Output (kg maize)								720					720 kg
	Output (kg beans)								90					90 kg
	Value of output ($)								5,998					$5998
	Net revenue ($)*	**-17**		**-615**	**-212**	**-212**		**-6**	**5,928**					**$4866**
Hybrid optimal maize and beans, short season	Total labor requirement (days)	20							16	13	12	12	54	127 days
	Value of non-labor inputs ($)									524	186	186		$897
	Output (kg maize)	720												720 kg
	Output (kg beans)	90												90 kg
	Value of output ($)	5,911												$5911
	Net revenue ($)*	**5,890**							**-17**	**-538**	**-199**	**-199**	**-56**	**$4883**

*Net revenue calculations assume that all outputs are sold, all inputs are bought, and labor is valued at Ksh 100 (or $1.03) per day.

Similar statistics are reported for non-maize annuals in Table 3. Cassava is significantly more profitable than maize and beans, and also uses less labor. If markets were perfect, a farm restricted to growing annual crops with our assumed labor requirements, yields, and prices would specialize in cassava. Of course, this is not what is observed on the landscape; most notably, the cultivation of maize and beans is quite common. The primary mechanism through which the model generates diverse annual cropping activities is by meeting household nutrition requirements, which is taken up in the next section.

Table 3: Non-maize annuals activities summary, per acre

Crop	Per-acre inputs, outputs, and values	January	February	March	April	May	June	July	August	September	October	November	December	Total
Sweet potatoes	Total labor requirement (days)	48		25	24	36	48					43	36	260 days
	Output (kg)			1750								1750		3500 kg
	Value of output ($)			2,081								1,447		$3528
	Net revenue ($)*	**-50**		**1,724**	**-25**	**-37**	**-50**					**1,706**	**-37**	**$3232**
Cassava	Total labor requirement (days)	8		16	16	16	8					26	16	106 days
	Output (kg)			3000								3000		6000 kg
	Value of output ($)			3,248								2,860		$6109
	Net revenue ($)*	**-8**		**2,983**	**-17**	**-17**	**-8**					**2,973**	**-17**	**$5891**
Sorghum	Total labor requirement (days)	16		6	20	20			5	14			9	89 days
	Value of non-labor inputs ($)			3										$3 kg
	Output (kg)								180				270	450 kg
	Value of output ($)								452				455	$907
	Net revenue ($)*	**-17**		**-9**	**-17**	**-17**			**444**	**-12**			**446**	**$819**
Groundnuts	Total labor requirement (days)	16		8	48		56		24	10				162 days
	Value of non-labor inputs ($)			107										$107
	Output (kg)									70				70 kg
	Value of output ($)									807				$807
	Net revenue ($)*	**-17**		**-7**	**-7**		**-7**			**800**				**$762**

*Net revenue calculations assume that all outputs are sold, all inputs are bought, and labor is valued at Ksh 100 (or $1.03) per day.

Human nutrition

Understanding land use patterns in a semi-subsistence economy requires a realistic portrayal of nutritional concerns. While our ultimate goal is to characterize the potential of market-based interventions such as payments for carbon sequestration to change land use decisions, the effects on land and labor use choices of a household's choice to consume a nutritionally adequate diet has become an integral part of the model's structure. Since we do not have information on farmer preferences among nutrient sources and other goods/services they could purchase, we chose to fix the essential food consumption "basket" based on physiological requirements over a given set of nutrients. In other words, we assume a complete lack of substitutability between necessary nutrients and the consumption of non-food items. The model treats any improvement in food quantity and quality above the bare minimum established by the food consumption basket as "discretionary," in the sense that the household will first maximize income and then allocate it between additional food and other desired items such as clothes or recreation (though these items are not explicitly identified in the model). We follow the approach of Börner, et al., (2009) for another setting in western Kenya, considering the energy, protein, vitamin A, and fat content of foods and requiring that a minimum standard be met for each in the overall essential consumption basket chosen in the household. Because the model maximizes disposable income subject to this constraint, it selects the basket of foods that provides this minimum at the lowest possible cost, where cost is measured in terms of the household shadow value of food.[12]

[12] The shadow value of a given food item is the lesser of two measures of value: the market price plus transactions costs or the production costs including the opportunity cost of household labor inputs. In a household very distant from product markets, home provision may be preferable to purchasing even if production costs are high

Table 4 and Table 5 present statistics for the nutrient content of each crop. The first entry in Table 4 is the number of days of calorie requirements satisfied through the consumption of one acre of sweet potatoes. Comparing values, an acre of sweet potatoes is the most valuable for providing vitamin A, cassava for calories and protein, and groundnuts for fat. However, input and labor requirements for each crop are quite diverse, making these comparisons incomplete. Table 5 reports the per-nutrient costs for each food, scaled by daily requirement of each nutrient.[13] For each crop, the top left value reported is the number of labor days required to produce enough of the crop to generate 3,000 calories. In the next row, the same quantity of the crop is valued at the lowest and highest market prices (based on monthly price variation, discussed in the next section). The final row reports the "farm value" for the same quantity of the crop, based on net revenues computed in Table 2 and Table 3. "Farm value" can be interpreted as the farmer's back-of-the envelope calculation of the opportunity cost of producing a day's worth of calories of the given crop, assuming that s/he pays all labor at the market value. The other columns in the table report the labor time cost, market value, and farm value of producing a day's worth of protein, vitamin A, and fat, respectively. For all nutrients and crops, the farm value is always higher than the lower market value, and is often higher than the upper market value. Therefore, annual crops will be produced, rather than purchased, only if their purchase and consumption are necessary during high-price months or if transportation costs are high enough to make purchasing prohibitively expensive. Comparing values across crops in Table 5, it is clear that sorghum is the cheapest source of both energy and protein in terms of market and farm value, whereas cassava is cheaper in terms of labor. By all measures, sweet potatoes are the least expensive source of vitamin A and groundnuts are the least expensive source of fat.

Table 4: Days of nutrient requirements fulfilled through annual yields, per acre

Crop	Energy	Protein	Vitamin A	Fat
Sweet potatoes	1283	1493	8400	700
Cassava	2800	1920	120	1200
Sorghum	518	1320	12	1440
Groundnuts	134	432	1	3168
Maize and beans*	768	1765	107	3087

*Maize and beans are measured in the proportion of intercropped hybrid optimal yields, namely 3:1.

due to the high cost of transportation. In a household very distant from labor markets, the production costs will include very high shadow values of household labor since farm activities compete for scarce household labor.

[13] FAO (1997) sets these requirements at 3000 kilocalories, 37.5 grams of protein, 625 micrograms of vitamin A, and 10 grams of fat for a 50 kg adult male.

Table 5: Cost to fulfill daily nutrient requirements through consumption of each annual

Crop	Cost measure	Energy	Protein	Vitamin A	Fat
Sweet potatoes	Labor days	0.20	0.17	0.03	0.37
	Market value ($)*	(0.2, 0.36)	(0.17, 0.31)	(0.03, 0.05)	(0.36, 0.65)
	Farm value ($)	2.52	2.16	0.38	4.62
Cassava	Labor days	0.04	0.06	0.88	0.09
	Market value ($)*	(0.15, 0.25)	(0.22, 3.47)	(3.44, 55.56)	(0.34, 5.56)
	Farm value ($)	2.10	3.07	49.09	4.91
Sorghum	Labor days	0.17	0.07	7.42	0.06
	Market value ($)*	(0.14, 0.28)	(0.06, 1.01)	(6.13, 111.33)	(0.05, 0.93)
	Farm value ($)	1.58	0.62	68.25	0.57
Groundnuts	Labor days	1.21	0.38	215.73	0.05
	Market value ($)*	(0.52, 0.63)	(0.16, 2.16)	(91.91, 1243.24)	(0.02, 0.29)
	Farm value ($)	5.70	1.76	1014.74	0.24
Maize	Market value ($)*	(0.16, 0.33)	(0.07, 0.15)	(1.11, 2.35)	(0.04, 0.08)
Beans	Market value ($)*	(0.45, 0.89)	(0.08, 0.16)	--	(0.32, 0.63)
Maize and beans**	Labor days	0.29	0.21	1.22	0.19
	Market value ($)***	(0.19, 0.39)	(0.07, 0.15)	(1.47, 3.06)	(0.05, 0.1)
	Farm value ($)	11.18	8.02	46.72	7.39
**These are the upper and lower bounds for all monthly prices.					
**We assume long season hybrid optimal maize and beans parameters.					
***Maize and beans are assumed purchased in the same proportion as they are intercropped.					

Maize and beans are surprisingly unattractive by these measures. Maize is comparable to sorghum as a source of calories and the maximum market price of a day's worth of protein or fat provided in maize is less than the maximum market prices for these nutrients provided in any other foods. Beans are even less attractive than maize by these nutritional price measures, providing no vitamin A or nutritional advantages over the other crops. On the ground, however, maize occupies significant amount of cropland and absorbs significant amount of household labor, and beans are very commonly intercropped with maize; van Rheenen, et al., (1981) remark on the "persistent refusal by farmers to abandon the system of mixed cropping" throughout Africa (p. 193). These authors' research on the use of intercropping to reduce crop disease and pest incidence is just one example of the many factors beyond direct profitability and nutrient provision leading to crop choice that remain beyond the scope of our model. In response, we introduce maize and bean self-sufficiency constraints to generate an allocation of land to this intercropping activity that is consistent with what is observed on farms. The rationale and the methods employed are discussed at the end of this section.

Perennial and livestock products, and their production technologies

Two types of woody perennials are included: mango and *Eucalyptus grandis* trees. Mango fruit outputs are based on grafted Ngowe mangoes (Griesbach, 2003). *Eucalyptus* wood production coefficients are taken from Food and Agriculture Organization (1979).[14] We assume that trees are grown with the following outputs in mind: fruit, fuelwood from prunings, fuelwood

[14] We assume that woodlot biomass grows at the same rate reported for regularly thinned trials in the Transvaal of *E. grandis* as studied by van Laar (1961) and reported in FAO (1979). We chose data associated with the least productive sites for which the same site index was shared by both thinned and unthinned trials. We halve the quantities in order to scale the data to estimations for the Siaya District by L. Anjeho. We also use his estimate of 700 trees per acre, slightly higher than in the Transvaal, to scale planting and harvesting costs and labor.

from harvested trees, and carbon payments from sustained woodlots. We assume that carbon payments will be generated through two types of contracts: one that provides constant annual payments (with the first year's payment double to subsequent payments to offset some establishment costs) and another with quintannual payments that increase proportional to the carbon sequestered. We have excluded timber (pole) products in the simulations, despite their being a well-recognized and remunerative output of *E. grandis*.[15]

We are left with three perennial activities: mangoes, which produce fruit and a small amount of regular pruning for fuelwood and may be chopped down for more fuelwood at any time; traditional *Eucalyptus* woodlots, which produce a fuelwood through prunings and may also be harvested at any time; and no-harvest *Eucalyptus* woodlots, which generate prunings and carbon payments but may not be chopped down before the end of the contract. Labor inputs and net revenues, assuming a constant value of labor, are reported in Table 6 and

Table *7*. The first years of all perennial activities yield large negative net revenues since no outputs are ready for sale. Traditional and no-harvest woodlots yield the same quantities of pruned fuelwood; in comparison, no-prune woodlots grow faster and larger.

Our selection of *Eucalyptus grandis* as the primary source of on-farm and marketable fuelwood should not be interpreted as an exhaustive account of options available to farmers in western Kenya. As the National Academy of Sciences (1980) warned in their introduction to firewood crops in the developing world, there well may be better solutions for the long-term and "in any trials of fuelwood plantations local species should always be given first priority". The very high yields of *E. grandis* and our abstraction away from any negative effects it may have on soil nutrients and water availability make it more attractive in the model than may be expected from a farmer's perspective. This means that the optimization procedure in the model faces fewer hurdles to woodlot adoption than a farmer who cares about tree-crop interactions.

[15] Unavailability of data on pole prices and marketing costs precluded the inclusion of building poles at this juncture.

Table 6: Woodlot activities summary, per acre

Crop	Per-acre inputs, outputs, and values	January	February	March	April	May	June	July	August	September	October	November	December	Total
Eucalyptus woodlot planting, vintage 1	Total labor requirement (days)				26			2				2		30 days
	Net revenue ($)			**-8325**	**-27**			**-2**				**-2**		**-$8356**
Eucalyptus woodlot pruning and spraying, vintages 3-4	Total labor requirement (days)			114						114				228 days
	Net revenue ($)			**1705**						**1705**				**$3411**
Eucalyptus woodlot pruning, vintages 5-9	Total labor requirement (days)			63						63				126 days
	Net revenue ($)			**10375**						**10375**				**$20749**
Eucalyptus woodlot pruning, vintages 10-18	Total labor requirement (days)			140						140				280 days
	Net revenue ($)			**13298**						**13298**				**$26597**
Eucalyptus woodlot harvesting, if harvested, vintages 3-4	Total labor requirement (days)												0	0 days
	Net revenue ($)												**1673**	**$1673**
Eucalyptus woodlot harvesting, if harvested, vintages 5-9	Total labor requirement (days)												175	175 days
	Net revenue ($)												**4061**	**$4061**
Eucalyptus woodlot harvesting, if harvested, vintages 10-18	Total labor requirement (days)												700	700 days
	Net revenue ($)												**6584**	**$6584**
Eucalyptus woodlot harvesting, if harvested, vintages 18+	Total labor requirement (days)												700	700 days
	Net revenue ($)												**7842**	**$7842**

*Net revenue calculations assume that all outputs are sold, all inputs are bought, and labor is valued at Ksh 100 (or $1.03) per day.

Table 7: Mango activities summary, per acre

Crop	Per-acre inputs, outputs, and values	January	February	March	April	May	June	July	August	September	October	November	December	Total
Mango planting, fruit harvesting and pruning, vintage 1	Total labor requirement (days)			14	7	7	7	7						42 days
	Net revenue ($)			**-15**	**-7**	**-7**	**-7**	**-7**						**-$44**
Mango fruit harvesting and pruning, vintages 2-4	Total labor requirement (days)		0		1				0		1			3 days
	Fruit output (kg)												576	576 kg
	Net revenue ($)		**-1**		**-1**				**0**		**-1**		**238**	**$235**
Mango fruit harvesting and pruning, vintages 5-8	Total labor requirement (days)				3				3					6 days
	Fruit output (kg)	785											785	1571 kg
	Net revenue ($)	**324**			**-3**				**-3**				**324**	**$642**
Mango fruit harvesting and pruning, vintages 8+	Total labor requirement (days)		4		3				4					10 days
	Fruit output (kg)	2305											2305	4610 kg
	Net revenue ($)	**952**	**-3**		**-3**				**-3**				**952**	**$1894**
Mango fuelwood if harvested, vintages 2-4	Total labor requirement (days)												10	10 days
	Net revenue ($)												**151**	**$151**
Mango fuelwood if harvested, vintages 5-8	Total labor requirement (days)												21	21 days
	Net revenue ($)												**227**	**$227**
Mango fuelwood if harvested, vintages 8+	Total labor requirement (days)												20	20 days
	Net revenue ($)												**256**	**$256**

*Net revenue calculations assume that all outputs are sold, all inputs are bought, and labor is valued at Ksh 100 (or $1.03) per day.

Livestock is another important multi-period option for the archetypical farmer. The model incorporates cattle, goats, and sheep, which can be purchased, born/raised on-farm, and sold. For simplicity, we assume that all adult female livestock produce offspring in the month of July. Cows produce milk for three months after giving birth, some of which can be consumed by the family but not sold. Half of the calves, lambs, and kids are female. A vintage-specific proportion of each type of animal dies each year.

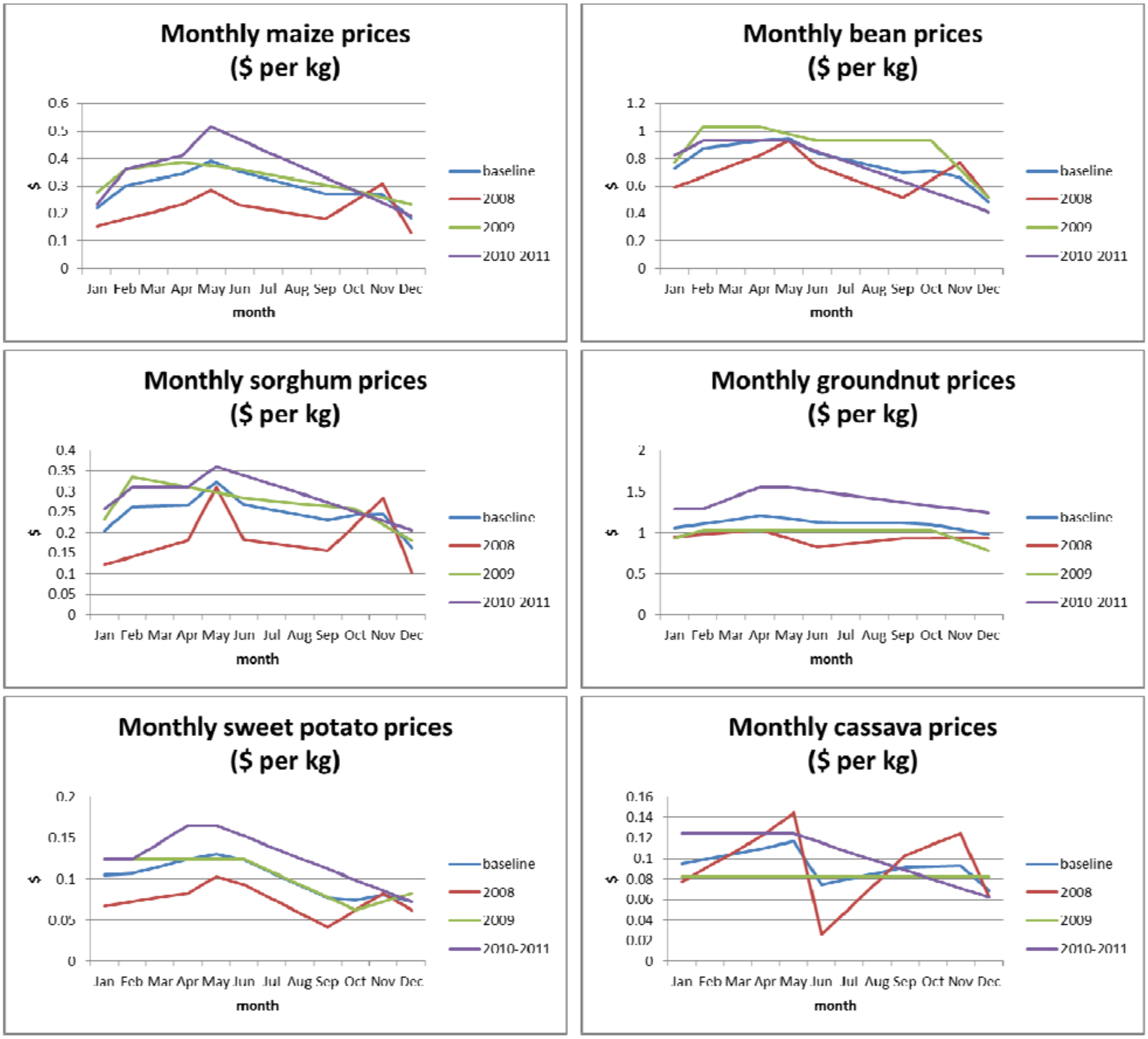
Markets and market participation

The model includes a distinction among three different types of purchasing behavior: the purchase of food and fuel essential for survival, monetary farm investments, and expenditures of disposable income. Examples of these three types of expenditures are dried cassava, bike tires, and shoe leather, respectively. Cassava is processed on-farm or bought to supplement grain stocks to feed the family; consumption of both purchased and home-produced food to meet nutritional requirements is *essential*. Because the farm household in the model uses a bicycle marketing purposes, bike tires enter the model as a *productive investment*. Shoe leather purchases do not enter the explicit farm accounts but rather come out of *disposable income*; they are considered by the model to be purely discretionary. This categorization allows us to rank household objectives: survival (through consuming food and fuel) comes first, but is satisfied in the least costly way to ensure that household assets are best leveraged to generate long-run profits.

