MULTI-AGENT SIMULATION FOR THE TARGETING OF DEVELOPMENT POLICIES IN LESS-FAVORED AREAS

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Abstract

Complex combinations of biophysical and socioeconomic constraints characterize the less-favored rural areas in developing countries. More so, these constraints are diverse as they vary considerably between households even in the same community. We propose Multi-Agent Systems as a modeling approach well suited for capturing the complexity of constraints as well as the diversity in which they appear at the farm household level. Given that empirical multi-agent models based on mathematical programming share the characteristics of bio-economic farm models plus some additional features, one may interpret bio-economic farm models as a special case of multi-agent models without spatial dimension and direct interaction. Evidently, spatially-explicit, connected multi-agent models have higher requirements in terms of development costs, empirical data and validation. Therefore, we see them as a complement, and not a substitute, to existing bio-economic modeling approaches. They might be the preferred model choice when heterogeneity and interactions of agents and environments are significant and, therefore, policy responses cannot be aggregated linearly. We illustrate the strength of empirical multi-agent models with simulation results from Uganda and Chile and indicate how they may assist policymakers in prioritizing and targeting alternative policy interventions especially in less-favored areas.

Keywords

Diversity of constraints to agricultural development, empirical multi-agent systems, bio-economic modeling, ex ante assessment of policy options

1. Introduction

A wide diversity in terms of biophysical conditions, farm resource endowments, and social structures characterize the less-favored rural areas of developing countries (Ruben and Pender, 2004; Kuyvenhoven, 2004). This diversity translates into a long list of factors constraining agricultural development: uncertain rainfall, poor soil fertility, steep slopes, lack of irrigation, poor physical infrastructure, high transaction costs, imperfect and missing capital, land and product markets, etc. (idem.). The abundance of these constraints as well as their interaction creates an overwhelming level of complexity. All constraints can be, or have been, shown as important. Yet policy intervention is costly and resources are limited. Ranking of constraints and prioritizing policy interventions is thus important to ensure that the limited funds are spent efficiently.

Bio-economic simulation models are suitable tools for disentangling complex relationships and have been widely applied for this purpose (Barbier, 1998; Holden and Shiferaw, 2004; Holden et al., 2004; Deybe and Barbier, 2005). These models are, however, not fully capable of capturing the heterogeneity in biophysical and socioeconomic constraints and the interaction between these. We argue that Multi-Agent Systems (MAS) is a modeling approach well suited to complement these bio-economic models when heterogeneity and interaction are important. MAS are therefore of particular relevance for developing tools to support policy targeting in the less-favored areas (LFAs).

The paper is organized as follows. We first shortly elaborate on the specific policy challenges posed by LFAs. We then describe multi-agent simulation as a well-suited approach for integrating the many constraints characteristic of LFAs into a single modeling framework. We illustrate the applicability of MAS models with empirical research from Uganda and Chile.

The last section of the paper summarizes the foregoing in terms of relevance for research and policymaking and draws conclusions.

2. Diversity and interaction of constraints

A defining feature of LFAs is that biophysical and socioeconomic constraints are more binding than in the favored areas. This creates particular challenges for farm households, researchers and policymakers alike.

2.1. The challenge of agricultural growth in the LFAs

At the farm household level, we can broadly divide these constraints into biophysical and socioeconomic ones plus an interaction between these two. At the aggregate level, the diversity between farm households creates an additional constraint to development. We shortly detail on these in the following.

1. The biophysical constraints faced by farm households in the LFAs are not unique to the LFAs but their intensity is more severe than in the favored areas. Crop growth is limited by short growing periods due to seasonal drought, flood, or stresses posed by unfavorable soil physical properties such as low soil depth, salinity, poor drainage or water holding capacity, or susceptibility to erosion—to name a few. Because of these constraints, the yield premium from farm technology adoption is usually lower in LFAs than in favored areas while the seasonal yield variability is usually higher (e.g. de Rouw 2004).
2. In addition to the biophysical constraints, farm households in the LFAs face also more socioeconomic constraints (Ruben and Pender, 2004). These constraints include high transaction costs, for instance, resulting from geographic insulation, imperfect and missing input and output markets, as well as from poor infrastructure and public

services, which can be a consequence of past neglect in development policies (Kuyvenhoven, 2004).

3. The interaction between biophysical and socioeconomic constraints creates additional binding constraints for agricultural growth in LFAs. For example, fertilizer is used at sub-optimal levels when farm households are uncertain about the returns to fertilizer use, which results from a large variability in both rainfall and output prices (Vlek, 1990).
4. A characteristic of farm households in LFAs is their large heterogeneity in terms of biophysical and socioeconomic constraints. Often, the farm households have different land qualities and differential access to markets. The opportunities to adopt improved technologies or to seek off-farm employment can also not be assumed equal for all farm households. The potential for rapid technology diffusion tends to be lower in environments with a high degree of network diversity (Rogers 1995).

