

Multi-Agent Systems for the Simulation of Land Use Change and Policy Interventions

Pepijn Schreinemachers and Thomas Berger
*Universität Hohenheim
Germany*

1. Introduction

Multi-Agent Systems (MAS) are increasingly used as simulation tools to disentangle and explore the complex relationships between environmental change, human actions, and policy interventions. The strength of these models lies in their ability to combine spatial modelling techniques, such as cellular automata or geographical information systems (GIS), with biophysical and socioeconomic models at a fine resolution (Parker et al. 2003). MAS are flexible in their representation of human decisions concerning natural resources and therefore appeal to scholars from diverse backgrounds, such as sociology, geography, and economics.

The behaviour of individual actors can be modelled one-to-one with computational agents which allows for direct observation and interpretation of simulation results. Large part of their fascination—especially to scholars who are otherwise sceptical of any attempt to quantify and model human behaviour—rests on this intuitive and potentially interactive feature. Scholars have combined MAS with role-playing games in which a group of resource users, typically farmers using some common-pool resource, specify the decision rules of computational agents and study how these rules affect people's well-being and their natural resources (Bousquet et al. 2001; Becu et al. 2003; D'Aquino et al. 2003).

In this chapter we reflect on the use of multi-agent models for the ex-ante assessment of policy interventions on land use dynamics with emphasis on developing country agriculture. Field experiments can be costly and time-consuming or might be infeasible when it involves social experimentation; for example, assessing the impact of new policies in the area of water privatization, a control group might have to be deprived of public services. Simulation models can be useful under such circumstances. For instance, plant breeders and agronomists can use simulation models to study the effect of water shortages on crop yields instead of measuring it in the field.

Understanding the dynamics of coupled human-environmental systems is, however, more complicated than non-coupled systems due to nonlinearities and emergent behaviour. Scientific disciplines usually focus on isolated aspects of the system, such as hydrology, crops, or farm households but even if knowledge on all parts of the system were available, these pieces of knowledge could not simply be aggregated to predict the overall system behaviour. MAS can be one approach to combine various disciplinary models; by allowing

interactions between components as well as between elements within each component such model can reproduce nonlinear patterns and emergent behaviour.

At Hohenheim University, we have developed a software package called MP-MAS for empirical applications to study sites in Thailand, Uganda, Chile and Ghana (Berger 2001; Berger et al. 2006; Berger et al. 2007b; Schreinemachers et al. 2007). MP-MAS distinguishes itself clearly from most other agent-based land use models in its use of a constrained optimisation routine, based on mathematical programming (MP), for simulating agent decision-making. Section 2 discusses options for representing human behaviour in MAS and explains the rationale for choosing MP as the core decision-making routine of agents. Section 3 describes the implementation of MP-MAS and its various features. Section 4 outlines how we parameterise our software with empirical data and section 5 explains the procedures for model validation. Section 6 presents results from a case study in Uganda and section 7 concludes.

2. Modelling human behaviour with computational agents

Agent-based models of land use and land cover change couple a cellular component that represents a landscape with an agent-based component that represents human decision-making (Parker et al. 2002). MAS have been applied in a wide range of settings, for overviews see Janssen (2002) and Parker et al. (2003), yet have in common that model agents are autonomous decision-makers who interact and communicate and make decisions that can alter the environment. Most MAS applications have been implemented with software packages such as Cormas, NetLogo, RePast, and Swarm (Railsback et al. 2006). The philosophy of agent-based modelling has always been to replicate the complexity of human behaviour with relatively simple rules of action and interaction. In the following we discuss options for implementing the decision making of agents in MAS applied to land use simulation.

2.1 Agent behaviour based on heuristics

Agent decision-making in most land-use MAS has been represented as behavioural heuristics, also called condition-action rules, stimulus-response rules, or if-then rules. One simple example would be a rule that agents must grow maize to meet their subsistence needs, but if subsistence needs are met then agents grow coffee on the remaining plots. The use of heuristics can be justified from the concept of bounded rationality, which refers to the limited cognitive capabilities of humans in making decisions. Herbert Simon described bounded rationality as a search process guided by rational principles, what he called *satisficing*—a word created by blending *satisfying* with *sufficing* (Gigerenzer and Goldstein 1996). Satisficing is a decision-process that goes on until an aspiration level is reached (Selten 2001). This process not only holds for the decision to grow maize but also for the selection of maize varieties. Before planting, the farmer does not endlessly shop around to find the optimum variety for his soils (with the optimum being some weighted calculation of all relevant criteria: yield, maturity, disease resistance, tolerance, fodder quality, etc.). Instead he is much more likely to go to the usual farm shop and buy the same seed as last year or, if perhaps not so satisfied with last year's crop, to try a different variety recommended by a peer or the shopkeeper.