We assume that the farm household is a price-taker in all markets.[16] This does not mean that prices are stable; prices do vary seasonally and these seasonal variations are introduced through monthly-indexed price parameters. The model requires a complete set of input/product prices for each month of the simulation time horizon, for all inputs and products (even those not chosen by an optimizing farmer for production, consumption or sale). Lacking long-term price series relevant for the research site, we assume that monthly prices are the same across all years of the simulation, and we set them equal to the three-year average observed at the Wagai Division level for all annual outputs. Figure 2 presents these data. They were compiled in July, 2011, and observations from early 2010 are missing, so these years were consolidated to generate a full third year of observations. Sweet potato and cassava prices are used as proxies for food purchases and crop sales. Maize, bean, sorghum, and groundnut prices are used additionally for seed input costs. Food and input purchases, as well as crop sales, are month-specific decision variables in the model. Monthly variation provides an incentive for households to purchase supplies when prices are low and store surpluses until prices rise, but time-sensitive demands for cash and stock decay provide the opposite incentive.

[16] Prices do not respond to the extent of household engagement in input or product markets.

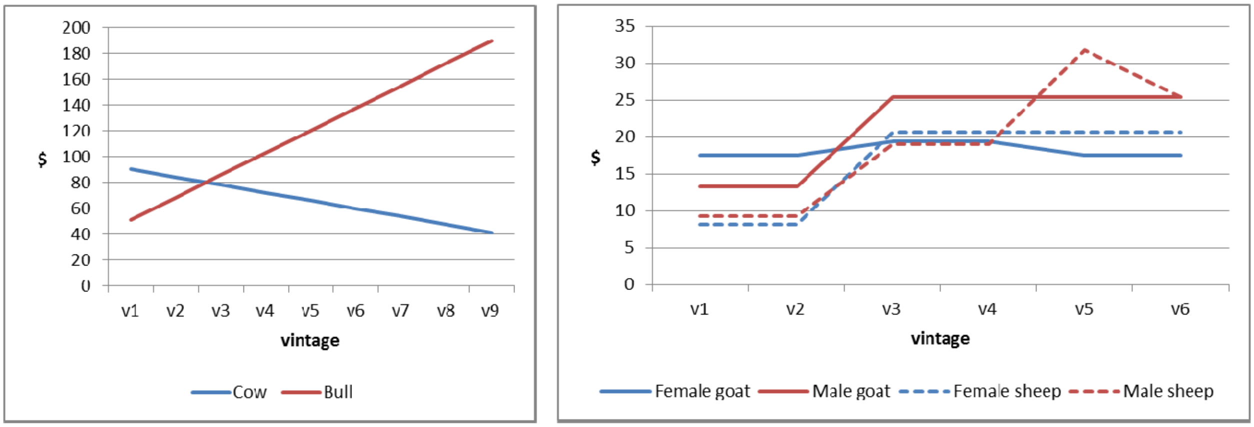
Figure 2: Annuals prices by month and over the entire simulation period



We have ignored monthly variation in livestock prices, assuming that price depends only on the age (vintage) of the animal, as shown in Figure 3. Red curves indicated male livestock while blue indicate female livestock. We assume increasing value of male livestock as they increase in weight. Female sheep increase in value as they grow, but cows and adult female goats decrease in value as their time left to produce offspring is reduced.[17]

[17] These prices were established through interviews with L. Anjeho.

Figure 3: Assumed livestock prices by vintage ($)



Market integration[18] in both product and labor markets is the outcome of decisions simulated in the model. Transportation costs, as well as price wedges representing other transactions costs, are explicitly included.[19] As the representative household decision-maker analyses the potential for each unit of land and labor to generate farm income, s/he implicitly derives "shadow values" for each home-produced consumption item, and also for household labor (Singh et al. 1986; Taylor and Adelman, 2003). When a shadow price for a given consumption item exceeds its farm-gate price, it is better to buy. When shadow prices for age- and gender-specific household labor exceed market wage rates, it is better to forgo working off-farm and hire as many workers as possible. The model contains some additional constraints to full market integration, namely monthly maximums for the quantities of products that can be sold, and the number of days of labor that can be hired-out or hired-in. These constraints are necessary to generate the diversity of observed farm activities.

Introducing price signals for carbon is a key function of the model, helping us determine the circumstances under which a smallholder with access to a hypothetical carbon market would increase the area dedicated to agroforestry systems, and what the extent of that increase might be. Carbon sequestration is introduced into the model as an additional 'output' of *Eucalyptus* land uses, with a contractual commitment made up-front *not* to harvest trees.[20] Unlike other products generated on-farm, some of which can be consumed directly, carbon sequestration only generates income; the decision-maker will choose a carbon-sequestering land use only if s/he intends to sell all of the carbon sequestered at the agreed-upon price. Two prices are of interest: that received by the coordinating agency and that which they pass along to farmers after all

[18] Market integration can be defined as the extent to which households participate in markets. It is enhanced when transportation costs are low relative to market prices and the farm value of home-grown produce.

[19] Transportation costs are defined in terms of per-trip prices for motorbike taxis and in terms of time, where the number of days per trip and upper limits on the number of kilograms per product per trip are specified for all transportation modes (motorbike, bicycle, and walking). They differ by gender of the person traveling; we assume that men travel faster and can carry more than women, but will only use bikes or motorbikes whereas women are willing to walk. In the baseline simulation, price wedges assume that there are additional transactions costs that make the perceived price of buying a product 25% higher than selling it. We chose 25% arbitrarily. Eliminating the price wedge generates infeasible results.

[20] The extent of this commitment is 25 years in the linear program, but the important feature of the time limit is that it exceeds the model simulation horizon.

monitoring costs have been deducted. We assume that the coordinating agency receives payments for accumulated carbon every five years and that administrative costs account for 70% of total carbon revenues. With a base price of $20 per ton of CO_2, the net present value of carbon sequestered by an acre of *Eucalyptus* is $807.32. We simulate two contracts for distributing the farmers' 30% share. In Contract 1, they receive 30% of the payments received by the agency as they arrive every five years. This amounts to per-acre payments of $115 in year 5, $132.44 in year 10, and $147.14 in year 15. The net present values of these payments (measured from the first year's perspective) assuming the agency has a 5% discount rate are $90.11, $81.31, and $70.78, which together sum to $242.19, the farmers' 30% share of the total carbon value. In Contract 2, farmers receive a flat payment every year of $21.01 except for year 1 when it is doubled to $42.02 to offset set-up expenses. The net present value of these payments also sums to $242.19.

Resource and other constraints

The representative household has three types of assets: labor, land, and cash. The availability of family labor, the flows of labor onto and off of the farm, and the allocation of labor (by age and gender categories) to all production activities is tracked on a monthly basis. We assume that land cannot be rented out (or in).[21] The types of activities (by technology) that can be performed sequentially are also restricted.[22] Note that the purpose of all of these constraints is to preclude the selection of production activities or technology choices that are agronomically *in*feasible. It is possible to modify what is agronomically feasible in the model by altering activity-specific input:yield ratios, which would (e.g.) be equivalent to "moving" the archetypical farm from one soil type to another, holding other things constant. While the amount of land available for cultivation is fixed over the model time horizon, cash will flow onto the farm when agricultural products or family labor are sold. Cash flows off again when agricultural inputs or food are purchased. The model tracks financial stocks and flows on a monthly basis, beginning with an initial endowment of cash.[23] After the first period, the amount of cash is an endogenous variable related to land use and marketing choices.

Time

The model spans multiple years in order to capture inter-temporal trade-offs between annual and perennial land uses and to test different trajectories of yields, prices, and carbon payments. The temporal extent of the model is determined by the analyst—we use a 15-year simulation time horizon. Within that user-determined temporal extent, there are several other time steps. Each year is comprised of two agricultural seasons; a short season (August to January) and a long season (January to August). Months are the shortest time step in the model, and are used to track labor flows, to measure and meet food security needs, and to capture

[21] We could choose to relax this constraint in the case of east Africa, but if land renting is allowed, a set of 'rules' will have to be determined that will govern this activity.

[22] For instance, maize harvesting can occur only if land preparation, planting, and weeding occurred previously, in the correct months. Harvesting more acres of maize than were planted would also be agronomically infeasible.

[23] The value of the initial cash endowment is somewhat arbitrary, as we do not have data on household cash-on-hand. For very low values, the model is infeasible as the household does not have enough resources to buy agricultural inputs even for annual subsistence crops. The higher the value, the more quickly the household can move away from subsistence production and toward cash crops.

variations in product prices. Perennial land tree crops and livestock are indexed by vintages; labor requirements and yields are vintage-specific and equations of motion guarantee that the technical coefficients are updated as long-term activities progress. Since carbon contracts are longer than the model horizon, the model credits the objective function not only with payments as they accrue, but also with the discounted value of carbon payments that would be received after the model horizon.

Maize and bean self-reliance

We assume that the profitability of alternative uses of time, land, and cash is *the* driving force behind land use decisions. However, issues associated with household food security, risk, and the household's disconnectedness from input and product markets affect land use decisions in ways that can create a 'gap' between what an informed, market-connected, profit-motivated farmer would choose to do, and what a typical smallholder in SSA would do when facing the same set of input/output prices and technological options. For this reason, we find it necessary to carefully consider self-provisioning activities, especially regarding maize.

We find that per-kilogram transportation costs and linear price wedges generate highly unrepresentative land use patterns within the optimization framework—maize farming disappears almost entirely in favor of mangoes and woodlots. These results are unsurprising given the per-nutrient production costs discussed in the nutrition subsection above, but unsatisfying in light of the predominance of maize and bean farming among sub-Saharan African smallholders (Nyoro, et al., 2004; van Rheenan, et al., 1981). Good policy analysis requires good operational decisions about how and why households acquire maize and beans—do they produce it or purchase it?—and why they choose these foods over alternatives such as sorghum. There are conflicting views. Kenyan agricultural policy has promoted national self-sufficiency in maize, and households have generally been viewed as net maize sellers, but surveys in the late 1990s found that 82% of households in the Western Lowlands region of Kenya (which include villages near Siaya) are net *purchasers* of maize (Nyoro, et al., 2004). Key informants in the Siaya District today confirm Omamo's (1995) claim that the area is a net maize importer. However, positive flows of these staples into the region are not sufficient to dismiss the potential predominance of staples production as well, especially if farm-dwellers rely on cash transfers from relatives in other areas to finance some, but not all, of their subsistence needs.

We have limited information on the household decision-making underlying the (observed) allocation of large amounts of land to maize and beans. The WKIEMP survey asked farmers (N=915) how many months per year they purchased grains (this was coded as "months of food deficits") and their total yearly grain expenditures. Ordering households by the number of deficit-months, approximately half were fully self-reliant in maize for at least nine months. The average monthly expenditure on maize was $16.40,[24] and is stable across the high and low levels of self-sufficiency. However, other relevant household characteristics vary across subsamples, in particularly borrowing behavior, expenditures on fertilizers and education, and the likelihood of

[24] All dollar values are based on an August, 2011, exchange rate of Ksh 96.90 per dollar (http://themoneyconverter.com/USD/KES.aspx, accessed 12 September 2011).

owning improved breeds of livestock.[25] Statistical tests for the differences in means are reported in Table 8

[25] Improved livestock are cross-breeds between local breeds and breeds imported from other region; improved cattle typically generate higher milk yields while still maintaining replacement rates and resilience (such as tolerance for drought) suitable for local conditions (Kahi, et al., 2000).

Table 8for some of these variables.

Self-provisioning for maize is correlated with higher transportation, labor, farm improvement, fertilizer, and improved seed expenditures and more engagement with the credit market. Smallholders who produce their own maize spend more on their children's education and have larger landholdings and more high-bred livestock. Maize self-reliance appears to result not from market exclusion but rather from broader self-reliance; while clearly not a purely exogenous variable, maize deficits provide a proxy for unmodeled mechanisms through which unobserved endowments and preferences can affect farm choices. In the absence of other relevant farm characteristics, we assume that preferences regarding maize self-reliance can serve as a constraint of land and labor use choices, and model them as such.

Operationalizing maize self-reliance for the model, we first compute the amount of maize a household must eat in one month if all their calories were derived from maize: 132 kg, termed *maizereq* in the model. Multiplying this by the average monthly price of maize, we arrive at an approximation of the total value of maize eaten by a household in one month: $40. But the average monthly grain expenditure reported in the survey data is well below this. To compute the share of food provided through purchase, we need a reliable estimate of monthly grain expenditure. One option is to use a simple average: $16.40. We chose a slightly more sophisticated econometric estimation technique to control for productive capacity and competing uses of labor.[26] The estimated coefficient is $19, with a standard error of $1.46, representing the weighted average over all farm and household sizes of the willingness to pay for an additional month of maize purchases. To construct the variable for the quantity of maize purchased, termed *maizepurch*, we divide the average monthly value of total maize consumption by this estimate of monthly maize expenditures to get the average share of monthly maize consumption that was purchased. We then multiply this term by the total household maize requirement to get 63 kg per month.

[26] Specifically, we use using two-stage least squares to estimate the effect of a one-month increase in food deficits on the yearly maize expenditure, controlling for total livestock units, household size, and farm acreage, with altitude and household type as instruments. In the sample, household types are female-headed (228), male-headed (830), orphan-headed (7), and polygamous (34).

Table 8: Sample characteristics by months of food deficit

Extent of food deficit (i.e. number of months of food purchases)	0-3 months	4-12 months	Difference (two-sided t-test)	
Sample characteristics	***Count***	***Count***	**--**	**--**
Number of households	648	612	--	--
Household type	--	--	--	--
Female-headed	103	124	--	--
Male-headed	473	354	--	--
Households with a member employed off-farm	376	439	--	--
Number taking loans	154	165	--	--
Household characteristics	***Average***	***Average***	***t***	***p-value***
Loan amount ($)	72.68	28.56	2.4815	0.0132**
Number of household members	6.52	7.18	-3.1075	0.0019***
Number of months when food was bought	1.06	7.34	--	--
Distance to water source (km)	0.71	0.80	-1.1552	0.2483
Per capita water consumption (# 20 liter cans)	0.99	0.92	1.4287	0.1533
Household expenditure ($)†	***Average***	***Average***	***t***	***p-value***
Children's education	230.99	107.02	3.451	0.0006***
House improvement	67.05	115.36	-1.1579	0.2471
Water (per capita, per day)	0.00	0.00	-2.707	0.0069***
Food	17.20	115.80	--	--
Food (per capita per food-deficit month)	3.06	2.54	2.7062	0.0069***
Health (per capita)	11.65	9.39	-0.9561	0.3392
Transport	39.25	24.52	2.2301	0.0259**
Other (funerals, church donations, weddings, etc.)	51.89	41.98	0.9933	0.3207
Farm characteristics	***Average***	***Average***	***t***	***p-value***
Number of parcels	1.53	1.81	-4.0975	0.000***
Farm area (ac)	8.65	3.57	4.0183	0.0001***
Land producing fodder from own-farm crop residues (ac)	1.46	0.68	3.0899	0.0021***
Land producing fodder from own-farm grassland (ac)	2.48	0.67	4.1852	0.000***
Communal land producing fodder (ac)	0.34	0.13	1.6191	0.1118
Government land producing fodder (ac)	0.01	0.01	0.5016	0.6657
Farm expenditure ($)†	***Average***	***Average***	***t***	***p-value***
Hired labor	84.35	20.37	4.2843	0.000***
Farm improvement	2.83	1.56	2.1437	0.0322**
Improved seed	25.56	6.64	5.3324	0.000***
Manure	0.26	0.16	0.8461	0.3977
Fertilizer	37.84	7.75	7.5873	0.000***
Implements	7.02	2.49	1.6953	0.0903*
Other	0.15	0.08	0.6314	0.5279
Livestock characteristics	***Average***	***Average***	***t***	***p-value***
Local breeds TLU‡	1.89	1.81	0.4407	0.6595
Cows	1.24	1.31	--	--
Chickens	8.37	6.49	--	--
Bulls	0.70	0.74	--	--
Sheep	1.68	1.17	--	--
Goats	1.66	1.52	--	--
High breeds TLU‡	1.53	0.44	7.2256	0.000***
Cows	1.50	0.41	--	--
Bulls	0.48	0.14	--	--
Chickens	0.07	0.00	--	--
Goats	0.03	0.00	--	--
Livestock expenditure ($)†	***Average***	***Average***	***t***	***p-value***
Purchases	24.51	13.12	2.1893	0.0288**
Veterinary (per TLU)	8.85	7.54	0.7457	0.4560
Fodder (per TLU)	4.01	2.23	1.3338	0.1826

Source: authors' calculations from 2005-2007 WKIEMP dataset
† Expenditures refer to the previous year unless otherwise noted.
‡ Total Livestock Units computed from a region-specific algorithm that sums the following coefficients multiplied by the number of each animal held: 0.5*cattle + 0.1*(sheep + goats) + 0.2*pigs + 0.01*chickens (Chilonda and Otte, 2006).

