Simulating soil fertility and poverty dynamics in Uganda: A bio-economic multi-agent systems approach

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This is a post-print accepted manuscript, which has been published in the journal Ecological Economics. Please cite this publication as:

Scheinemachers, P., T. Berger, J.B. Aune. 2007. Simulating soil fertility and poverty dynamics in Uganda: a bioeconomic multi-agent systems approach. Ecological Economics 64: 387-401.

You can download the published version at:
http://dx.doi.org/10.1016/j.ecolecon.2007.07.018

Abstract

Declining soil fertility and increasing rural poverty are major problems facing sub-Saharan agriculture. Bio-economic modeling has been used to analyze the complex interaction between ecological sustainability and rural poverty as well as to explore policy options promoting sustainable development. This paper shows that these models can be further advanced by adopting an agent-based modeling approach. This gives a more realistic representation of diversity in socioeconomic and biophysical terms, allows local interaction between households, and can yield an *ex-ante* assessment of the distributional consequences of policy intervention. This paper describes the modeling approach and illustrates it with an empirical application to two village communities in the Lake Victoria Crescent of Uganda. It is shown how the model system can be calibrated with and validated against empirical data. The model is used to analyze the potential effect of short-term credit, mineral fertilizer, and improved maize seed on poverty and sustainability. Simulation results suggest substantial reductions in poverty although the incidence of poverty would remain high and these innovations alone would have little effect on the long-term ecological sustainability of the system.

Keywords: Integrated modeling, agent-based modeling, Tropical Soil Productivity Calculator (TSPC), mathematical programming, MP-MAS, technology diffusion

1 Introduction

The fertility of Ugandan soils is widely reported to be in decline as nutrients lost through harvests, erosion, and leaching are insufficiently replenished (Wortmann and Kaizzi, 1998; Pender et al., 2004; Esilaba et al., 2005; Nkonya et al., 2005). At around 2 kg/ha, the use of mineral fertilizers in Ugandan agriculture is extremely low (FAO, 2007). High fertilizer prices, as compared to the price of crop output, and insufficient access to credit have been identified as major constraints to fertilizer use in Uganda as well as in other parts of sub-Saharan Africa (Yanggen et al., 1998; Crawford et al., 2003; Jayne et al., 2003; Nkonya et al., 2005; Woelcke, 2006).

The first objective of this paper is to analyze the potential benefit from greater access to mineral fertilizers and short-term credit. Previous research tackling such questions often used bio-economic farm household models (Ruben and van Ruijven, 2001; Holden and Shiferaw, 2004; Janssen and van Ittersum, 2007). This approach, based on mathematical programming (MP), has proved useful to integrate economic with biophysical models. Yet, most bio-economic farm household models are non-spatial, capture only little real-world heterogeneity in socioeconomic and environmental terms, and do not capture interactions between households.

The second objective of this paper is to show that these limitations can be largely overcome by adopting an agent-based modeling approach. Multi-agent systems (MAS) are spatial models using layers of grid cells to represent a physical landscape; they capture heterogeneity by representing all farm households as individual agents and these agents can interact based on pre-defined heuristics (Berger et al., 2006). The paper shows that such integrated MAS can be based on bio-economic farm household models and can be calibrated and validated in a similar vein.

The paper starts by delineating the present model to other similar agent-based modeling approaches. After introducing the study area in Uganda, each model component is described in detail on the basis of this empirical application. This is followed by a validation of the baseline scenario. We then present simulation runs in which we analyze how access to short-term credit and innovations could affect poverty and sustainability. Finally, the methods and results are discussed and the paper ends with a conclusion.

2 Delineation to other agent-based modeling approaches

Advances in land use cover change (LUCC) models and multi-agent systems (MAS) have opened new possibilities for integrating models. Initial attempts with cellular automata, which were a kind of 'thinking pixels', have gradually turned into more complex representations of farm households. In a previous issue of this journal, Boulanger and Bréchet (2005) compared the potential of six modeling approaches to inform policy makers on sustainable development. They found MAS to be the most promising simulation model for its bottom-up structure that captures micro/macro linkages, its interdisciplinary potential, and its realistic representation of agents and their environment.

The present model falls into the class of multi-agent systems applied to land-use/cover change (MAS/LUCC). These models couple a cellular component representing a landscape with an agent-based component representing human decision-making (Parker et al., 2003; Robinson et al., 2007). MAS/LUCC models have been applied on a wide range of issues in ecological economics such as land cover change (Deadman et al., 2004), irrigation management (Barreteau et al., 2001; Becu et al., 2003), migration and deforestation (Huigen, 2004; Le, 2005), rangeland management (Janssen et al., 2000), technology adoption in agriculture (Berger, 2001), and sustainable land use (Matthews, 2006). The present MAS approach distinguishes itself most clearly from most other approaches in three aspects that are detailed in the following.

First, the present approach uses MP to simulate human decision-making and to integrate this decision-making with the biophysical part of the model. Balmann (1997) pioneered the use of MP in agent-based models and was followed by empirical applications of Berger (2001) and Happe (2004). The use of MP at the core of the decision-making procedure is suitable to capture agent heterogeneity and economic trade-offs while its focus on constraints has a clear link to policy relevant questions (Schreinemachers and Berger 2006a).

Second, it uses the Tropical Soil Fertility Calculator (TSPC) to simulate soil dynamics and crop yields, which is suitable for data-scarce environments like this application to Uganda. In a comparable study to soil fertility changes in the mid-hill areas of Nepal, Matthews (2006) combines DSSAT crop models to simulate crop yields with the CENTURY model to simulate water and nitrogen dynamics. Yet, as the DSSAT crop models run on a daily time step it requires much more data than the TSPC, which in the present application runs on an annual time step.

Third, the model is able to simulate poverty dynamics by integrating econometrically estimated expenditure models into the core of the MP-based decision component. The poverty level for each agent is quantified as the difference between the simulated levels of food consumption and food requirements.

3 The study area in Uganda

The MAS model was calibrated to two villages, Magada and Buyemba, located in the Lake Victoria Crescent of southeast Uganda. These villages have been the subject of much previous research (Wortmann and Kaizzi, 1998; Brunner et al., 2004; Esilaba et al., 2005; Woelcke, 2006). The villages are densely populated (about 400 people/km^2) and cover an area of about 12 km^2. High population density and rapid population growth have put pressure on the capacity of the land to supply food in sufficient amounts, which is a phenomenon also observed in many other parts of sub-Saharan Africa (Drechsel et al., 2001). Wortmann and Kaizzi (1998) found that soil fertility in the area is generally low and declines rapidly. Climatic conditions allow the sequential cultivation of two crops per year. Cassava, sweet potato, and bean are the main food crops, coffee is the main cash crop, while maize and plantain are both sold and home consumed. Farm households predominantly rely on the hand hoe in their crop management; the use of external inputs such as fertilizers, pesticides, and improved seeds is rare.

3.1 Data

Socioeconomic data were derived from three sources: the Uganda National Household Survey (1999-2000) including over 10,000 households from almost all parts of the country; a survey by the International Food Policy Research Institute (IFPRI) including 451 farm households (2000-2001) selected from about 100 Ugandan communities; and a survey by the Center for Development Research (ZEF-Bonn) including 106 farm households surveyed in the two study villages (1999-2000). Spatial data were obtained from geo-referenced soil samples and a Digital Elevation Model of the study villages as described in Berger and Schreinemachers (2006a). The biophysical part was parameterized from secondary data.