Behavioural heuristics have been implemented in most land-use MAS with fairly simple decision trees. For instance, Jager et al. (2000) in a theoretical application used six decision nodes, Becu et al. (2003) in an empirical application to Thailand used 13 nodes, and Castella et al. (2005) used 24 nodes with these last two applications also employing continuous feedback loops. The use of decision trees, and heuristics in general, is intuitive as agent behaviour is straightforward to follow from the tree's structure. Because they are transparent, they are easy to validate by farmers or experts. Constructing a decision tree is, however, not straightforward. The researcher needs to identify not only the most important decisions, but also in the correct sequence and appropriate values at which the tree branches (e.g. saturation levels). Decision trees can be parameterised using sociological research methods (Huigen 2004), data-mining techniques applied to survey data (Ekasingh et al. 2005), participatory modelling and role-playing games (Barreteau et al. 2001; Becu et al. 2003), laboratory experiments (Deadman 1999), group discussions (Castella et al. 2005), or expert opinion.

2.2 Agent behaviour based on optimisation

Several studies justified the use of heuristics on the grounds that the economic model of utility maximisation is unrealistic or that empirical evidence has shown that people use simple heuristics to make decisions (Parker et al. 2003). Optimising agents would be cognitive supermen able to process large amounts of information on all feasible alternatives and always select the best one. For this ability, optimising behaviour is frequently criticised (and occasionally ridiculed) as unrealistic and not describing the way real people think (e.g. Todd & Gigerenzer 2000).

Agricultural economists will agree that farm households in developing countries do not perform complex algebra to make optimal decisions. Applied models of farm household decision-making in developing countries are also much different from textbook examples of pure profit maximisation and regularly include risk and uncertainty, limited information, and non-profit goals. Yet the assumption of optimal decision-making clears the way to focus on the hypothesised sources of inefficiency: lack of physical infrastructure, failing institutions, market imperfections, and limited information flows, all of which have clear policy relevance. This points us to a key difference between the heuristics and optimisation approach in that the latter seeks to identify inefficiencies not in the limited cognitive capacity of the human mind but in structural factors external to the decision-maker, which may be addressed through policy intervention.

In land-use simulation, optimising agents have been implemented in MAS using a variety of optimisation techniques. For instance, Balmann (1997), Berger (2001), and Happe (2006) used mathematical programming while Manson (2005) used genetic programming to optimise agent land-use decisions. Neural networks could also be used to optimise land-use decisions but we are unaware of any such empirical application. Different from the heuristic approach, MP requires the explicit specification of an objective function. In applications to farm households in developing countries, objectives of agents usually include cash income, food, and leisure time, which can be either specified in monetary units or in terms of utility. It is noted that heuristic approaches commonly use the same objectives (Deadman et al. 2004).

2.3 Synthesis

As argued above, MAS have traditionally been multi-disciplinary approaches in which a large variety of theories and methods co-exist. This also holds for the representation of agent

decision-making in these models. There is no superior decision-model as the choice of decision model depends as much on the research question as on the taste and scientific background of the researcher. Table 1 synthesises the main points of discussion.

	Criterion	Heuristic agents	Optimising agents
1	Focus	Decision process as much as decision outcomes	Decision outcomes
2	Sources of inefficiency	Internal: the limited cognitive capacity of the mind	External: imperfect markets, physical infrastructure, etc.
3	Strengths	Simulating broad categories of land use (e.g. pasture, fallow, crops) Inclusion of multiple stakeholders, each with their own heuristics Validation through stakeholder interaction	Representing heterogeneity through detailed crop and input choices Can capture economic trade-offs Flexible as agents are object-oriented (rather than decision-oriented) Providing quantitative policy support
4	Data needs	High for well-designed and detailed heuristics	High for well-designed and detailed optimisation models
5	Calibration	Relatively quick and easy	Time consuming, especially for detailed models
6	Data source	Laboratory experiments, role-playing games, expert opinion	Surveys, crop-yield experiments, expert opinion

Table 1. Comparison of approaches

The heuristic approach works especially well in abstract and experimental applications or in empirical applications where the objective is not to quantify change but, for instance, to support collective decision-making processes (e.g. D'Aquino et al. 2003). In group discussions it is much easier to present a decision tree than to explain an MP model. If the objective is to quantitatively support policy intervention and to get detailed knowledge about the agricultural land-use systems then an MP model including detailed production and consumption functions is perhaps the more suitable method.