* Reject equal means at 1%
** Reject equal means at 5%
** Reject equal means at 10%

Using all this information, the maize self-sufficiency constraint is as follows:

$$\sum_{mz}(yieldm_{mz,"maize","m1"}MLAND_{t,"m1",mz} + yieldm_{mz,"maize","m8"}MLAND_{t,"m8",mz}) \geq 12maizereq - monthbuy * maizepurch$$
$$= 1582 - 63monthbuy$$

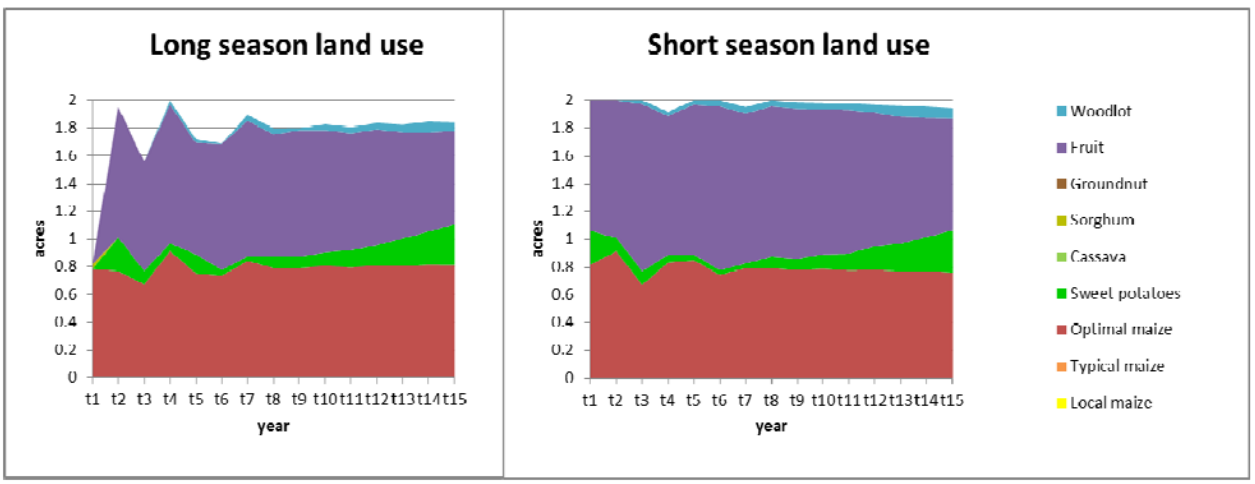
In words, the amount of maize produced each year must not drop below what is needed to fulfill *all* required calories through maize, net of what is purchased.[27] When activated, the constraint requires maize production of at least 827 kg per year (if partial purchases take place in all 12 months) and up to 1582 kg per year (if maize is never purchased).

III. Baseline and Policy Simulations

Once technical parameters and initial conditions are chosen, the model produces a wealth of outputs, including; land and labor use trajectories over time; woody perennial stands and livestock vintages by year; an accounting of monthly product sales, purchases, essential consumption, and inventories; and monthly disposable income. Graphical accounts of selected results are provided below for the baseline simulation, and also for some basic sensitivity analyses performed to assess the robustness of the model.

The baseline simulation – selected results

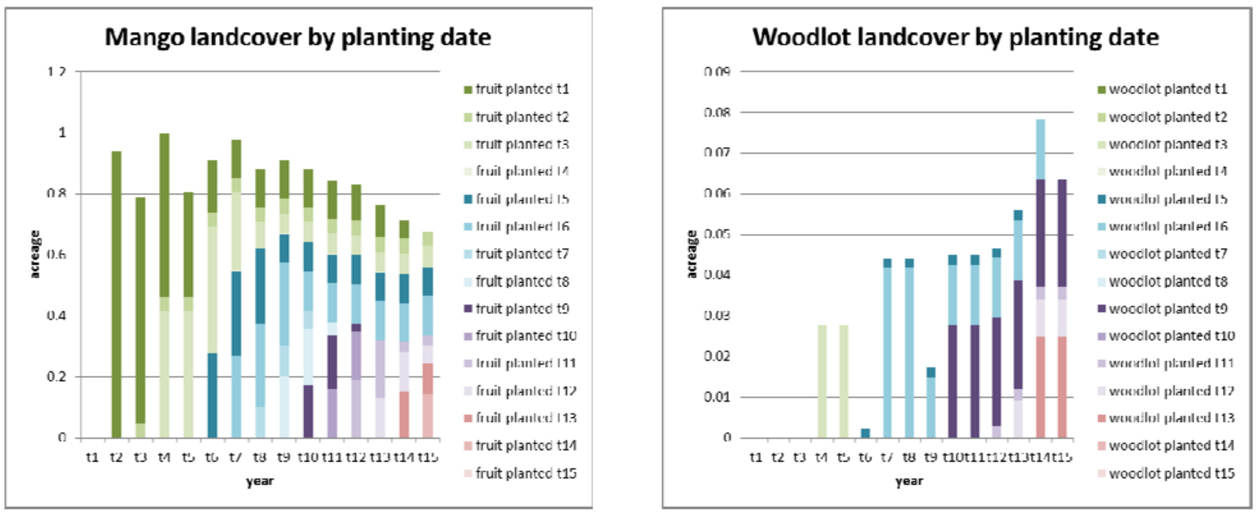
Figure 4: Baseline land use choices



[27] For instance, we would force a representative household with zero months of food deficit to produce enough maize in a year to satisfy the minimum caloric requirement solely through maize. We do not force the household to eat all this maize; they may choose to sell some and fulfill some of their nutrition through the production or purchase of other foods.

In the baseline scenario, we simulate the optimal use of two acres of land by a six-person household purchasing some, but not all, of its maize for seven months each year.[28] It is best to focus on the last 12 years of the simulation, as the first few years or so represent the transition from our choice of initial conditions to a steady state more adapted to the technical parameters and policy/price setting included in the model.[29] Yearly land use choices are displayed in Figure 4, indicating a maize and mango farm with a small woodlot and an expanding sweet potato plot. As can be seen in Figure 5, the transition from initial conditions to a steady state involves the immediate planting of nearly an acre of mango trees and the gradual investment in some *Eucalyptus* trees starting with 0.03 acres in year 3. Once planted, not all trees are kept on a long-term basis; some of each vintage of tree is harvested for fuelwood after just a few years of growth and replaced with younger trees.

Figure 5: Baseline perennial land uses by vintage



Livestock holdings settle at around two cows or bulls, half a sheep, and one goat.[30] The number of livestock of each age (or vintage, here) is reported over time in Figure 6.[31] The model treats livestock much as it treats trees; diversifying ages and using non-integer values. While it is not realistic to imagine a household with a cattle portfolio comprised of 0.46 one-year-olds, 0.89 three-year-olds, and 0.89 four-year-olds, as our representative farm has in year five, the simulation gives a sense of household preferences over livestock vintages.

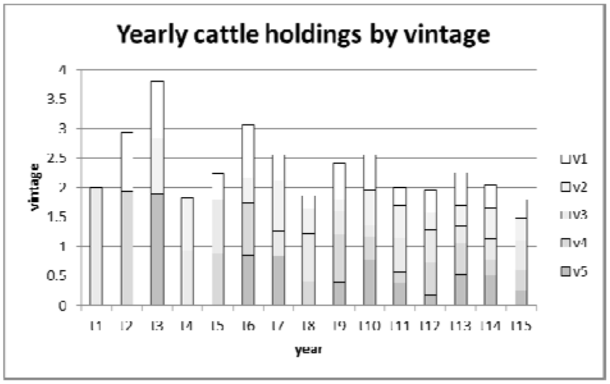
[28] In the baseline, we assume that a maximum of 63 kilograms will be purchased in each of the seven purchase-months.

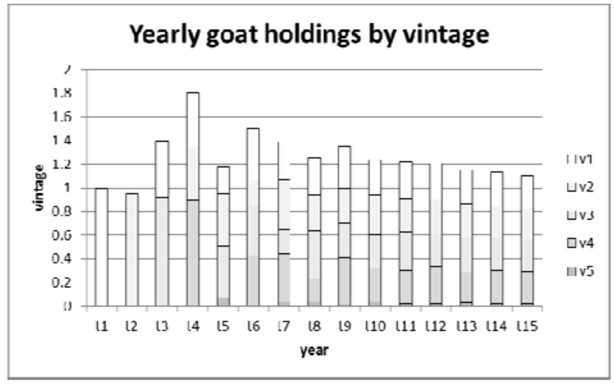
[29] The model simulation is run out to 20 years; only the first 15 years of the results are reported here, due to the distorting effects of the model's terminal conditions (a common problem with this class of models).

[30] The number of cows held of each vintage in a given month is always the same as the number of bulls. While cows are attractive because they produce offspring, bulls have a higher sales price.

[31] Graphics for sheep are excluded because they demonstrate the same pattern as goats. In every year, holdings of each vintage of sheep are equal to exactly half of goat holdings.

Figure 6: Baseline livestock holdings[32]





The household has many tasks over which labor can be allocated. Annual crops require land preparation, planting, fertilizer application, weeding, harvesting, and post-harvest processing. Perennial crops are planted, maintained, and sometimes harvested. Meanwhile, off-farm activities include gathering fuelwood, herding, transporting harvest to market and purchased food home from the market, and transporting purchased and sold livestock. Many of these tasks may be completed by hired male labor. Meanwhile, adults on the farm may choose to seek outside employment. However, not all household adults will be able to find off-farm employment during periods of low labor demand. Similarly, in times of peak labor demand, the household cannot expect to hire as many laborers as it might desire at a given wage, which varies seasonally. These constraints are introduced into the model as upper bounds on the amounts of labor that can be hired-out and hired-in each month, and are represented graphically below in Figure 7. Optimal labor use on the farm in the baseline scenario is broken down in Figure 8, which displays the total yearly labor use by category each year (on the left) and for a given year (year 8) on the right. The hired-in labor constraint is binding August, a crucial month for maize harvesting. In August, December, and January maize harvesting and post-harvest processing occupy all household labor, and these are the only months when the hired-out labor constraint is non-binding.

[32] As the animals age, they are represented by darker bars; newly born livestock show up as white bars. Note that in contrast to perennial land uses, older vintages can show up in the farm system without being preceded by younger vintages due to livestock purchases.

Figure 7: Limits on labor flows onto and off of the farm, by month

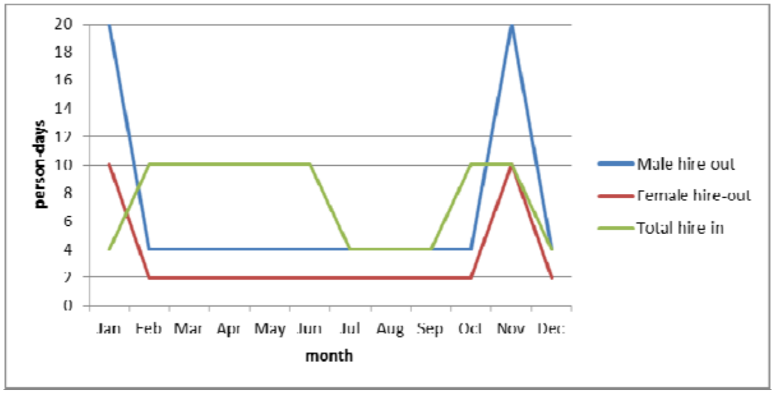
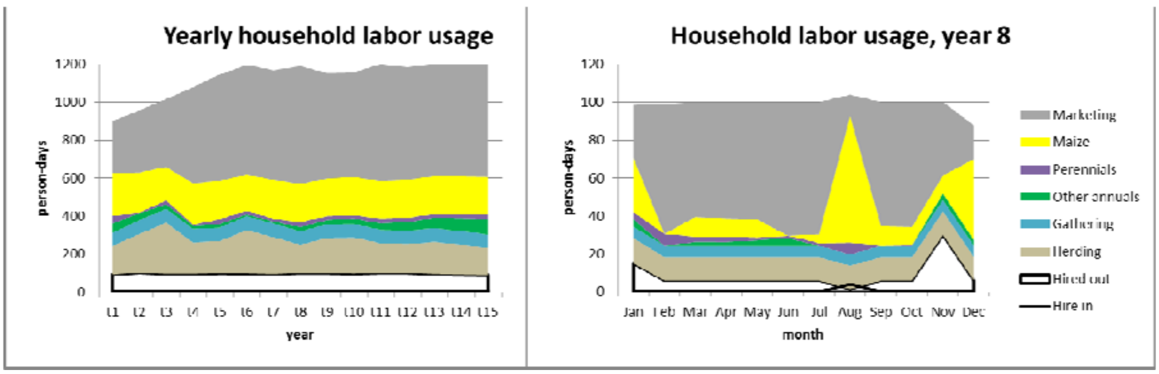


Figure 8: Baseline labor use choices, by year



Essential food consumption is a diverse mix of cassava, sweet potatoes, maize, mangoes, sorghum, and milk and is relatively stable over the years, though not the months, of the simulation period. Maize and sorghum represent 28 and 14 percent of total calorie consumption, respectively, in the final 10 years of the simulation reported here, comparing well to the FAO's approximation that 40 to 60 percent of total dietary energy comes from staple cereals in African countries (1997). These results are shown in Figure 9 , which tracks household monthly consumption of each product. In the left-hand panel, total household consumption is reported for each year; in the right-hand panel, year eight of the simulation period is disaggregated to show each month's consumption. Within a given year, purchased sorghum makes up for depleted home stocks of maize in January, April, June, July, and December. Cassava, a relatively inexpensive source of nutrients, is purchased year-round. Mangos are consumed during harvest months (December and January), but not during other months because they cannot be stored. Mangoes are substituted with purchased or grown sweet potatoes in other months. Fuelwood consumption is fixed at 150 kilograms per month, or five kilograms a day, over the entire simulation period.

Figure 9: Baseline food and fuel consumption

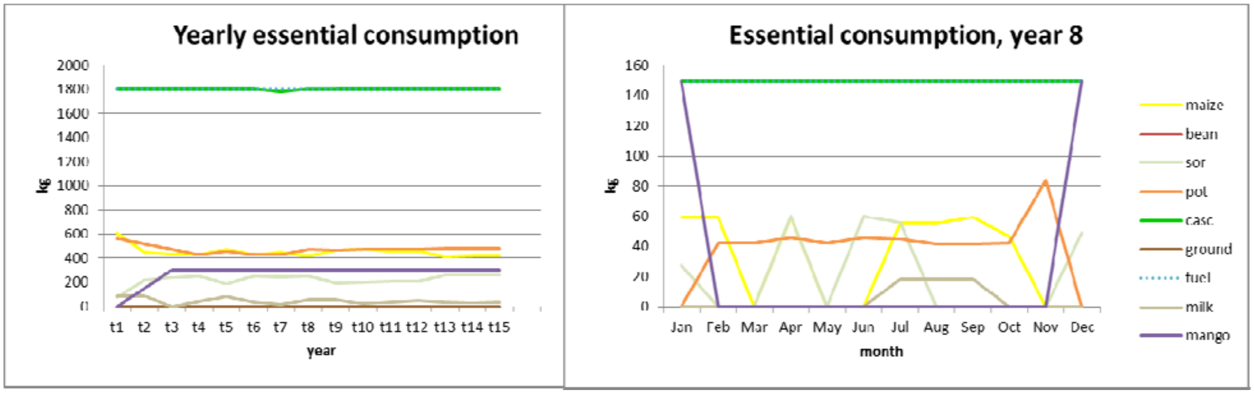


Figure 10 reports average annual purchases and sales of foods and fuelwood for each year of the baseline simulation (left-hand panels) and monthly values for year eight (right-hand panels). The most commonly sold item from the household is fuelwood, generated both through off-farm gathering and through pruning and cutting down trees on-farm. Fuelwood pruning occurs in February and August, but sales drop in August because there are competing uses of household labor. Maize is an important cash crop, some of which is sold at harvest time and more is sold in May when the price is at its seasonal peak. Beans are sold during harvest time. This annual pattern of staple sales, ignoring the small maize peak in May, reflects the negative impact of on-farm food stock deterioration[33] in the months following harvest vis-à-vis the revenue that could be gained from waiting to sell until prices rise. Reducing the values of inventory depreciation and the discount rate would smooth sales over time.

For this baseline case, the average monthly disposable income earned by the household over the entire 20-year simulation period reported here is $44.30 per month, or $0.25 per person per day. Applying a 10% discount rate to each month's disposable income, this is $21.06 for monthly household income, or $0.12 daily individual income. Recall that disposable income is computed after all necessary essential consumption requirements are met. The discounted per capita value of average daily essential consumption adds another $0.28.[34] Sources of this income are broken down below in Figure 11, which displays the total yearly revenue by category, savings, and consumption each year (on the left) and for one year (year 8) on the right.

[33] Stock deterioration is assumed to be 10% per month for all products except milk and mangoes, which cannot be stored.

[34] We use monthly prices as assumed by the model for all annual products and mangoes to compute this value. Milk is valued at $0.37 per liter, based on 2009 data for Kenya from FAOSTAT (http://faostat.fao.org/site/570/default.aspx, accessed 9 December 2011).