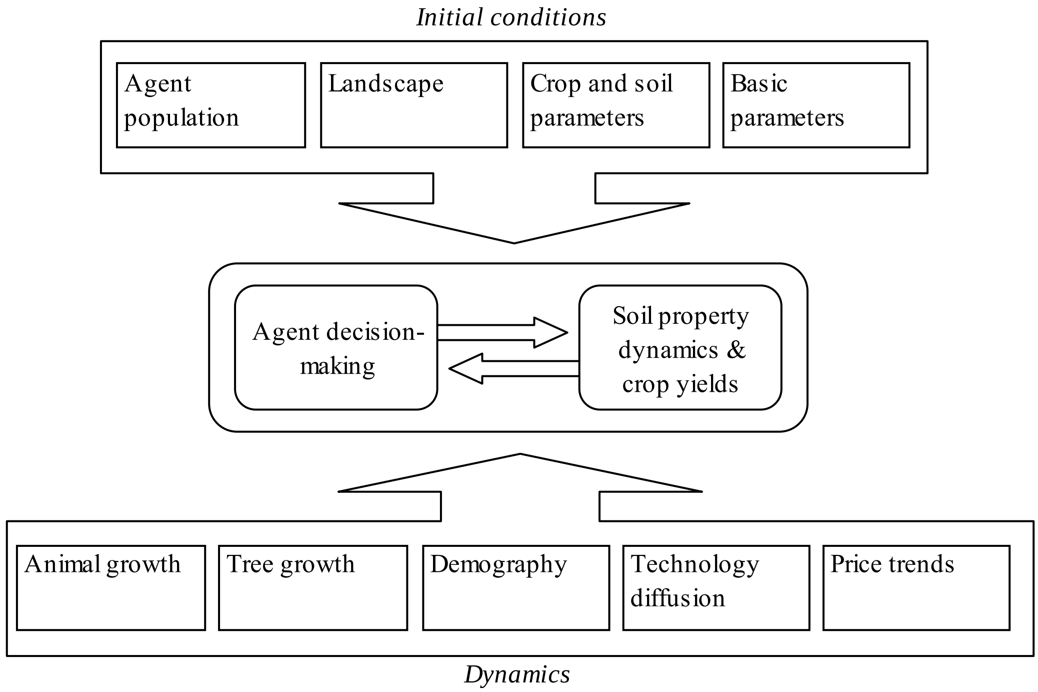
4 Model description

4.1 Component-based model design

The modeling approach used in the paper is called MP-MAS, which stands for mathematical programming (MP) based MAS. It builds on previous work by Berger (2001); a freeware version and manual are available for download at http://www.uni-hohenheim.de/mas/software. MP-MAS has a component-based model design with its source code written in C++ object-oriented programming language. Depending on the needs of a particular application, existing components can be included or excluded while new components can be developed and plugged into the model. Input data for each component are organized in separate Microsoft Excel workbooks, which are converted into plain text ASCII files when running the model.

Figure 1 shows the model design with each box representing a separate component. Three groups of components can be distinguished. At the nucleus of the model is the bio-economic component that simulates the decision-making process, crop yields, and soil fertility changes. A group of four components define the initial conditions for each agent, such as the location of plots, the fertility of the soil, the composition of the households, and parameter values that initiate the model. Another group of five components define the dynamics, including animal and tree growth, technology diffusion, demography, and price changes.

Figure 1: Components of the MP-MAS as applied to Uganda



4.2 The agent decision model

The agent component consists of an economic model, which uses recursive MP models to simulate the decision-making of real-world farm households. It builds on a long tradition of whole farm programming models in agricultural economics (e.g., Hazell and Norton, 1986; Dillon and Hardaker, 1993).

Any MP model has three parts. The first part is an explicit specification of all possible decisions related to agriculture (also called activities or decision variables); these include growing crops, raising livestock, and selling, consuming, and purchasing agricultural products. The second part is a utility function that specifies how much each activity contributes to the attainment of the decision-makers' objectives; in the present model these objectives include household net cash income – i.e., the farm cash surplus plus other household receipts (Dillon and Hardaker 1993), household consumption of food produced on the farm, and the expected future farm cash surplus and home consumption from investments. The third part is a set of equations that link the decision variables and constrain them to only feasible solutions; for instance, they ensure that an agent does not cultivate more land than it actually has available.

Agent decision-making is simulated by a computerized search for a combination of activities that yield the greatest objective value while not violating any constraints. The non-linear response of crop yields to alternative combinations of inputs was captured using a piecewise linear segmentation. The model included 11 crops and 7 intercrop combinations. Each crop was segmented into 90 activities by specifying different combinations of land quality, management, and fertilizers. Table 1 shows a concise version of the MP matrix. The full matrix has 2350 activities and 556 constraints. For more details about the model equations and parameters the reader is referred to Schreinemachers (2006).

Two novelties about the MP model are worth mentioning (for more detail see Schreinemachers and Berger, 2006a; b). First, the consumption part includes a detailed budgeting system that allocates the income from farm and non-farm activities to savings, non-food expenditures (using a modified Working-Leser model), and eight categories of food products (using a Linear Approximation of the Almost Ideal Demand System (LA/AIDS). By converting the expenditures on each food category into energy units, it gives an estimate of (consumption) poverty. A second innovation is a three stage decision model that separates the decisions to invest, to produce, and to consume while capturing the interdependencies between each stage.

Figure 2: Dynamics and interaction of soil processes and farm decision-making

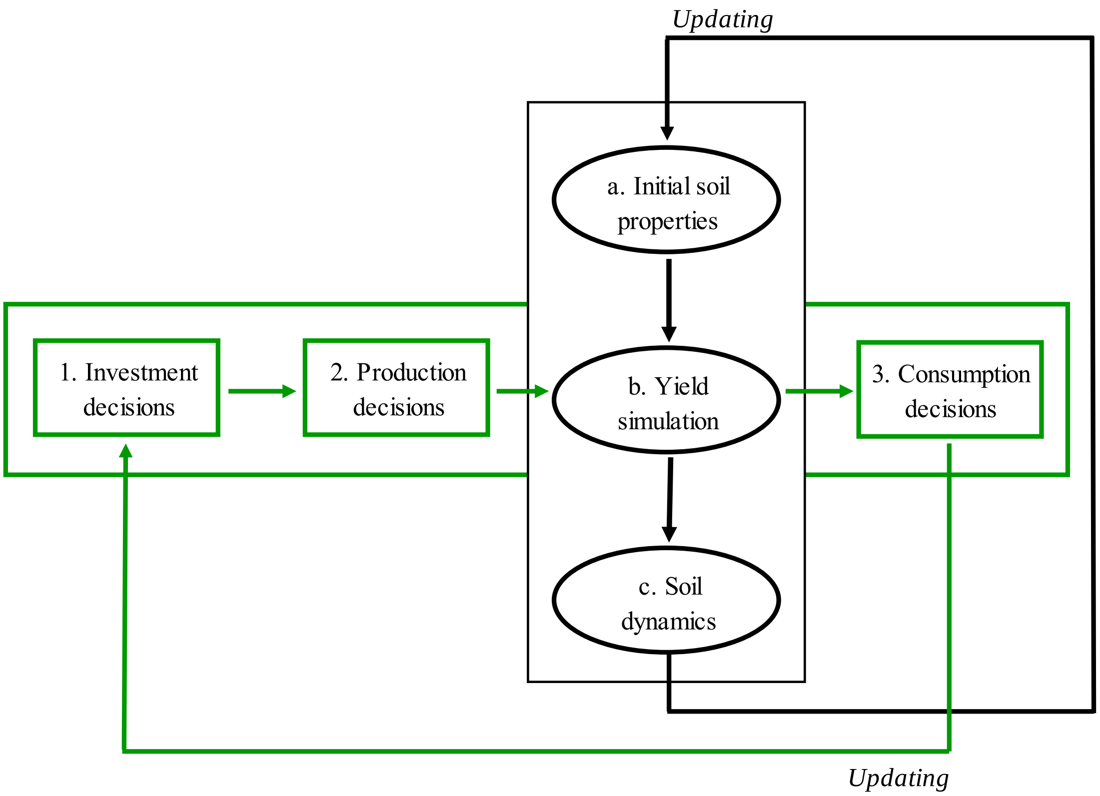


Figure 2 conceptualizes the annual sequence of farm household decision-making as three horizontally ordered rectangles; this sequence is repeated for all agents over the simulation horizon, which was set to 15 years. An MP model is solved for each agent at each stage. Investment and production decisions are based on expected yields and expected prices. The biophysical model, simulating crop yields, intersects the decision sequence after input decisions have been made in the production stage. Expected yields and expected prices are then replaced by simulated actual yields and actual prices after which the obtained income is allocated to consumption and savings in the consumption stage. This figure also shows the interdisciplinary nature of the MAS model, as impact indicators (nutrient stocks and food consumption) are incorporated into the model's kernel where they interact through the crop yield equation.