One advantage of MAS is the flexibility to combine and integrate different decision models. The use of one type of agent decision-making does certainly not exclude the use of other types as some heuristic models can easily be formulated in terms of an MP model and vice versa (Schreinemachers and Berger 2006). When using an optimisation approach, heuristics can additionally be used to capture many other aspects of household decision-making. These heuristics can either be directly included in the MP model or implemented in the source code. In Schreinemachers and Berger (2006) we defined four categories of heuristics:

- *Behavioural heuristics directly related to production and consumption decisions of farm households:* For instance, crop rotation requirements or the observation that vegetables are only grown close to the farmstead. These rules should be included as constraints in the MP model as they constrain production decisions.
- *Behavioural heuristics indirectly related to production and consumption decisions:* For instance, Berger (2001) in a MP-based application to Chile included a rule that if the income of an agent is below the opportunity cost of labour then the agent migrates out

of the region. Such rules should be implemented outside the MP in the MAS source code because they do not constrain production decisions but are an evaluation of decision outcomes.

- *Behavioural heuristics of agent interaction*: For instance, the communication of information among agents. These rules should be implemented outside the MP as they go beyond the decisions of an individual agent.
- *Behavioural heuristics related to exceptional circumstances*: For instance, how to re-allocate the land if an agent's last household member deceases, and what to do if the household agent does not produce enough food and income to sustain itself? In the case where no household members are left, the rule should be implemented outside the MP as the agent ceases to exist. Yet, when the agent does not immediately cease to exist, as is the case when income is not enough for subsistence, the rule is best handled inside the MP.

3. Description of MP-MAS

3.1 Component-based architecture

The modelling approach we developed for land use simulation is called MP-MAS, which stands for mathematical programming 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 architecture with its source code written in C++. 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 at the start of the model run. The following sections are largely based on Schreinemachers et al. (2007) and describe the application of MP-MAS to a case study in Uganda, in which we simulated the introduction of new maize varieties and policy programs to address soil degradation and rural poverty. For an application of MP-MAS to water management we refer to Berger et al. (2007a).

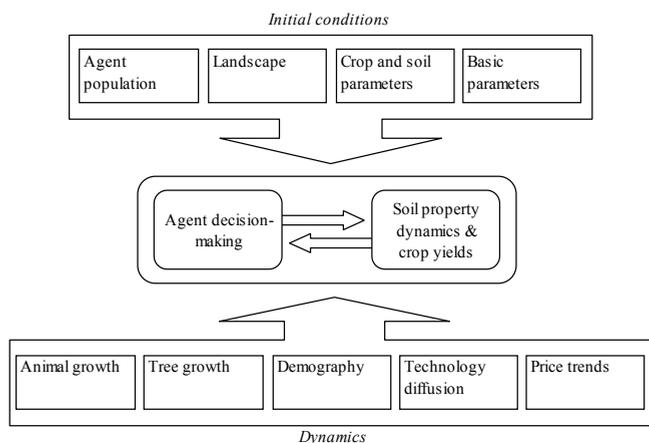


Figure 1. Components of the MP-MAS as applied to Uganda

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.

3.2 The agent-based 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 (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 model here these objectives include household net cash income – i.e., the farm cash surplus plus other household receipts, 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 computerised 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 different combinations of inputs was captured using a piecewise linear segmentation. The model includes 11 crops and 7 intercrop combinations; each crop was segmented into various activities by specifying different combinations of land quality, management, and fertilizers. 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. 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; this is described in Schreinemachers & Berger (2006).

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, here: 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.