Figure 10: Baseline sales and purchases

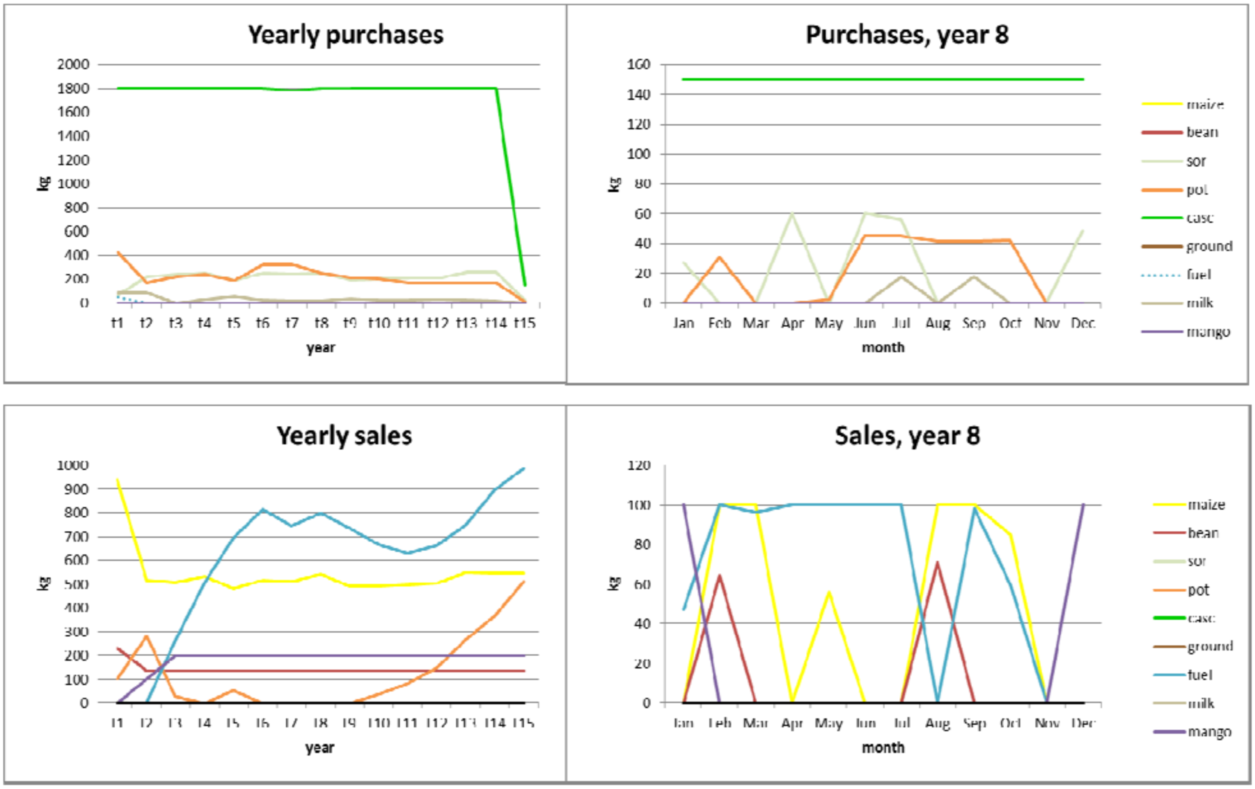
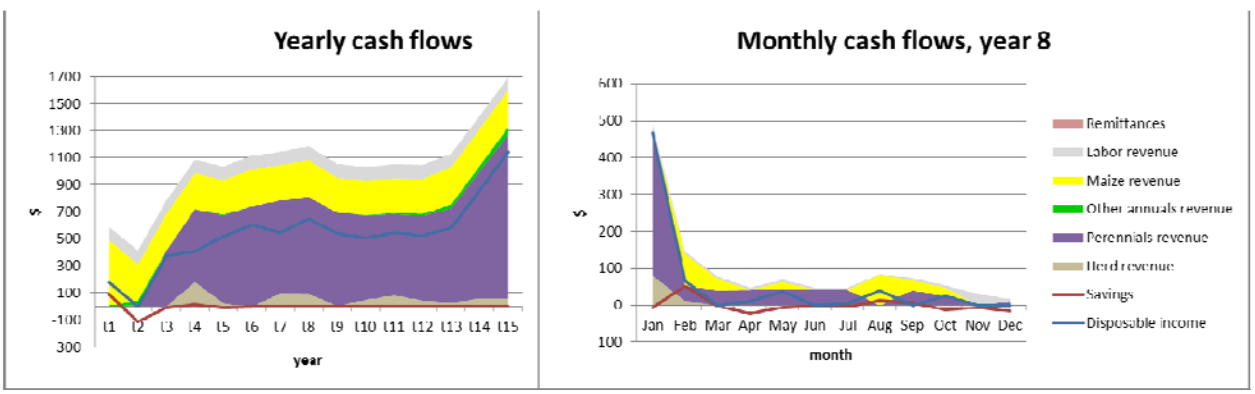


Figure 11: Baseline income, savings, and disposable income (by source)



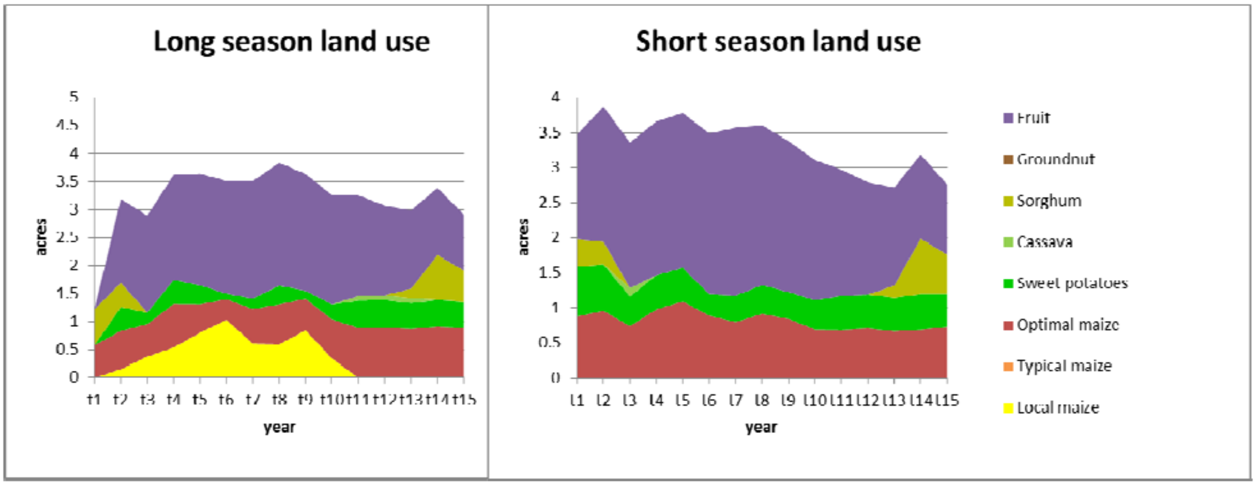
Testing the baseline model

The following subsections present some of the results of a series of tests of the baseline model that were undertaken to assess the responsiveness of model results to variations in selected initial conditions, constraints and other technical parameters.

Responses to changes in farm size

Recall that a six-person household compares well with both median and average household size in the WKIEMP sample, but that two acres is smaller than both the median and average land endowment. To test the effects of model results of farm size, we ran an auxiliary simulation doubling the land endowment, while holding constant the household size and limits to labor flows onto and off of the farm. Under these assumptions, farm labor constraints become increasingly binding and the household is unable to fully utilize all four acres. This is seen below in Figure 12.

Figure 12: Land use choices with four-acre land endowment



The composition of household activities shifts when the land endowment is doubled. Household members forgo woodlots entirely and increase the area dedicated to mango trees to 1.3 acres, as is shown in Figure 13. They grow more sweet potatoes and, in earlier and later points in the simulation period, more sorghum. One surprising outcome highlighted in Figure 14 is the substitution of some optimal hybrid maize for local varieties in years two through 10. This is driven by the increased competition for labor in August, when long-season maize is harvested and mango trees are pruned. When the household has surplus land and therefore no physical constraint on how many mango trees to plant, they fulfill the maize self-sufficiency constraint through the use of lower-yielding maize varieties.[35]

[35] Eliminating the minimum maize acreage requirement would likely lead to increases in idle land in these periods.

Figure 13: Perennial land uses by vintage with four-acre land endowment

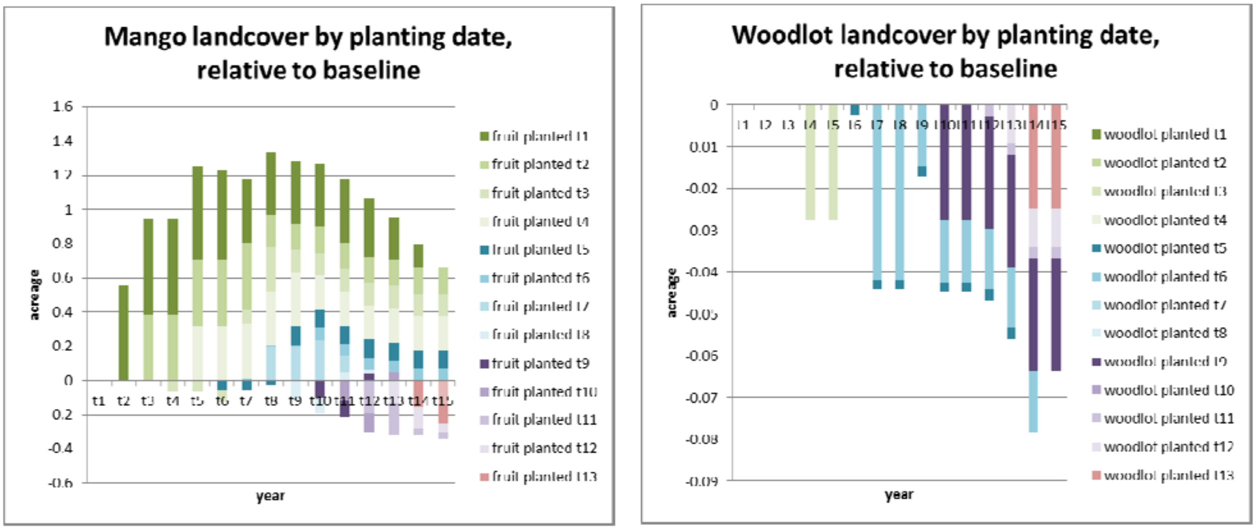
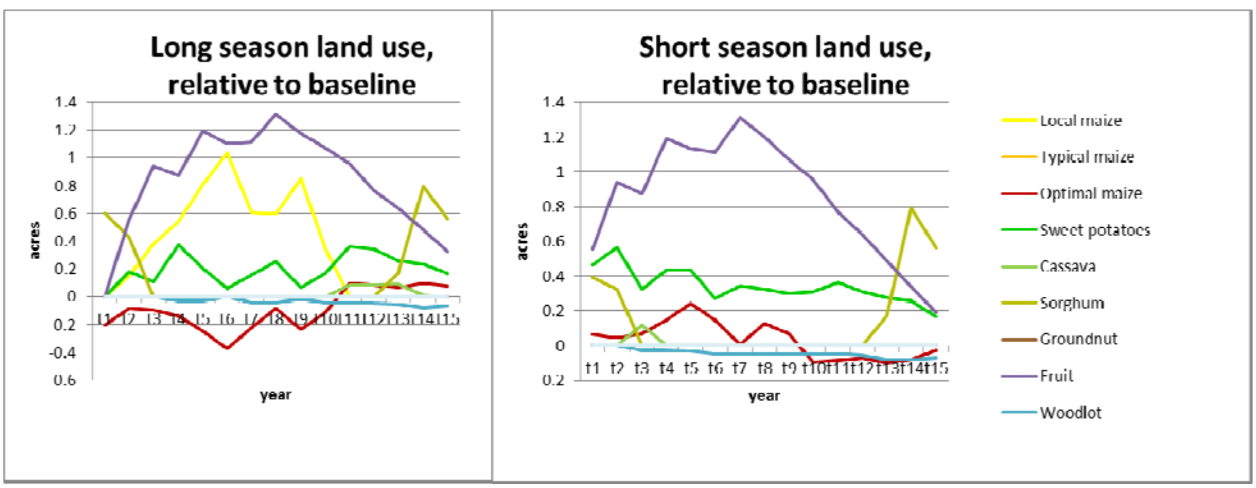
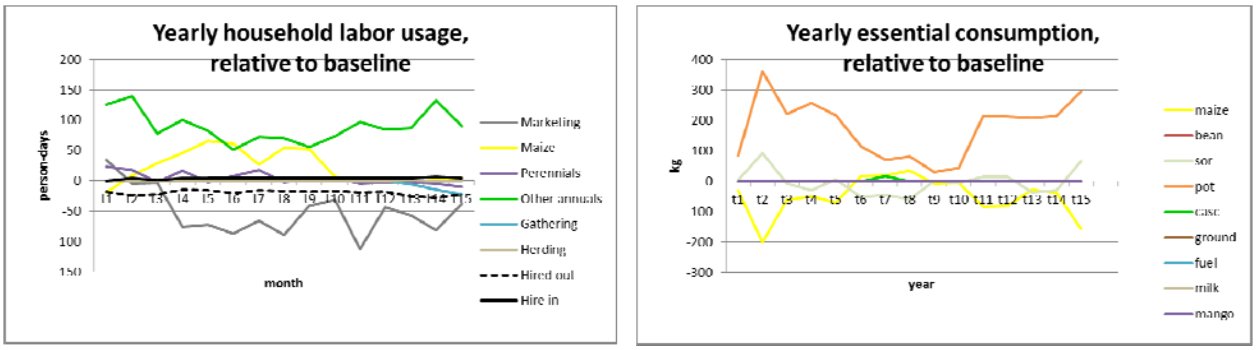


Figure 14: Land use choices with four-acre vs. two-acre land endowment



The increase in mango planting increases labor requirements for this activity in early years of the simulation period, but these are offset by the lack of woodlots in later periods. Herd size and composition do not change in response to the change in land endowment, and therefore herding labor remains constant. The clearest effect on daily household activities is the decrease in woodlot pruning, harvesting, and fuelwood marketing, and the increase in sweet potato planting, marketing, and consumption. These outcomes are reported below in Figure 15.

Figure 15: Household outcomes when land endowment is doubled

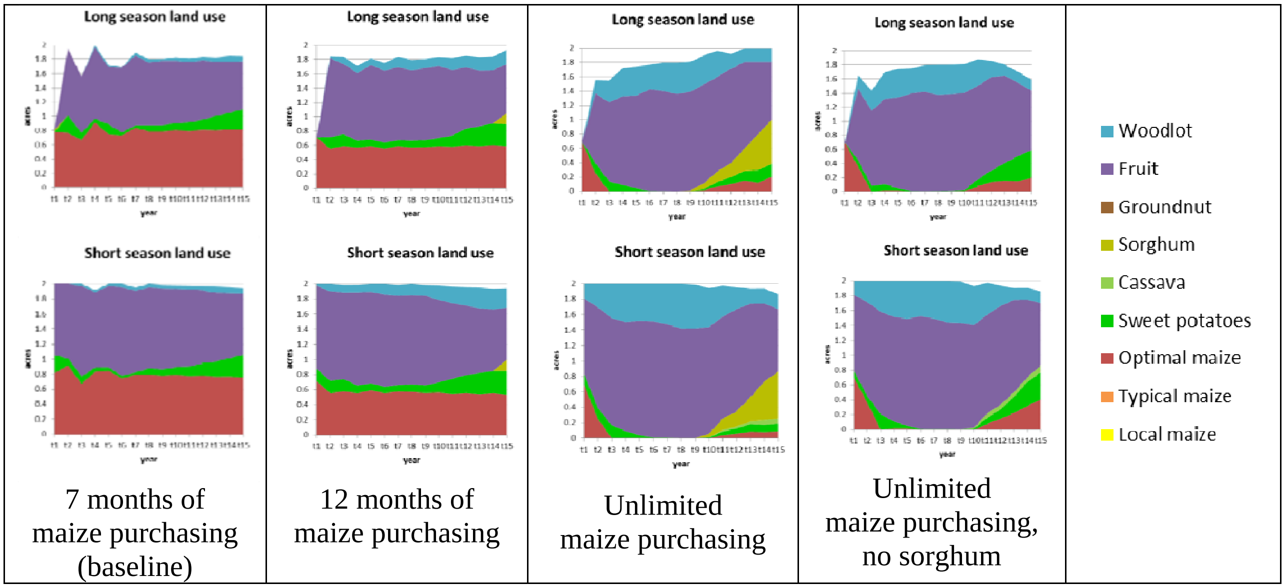


The importance of maize self-reliance assumptions

In the baseline scenario, maize covers a little less than half of the farm area and is one of the main household activities, especially during harvest times.[36] Here, we explore the extent to which area dedicated to maize is due to our maize self-sufficiency constraint as opposed to income-maximizing or nutrition-satisfying behavior. Recall that maize self-reliance is parameterized through the maximum number of months the household is allowed to buy maize, assuming that maize is their only source of calories. When *maizepurch* is low, the household must grow more maize. As expected, ramping *down* the maize self-reliance constraint results in less land being allocated to maize and beans. The more maize the household is allowed to buy, the more maize land is replaced with *Eucalyptus*, mangoes, and sweet potatoes. As the mango trees mature, harvests approach the upper bound on marketing capacity for mango fruits, and mango trees are felled for fuelwood. In the third panel of Figure 16 below, we see that when maize purchases are allowed in all 12 months, mango trees are replaced with woodlots, sweet potatoes, and sorghum in the final years of the horizon.

[36] Herding requires about the same amount of male labor as maize-growing.

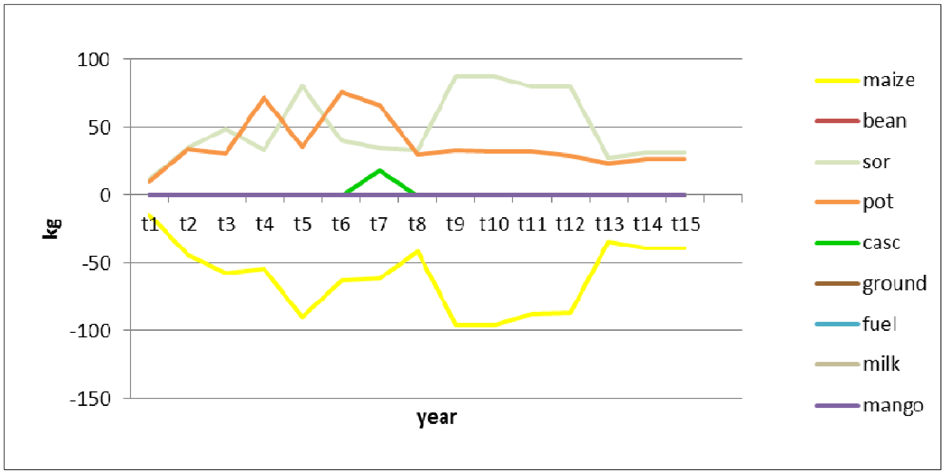
Figure 16: Land use under different maize purchase allowances



The third panel of Figure 16 shows that without the maize self-reliance constraint, our representative household would grow maize only at the beginning of the 15-year simulation period, very quickly replacing it with cash crops (mangoes) traded for essential consumption products and disposable income on the market. In year nine, the household begins to replace some of its mango trees with sorghum. This does not precipitate a decrease in mango sales, since the now older trees are producing more fruit per acre. Unlike mangoes, however, sorghum is not a cash crop. Home-produced sorghum begins to displace purchased sorghum in the essential food consumption basket as its landcover increases. To a small extent, this same dynamic is also observed for cassava. The switch to sorghum is driven by the essential consumption constraint and the relatively low per-unit costs of the nutrients sorghum provides. This can be seen in a final simulation in which sorghum is removed from the model as an activity choice. In this case, mangoes are replaced by sweet potatoes, maize, and beans in later years of the model horizon.

Note that the parameterization of purchase months actually affects the maize acreage, rather than maize purchases. With a high value of *maizepurch*, the household chooses to allocate its cash to consumption items other than maize, once monthly essential consumption constraints for each nutrient are satisfied. As explored above in Section II, maize and beans are very expensive sources of nutrients, whether they are produced on-farm or bought in the market. As a consequence, we find that it never makes sense for a household to buy maize or beans; if forced through the maize self-sufficiency constraint, however, maize and bean will be cultivated. Therefore, a household allowed to purchase maize during each of the 12 months in each year of the simulation period actually ends up purchasing no maize, choosing instead to invest in perennials, grow and eat more sweet potatoes, and increase disposable income. This can be seen in Figure 17 below. Reducing the number of months during which the household is allowed to purchase maize results in increased maize and bean cropping rather than purchases.