A large number of coefficients in the MP matrix are tailored to each individual agent in a sequential fashion: resource endowments on the right-hand-side, crop and livestock yields, food energy needs, coefficients in the expenditure functions, and access to innovations. Agent-specific coefficients are printed in bold in Table 1.

4.3 Soil fertility dynamics and crop yield

Following the vertically ordered ovals in Figure 2, crop-soil processes were conceptualized as a continuous sequence of three stages:

1. The computation of yield limiting factors based on soil properties (at the start of the period) and applied levels of variable inputs (fertilizer and labor).
2. The computation of crop and residue yields.
3. The updating of soil properties based on the harvested amounts of crop yields and residues and natural processes such as erosion, deposition, leaching, and decomposition.

These three phases were modeled using an extended version TSPC (Aune and Lal, 1995; 1997; Aune and Massawe, 1998). The TSPC was specifically designed for tropical soils and includes nitrogen, phosphorus, potassium, soil organic carbon, and acidity (pH) as determinants of crop yield. Acidity is often a limiting factor in highly weathered tropical soils, but is commonly omitted in crop models designed for temperate regions where acidity levels do not commonly constrain crop yield. In forest soils in Uganda organic P when mineralized will provide a major source of available P (Udo and Ogunwale, 1977) and significant correlations have been found between soil organic matter and response to P and between soil organic matter and extractable P (Foster, 1981). Based on soil analyses results from Foster (1976), a response function was established between available P and yield. Release of P was calculated based on the release from the organic P pool, because the organic P pool has been found to represent 60 to 80 % of the active P fraction. The C:P ration was set to 100 (Shepherd and Soule, 1998).

Following Figure 2, initial soil properties together with management decisions determine crop yields. The TSPC simulates crop yields based on empirical crop yield functions that resemble a Mitscherlich-type of crop yield response as factors are assumed complementary and yields plateau if a factor is in limited supply. This non-linear crop yield equation computes the yield of crop *i* at plot *k* and at time *t* as:

$$Y_{ikt} = p_i * F_{LABikt} * F_{NAV_{ikt}} * F_{PAV_{ikt}} * F_{KAV_{ikt}} * F_{SOC_{ikt}} * F_{pH_{ikt}} * h_{ij} * g_i \tag{1}$$

with Y_{ikt} denoting yield (kg/ha/season) and p_i the yield potential of crop *i*, the subsequent six variables are reduction factors for management (F_{LAB}), available nitrogen in the soil (F_{NAV}), available phosphorus (F_{PAV}), available potassium (F_{KAV}), soil organic carbon (F_{SOC}), and acidity (F_{pH}). The factor h_{ij} adjusts the yield of crop *i* if intercropped with a crop *j*. Finally, g_i is an adjustment factor that fits the equation to an observed level of yield.

All reduction factors were specified as logarithmic functions while soil organic carbon was taken as a quadratic function. Factors were scaled from 0 to 1; the closer to zero, the stronger it constrains yields and the lower the efficiency of all other factors. Factors with a value of one do not limit crop yield. The crop reduction factors were obtained by analyzing fertilizer experiments and corresponding soil data in Uganda and elsewhere if no data were available from Uganda (Foster, 1976; Obiagwu, 1995; Kaizzi and Wortmann, 2001; Smithson et al., 2001). As reduction factors came from different sources, correlations could not be taken into account in the calibration of the crop yield equations. The effect of labor was estimated econometrically for each crop by fitting farm household survey data to a Cobb-Douglas production function using stochastic frontier analysis (see Schreinemachers 2006 for details).

Yield functions were parameterized for 11 crops plus one fallow activity. In descending order by cultivated area, these crops included: maize (in three varieties), bean, cassava, sweet potato, coffee, plantain, groundnut, millet, and sorghum. Cassava and plantain were treated as annual crops although farm households sometimes postpone harvesting cassava as its tubers preserve well in the soil. Coffee was the only perennial crop included.

In Uganda it is common to find several different crops simultaneously grown on a single plot. As soil dynamics are not just a function of present land use but also of the land use history, the soil model would need to keep track of all crops and inputs at a subplot level. As this would overly complicate the model, it was simplified by averaging the crop-specific calculations to the grid cell level at the end of each period. Acreage weights were used for this purpose, which were calculated as the proportion of the grid cell that a crop occupies in a year. This is a justifiable approach as long as the size of the grid cells is small.

4.4 Components defining the initial conditions

4.4.1 Agent population

The study area included 520 farm households and each was represented by a unique computational agent in the model. Agents were empirically parameterized by applying

Monte Carlo techniques on a random sample of farm households as described in Berger and Schreinemachers (2006). This procedure ensures a realistic representation of agent heterogeneity by varying the following five aspects:

- land quantity (hectares) and quality (soil physical and chemical properties, and land-use history);
- labor quantity (household size) and quality (sex and age composition);
- livestock quantity (number of animals) and quality (species and age);
- quantity of permanent crops (ha of coffee) and quality (age of plantation); and
- knowledge as approximated through membership of an innovation group.

There are other sources of heterogeneity that one can think of, such as variation in price expectations, household objectives, incidence of crop pests, human sickness, farming skills, and educational levels; these were not considered in the present model, but could, if empirical data were available.

4.4.2 The landscape

The real-world landscape is represented by a grid of cells, 0.5 ha in size, which is about the size of the smallest agricultural field cultivated by farm households in the study area. Spatial information was organized in layers, including the location of plots, the location of the farmsteads, and soil properties.

The economic and biophysical models were integrated at a plot level, which can be seen as a compromise between the household level of the economic model and the crop level in the biophysical model. Agent decisions were made spatial by specifying plot specific activities and yield expectations in the MP matrix. Up to five plots were included in the matrix. If an agent owned more than five grid cells (2.5 ha) then cells with the most similar land suitability were merged.

4.4.3 Crop and soil parameters

The crop and soil parameters of the TSPC model were organized in a separate Excel workbook so that the user can adjust parameters without having to update the C++ source code. All parameters can be found in Schreinemachers (2006).

4.4.4 Basic parameters

The basic parameter file enables the user to switch on or off model components and it sets certain parameter values that are used by more than one component. For instance, it sets the size of a grid cell, it defines the number of plots included in the decision model, and it specifies the number of livestock species included.

4.5 Components defining model dynamics

4.5.1 Technology diffusion

Technology diffusion was based on individual network-thresholds as described in Berger (2001). An individual network threshold is the proportion of peers in a network who must have adopted before the individual will consider adopting as well. An agent with a low threshold value is risk-taking, while an agent with a threshold value closer to unity is risk-averse as it needs much information before it will consider adopting. Each agent was allocated one out of five possible threshold values based on empirical data from the household survey.

The diffusion of innovations was simulated as a two stage procedure as shown in Figure 3. In the first stage, the agent compares the adoption level in the network with its own threshold; if the first exceeds the second then the innovation becomes accessible to the agent and enters the MP model, which by solving simulates the adoption decision. The innovation is adopted if it is selected among the decision variables, which increases the aggregate adoption level in the network, making the innovation accessible for agents with higher threshold values in the following periods of the simulation.