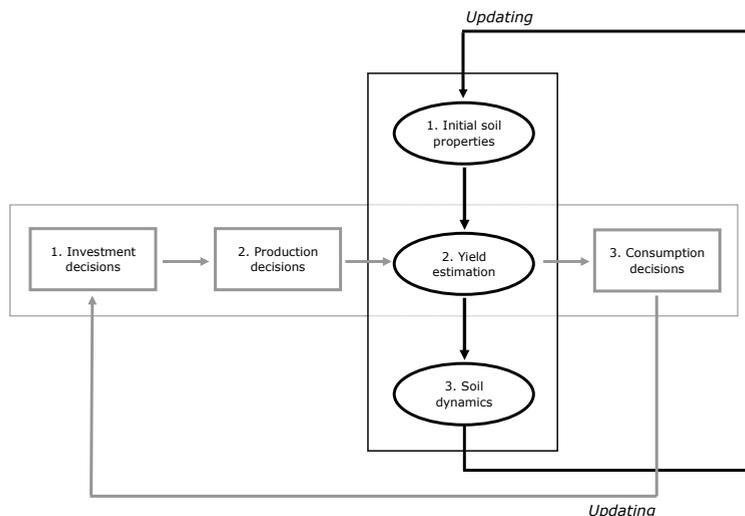


Figure 2. Dynamics and interaction of soil processes and farm decision-making

3.3 Soil fertility dynamics and crop yield

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

- The computation of yield limiting factors based on soil properties (at the start of the period) and applied levels of variable inputs (fertilizer and labour).
- The computation of crop and residue yields.
- 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 modelled using an extended version of the Tropical Soil Productivity Calculator 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. Following Figure 2, initial soil properties together with farm 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:

$$Y_{ikt} = p_i * F_{LABikt} * F_{NAVikt} * F_{PAVikt} * F_{KAVikt} * F_{SOCikt} * F_{pHikt} * h_{ij} * g_i \quad (1)$$

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_j 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 can be obtained by analysing fertilizer experiments and corresponding soil data.

3.4 Agent interactions

Various types of agent interactions can be captured in MP-MAS, ranging from exchange of water and land rights on local markets, upstream and downstream use of irrigation water, to diffusion of innovations. In the present application, technology diffusion was implemented as a behavioural heuristic of agent interaction and 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 adoption. 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. The advantage of using this approach is that network-thresholds can be estimated from empirical data.

The diffusion of innovations can then be 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.

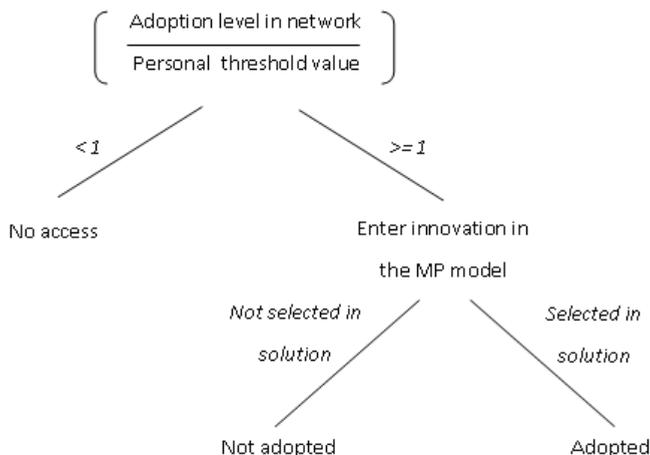


Figure 3. Decision tree for technology adoption

4. Empirical parameterization

When generating empirically based MAS, every computational agent must represent a single real-world farm household. Our method for this was previously described in Berger and Schreinemachers (2006) and this section is largely based on this.

To increase the quality and detail of empirical data, random samples are typically preferred to population censuses or censuses of agriculture (Carletto 1999). In the Uganda study, data were collected for about 17 percent of the 520 farm households in the study area by means of a random sample survey. The challenge was to extrapolate the sample population to parameterise the remaining 83 percent of the agents that have no corresponding farm household in the survey. The most obvious strategy would be to multiply every farm households in the sample by a factor six. Average values in such agent population would exactly equal those of the sample survey. This copy-and-paste procedure, however, is unsatisfactory for the several reasons:

First, it reduces the variability in the population. A sampling fraction of 17 percent gives six identical agents, or clones, in the agent population. This might affect the simulated system dynamics, as these agents are likely to behave analogously. It becomes difficult then to interpret, for instance, a structural break in simulation outcomes: is the structural break endogenous, caused by agents breaking with their path dependency, or is the break simply a computational artefact resulting from the fact that many agents are the same? This setback becomes the more serious the smaller the sampling fraction is, because a higher share of the agents is identical.