Figure 17: Yearly essential consumption when maizepurch=*12 compared to the baseline*



The land-use patterns under the 12-purchase-month scenario are represented differently in Figure 18. Once a steady state is reached, maize and bean acreage is 0.2 acres less than in the baseline simulation. It is initially replaced with approximately 0.1 acres each of mangoes and woodlots, but mangoes are later replaced with sweet potatoes and sorghum. Figure 19 demonstrates slight adjustments in the vintage portfolios of the tree crops. Mangoes planted in earlier years are kept longer, allowing the household to forgo later plantings.

Figure 18: Land use when maizepurch=*12 compared to baseline*

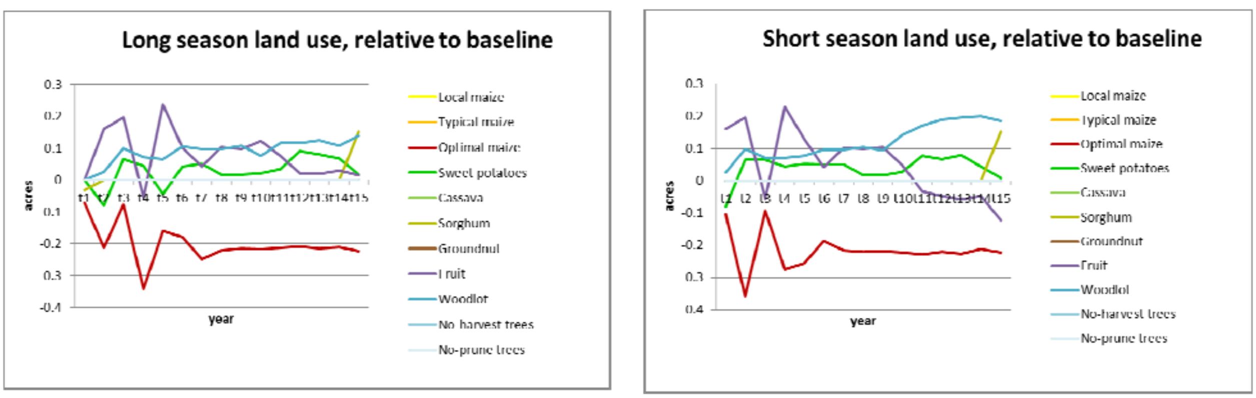
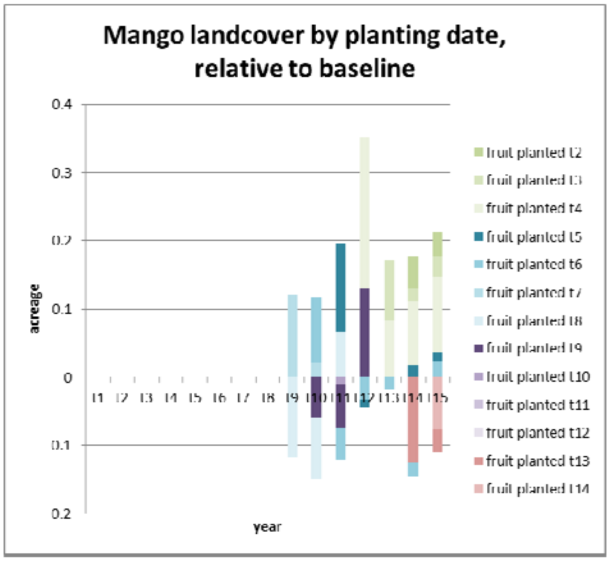
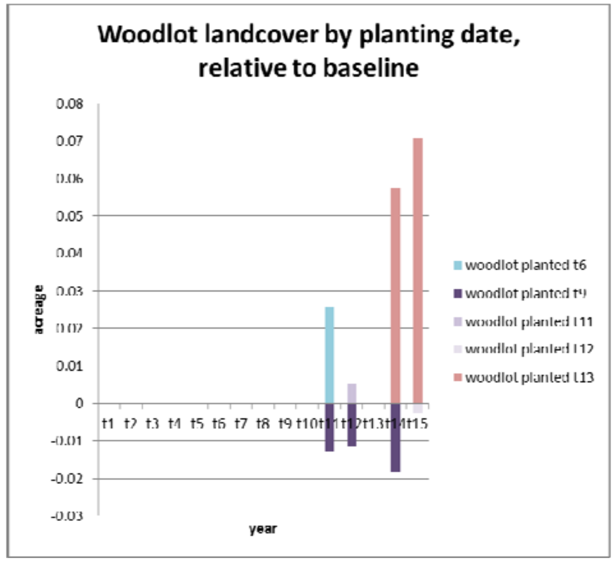


Figure 19: Perennial land use by vintage when maizepurch=*12 compared to baseline*





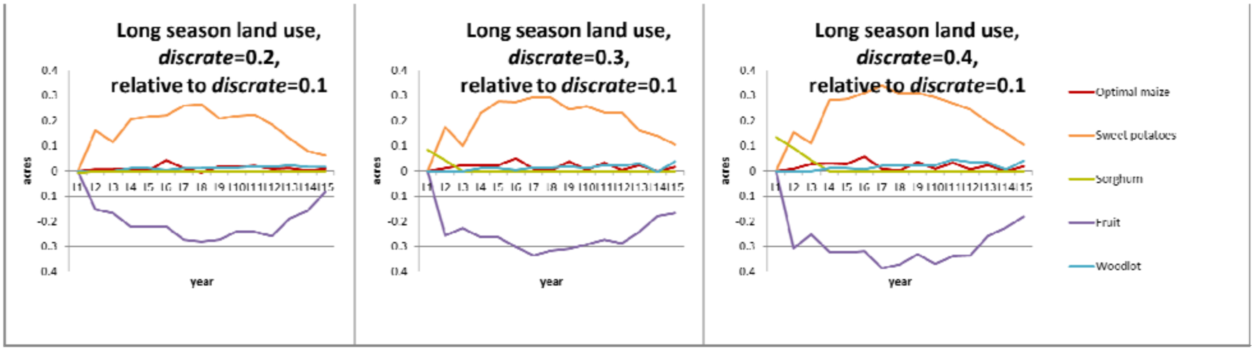
Responses to changes in the discount rate

The baseline scenario assumed a discount rate of 0.1, which implies that a dollar earned a year in the future is worth \$0.91 to the household decision maker right now.[37] Perennials lead to relatively high incomes per acre once they have matured, but come at the cost of earlier income from annuals. Therefore, we expect that land and labor allocated to perennials should be responsive to our choice of the discount rate. In this model, increasing the discount rate is bad for mangoes, but leads to slight increases in woodlot acreage due the decrease in mango prunings available for fuelwood. Land is allocated to sweet potatoes instead, with a slight increase in hybrid optimal maize and beans. At a discount rate of 0.3, sorghum is also grown during the long season during years one and two; with a discount rate of 0.4, some sorghum is maintained during the short season from years one through three.[38] The important features of these results are summarized below in Figure 20.

[37] The model keeps track of disposable income on a monthly basis; a dollar earned a month from now is worth a little over \$0.99 now.

[38] Recall that sorghum is planted at the beginning of the long season and yields a small amount of grain during the normal long season harvest. However, with no addition labor except harvest, the same plants will produce much higher yields at the end of the short season.

Figure 20: Land use choices with varying discount rates, relative to the baseline



Responses to changes in the revenue risk parameter

The baseline model accounts for seasonal variations in product prices and yields, but assumes that household decision makers know about seasonality and long-term price trends with certainty. Thus, we have not yet captured any risk attitudes about the potential the effects of bad weather on yields or of exogenous market conditions affecting prices. In reality, smallholders are aware that prices and yields vary between years. Based on data collected at the division level, we observe significant variations around the mean price of each annual crop,[39] though all years follow the same general seasonal pattern. With this information, we incorporate price risk into the model as follows.

First, recall that in the baseline model, households are assumed to maximize the discounted stream of disposable income over the entire decision time horizon, including the terminal value of the farm, subject to the agroecological and other constraints. Price risk can enter the objective function via a penalty term denoted the Mean of Total Absolute Deviations, or MOTAD (Hazell and Norton, 1986). "Deviations" are the difference between the revenue expected from a given basket of sold produce in a particular "state of nature" from the mean revenue expected to be generated by that basket over all states of nature. The MOTAD is computed by taking a weighted sum of revenue deviations over all states of nature, placing larger probability weights on more likely outcomes. Because each deviation is arithmetically related to the mean, it turns out that the weighted sum of the positive deviations is exactly the same (though of the opposite sign) as that of the negative deviations; hence the term: total *absolute* deviations. If there is no variation whatsoever over the distribution of outcomes, all the positive and negative deviations will be zero, as will their weighted sums.

Note that this approach *does* distinguish between aversion to losses and aversion to volatility. A relatively stable distribution with large but infrequent high values and a low mean will initially appear equivalent to a distribution with low-magnitude volatility around a higher mean. The MOTAD term in the objective function will be indistinguishable in each of these environments; however, disposable income associated with the latter will be higher, since it is constructed from average revenues.

The MOTAD term is scaled by a risk-aversion coefficient we call $\Phi_{revenue}$, or *revphi*. In a linear optimization framework, this is equivalent to using the original objective function (without

[39] See Figure 2, above.

$\Phi_{revenue}$) and adding a new constraint that requires the MOTAD term to equal a scalar multiple of $\Phi_{revenue}$, which we denote λ for expository purposes. Imagine solving the linear program for multiple of values of λ. The higher is λ, and thus $\Phi_{revenue}$, the more revenue variation the decision-maker can tolerate, which leads to a higher value of the objective function. The risk aversion parameter therefore represents the trade-off between aversion to revenue variation and desire for additional disposable income. In this linear framework, $\Phi_{revenue}$ does not have direct theoretical interpretation, but it does serve as a descriptive technique for fleshing out the effects of risk attitudes on choices.

In Figure 21, we present selected land-use results from four experiments with revenue risk aversion: *revphi*=1, *revphi*=2, *revphi*=2 with no maize self-sufficiency constraint, and *revphi*=2 with no maize self-sufficiency constraint and sorghum excluded from land use and essential consumption choices. Baseline outcomes appear in column one. For the lower risk aversion coefficient (*revphi*=1), land uses remain unchanged vis-à-vis the baseline for the first 10 years of the simulation period, aside from the 0.1-acre substitution of mangoes for sweet potatoes in the second year. In year 11, however, groundnuts are planted. The increase in prices of all annual crops has made groundnuts' advantage in terms of fat provision relatively more attractive than maize and beans. The following year when mango yields are high enough to induce a reduction in the amount of land allocated to mango trees,[40] price variations lead to replacing the harvested mango trees with sorghum, rather than sweet potatoes as in the baseline case. Increasing the risk aversion parameter to *revphi*=2 (column three in Figure 21) brings about a dramatic inter-annual changes in the amount of land dedicated to sorghum, vis-à-vis the baseline.

[40] This result comes from the 100 kg maximum for mango sales per month.

Figure 21: Effect of revenue risk aversion on land use

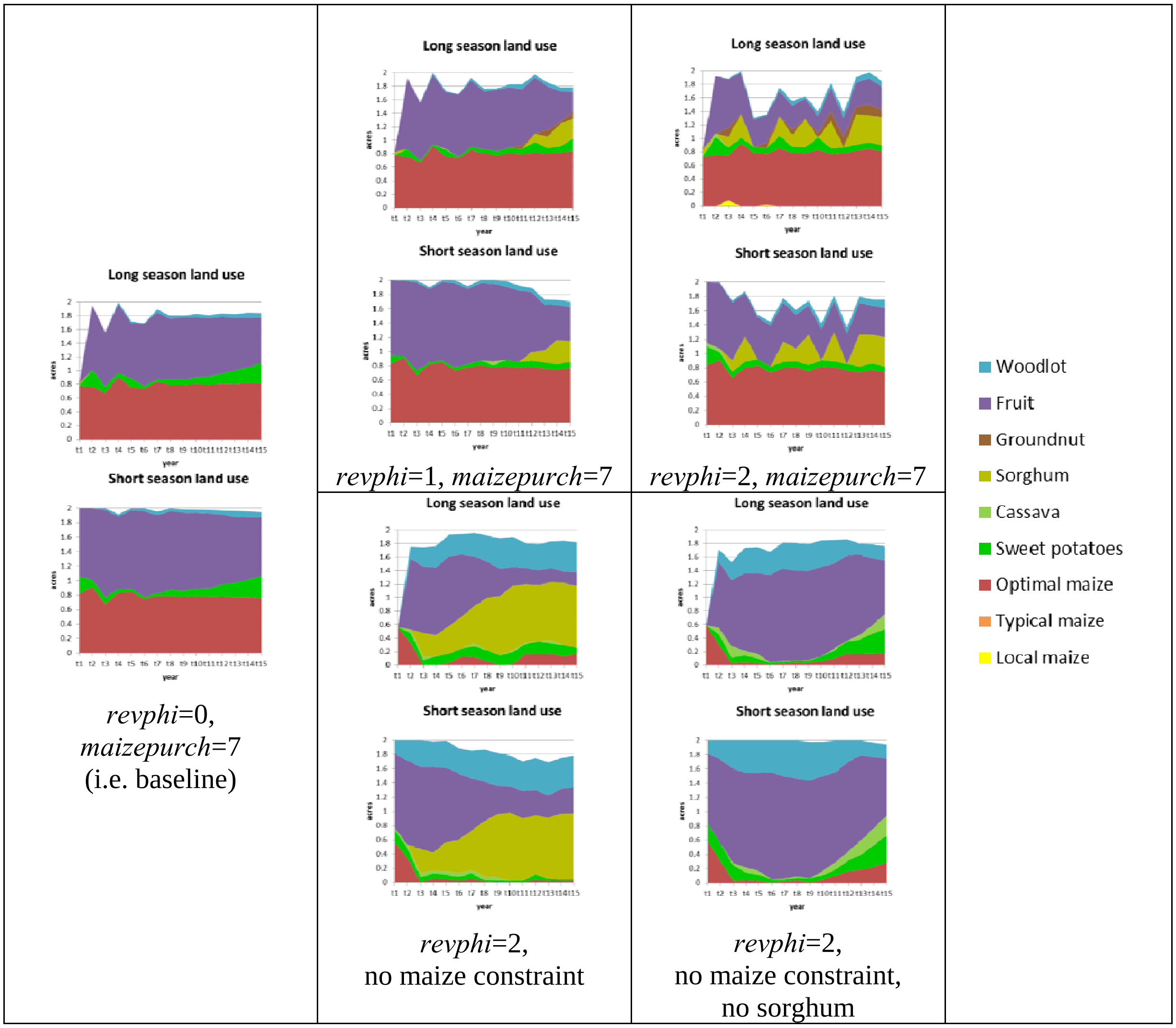


Figure 22 and Figure 23 present details of the effects of revenue risk aversion on land use choice relative to the baseline simulation. For *revphi*=1, the timing rather than the total planting of perennials changes relative to the baseline. Increasing the value of the risk parameter to *revphi*=2 results in a substitution of land from mangoes to sorghum. The effect of a small amount of revenue risk aversion is an earlier investment in cash-generating activities; for a higher level of revenue risk aversion, the need to steer away from possibly pricey purchased items reverses this land use result.