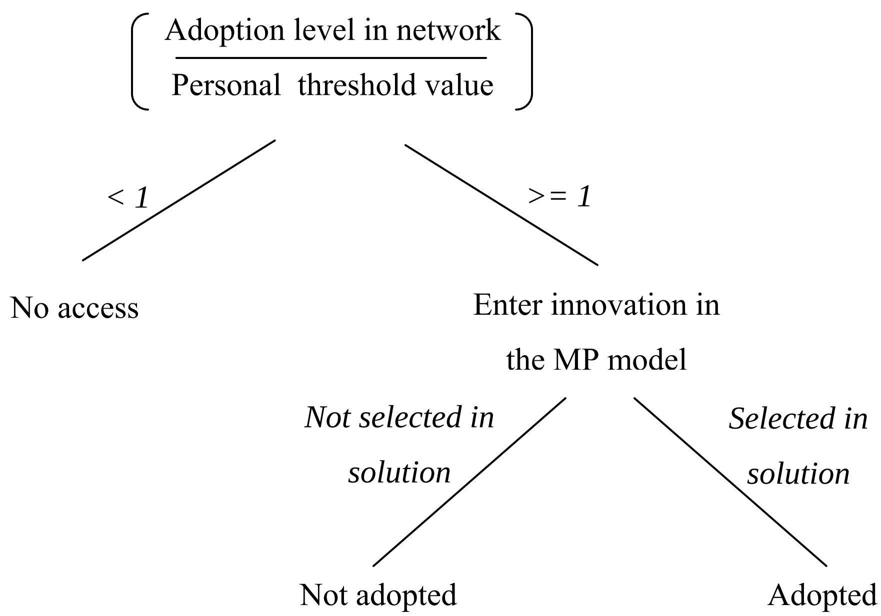


Figure 3: Decision tree for technology adoption

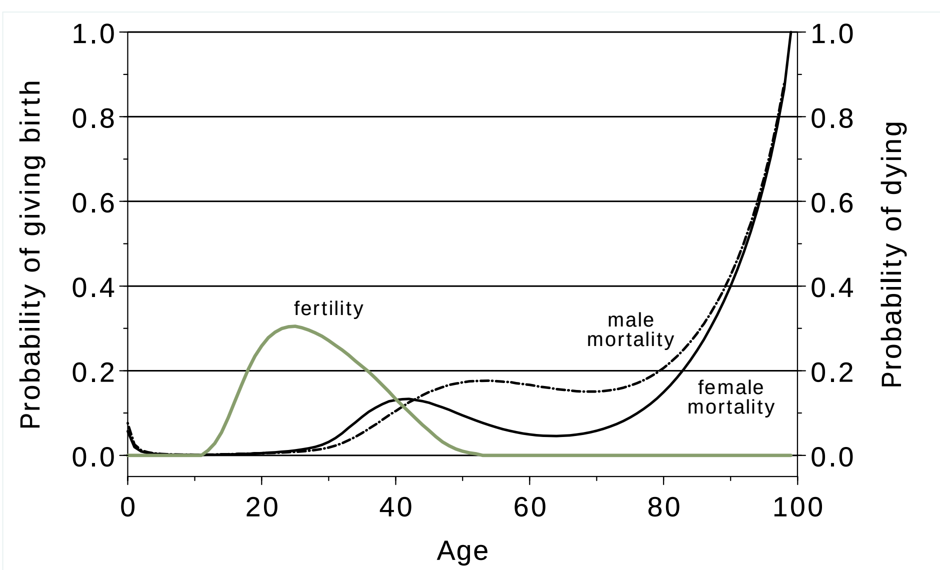
Networks of technology diffusion are the only type of agent-agent interactions in the present model application. Land and labor markets were excluded as less than two percent of the agricultural land was annually transacted among households and labor sharing agreements are nowadays rare. Though the hiring of labor was included, this was not handled through an internal labor market.

4.5.2 Demography

Uganda has one of the highest fertility rates in sub-Saharan Africa with a woman bearing about six children on average in a lifetime (The World Bank, 2004). However, mortality rates are also high with male infants having just 25 percent chance of surviving to the age of 65 (*ibid.*).

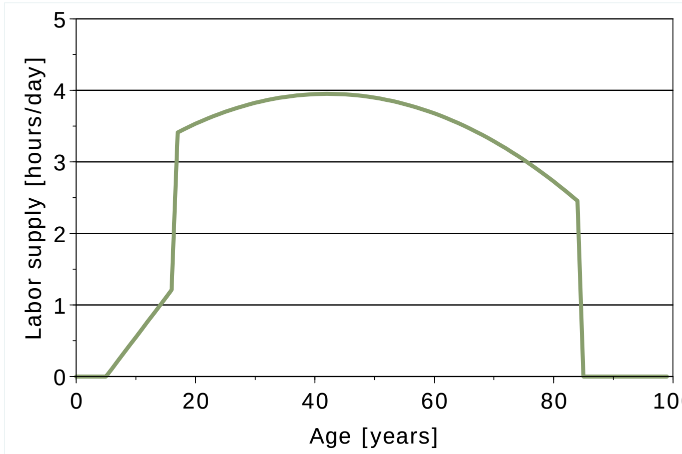
For the sake of simplicity, family planning was not endogenous in the model but currently observed sex- and age-specific fertility and mortality rates were uniformly imposed on all members. The fertility rate was expressed as the probability of bearing a child and the mortality rate as the probability of dying at a certain age. Data were derived from Feeney and Zaba (2001). These probabilities were applied to each household member at the end of each period, thus creating a random demographic simulation component. Figure 4 shows the two demographic trends included in the model. Two lines depicts the probability of dying at a certain age (also called the force of mortality) while the other line depicts the female probability of giving birth.

Figure 4: Age-specific mortality and fertility rates for Uganda



Source: Based on Feeney and Zaba (2001)

Figure 5: Age-specific agricultural labor supply



Source: Estimated from the 2000-2001 IFPRI Survey. *Note:* Child labor supply was approximated by a linear function that matches the average child labor supply (0.6 hours/day) in the peak season. It was assumed that labor supply drops to zero at the age of 85 years, though few agents survive to this age due to high mortality.

Agents, like the households they represent, are made up of members who have sex and age characteristics. The demographic composition of the agent affects its behavior through the labor supply and consumption needs, which will be detailed in the following.

Agricultural labor supply for each member was specified as a function of age and sex and parameterized by multiple regression analysis. As labor data are notoriously hard to collect and can have large measurement errors it is important to estimate the labor supply and demand from the same source so that possible data errors are likely to cancel out. The IFPRI 2000-2001 survey did not record labor hours for individual household members, only total adult and child labor. The function was therefore parameterized by regressing the average adult daily labor supply on the age of the household head while controlling for the effect of total household size, the share of children, and location dummies.

Resource endowments in the MP component should, however, not reflect the average labor supply estimated from regression but the maximum labor supply. To correct the function, the average labor supply (3.15 hours/day) was compared with the labor use in the September peak season (3.92 hours/day) and the difference (0.77 hours) was used to shift the labor supply function upward to approximate the maximum labor supply. Figure 5 shows the agricultural labor supply for males; the difference between male and female labor supply was insignificant and the same labor supply function was therefore used. Significant differences were, however, found between male and female labor use per crop, and these were included as separate constraints in the MP model.

4.5.3 Price trends

Prices include input prices, selling prices, and the valuation of agricultural products that are home consumed. In addition, the model requires an expected price for future output from investments in livestock and coffee plantations that influence the investment decision. As the research area is small, all prices were taken as exogenous in the model and were specified for each year in the simulation.

4.5.4 Animal growth

Goats and cows are the main types of livestock in the present model. Labor, feed, pasture, and cash are the inputs to livestock production while manure, milk, offspring, and meat are its outputs. As only few data were available on livestock production in Uganda, literature values were used instead.

The production cycle was divided into four periods (birth, puberty, maturity, and slaughter) while input requirements and production values were interpolated between these (see Schreinemachers 2006 for parameters). Animal feeding was modeled based on metabolizable energy units. Metabolizable energy requirements were computed following Close and Menke (1986) as the sum of energy required for maintenance, milk production, gain in animal weight, and weight gain during pregnancy. Agents had to meet these requirements by feeding their livestock with crop residues and/or grain, metabolizable energy values for which were derived from Close and Menke (1986) and Bakrie et al. (1996).

Manure production was specified as a function of feed intake by assuming that an average kilogram of dry matter feed contains 9 MJ of energy and has a digestibility of 50 percent (Livestock Environment and Development (LEAD) Initiative, 1999). Farm households in the study area did not manage animal manure and an equal distribution of manure over the plots was therefore assumed.

4.5.5 Tree growth

Coffee was the only perennial crop included. As for livestock, few empirical data were available on the production cycle of smallholder coffee plantations in Uganda, and secondary data had to be used instead. A five year pruning cycle and a maximum age of 32 years for a coffee tree were assumed.

5 Model validation

One advantage of MP models is that not all equations have to be estimated from a single data set as separate estimates based on primary data, secondary data, and expert opinion can be combined. The trade-off of this flexibility in model calibration is an increased importance of testing whether the model is a valid representation of reality. This is an inherently subjective exercise to which we will return in the discussion section.