Second, the random sample contains a sampling error of unknown magnitude, which is also multiplied in the procedure. When using the copy-and-paste procedure, only a single agent population can be created, while for sensitivity analyses a multitude of alternative agent populations is needed. For these reasons, the procedure for generating agent populations is automated using a Monte Carlo approach, to generate a whole collection of possible agent populations.

4.1 Monte Carlo approach

Monte Carlo studies are generally used to test the properties of estimates based on small samples. It is thus well suited to this study, where data about a relatively small sample of farm households is available but the interest goes into the properties of an entire population. The first stage in a Monte Carlo study is modelling the data generating process, and the second stage is the creation of artificial sets of data.

The methodology applied here is based on empirical cumulative distribution functions. Figure 4 illustrates such a function for the distribution of goats over farm households. The figure shows that 35 percent of the farm households in the sample have no goats; the following 8 percent has one goat, etc. This function can be used to randomly distribute goats over agents, as well as all other resources in an agent population. For this, a random integer between 0 and 100 is drawn for each agent and the number of goats is then read from the y-axis. Repeating this procedure many times recreates the depicted empirical distribution function. By varying the random seed number, the procedure yields a different agent population each time.

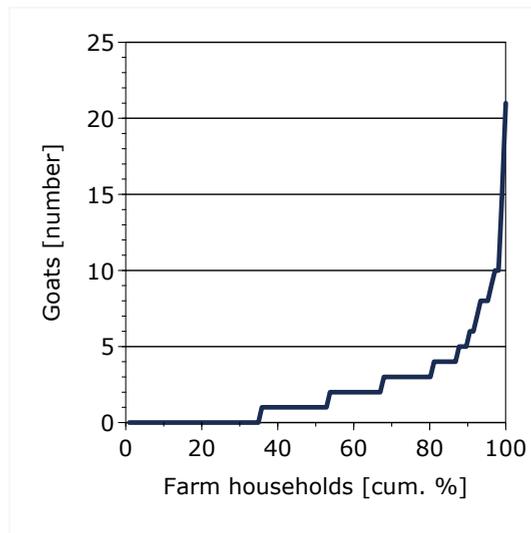


Figure 4. Empirical cumulative distribution of goats over all households in the sample

This straightforward procedure can allocate all resources to the agents; but each resource will then be allocated independently, excluding the event of possible correlations between different resources. In reality resource endowments typically correlate; for example, larger households have more livestock and more land. To include these correlations in the agent populations, first the resource that most strongly correlates with all other resources is identified and used to divide the survey population into a number of clusters. Empirical cumulative distribution functions are then calculated for each cluster of sample observations.

In the Uganda study, the sample was divided into clusters defined by household size because this was the variable most strongly correlated with all other variables. Cluster analysis can also be used for this purpose if several variables show strong correlations, but clusters produced this way are more difficult to interpret, especially when many variables are used. Nine clusters were chosen, as this number captures most of the different household sizes and allocates at least five observations to each cluster. Each agent was then allocated quantities of up to 80 different resources in the Monte Carlo procedure. These resources included 68 different categories of household members (34 age groups of two sexes), 4 livestock types (she-goats, billy goats, cows and young bulls), area under coffee plantation, female head of household, liquidity, ratio of equity and debt capital, plus innovativeness. Agents were generated sequentially, that is, agent No.1 first draws 80 random numbers in 80 different cumulative distribution functions before agent No. 2 does the same.

As most resources only come in discrete units, a piecewise linear segmentation was used to implement the distribution functions. Five segments were chosen as this captured most resource levels; more segments would be needed if the number of resource levels per cluster is larger than five or if many resources have continuous distribution functions.