2.2. The challenge of targeting policy interventions

The heterogeneity of biophysical and socioeconomic constraints in LFAs and the multitude of their interactions pose great difficulties to the design of development policies. In order to be effective, the most binding constraints at the farm household level should be the target of policy interventions and guide public investments in agricultural R&D. From the complexity of the planning problem in LFAs derives a challenge for researchers to provide scientific information for policy targeting and *ex ante* technology evaluation.

In a previous special issue of this journal, several bio-economic modeling approaches were presented that might support the development and formulation of policy interventions (Kuyvenhoven et al., 1998). These bio-economic approaches quantify the biophysical and socioeconomic constraints and model them within a single framework to analyze the human-environment interactions and the likely effects when particular—biophysical or socioeconomic—constraints are relieved (see also the more recent work of Holden et al., 2004; Deybe and Barbier, 2005).

The scientific challenge, however, is to apply bio-economic models when policy interventions and/or environmental changes are likely to cause large differences in individual policy responses. In general, this is the case when farm households differ considerably in terms of factor endowments and decision-making processes and when resources are exchanged locally or in networks. Another challenge for bio-economic modeling is to allow for a sufficient degree of spatial and temporal complexity, since changes in the natural environment, the market environment, and the introduction of improved technologies typically involve long-term interacting processes. This is especially important for the *ex ante* evaluation of plant breeding programs which will usually take about ten years to release newly adapted varieties for LFAs. In the remainder of this paper, we present multi-agent simulation as a promising tool for capturing more fully the heterogeneity over space and time and for providing information for policy targeting by means of computational experiments.

3. Agent-based bio-economic models

Multi-Agent Systems (MAS) is a quite recent concept, originating in the computer sciences; it has rapidly diffused to other disciplines and is now broadly applied to the analysis of complex systems (Gilbert and Troitzsch, 1999; Janssen, 2002; Parker et al. 2003). MAS is also of great interest to scenario analyses of agricultural development opportunities in LFAs, because it is highly suitable for representing interlinked socioeconomic and biophysical systems.

3.1. Multi-Agent Systems and human-environment interactions

Parker et al. (2003) reviewed applications of MAS to the modeling of land-use decisions and subsequent land-cover changes. They defined multi-agent models of land-cover and land-use change (MAS/LUCC) as consisting of two key components. The first component is a cellular model that represents the landscape under study. This cellular model may draw on a number of specific modeling techniques such as *Cellular Automata*, *Spatial Diffusion Models*, and *Markov Models*. In cellular automata, for example, each cell has discrete states, which can change over time according to pre-defined rules that take into account spatial interactions with neighboring cells (for more details on the cellular model component see Parker et al., 2003). The second component is an agent-based model that represents human decision-making and interactions. It consists of autonomous decision-making units (computational agents), an environment through which agents interact, rules that define the relationship between agents and their environment, and rules that determine the sequencing of actions.

According to the type of rules, Berger and Parker (2002) classified MAS/LUCC into *abstract*, *experimental*, and *empirical* applications (a fourth class of *historical* applications is not of concern here). In abstract MAS, the rules of agents and environment are hypothetical and simple. The intention is not to represent reality as closely as possible, but to reduce it to its essential features and thereby study the underlying (social) mechanisms of land-use change. In experimental MAS, the computer model serves as a platform for interaction of real human actors. D'Aquino et al. (2003), for example, applied MAS to accompany collective decision-making processes related to the management of natural resources. In role-playing games, participants are first asked to define the decision rules of different resource users. Computational agents are then implemented according to these decision rules and interact within a simplified environment. Participants may observe their computational 'analogs,' change the agents' rules of behavior for the next simulation experiment, and thereby learn how to improve their real-world management rules. In empirical MAS, in contrast, the rules of both the agents and the environment are based on empirical observations or on *ad hoc* parameters that serve as realistic substitutes for lacking empirical data. Simulation experiments are used to frame possible land use dynamics and to explore the policy feasible space.

In this paper, the focus is only on empirical multi-agent models. In this type of models, a computational agent typically represents a farm household who combines individual knowledge and values, information on soil quality and topography (the biophysical landscape environment), and an assessment of the land management choices of neighbors (the spatial social environment) to make land-use decisions. Figure 1 shows the spatial data representation of an empirical MAS/LUCC.