McCarl and Apland (1986) separated model validation into 'validation by construct' and 'validation by results'. The first type of validation we have sought to tackle by building the MAS model on well-established theories in economics and agro-ecology and by including model components, such as production functions and expenditure models, which are little disputed.

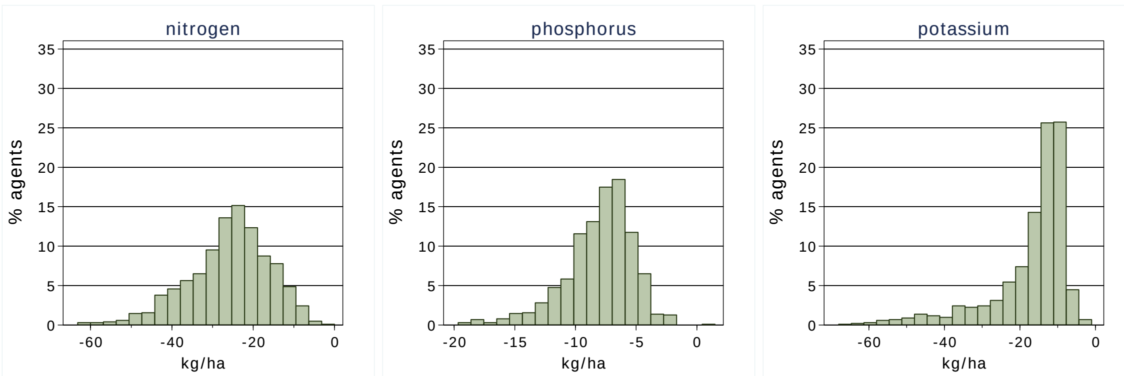
The validation of the results was accomplished in three steps. First, econometrically estimated functions were validated using standard statistical methods (signs of the parameters, significance, and predictive power of the model). Second, separate components (expenditure model, production functions, crop-soil model, agent populations) were validated by comparing observed values with predicted values. Third, the MP-MAS model – combining all the separate components – was validated by comparing observed values with predicted values from running the baseline scenario.

This baseline scenario was defined as the simulation run that reflects the present situation and the present sources of change. The baseline assumes that current trends in demography, soil processes, and the diffusion of innovations will continue and that there are no new external interventions. The following sections highlight the third step of this validation procedure with respect to the main indicators in the model: soil nutrient balances, crop production, and poverty levels.

5.1 Soil nutrient balances

Soil nutrient studies are usually based on in-depth information about a single or limited number of 'representative' farm plots. In reality, there is a wide variation of nutrient dynamics between plots – depending on soil physical/chemical properties, crops, management, and input use. The simulation results of the MAS reproduced such variation between the agents as Figure 6 shows for three main macronutrients.

Figure 6: Simulated nutrient balances

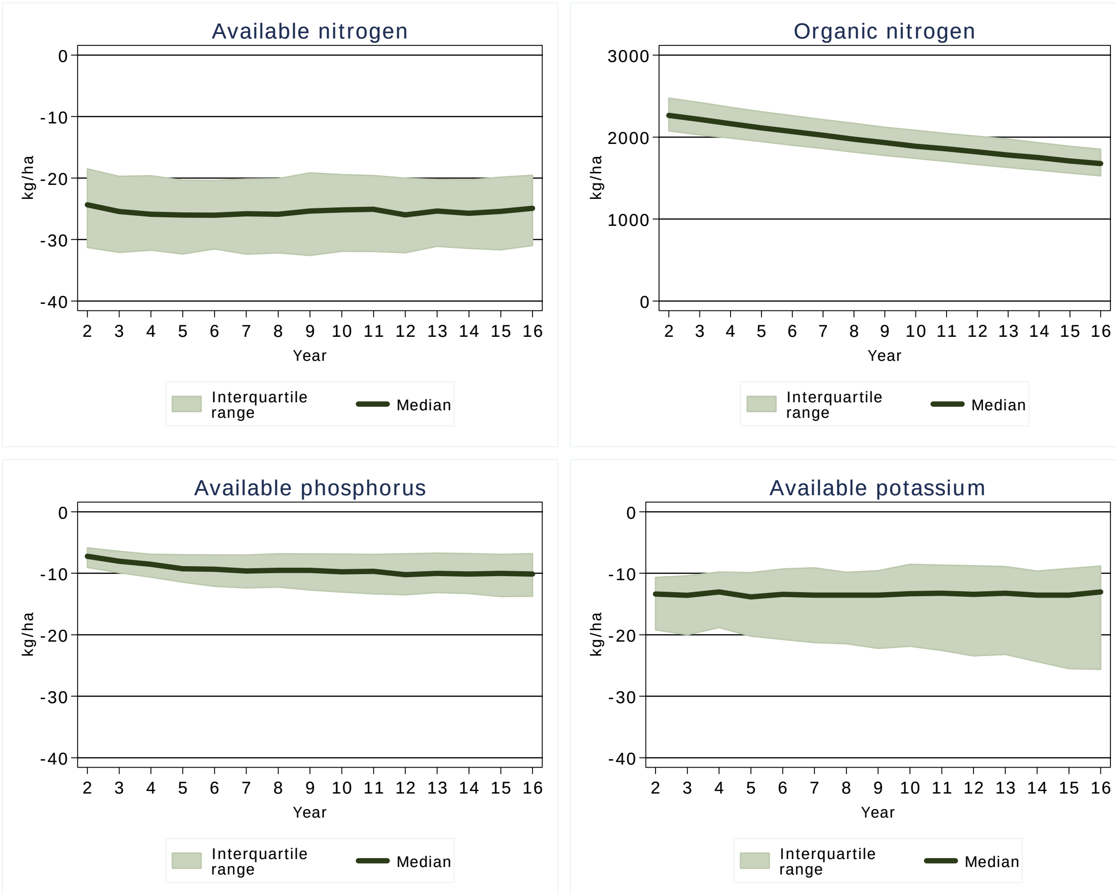


Note: Simulated means over year 2-3 in the baseline scenario.

In addition, Figure 7 shows the development of the median nutrient loss and interquartile range over 15 years of the simulation. It shows that the loss of soil nutrients is about constant over time, implying a constant decrease in the total stock of organic N (upper right diagram).

In absence of detailed field data, it was impossible to validate these simulation results based on direct observation. Average values from literature were therefore used to benchmark the results as shown in Table 2. The table includes a study by Wortmann and Kaizzi (1998) who did a soil nutrient study including one of our two villages; their estimates are relatively high compared to our results and to similar studies in other parts of Uganda and Kenya. Because of a large uncertainty regarding actual nutrient losses, it was not attempted to fit the MAS to the Wortmann and Kaizzi study.

Figure 7: Simulated annual change in soil properties



Note: Simulation results from baseline scenario. Interquartile range is the range between the 25th and 75th percentile

Table 1: Nutrient balances in Sub-Saharan Africa

Location	Balance (kg/ha/year)			Source
	N	P	K	
This study	**-25**	**-8**	**-13**	**-**
Uganda, Mukono district	-49.0	-13.3	-17.3	1)
Uganda, Arua district	-33.4	-6.0	-7.3	1)
Uganda, Palissa district	-21.2	-8.2	-43.0	2)
Uganda, Kamuli, Iganga & Mpigi districts	-30.6	-4.0	-38.9	2)
Magada village, Mayuge District	**-108**	**-14**	**-94**	**3)**
Eastern Uganda (average 8 villages)	-83	-10	-60	3)
Western Kenya	-76.0	-3.8	-	4)
Kenya, Machakos District	-53.0	1.0	-9.0	5)
Sub-Saharan Africa (total)	-22.0	-2.5	-15.0	6)

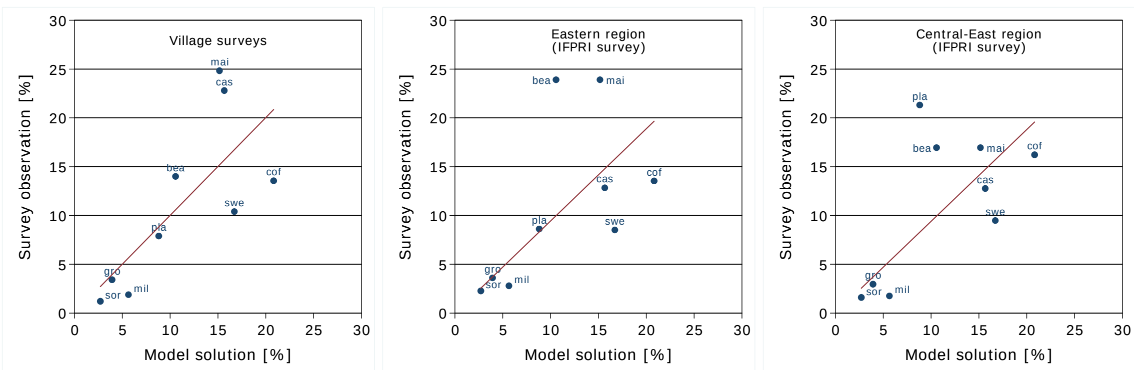
Sources: 1) Aniku et al., 2001; 2) Wortmann and Kaizzi, 1998; 3) Kaizzi et al., 2003; 4) Shepherd et al., 1995 Shepherd et al., 1996 (as cited in Wortmann and Kaizzi, 1998: 115); 5) De Jager et al., 2001; 6) Stoorvogel et al., 1993 (as cited in Wortmann and Kaizzi, 1998: 115). *Note:* Median values are shown for this study.