4.2 Checks for statistical consistency

In order to get both statistically consistent and realistic agents, the generated agent populations were submitted to three tests at various levels of aggregation:

- *Checks for inconsistencies at the population level:* The average resource endowments of the agent population have to lie within the confidence intervals of each estimated sample mean. If not, the agent population generated from this seed value is rejected, and the agent random assignment is repeated with a new seed.
- *Checks for inconsistencies at the cluster level:* The generated average resource endowments have to lie within the confidence interval of the estimated sample mean, and the correlation matrix of the agent population has to reflect the correlation matrix of the sample population. Otherwise the agent population is rejected.
- *Checks for inconsistencies at the agent-level:* An agent with 20 household members is very unlikely to have only one plot of land. Yet, because of the randomness of the resource allocation, unrealistic settings can occur in the agent population. By defining a lower and/or upper bound for some critical combinations, this problem can be overcome. If a resource combination lies outside such bound the generated agent is rejected, and the random assignment of this particular resource combination is repeated. Two sets of bounds are included. The first set defines minimum land requirements for livestock and the second set defines demographic rules to ensure realistic family compositions.

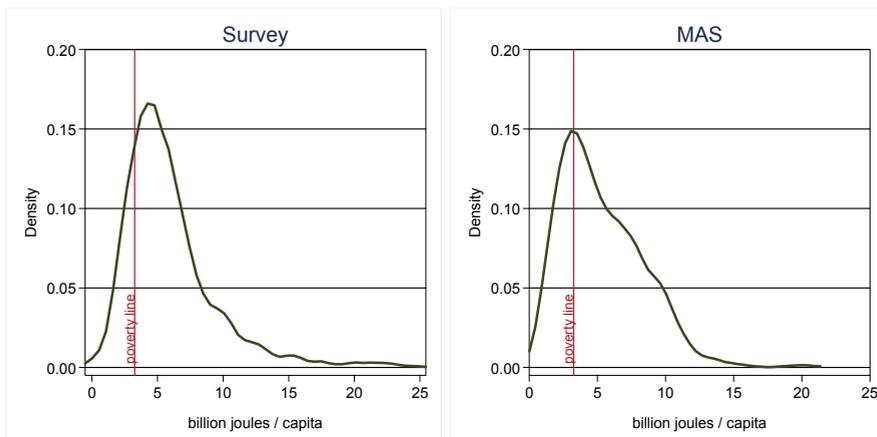
The Monte Carlo approach outlined here works well if correlations among agent characteristics are not too tight. If individual agents, clusters of agents or entire agent populations are continuously being rejected on one of the above three criteria, then the cluster-specific distribution functions have to be fine-tuned. By skewing the distribution functions towards otherwise under-represented combinations of agent characteristics—as was necessary in on-going research in Chile—the random assignment may then still yield statistically consistent agent populations.

5. Model Validation

McCarl & 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. This third step in the validation procedure was performed for the main indicators in the model: soil nutrient balances, crop production, and poverty levels. We here give an example for the validation of poverty levels while the reader is referred to Schreinemachers et al. (2007) for more details.

Poverty levels were validated by comparing the distribution of food energy consumption between the survey population and the agent population, using a kernel density function as shown in Figure 5. The vertical line in the figure indicates the poverty line, which was defined as the minimum food energy intake of an average male adult (3.259 billion Joules per annum). The kernel estimates were not fully comparable because the survey estimate of food energy consumption was based on a much larger area of Uganda. Yet, the figure shows the similarity between both distribution functions; both 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.



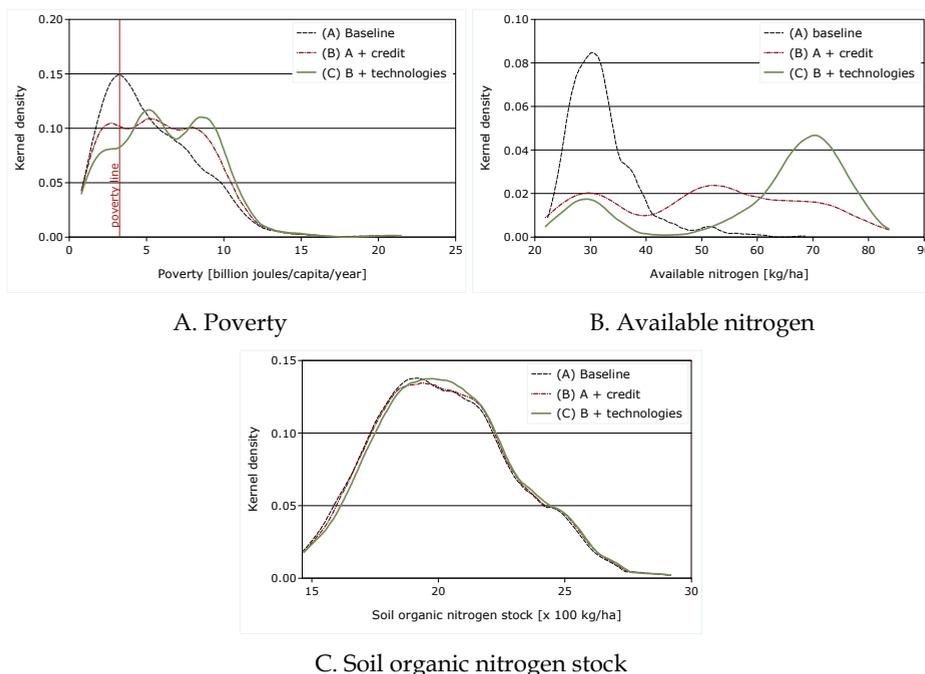
Notes: In male adult equivalents. Epanechnikov kernel used. The survey estimate is based on the farm households in southeast Uganda as recorded by the 1999-2000 UNHS.