Figure 22: Detailed effect of revenue risk aversion on land use when revphi=*1*

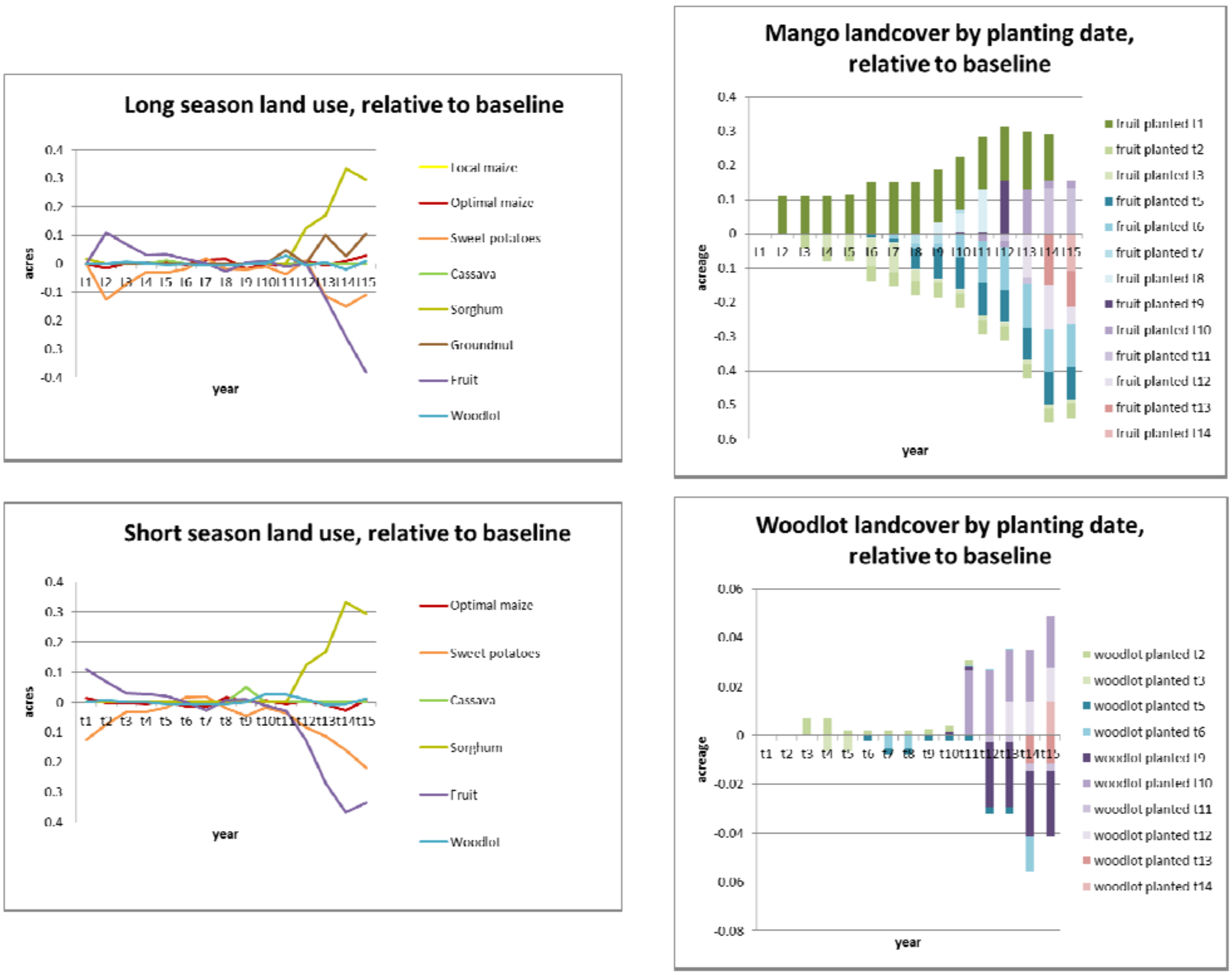
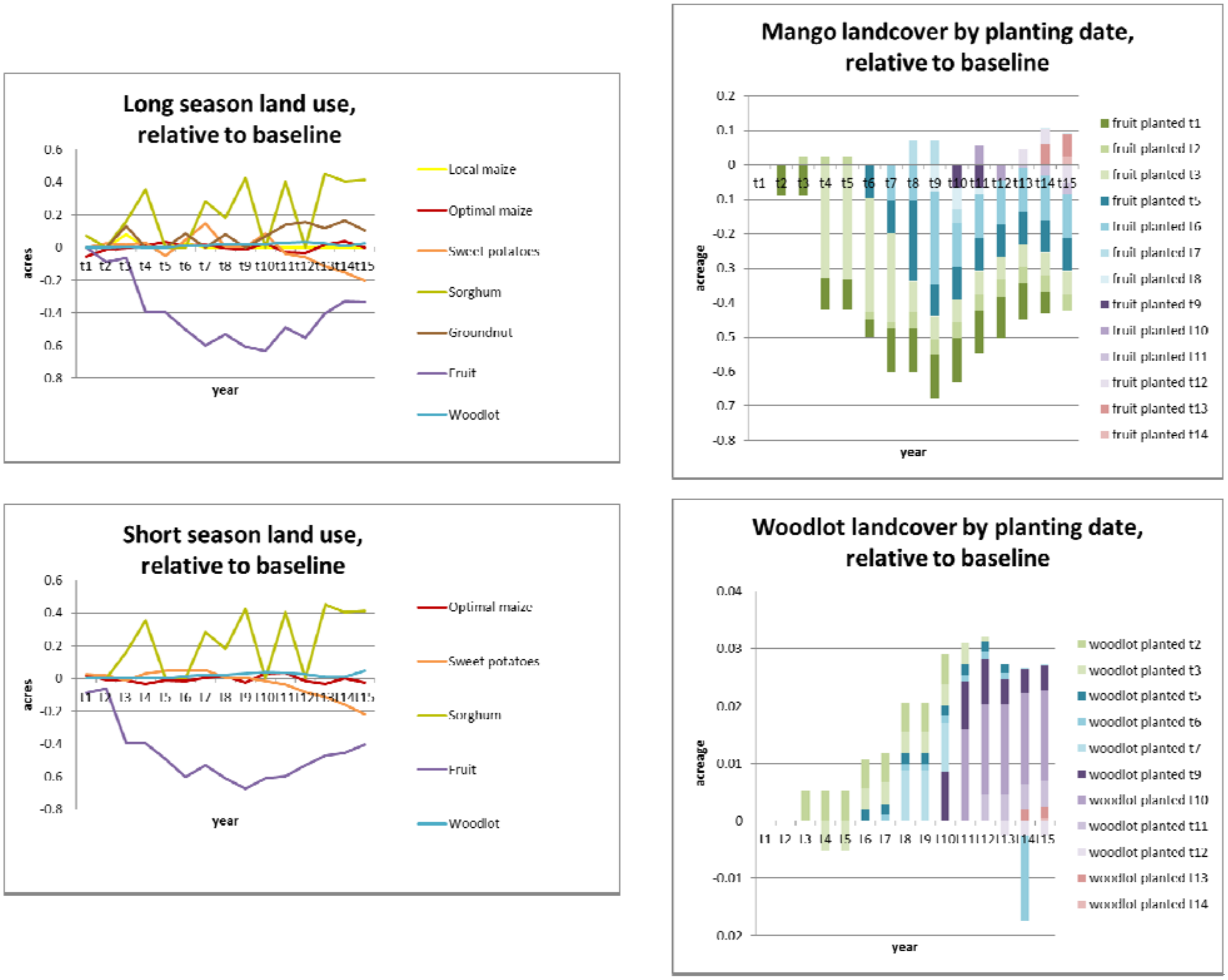


Figure 23: Detailed effect of revenue risk aversion on land use when revphi*=2*



The effects on food purchases and sales of higher values of *revphi* are presented in Figure 24. With *revphi*=2, the shift from cassava purchase and consumption begins right away; cassava consumption is reduced and replaced with increases in purchased and home-grown maize and sorghum; this allows the household to gradually discontinue cassava purchases and engage in more self-provisioning. This preference for sorghum, which was exposed in our previous tests of relaxing the maize self-sufficiency constraint, is even more pronounced when risk aversion is combined with the complete absence of maize planting requirements.

Figure 24: Produce flows when revphi*=2 relative to baseline*

Responses to changes in the yield risk parameters

Thus far, we have only considered price risk. However, a valid case can be made that yield variation is at least as important as price variation. Unfortunately, we have very limited data on yield variations at the farm level. District-level production statistics from 2008-2011 are measured in terms of acres achieved, with very little variation in the estimates of kilograms harvested, and no disaggregation by type of maize activity chosen. In lieu of time series data with which to estimate farm-level yield variation, we generate a triangular distribution for annuals[41] yields based on interview reporting on “good,” “bad,” and “normal” yields.

The approach we take to model yield risk is as follows.[42] Yield variability affects smallholder farms by changing the relative shadow prices of home-produced consumption items as well as the expected income from selling farm produce. If the harvest of a given crop is lower than expected, the farm may adjust its plan by selling less, eating less, or some combination of the two strategies. The choice of strategy is integrally related to decisions regarding other crops and purchases. If yields and prices are negatively correlated, which is likely in local markets, there will be more incentive to sell the scarce goods and substitute consumption towards cheaper or more plentiful goods. For instance, if maize yields are bad but sweet potato yields are good, the farm household may eat sweet potatoes instead of maize. Compared to a year with average

[41] We do not consider variation in perennial yields.

[42] As far as we know, this is the first paper to adapt Hazell and Norton’s (1986) MOTAD approach to capture yield risk.

yields, this strategy will result in considerably lower sales of sweet potatoes but only slightly lower sales of maize, even though it was the maize crop that suffered.

To capture this description of yield variability, we generate a new variable capturing yield deviation, which is scaled by a yield risk aversion parameter (Φ_{yield}, or *yieldphi*) and subtracted from inventory. This approach reflects the behavioral assumption that the farm decision-maker prepares for a situation in which post-harvest inventories of highly variable crops are lower than average. An income-maximizing farm subject to the essential consumption constraint as well as this self-imposed penalty will choose a mix of crops more weighted toward satisfying nutritional needs. The higher the penalty, the lower will be the appeal of risky farm activities even if their average revenues are high. Assuming the household is equally averse to negative realizations of all annuals yields, we performed simulations with equal values of Φ_{yield} for all products, starting at 0.1.[43]

Figure 25 denotes the resulting changes in land use relative to the baseline. The appearance of the farm is mostly unaffected, with no changes in landcover for most annuals and only small changes in the landcover for woodlots. From years five through 10, there is a small shift from sweet potatoes to mangoes, and this reverses in later years. The possibility of low sweet potato yields in early periods leads the household to reallocate land from this risky crop to mangoes, whose yields will be certain once the trees have matured (by assumption). During these years, sweet potatoes are purchased, rather than produced at home, as is shown in Figure 26. By year 10, the household is harvesting more mangoes than can be transported to market, and so mango trees are cut down and replaced by sweet potatoes. Note that this response was present in the baseline case as well; when yield risk aversion is incorporated, the substitution between mangoes and sweet potatoes is slightly more pronounced. Due to the change in land uses, sweet potatoes displace maize as both a consumption good and a cash crop in later years of the simulation.

As discussed in the previous section, there are multiple effects of revenue risk aversion on mangoes: if their price is relatively stable, it behooves the household to invest in them sooner; however, if consumption items are likely to be expensive, the household will allocate land toward consumable annuals rather than mangoes. It turns out that the joint effect of revenue risk aversion and yield aversion favors the latter result. As shown below in Figure 27, when *yieldphi*=0.1 and *revphi*=2, the household allocates land toward sweet potatoes instead of mangoes. However, the magnitude of this land use change relative to the baseline is very small. More significant changes occur in the flow of products on and off the farm, and the choice of consumption items. Relative to the simulation in which only yield risk aversion is captured, the further incorporation of revenue risk aversion leads the representative household to engage more in the market for sweet potatoes, selling them in some years and buying them in others. The maize self-sufficiency constraint still ensures that a significant amount of land is dedicated to maize and beans, but the relative cheapness of sorghum leads the household to exchange more of its maize for sorghum.

[43] Like $\Phi_{revenue}$, Φ_{yield} has no direct cardinal interpretation.

Figure 25: Land use choices when yieldphi=*0.2 and* revphi=*0, relative to the baseline*

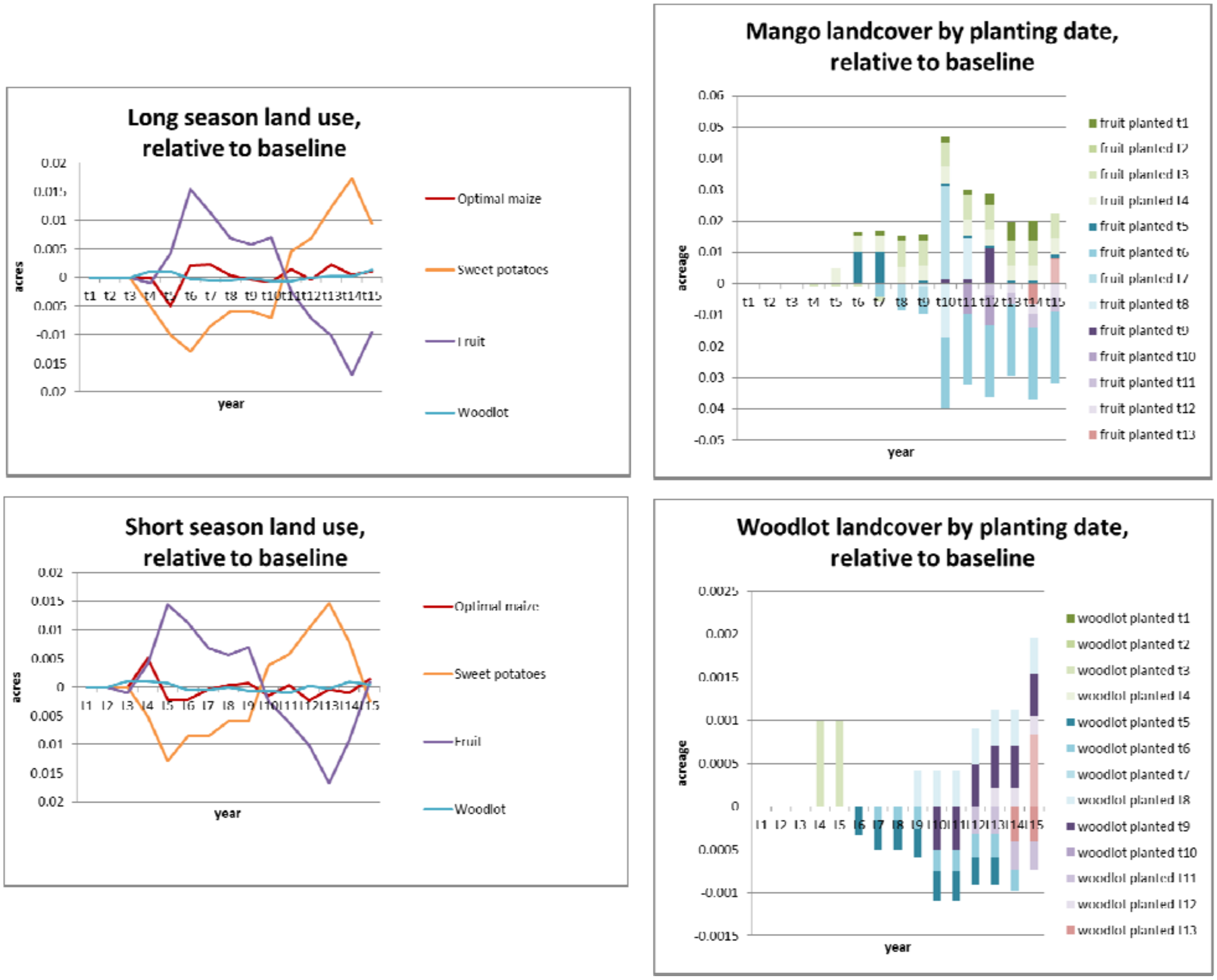
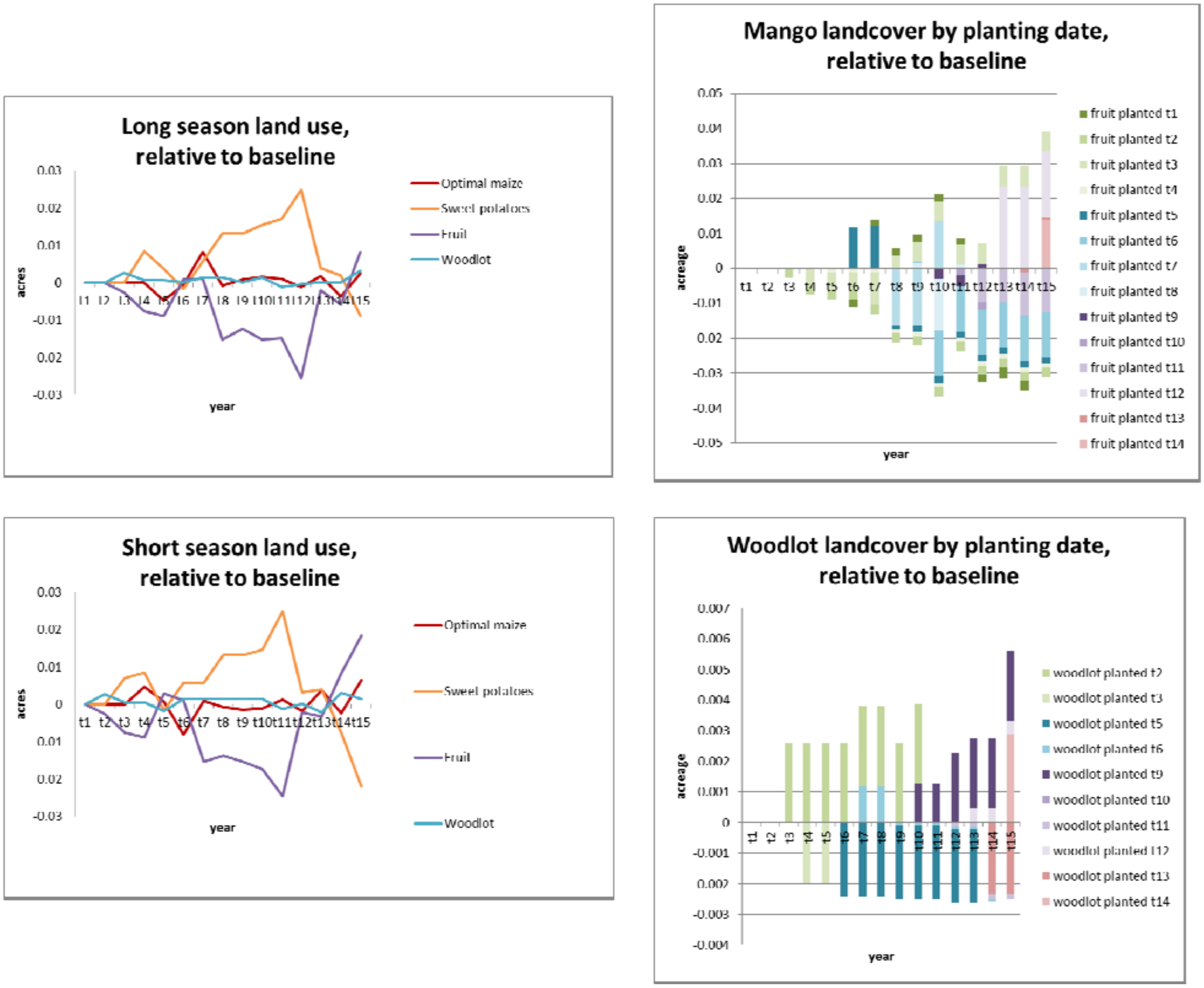


Figure 26: Product flows when yieldphi=*0.2 and* revphi=*0, relative to the baseline*

Figure 27: Land use choices when yieldphi=0.2 and revphi=2, relative to the baseline



Summary of baseline results and robustness tests

Key statistics from the various tests described above are reported below in

Table 9. The three income figures exclude the value of food and fuel consumed other than that purchased in addition to the minimum requirements, which is around $0.28 per capita per day (when discounted and valued at market prices). Doubling the land endowment significantly increases household income and leads to a doubling of area in woody perennials. Area in maize does not double, however, reflecting the satisfaction of the maize self-reliance constraint and the lack of profitability of maize relative to other land uses. Relaxing the maize self-reliance constraint allows maize acreage to decline and incomes to rise; eliminating sorghum from the available technologies reduces incomes. Changing the discount rate leads to expected changes in acreage of woody perennials; the higher the discount rate, the less the household values income earned from slow-yielding perennials in the future relative to resources sacrificed in earlier periods. Revenue risk aversion also reduces investment in woody perennials, while

yield risk aversion has little effect. When taken together, yield risk aversion offsets the effect on land use choices of revenue risk aversion.

Table 9: Model simulation summary statistics

Simulation	Total farm household income (NPV, $)	Income per household per year (CV, $)	Income per person per day (CV, $)	Total area in maize (ac)	Total area in woody perennials (ac)
Baseline	3790.48	531.63	0.25	0.79	0.83
Land endowment doubled	4843.82	742.51	0.34	0.94	1.63
Maize self-reliance relaxed (maizepurch=12)	4697.53	676.93	0.31	0.58	0.99
No maize self-reliance	5925.29	886.01	0.41	0.10	1.44
No maize self-reliance, no sorghum	5612.59	837.31	0.39	0.14	1.44
Discount rate of 0.2	3793.57	532.54	0.25	0.79	0.82
Discount rate of 0.3	4067.05	547.54	0.25	0.79	0.59
Discount rate of 0.4	4031.12	539.83	0.25	0.80	0.56
Revenue risk aversion (revphi=1)	3017.81	451.68	0.21	0.79	0.79
Revenue risk aversion (revphi=2)	1361.26	155.80	0.07	0.79	0.45
Revenue risk aversion (revphi=2), no maize self-reliance	5164.58	720.37	0.33	0.11	0.87
Revenue risk aversion (revphi=2), no maize self-reliance, no sorghum	5511.02	826.16	0.38	0.13	1.38
Yield risk aversion (yieldphi=0.2)	3674.95	517.63	0.24	0.79	0.83
Both types of risk aversion (revphi=2, yieldphi=0.2)	3270.96	470.75	0.22	0.79	0.81

NPV refers to net present value, or the value of income discounted to the first year's perspective. CV refers to current value, or the value at the time of computation. These income figures do not include the value of the consumption of food and fuel.