5.2 Crop production

It was first tested if the individual MP problems gave feasible solutions for all agents; if this was not the case then the matrices were analyzed and changes made where necessary. Price experiments were furthermore conducted to test if an increase in the price of a crop led to this crop increasingly being selected. Finally, observed survey values about crop yields, land-use, and intercropping were compared with simulated values from the first five years of the baseline as shown in the following figures.

Figure 8 compares the simulated land-use pattern, as a percentage of the total cropping area, with the observed land-use pattern. Validation was complicated by a high variation in observed values among surveys and areas within the surveys. The left diagram validates the predicted land-use against the 1999-2000 ZEF Survey. The regression fit falls exactly together with a 45^o-line from the origin, which indicates a good model fit (coeff.=1.00, SE=0.15. R^2=0.82). The second and third diagrams validate model results against the IFPRI Survey, which was used to estimate crop yields, and shows a somewhat lower fit. Unsurprisingly, the fit was worst when taking the central and eastern region in the survey together as in the right-most diagram.

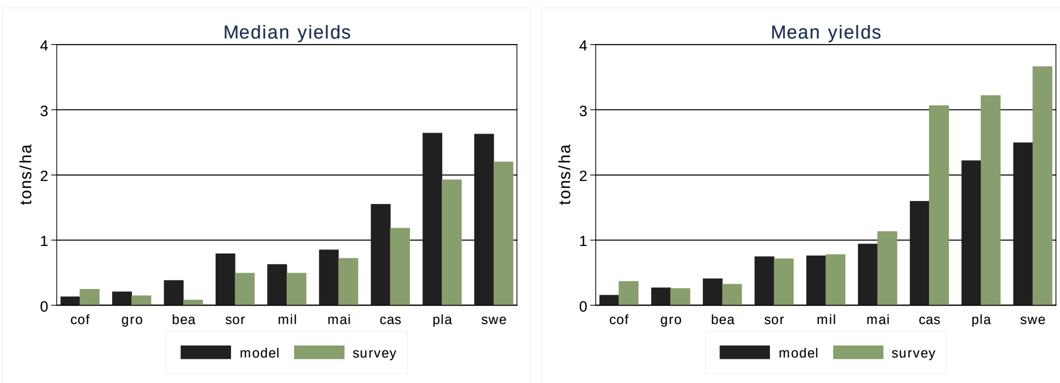
Figure 8: Observed versus simulated land-use



Notes: Simulated means over year 2-3 in the baseline scenario. Line segments indicate the linear regression fit of survey vs. model estimates without a constant term. Model fit: Coeff=1.00; SE=0.15, R^2=0.82 (left); Coeff=0.94; SE=0.18, R^2=0.74 (middle); Coeff=0.94; SE=0.16, R^2=0.79 (right). Crop codes: cof=coffee; gro=groundnut; bea=beans; sor=sorghum; mil=millet; mai=maize; cas=cassava; pla=plantain; and swe=sweet potato.

Figure 9 compares simulated crop yields with observed crop yields as estimated from the IFPRI Survey. The survey mean and median differed widely, because the survey data did not have a normal distribution (right-skewed). This distribution was not well replicated by the model as the simulated crop yields approximated a normal distribution. This positive skew in the survey data was strongest for sweet potato, plantain, and cassava. Crop yields for these continuously harvested crops are, however, notoriously difficult to estimate and statistical errors might therefore explain their deviant distribution. For this reason, it was not tried to bring the model results closer to the survey values. The discrepancy, however, points to one challenge for MAS models, which is to reproduce not just averages but also the underlying distributions.

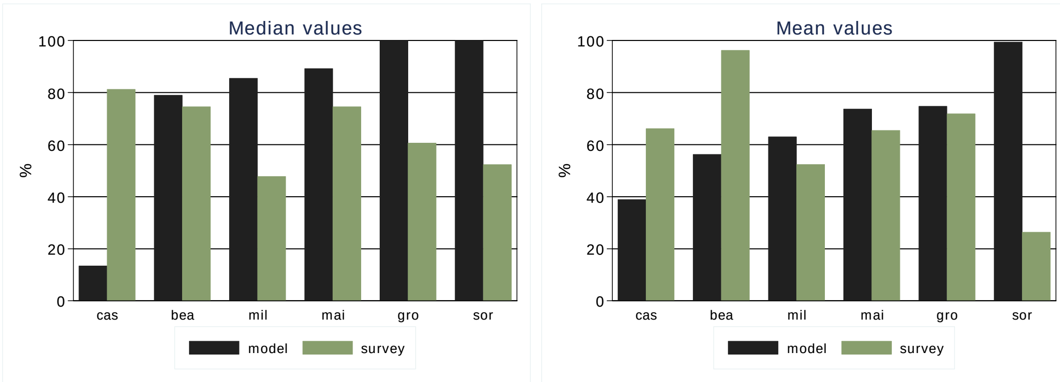
Figure 9: Validation of median and mean crop yields



Notes: Simulated medians and means over year 2-3 in the baseline scenario. See Figure 8 for an explanation of crop codes.

Figure 10 compares the simulated and observed pattern of intercropping. The percentage intercropping was calculated as the area intercropped divided by the total area under the crop. Again, the diagrams show that the survey mean and median differ widely, which points to a skewed distribution. The model overestimated the intercropping of sorghum and underestimated it for cassava, while for the simulated values for the other crops fell in between the survey mean and median.

Figure 10: Validation of median and mean share of intercropping



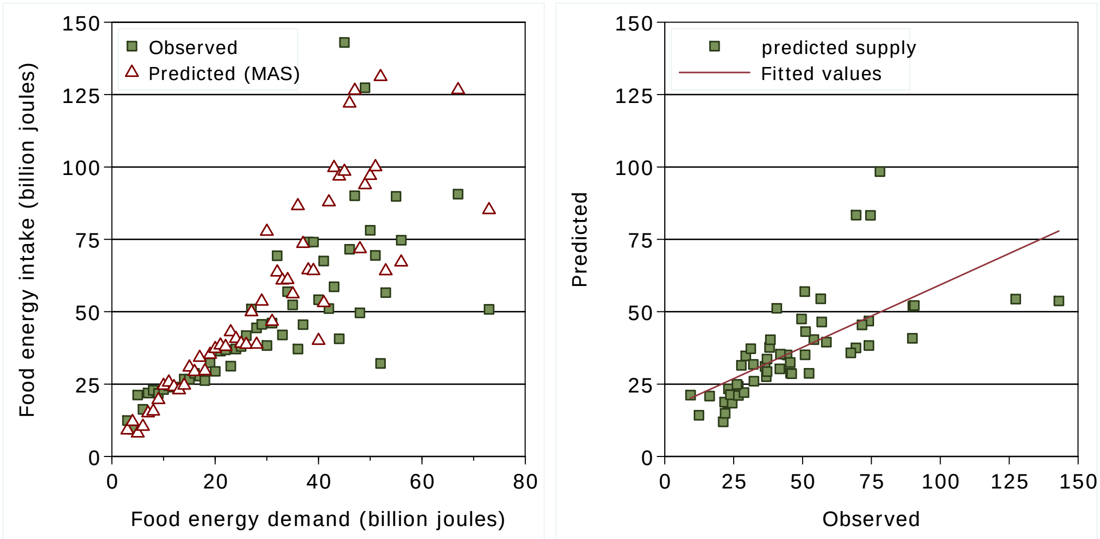
Notes: Simulated medians and means over year 2-3 in the baseline scenario. See Figure 8 for an explanation of crop codes.