Figure 5. Validation per capita food energy consumption

6. Simulating the impact of improved maize and mineral fertilizer

In the following, we present results of simulation experiments from a case study in Uganda, previously published in Schreinemachers et al. (2007). The study is about soil fertility decline in Uganda, which is a problem in many countries of sub-Saharan Africa. High population pressure and rapid population growth put pressure on the capacity of the land to supply food in sufficient amounts. The Ugandan government has therefore prioritized the introduction of improved maize varieties 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 assumes 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. 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 is 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 6 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.



Note: Simulation for 520 agents in three scenarios averaged over 15 years. Epanechnikov kernel used. Figure 6. Simulated effect of credit and technologies on poverty (A), available nitrogen (B), and the stock of soil organic nitrogen (C)

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 and innovations 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 technologies 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 impact 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.

7. Conclusion

This chapter showed how MAS models can capture the complexities of human-environment systems. Two alternative designs of agent decision-making algorithms were discussed: heuristics and optimisation. On the basis of an empirical study on soil fertility decline in Uganda, it showed that both the designs can be combined. The empirical application furthermore illustrated the calibration and validation of the agent-based simulation models and their use as tools to explore the impact of alternative policy interventions on land use and socio-economic dynamics.

8. Acknowledgement

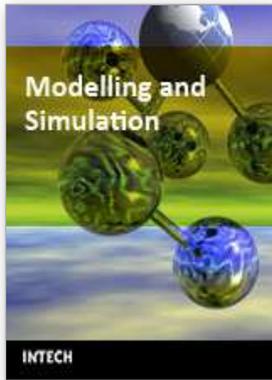
The authors gratefully acknowledge the financial support of the Robert Bosch Foundation. The research in Uganda was conducted under scientific agreements between the Center for Development Research (University of Bonn), the Institute for Regional Studies (Seoul National University), Noragric (Norwegian University of Life Sciences), and the International Food Policy Institute (IFPRI). We thank our colleagues Soojin Park, Hosangh Rhew, and Jens B. Aune for their inputs.

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Modelling and Simulation

Edited by Giuseppe Petrone and Giuliano Cammarata

ISBN 978-3-902613-25-7

Hard cover, 688 pages

Publisher I-Tech Education and Publishing

Published online 01, June, 2008

Published in print edition June, 2008

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How to reference

In order to correctly reference this scholarly work, feel free to copy and paste the following:

Pepijn Schreinemachers and Thomas Berger (2008). Multi-Agent Systems for the Simulation of Land Use Change and Policy Interventions, Modelling and Simulation, Giuseppe Petrone and Giuliano Cammarata (Ed.), ISBN: 978-3-902613-25-7, InTech, Available from:

http://www.intechopen.com/books/modelling_and_simulation/multi-agent_systems_for_the_simulation_of_land_use_change_and_policy_interventions

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University Campus STeP Ri
Slavka Krautzeka 83/A
51000 Rijeka, Croatia
Phone: +385 (51) 770 447
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InTech China

Unit 405, Office Block, Hotel Equatorial Shanghai
No.65, Yan An Road (West), Shanghai, 200040, China
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元
Phone: +86-21-62489820
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