Modeling the land use and labor allocation choices of small-scale, semi-subsistence farmers is challenging. Simple net present value (NPV) calculations generally suggest that farmers faced with a given set of technical parameters and relative prices should specialize in a particular crop, and (perhaps) shift from one crop to another if technologies or relative prices change. Visits to small-scale farms and reviews of data on such farms presents a different reality—farmers engage in array of activities that are ‘sub-economical’ from a simple NPV perspective, and farm-level decisions are often less responsive to technology changes, new cropping options and changes in relative prices than one might expect. More sophisticated NPV analyses that incorporate yield and price variability can lead to a more refined economic ranking of alternative production activities (including the off-farm sale of household labor), but specialization in one activity is still usually the recommendation.

The modeling challenge, then, is to better understand and capture the factors that lead to on-farm diversification of production activities at a given site, for a given type of farm and farm household. Several candidate factors emerge. First, farmers may have strong preferences (based on their own experiences, or advice from other farmers or actors) regarding food self-reliance. Second, due to seasonal or other market imperfections, farmers may not be able to purchase all of the inputs or sell all of the outputs they would choose to. Third, on-farm activities compete for labor, cash and land in ways that NPV analyses do not capture. Fourth, farmers may be averse to risk associated with prices, yields, or both, and this aversion may cause them to choose collections of activities.

The farm-level bioeconomic model presented above addresses all of these issues, and generates baseline results for land use, labor use and purchases/sales, food purchases and sales, livestock purchases and sales, and fuelwood production/collection and sales that are generally consistent with patterns for these choices that were observed at the study site or contained in data for similar small-scale farms from nearby sites. Results also capture the low levels of cash income that can be generated by small-scale farming systems at the research site. The model 'reacts' as one would expect to changes in key technical and price parameters, and to changes in key constraints, e.g., increases in farm size lead to increases income and only small changes in land use patterns, and improvements in market integration lead to specialization.

No model is perfect, and the current version of this model has a few flaws that need to be addressed. Two are mentioned here; others are noted in the text and in footnotes. First, the amount of land dedicated to mangos is larger than those observed on farms during field visits – the current version of the model may offer too many opportunities for mango sales. Second, while the essential food consumption constraint ensures that simulated diets are diversified, the high levels of cassava and sweet potato consumption, and the high number of months of no-maize consumption, both deviate from observed food habits—data on food habits need to be more explicitly introduced into the model.

Bearing those imperfections and others in mind, by and large, we are satisfied that the model contains enough of the key features of the smallholder farming system to be used to examine the effects of technology/policy changes or climate change on the land use patterns and incomes of small-scale farmer at or near the research site.

IV. Policy and Climate Change Experiments

The effects of climate change

Our climate change simulations are based on the effects of changes in precipitation and ambient air temperature on maize yields. These adjustments are directly informed by projections from a forthcoming ICRAF study by Eike Luedeling whose goal is to identify the climatic factors most likely to reduce food security, and to design adaptation strategies to address this problem. He uses a weather generator to synthesize 25 draws of year-long weather patterns in three decades (2020s, 2050s, and 2080s) under two climate scenarios (reduced and "business-as-usual" emissions), which are then repeated using three distinct climate models.[44] Relevant weather data generated include mean, minimum, and maximum temperatures per season, and length of rainy seasons. Using crop growth models, the direct effects of changes in these variables were then related to yields, which were compared to a baseline.

All climate change models predicted a notable decrease in suitability of maize, with much milder effects for sorghum, suggesting that sorghum should become relatively more attractive over time. Maize is shown to be more susceptible to minimum and maximum temperature increases than number of rain days, especially during the long season. Sorghum was negatively affected by temperature increases, particularly an increase in minimum temperatures, whereas the effect of changes in rainfall depended on the stage of plant growth. These results were

[44] The models are HADCM3, the Hadley Centre Coupled Model, version 3; CCCMA CGCM2, the Canadian General Circulation Model 2 by the Canadian Centre for Climate Modelling and Analysis; and CSIRO Mk2, the Atmospheric Research Mark 2b, by Commonwealth Scientific and Industrial Research Organization.

common on all soil types.[45] Effects of climate change on groundnut production were similar to those of maize and sorghum, though increased rainfall was shown to be much more likely to be beneficial. Yield variation during both seasons of maize production and long-season sorghum production were low, and yield declines demonstrated little sensitivity to the choice of climate model or greenhouse gas emission scenario. Short-season sorghum productivity was subject to higher variation and to steeper declines in the 2050s and 2080s. Groundnut yields dropped drastically in all climate change scenarios, but variability decreased during the short season.

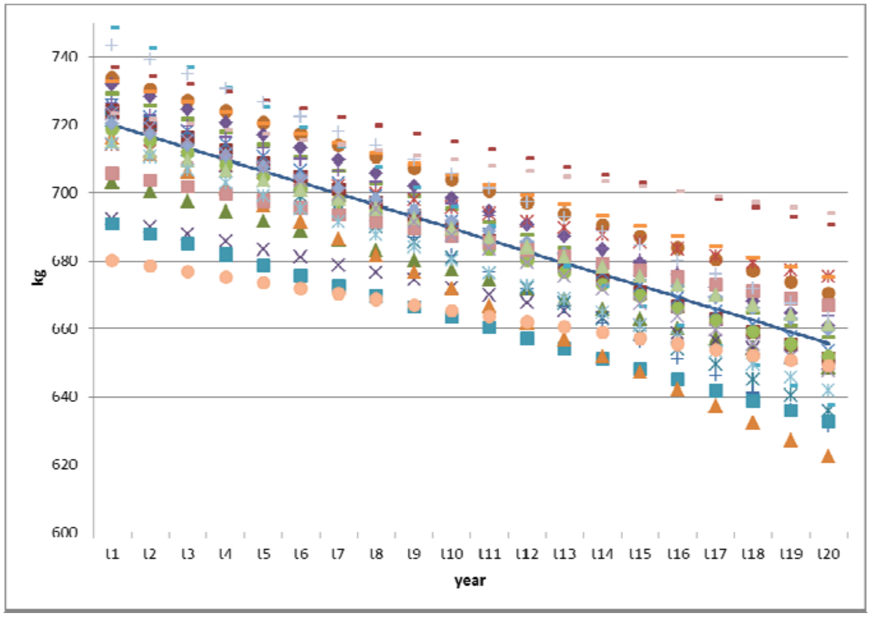
This level of detail was not possible for the remaining products included in the bioeconomic model, namely beans, sweet potatoes, cassava, mangoes, and fuelwood. However, Luedeling's study does present some preliminary suggestions about the likely effects of climate change on some of these products. Most scenarios indicated increasing suitability at our research site for mango, cassava, and sweet potato production as temperatures increased, though increased rainfall could reduce mango yields. Any substitution toward these crops and away from maize, sorghum, and groundnuts in the bioeconomic model will likely be lower than if detailed projections were available for tubers and woody perennial.

We scale Luedeling's baseline maize yields to those of our hybrid optimal technologies and then create a new yield distribution based on his 2020s simulation using the HADCM3, under the business-as-usual scenario.[46] We then perform two experiments. First, we rerun the baseline with the 2020s yields, rather than our baseline. Second, we simulate a gradual (i.e. linear) adjustment from the baseline to the 2020s yields. We assume that yields will decline linearly for all draws from the distribution, and that the representative farmer will experience the hybrid optimal maize yields equal to the average of the distribution for each year. The resulting maize yield distribution for this experiment is depicted graphically in Figure 28. Note that only year 1 and year 20 come from Luedeling's study; we interpolate the intermediate values. The first experiment uses the t20 mean for the entire simulation period.

[45] We chose simulations based on Orthic Ferralsol soil. This soil type is yellow-red and highly weathered with low fertility and is common in the humid tropics (Chesworth, 2008).

[46] The percentage change between our baseline and our 2020s distribution are identical to that of Luedeling's two series; the modification is necessary to scale his yields to our representative farmer.

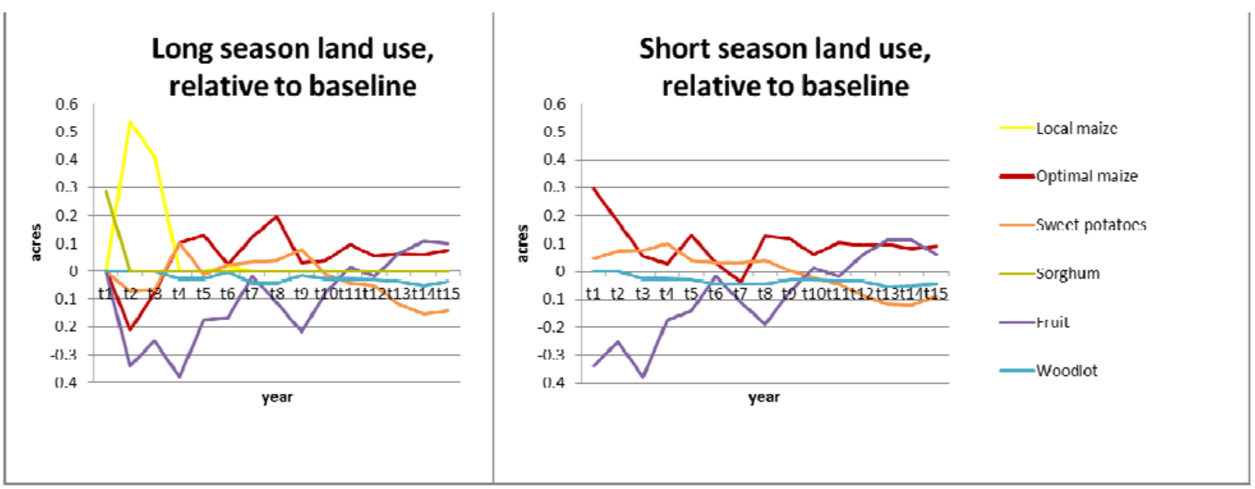
Figure 28: Maize yield declines over the 20-year simulation period



Experiment 1

Taking the lowest yields from Figure 28 above, we see notable differences in both maize and mango acreage over the 15-year reporting horizon. This response is almost entirely driven by the maize self-reliance constraint, which mandates that land allocated to maize must go up if yields go down. As shown in Figure 29, land is taken out of mangoes in earlier years and out of sweet potatoes in later years once the remaining mango trees have matured enough for fruit to serve as an alternative cash crop.

Figure 29: Land use changes under "business-as-usual" 2020s expected maize yields



Experiment 2

Now we simulate a gradual adjustment from the baseline to the yields used in Experiment 1. Results mimic those of Experiment 1 but at lower magnitudes (Figure 30). As before, initial mango acreage is lower than the baseline, but the difference is more than made up in later periods. It may seem surprising that a reduction in maize yields over the entire period results in more mangoes in later periods, relative to the baseline. This is driven by the gradual reduction in mangoes in the baseline simulation starting in year four, which is due to the joint effect of two assumptions: the number of fruit that can be harvested per tree increases as the trees age, but the household can never transport more than 150 kilograms to the market per month. When maize yields are lowered, the household has fewer means to invest in mangoes early-on, with consequences for consumption, purchases and sales (Figure 31). For this reason, the ramping up of mango acreage observed in early periods in the baseline occurs later in these two experiments.

Figure 30: Land uses changes due to climate-change-induced maize yield declines

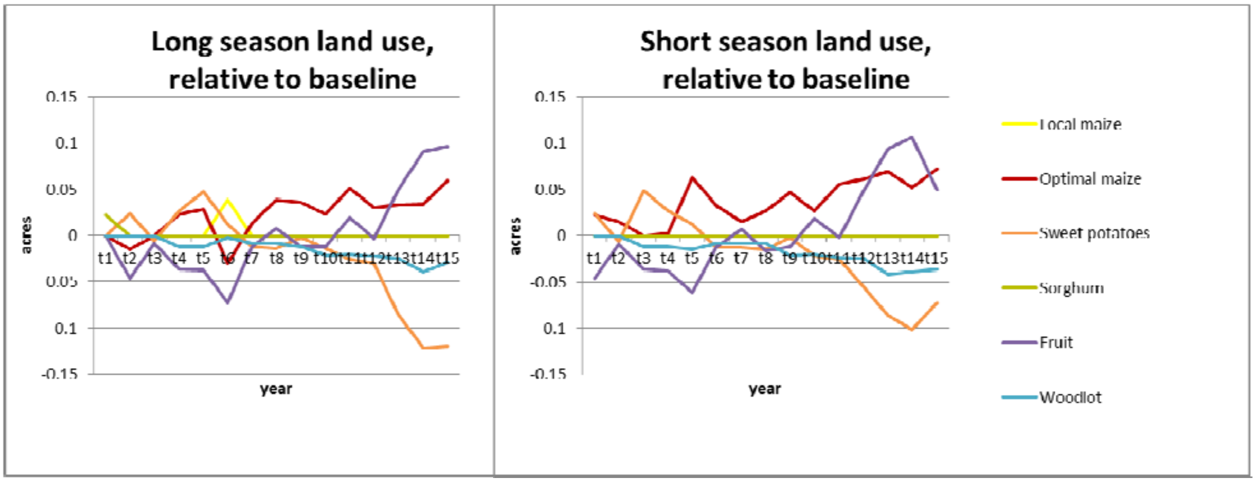
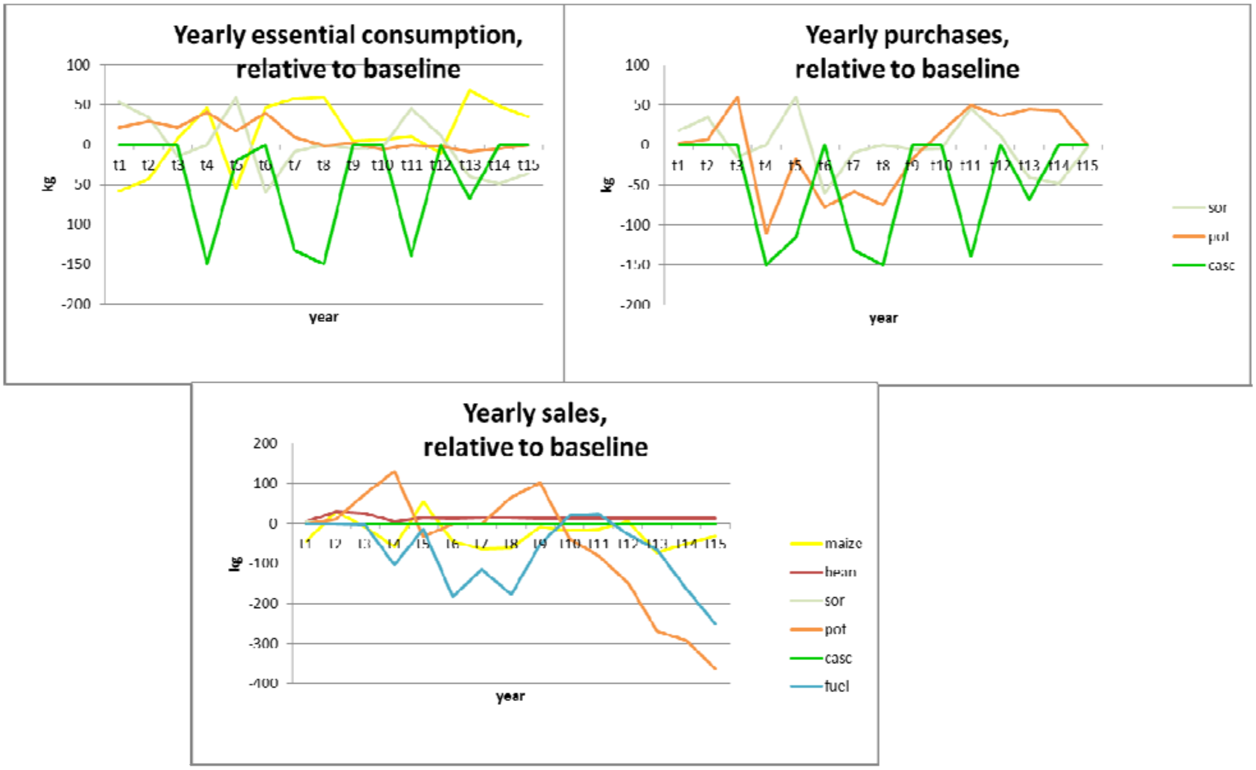


Figure 31: Product flows under gradual yield declines



Introducing risk aversion into the simulation mitigates the optimizing decision-maker's response to maize yield declines. The left-hand panel of Figure 32 above shows the effect of gradual yield declines on land use choices when accounting for yield risk aversion, but not price risk aversion. Compared to Figure 30, which did not account for any risk aversion, the magnitude of the effect of yield declines is smaller and limited only to years two through six. By planting mangoes on land that would have gone to sweet potatoes in the absence of risk aversion, the household is shifting from an activity that has uncertain immediate returns to one that has certain future returns. This result is reversed when price risk aversion is also included, as can be seen in the right-hand panel of Figure 32. Now that variation in prices is accounted for, the household can no longer afford to shift land out of annual crops in order to capture higher future mango revenues; instead the farmer plants more sweet potatoes which are then traded for maize. This is one of the few simulations in which we have found the optimizing farm household *buying* maize. Notice in Figure 33 that years of maize purchase coincide with years of maize sales. The household is so constrained in this simulation that maize arbitrage has become profitable—buying maize during harvest times when it is cheap and then reselling it later. In most other simulations, this kind of arbitrage is eliminated through a no-arbitrage constraint.