5.3 Poverty

The consumption component was validated by comparing simulated results with observed values for income and food consumption. For this, sample households were divided into categories of household size. Households with a size of 2.5–3.5 billion joules were taken into category 2, households with a size of 3.5-4.5 into category 3, etc. Average household size and food energy consumption were calculated for each category from the survey and plotted against simulated values.

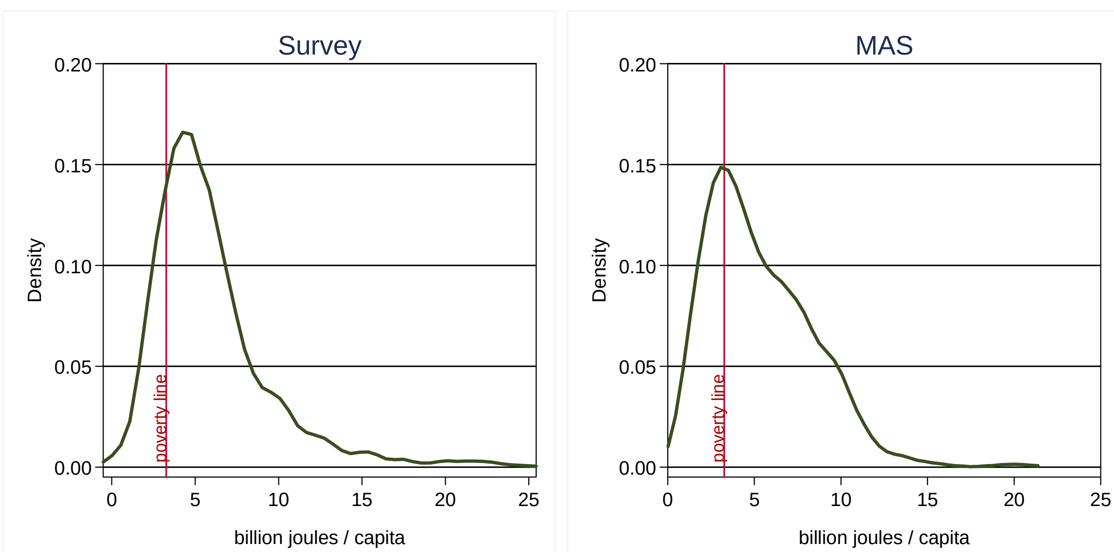
The left diagram of Figure 11 plots the household categories against food energy consumption for both the survey observations and simulation outcomes. The figure shows a relatively close match between model results and survey estimates, especially for smaller households, while the fit is worse for larger households which show much more variation in their food energy intake but only constitute a minority of the households.

Figure 11: Validation of the consumption component



Notes: Model values are simulated means for 520 agents over the first 5 years of the simulation assuming constant soil fertility levels. Model fit for right diagram: coeff=0.77; SE=0.04; R2=0.88.

Figure 12: Validation per capita food energy consumption



Notes: In male adult equivalents. Epanechnikov kernel used. The vertical lines indicate the poverty line of 3.259 billion joules, at which agents' food energy demand equals supply. The survey estimate is based on the farm households in southeast Uganda as recorded by the 1999-2000 UNHS.

In addition, the distribution of food energy consumption was scrutinized at the agent level using a kernel density function. Figure 12 plots the kernel distribution for both the survey (left diagram) and the MAS simulation (right diagram). Again, the kernel estimates are not fully comparable because the survey estimate was based on a much larger area and population and the average household sizes were different. The figure shows that both distribution functions are similar in shape and have a positive skew as a small share of the households reaches high per capita food energy intakes. The share of households in poverty is somewhat greater in the MAS than in reality as indicated by a larger area under the curve left of the poverty line. Yet, considering the limited data available for validation, we contented ourselves with these results.

6 Model results: the impact of improved maize and mineral fertilizers

The model was used to analyze the potential impact of improved access to short-term credit and technologies. The baseline scenario, which assumed the continuation of current dynamics, was compared with two alternative scenarios. In the first policy scenario, a new credit program for technology innovation was introduced at a 34% annual interest rate, which is the average interest rate estimated from the 2000-2001 IFPRI Survey. The credit could only be used for purchasing two types of innovations: seeds of two improved maize varieties and two types of mineral fertilizers. In the baseline scenario the access to these technologies was constrained by the network diffusion model. In the second scenario this constraint was relieved and agents were given full access to these technologies and short-term credit so as to analyze the maximum effect that this policy program could have.

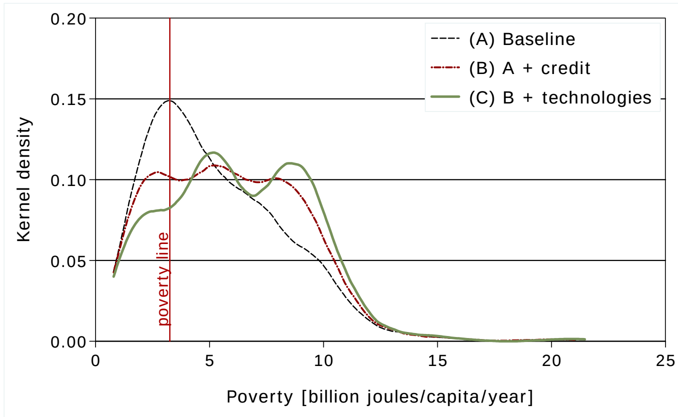
Figure 13 shows the simulation results for these scenarios in terms of three indicators: poverty (measured in per capita food energy consumption), the total stock of nitrogen in the soil, and the amount of available nitrogen for plants. The results are shown as kernel density graphs, which are suitable to show the distributional effects of the three scenarios. For this, the values for each indicator were averaged per agent over all time periods.

Diagram (A) compares the average 15-year well-being of agents between the three scenarios. In the baseline scenario, 28.9 percent of the agents fell below the poverty line, which was defined as the level of consumption where food supply equals the physical food demand. Access to credit reduced poverty, as indicated by the shift of agents across the vertical poverty line. The incidence of poverty in this scenario was 24.4 percent, which corresponds to a 15.3 percent reduction in poverty. Results of the third scenario show that the incidence of poverty would be further reduced to 19.8 percent by improving the access to innovations in addition to credit, as 31.3 percent of the agents moved across the poverty line as compared to the baseline scenario. It is, however, noted that the present model does not expose the agents to the vagaries of pests, weather, and prices, which could reduce the simulated positive effect of mineral fertilizers, improved varieties, and short-term credit.

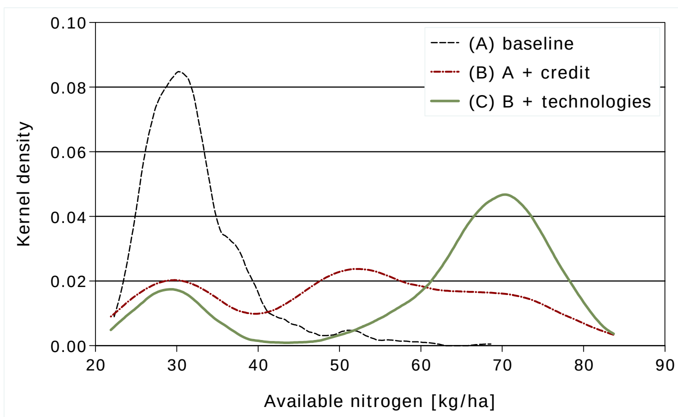
In terms of the sustainability of the agro-ecosystem, the results are mixed. The increased use of mineral fertilizers adds much to the amount of available nitrogen to the crops (Diagram B), thereby increasing crop yields and the well-being of agents. Yet, it does not improve the stock of nitrogen in the soil (Diagram C) and hence does not guarantee long-term ecological sustainability (*cf.* Ghosh, 2004).

Figure 13: Simulated effect of credit and technologies on poverty (A), available nitrogen (B), and the stock of soil organic nitrogen (C)

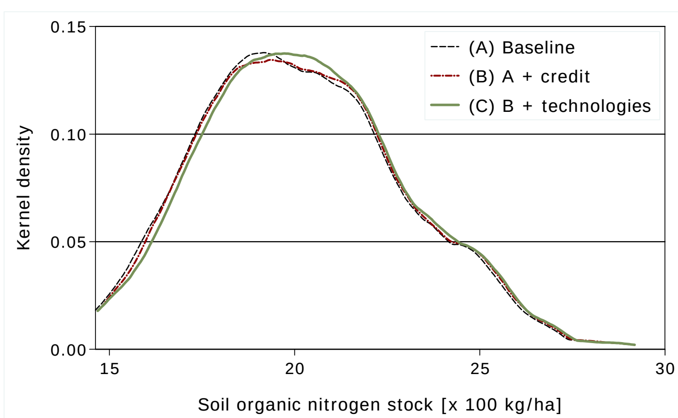
A. Poverty



B. Available nitrogen



C. Soil organic nitrogen stock



Notes: Based on simulated levels for 520 agents in three scenarios averaged over 15 years. Epanechnikov kernel used.

7 Discussion

The result that improved access to short-term credit, mineral fertilizers, and improved seeds can substantially improve the well-being of farm households confirms a large body of literature that identified access to credit and fertilizers as main constraints to an increased productivity in sub-Saharan agriculture. However, the results also showed that these innovations do not eliminate poverty as 19.8 percent of the agents remained in poverty in spite of having access to credit, fertilizers, and seeds. The analyses in this paper could be extended to compare different price levels and introduce soil conservation measures that could contribute to long-term sustainability. For instance, Shiferaw and Holden (1999) found that improving access to mineral fertilizers might discourage soil conservation if the returns to conservation are low and capital is constrained.

The use of agent-based modeling in resource management is not new. The idea of replicating real-world complexity by endowing agents with relatively simple rules of action and interaction has often led agent-based modelers to design decision models from scratch. The philosophy behind the MP-MAS approach is that there is no need to re-invent farm-based decision models; the approach therefore focuses on exploiting the synergies between bio-economic farm household and agent-based modeling. From a bio-economic model perspective, these synergies lie in capturing spatial and socioeconomic heterogeneity and agent interaction; from an agent-based perspective, these synergies lie in the use of well-established decision models, ease of integration with biophysical models, and the use of existing methods of model validation.

The paper has ventured much on this issue of model validation. Parker et al. (2003) saw it as one of the main challenges for MAS/LUCC models. Though MP-MAS can use existing validation methods for MP models, the record of applying these methods in bio-economic modeling is admittedly mixed. Janssen and van Ittersum (2007) reviewed 48 bio-economic farm models and found that only 23 of these publications showed a validation of results while only four did so quantitatively. The challenge of model validation is hence not unique to agent-based models but applies to bio-economic models in general.

The comparison of observed data to simulated data, as used in this paper, is no perfect test of validity. Neither would it help to separate survey data into sets for calibration and validation, commonly done in the natural sciences, as the MAS was calibrated from multiple data sets. To better check the validity of the model, one would have to set up simulation experiments related to the main model indicators (well-being, soil nutrients, technology adoption in this case) and compare the simulated changes to historical data. In the present application such historical data were unavailable and we had to settle for a one-step validation of the results. Hence the problem in validating this type of MAS is not so much a lack of validation methods but rather a lack of available data to validate the results against.

One additional challenge for empirical MAS models is that distributions of the outcome variable need to be validated in addition to averages and medians. That is, showing that the average behavior over all agents fits reality does not ensure the validity at the agent level, as positive and negative errors might cancel out. None of these challenges should, however, discourage agent-based modelers from applying their models to empirical questions: more and better data are becoming available and validation methods are gradually being improved.

8 Conclusion

This paper showed that bio-economic models can capture heterogeneity and agent interaction by taking an agent-based perspective. On the basis of an empirical study on soil fertility decline in southeast Uganda, it showed details about the design, calibration, and validation of the model. Simulation results suggest that improved access to short-term credit, mineral fertilizers, and improved seeds can substantially reduce poverty levels in southeastern Uganda although these innovations alone would not eliminate poverty. These three innovations can also increase the amount of nutrients in the soil but do not guarantee long-term ecological sustainability.

9 Acknowledgment

The authors gratefully acknowledge the financial support of the Robert Bosch Foundation and of Senator Dr. Hermann Eiselen who endowed the Josef G. Knoll Professorship at the University of Hohenheim. The research in Uganda was conducted under scientific agreements between the Center for Development Research (University of Bonn), the Institute for Regional Studies (Seoul National University), Noragric (Norwegian University of Life Sciences), and the International Food Policy Research Institute (IFPRI). We thank our colleagues Soojin Park, Hosangh Rhew, and Gerd Ruecker for their inputs into the landscape component. We also thank three anonymous reviewers for their constructive comments.

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Table 2: Mathematical programming matrix in concise form

	Land	Grow crop in sole stand	Grow crop in mixed stand	Invest in new coffee	Grow coffee	Fallow	Invest in new livestock	Maintain livestock	Sell livestock	Con-sume liquid means	Deposit liquid means	Short-term credit	Purchase inputs (inno-vations)
Objective											+C	–C	–C
Land (ha)	+1												
Land transfer (ha)	–1	+1	+1	+1	+1	+1							
Labor (hours)		+A	+A	+A	+A		+A	**+A**	**+A**				
Livestock (heads)							–1	+1	+1				
Liquid means (Ush)										–1	–1	–1	(+C)
Variable inputs		(+A)	(+A)	(+A)	(+A)								**(–1)**
Coffee plantation (ha)				–1	+1								
Current output (kg)		**–A**	**–A**		**–A**		–A	**–A**	**–A**				
Future output (kg)				**–A**	**–A**		–A	**–A**					
Crop rotations (ha)	–1	+A	+A										
Fallow req. (ha)	+1					–A							
Livestock feeding (J)		–A	–A			–A	+A	**+A**	**+A**				
Income identity (Ush)										–1	+C	–C	–C
Total expenditures													
Food expenditures													
Food consumption													
Food energy balance													
Food energy needs (J)													
Sell all livestock									–1				
Consume liquid means										–1			

	Sell produce	Sell produce in future	Feed livestock	Consume own food	Purchase food	Income transfer	Food expenditures	Food consumption	Food energy needs	Coping strategies	Transfer activities	Sign	Right-hand-side
Objective	+C	+C		+C									MAX
Land (ha)												=	**B**
Land transfer (ha)												=	0
Labor (hours)												≤	**B**
Livestock (heads)												≤	**B**
Liquid means (Ush)												≤	**B**
Variable inputs												≤	**B**
Coffee plantation (ha)												≤	**B**
Current output (kg)	+1		+1	+1								≤	0
Future output (kg)		+1										≤	0
Crop rotations (ha)												≤	0
Fallow req. (ha)												≤	0
Livestock feeding (J)			–A									≤	0
Income identity (Ush)	+C			+C		–1						=	0
Total expenditures						**+A**	–1					=	0
Food expenditures							**+A**	–1				=	0
Food consumption				–C	–C			**+A**				=	0
Food energy balance				–A	–A				+1	$-1E^{-31}$		≤	0
Food energy needs (J)									+1			=	**B**
Sell all livestock										**B**		≤	0
Consume liquid means										**B**		≤	0

Notes: C=price coefficients, A=technical coefficients, B=resource endowments. Negative coefficients on the left-hand-side of the equations indicate that resources are added while a positive coefficient means that the resource is used. $-1E^{-31}$ represents an infinitely large negative number. Coefficients printed in bold are agent and time specific. Coefficients and constraints are furthermore adjusted between the investment, production, and consumption stages. Technical coefficients for crop yield reflect last year's actual yields and are updated to simulated actual yields between the production and consumption stage. Investments are only possible in the investment stage. Land use decisions can not be revisited at the consumption stage. Food energy needs are only constraining in the consumption stage and coping strategies can only then be selected.