Figure 32: Land uses under gradual climate change and risk aversion

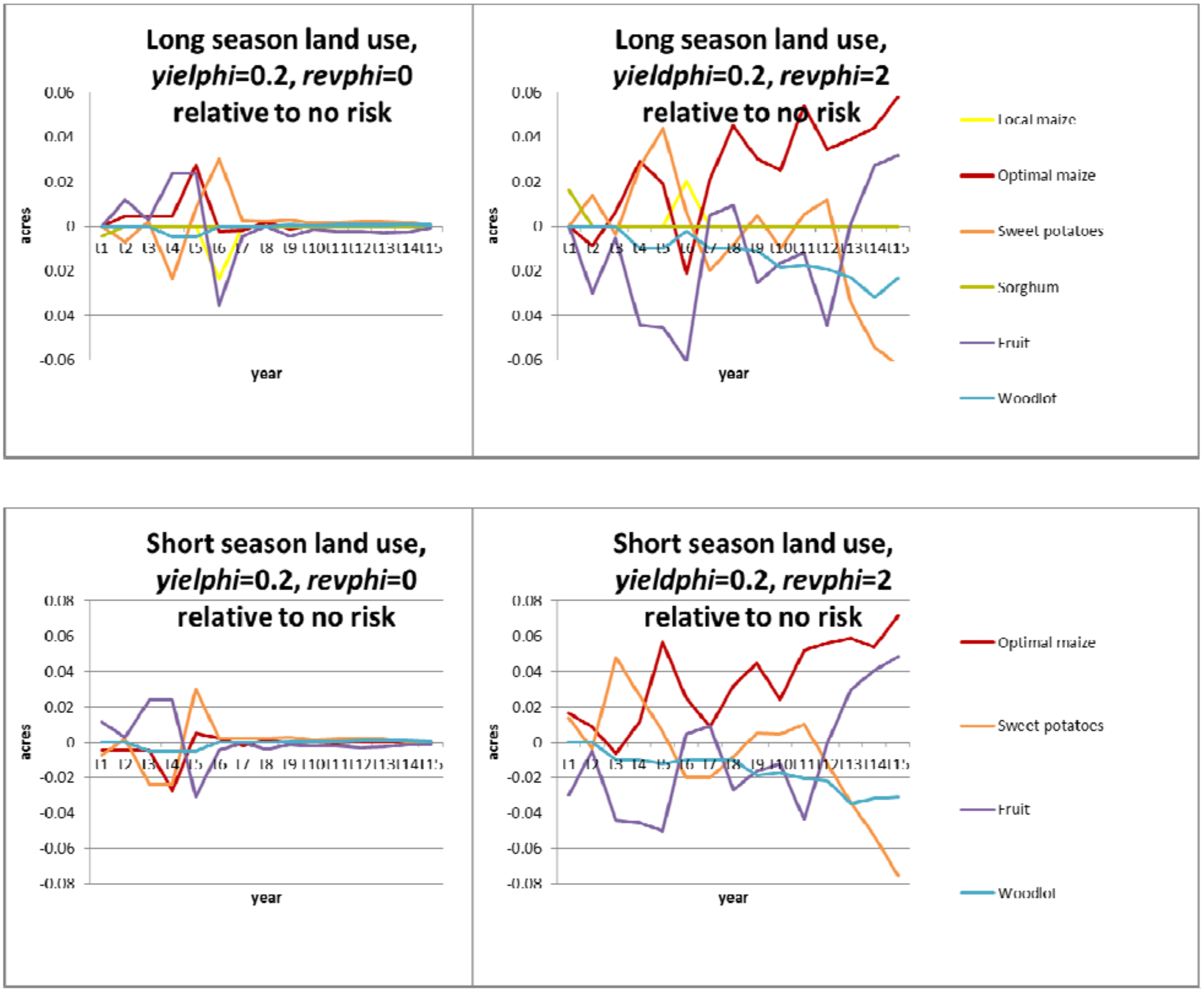


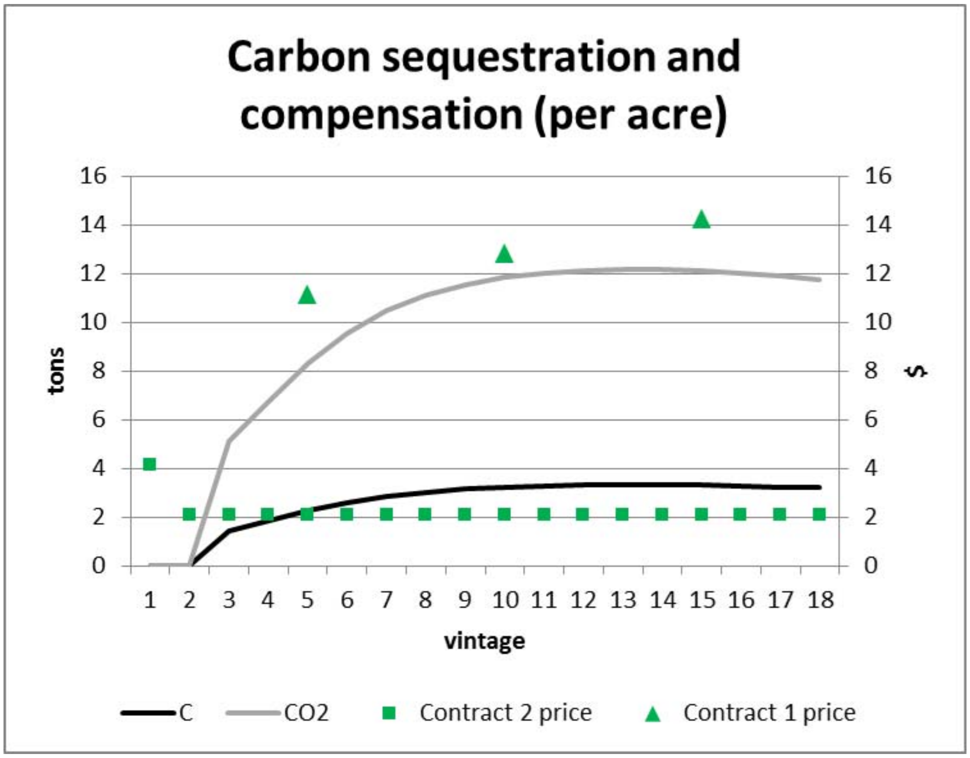
Figure 33: Product flows under gradual yield declines and both revenue and yield risk aversion

Payments for on-farm carbon sequestration

The model has been designed for analysis of the potential effects of payments for ecosystem services (PES), particularly carbon payments, on household incomes and land and labor allocation choices. We simulate a land-use diversion PES (Zilberman, et al., 2008), meaning that farmers have an opportunity to forgo agricultural activities over some area in exchange for direct payment based on the amount of carbon sequestered by the alternative land use. Here, this alternative is assumed to be a *Eucalyptus* woodlot that will never be harvested. In the simulations, we allow the carbon sequestered by unharvested *Eucalyptus* to vary by vintage. Henry, et al., (2009) estimate that woodlots sequester between 0.57 and 1.29 tons of carbon per year per acre. We impute yearly values based on vintage-specific *Eucalyptus* carbon stock reported in Onrizal, et al., (2001) and convert carbon to CO_2. These assumptions are represented graphically in the black and gray lines in Figure 34 below.

We incorporate into the model two carbon contracts that require farmers to commit not to harvest trees for the foreseeable future (i.e., beyond the model simulation period) but allow them to prune trees for fuelwood. Both contracts are based on a price of $20 per ton of CO_2, which is assumed to be transferred to the carbon project managers every five years. Due to high monitoring and program costs, only 30% is assumed to go to farmers. The two contracts differ in when these funds are distributed to farmers. Contract 1 guarantees payments every fifth year proportional to overall project income. Contract 2 distributes a constant per-acre payment to farmers for years two through 15 regardless of the age of trees. Under Contract 2, payments in the first year are double those in subsequent years to cover some of the establishment costs. The net present value of payments to farmers under both contracts is set equal to 30% of the net present value of total project income over the 15-year contract. The green triangles and squares in Figure 34 below represent the payments under Contract 1 and Contract 2, respectively.

Figure 34: Carbon contract specifications



We find that none of the contracts competes with other farm activities. For this reason, we increase the original price to $1000 per ton CO_2 and note the consequent effect on land uses. This price is 50 times the original specification, and amounts to quintannual payments to farmers of $550 to $720 per acre under Contract 1 and yearly payments of $103.55 (except for year 1, when this figure is doubled) per acre under Contract 2. Despite these high payments, neither contract attracts a high level of adoption nor are carbon-sequestering *Eucalyptus* woodlots ever planted before year 11. Contract 1 leads to the adoption of 0.0098 acres in year 11, but no subsequent planting. Under Contract 2, the farm household initially plants less in year 12, 0.0038 acres, but increases this to 0.039 by the end of the simulation period. Relaxing the maize self-sufficiency constraint significantly increases adoption under Contract 2, to an initial 0.06 acres that grows to 0.148 by year 15, though magnitudes are still low. These results are summarized in the figures below.

Figure 35: Land use choices under Contract 1, $1000 per ton

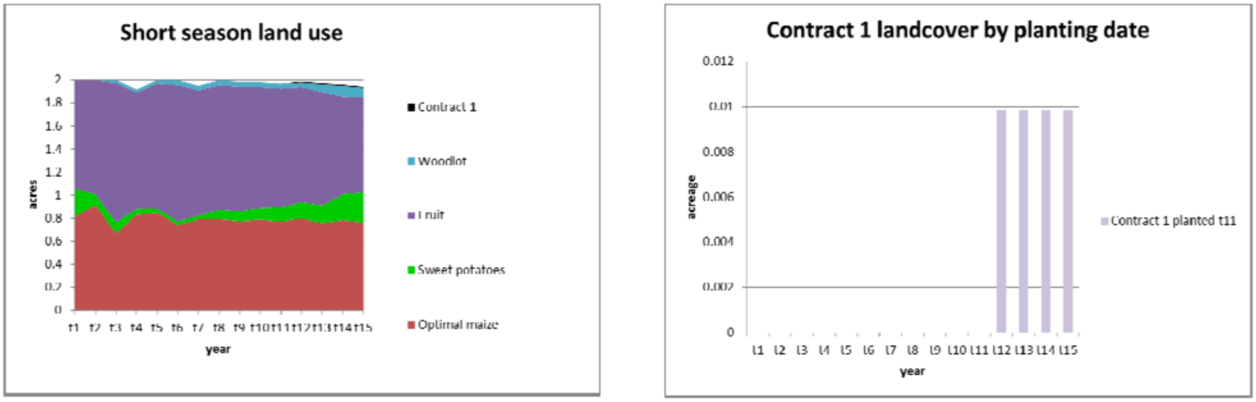


Figure 36: Land use choices under Contract 2, $1000 per ton

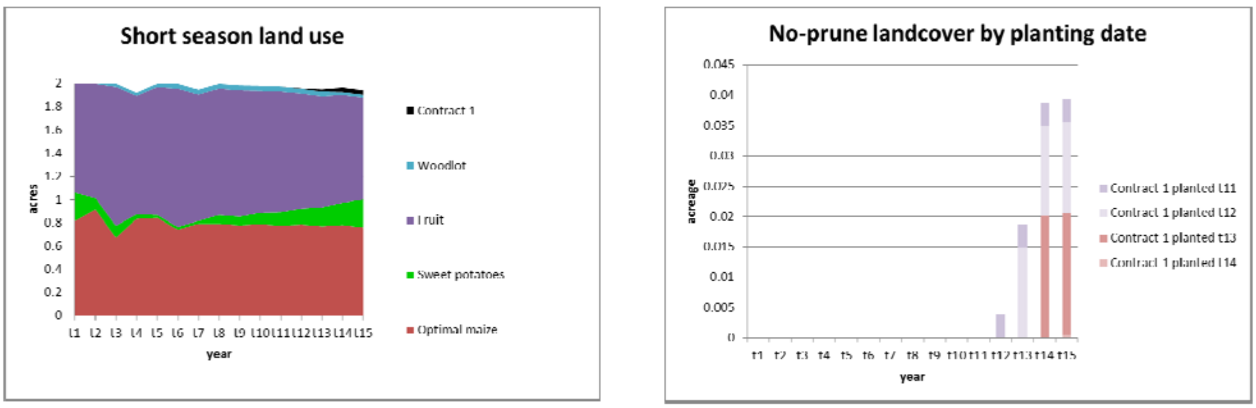
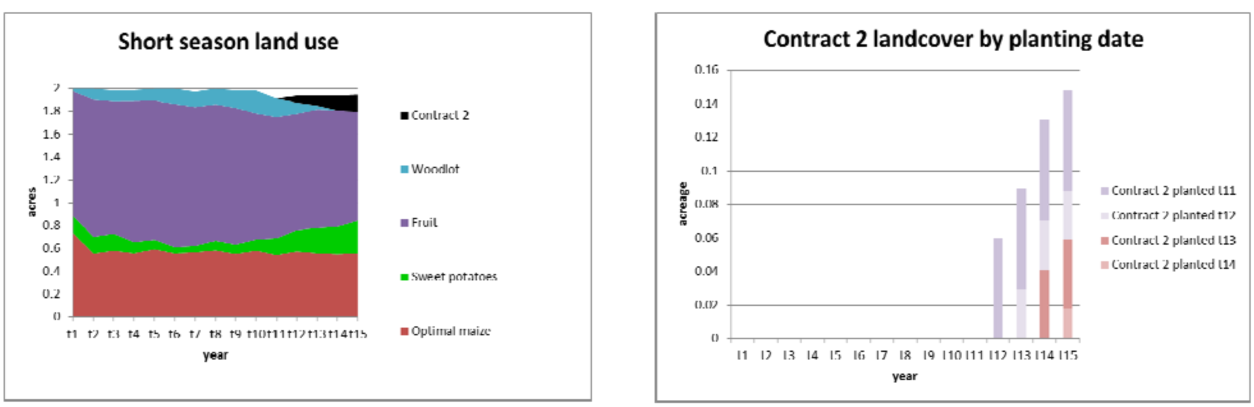


Figure 37: Land use choices under Contract 2, $1000 per ton, maizereq=*12*



Summary of the model simulations

The simulations reviewed in this and the previous sections demonstrate the model's responsiveness to the representative household's underlying conditions. In particular, we have seen that responses for maize self-reliance have a large effect on farm income, whereas the prospect of carbon payments will have relatively impact on income, land use, and total carbon sequestration. Accounting for risk aversion and the potential for declines in maize yields due to climate change reduces the land allocated to woody perennials, whereas relaxing maize self-sufficiency constraints frees up more land for them. These conclusions are reviewed in **Error! Reference source not found.** below.

Table 10: Model experiment summary statistics

Simulation	Total farm household income (NPV, $)	Income per household per year (CV, $)	Income per person per day (CV, $)	Total area in maize (ac)	Total area in woody perennials (ac)	Above-ground carbon stocks* (tons CO2)
Baseline	3790.48	531.63	0.25	0.79	0.83	N/A
Both types of risk aversion (revphi=2, yieldphi=0.2)	3270.96	470.75	0.22	0.79	0.81	N/A
Maize self-reliance relaxed (maizepurch=12)	4697.53	676.93	0.31	0.58	0.99	N/A
Experiment 1	2893.05	397.16	0.18	0.90	0.70	N/A
Experiment 2	3577.92	496.61	0.23	0.82	0.82	N/A
Experiment 2 with risk aversion (revphi=2, yieldphi=0.2)	3113.91	445.66	0.21	0.82	0.80	N/A
Contract 1, $1000 per ton	3803.04	536.81	0.25	0.79	0.83	0.04
Contract 2, $1000 per ton	3829.21	543.71	0.25	0.79	0.83	0.06
Contract 2, $1000 per ton, maize self-reliance relaxed (maizepurch=12)	4847.87	720.24	0.33	0.58	0.99	0.32

NPV refers to net present value, or the value of income discounted to the first year's perspective. CV refers to current value, or the value at the time of computation.
These income figures do not include the value of the consumption of food and fuel.
*Carbon stock calculations assume that net carbon accumulated by all annual and harvested perennial land-uses are zero.

The economic environment of the smallholder farm explored with the model is strongly influenced by the nutritional needs of its inhabitants, and this reduces the potential effect of any price-based policy intervention. Even at 50 times a reasonable price for carbon sequestration, the farm household does not have the resources to reallocate land to fulfill the contract while still meeting subsistence needs. The inseparability of their decisions about what to eat and what to grow complicates programs designed to enhance their incomes through land diversion payments for ecosystem services. The model presented here demonstrates the need for new policy interventions that speak to nutritional demands and preferences as well as income-maximizing behavior.

V. Conclusions and Policy Implications

We developed a mathematical model of resource-poor, small-scale agricultural household behavior in areas of eastern Africa where agroforestry initiatives and policies used to promote them might enhance food security, and increase incomes and ecosystem service flows. The model can assess (within limits) the extent to which policy-induced and other changes in the 'realities' faced by smallholders at or near the Kenyan research site affect land and labor use choices, and with what implications for farm household income.

The model is fundamentally an economic model in which the profitability of alternative uses of time, land and cash is *the* driving force behind decisions related to the use of a household's resources, some of which can be deployed off-farm. The model is a multi-period bioeconomic optimization model; temporal resolution and extent are choice variables of the analyst, but these choices are governed by agroecological and other factors; the spatial resolution of the model is the operational holding of a small-scale farmer. Archetypical production technologies and their associated input bundles were identified for all production and extraction activities, and complete sets of input and product price series were constructed, some varying on a monthly time step. With technical options and price series specified, the model chooses the land uses (product mix) and the production technologies (including the use of household and hired labor) that maximize the discounted stream of disposable income for an archetypical household, subject to a number of constraints. These constraints are socioeconomic (e.g., available family labor, off-farm employment options, available loans, and household essential consumption), agronomic (e.g., crop nutrient requirements, rotational requirements, pasture carrying capacity, and livestock birth and death rates), and market-related (e.g., limits on the amounts of products that can be sold in the market in a given time period), and were all made specific in the model.

The farm-level bioeconomic model generates baseline results for land use, labor use and purchases/sales, food purchases and sales, livestock purchases and sales, and fuelwood production/collection and sales that are generally consistent with patterns for these choices that were observed at the study site, or that are contained in data for similar small-scale farms in nearby sites. Baseline results also capture the low levels of cash income that can be generated by small-scale farming systems at the research site. The model 'reacts' as one would expect to changes in key technical and price parameters, and to changes in key constraints, e.g., increases in farm size lead to increases income but to only small changes in land use patterns, and improvements in market integration lead towards specialization.

We then test-drove the model to address two key issues. First, the model was used to examine the effects of climate change on smallholder resource use decisions and on income. Climate-change-induced reductions in maize yields led to increased land dedicated to maize to meet food needs, and to consequent reductions in income and in the amount of area dedicated to woodlots. These results support the notion that semi-subsistence smallholders may be particularly vulnerable to the effects of climate change, provide estimates of costs to households of yield declines attributable to climate change, and suggest technological and other options for reducing these costs.

Second, the model was used to assess the effects of payments for ecosystem services on land use choices. Two types of contracts for compensating farmers for accumulating above-ground biomass were included in the model—one offering an annual fixed, per-acre payment for planting and then retaining *Eucalyptus* trees with the option to prune and sell fuelwood, and another with the same terms except for less frequent compensation based on the additional carbon sequestered by the growing trees. Modeling results suggest that payments of at least $1000 per ton of CO_2, amounting to more than $100 per acre per year for farmers once administrative costs are considered, would be required to induce the archetypical farmer to begin to allocate farmland to *Eucalyptus*. Our results suggest that paying farmers, even the resource-poor farmer captured in this model, to sequester carbon could be an expensive proposition.

Acknowledgements – Jan Börner provided guidance in selecting among available modeling options and also provided code to support the launching of this research efforts; without his insights, efforts, and generosity this project could not have begun smoothly. Our fieldwork was coordinated by Luka Anjeho, with further support by Mark Ocholla and Millicent Akoth Omboga

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