<< Insert Figure 1: Spatial data representation of an integrated Multi-Agent System >>

The particular strength of empirical MAS is their ability to account for the heterogeneity and interdependencies among agents and their environment. The cellular model component provides a spatial framework to link socio-economic decision models with biophysical simulation models at disaggregated level, for example with models for soil productivity or water run-off (Vlek et al., 2005). MAS models are generally implemented via object-oriented programming languages, which provide an efficient and transparent way of organizing large amounts of data and handling complex model dynamics. Furthermore, their high degree of flexibility makes it possible to incorporate a large variety of agent decision rules such as profit maximization, minimum subsistence levels, or combinations of these rules. For the assessment of binding constraints and the valuation of natural resources (shadow prices), it is convenient to formalize the agent decision problem with the help of mathematical programming, a technique that has proven its suitability to represent the decision rules of land managers and farm households (Hazell and Norton, 1986: 10).

Balmann (1997) pioneered this combination of agent-based modeling and mathematical programming. He developed a hypothetical farm sector model and showed the theoretical effects of the spatial distribution of farms on both the land rent and the speed of structural change in agriculture. Berger (2001) developed an empirical MAS/LUCC model based on mathematical programming and applied it to the question of technology diffusion in an agricultural region of Chile. In the Chilean model, each farm agent has a separate objective function and individual resource constraints and updates its expectations for prices and water availability. In this respect, Berger's MAS model has the same characteristics as bio-economic modeling approaches based on independent, representative farm models (see for example, Ruben et al., 2000). There are, however, three important additional features that distinguish the MAS from the representative farm modeling approach:

1. *Number of farm models*: Each and all real-world farm households are represented by single model agents, that is, there is a one-to-one correspondence between real-world and modeled agents. *Monte Carlo* techniques have to be developed to generate model agent populations from sample data and to test the simulation results for robustness (see Berger, 2004).
2. *Spatial dimension*: The MAS model is spatially explicit and employs a cell-based data representation where each grid cell corresponds to one farm plot held by a single landowner. Sub-models of water run-off and crop growth are linked to this cell-based spatial framework.

3. *Direct interactions*: Several types of interactions among agents and their environment are explicitly implemented in the MAS model such as the communication of information, the exchange of land and water resources on land markets, the return flows of irrigation water, the irrigation of crops and crop growth.

This one-to-one MAS representation captures biophysical and socio-economic constraints and interactions at a very fine spatial resolution. Including this heterogeneity of constraints and interactions of farm agents and their biophysical environment broadens the scope of bio-economic modeling significantly. Phenomena that conventional models cannot easily address—such as local resource degradation, technology diffusion, heterogeneous policy responses and changes in farm structure—can now explicitly be modeled.

Given that MAS models share the characteristics of bio-economic farm models plus some additional features, one may interpret bio-economic farm models as a special case of MAS models without spatial dimension and direct interactions (*aspatial, non-connected* MAS). Evidently, *spatially-explicit, connected* MAS have higher requirements in terms of development costs, empirical data and validation. Therefore, we see MAS/LUCC as a complement, and not a substitute, to existing bio-economic modeling approaches. They might be the preferred model choice when heterogeneity and interactions of agents and environments are significant and, therefore, policy responses cannot be aggregated linearly (this is especially of importance, when farm types change over time). In the following subsection, we outline how a multi-agent modeling framework can be used for policy simulations in LFAs and how it may help in targeting policy interventions.

3.2. Policy simulations

There are several policy questions in the context of agricultural development of LFAs, where MAS simulations may generate useful information for decision making on public investments in R&D and targeting of policy interventions. Should funds be spent in crop breeding for stress resistance or in research for improved crop management? Should micro-finance be promoted or should agricultural inputs be subsidized? Which markets are the most distorted and exactly where should market regulations be targeted at? Simulating the likely policy responses of farm households and their impacts on the natural resource base provides information for *ex ante* technology evaluation and for targeting of policy interventions.

The complexity of the research problem at hand, however, suggests conducting multi-agent policy simulations according to the principle of *ceteris paribus*. Having successfully validated the simulation model, it is convenient to run a sequence of simulation experiments that stepwise isolate the effects of parameter changes. Table 1 outlines a sequence of computer experiments to investigate specifically for LFAs, which constraints farm households face in the adoption of new technologies and which policy instruments may induce them to adopt ecologically sustainable farming practices:

<< Insert Table 1: Sequence of MAS experiments for policy simulations in LFAs >>

Questions 1-5 in Table 1 can be answered with a static, non-connected bio-economic model specification, as location and interaction between farm-households need not be considered. Questions 6-9 require a dynamic, connected bio-economic model specification with spatial and agent interactions. The next section illustrates how these two bio-economic model specifications can be implemented within a multi-agent modeling framework, and what type of information can be generated through computer policy simulations.

4. Simulation experiments

Before presenting some simulation experiments from empirical model applications to Uganda and Chile, we have to make two reservations. First, although both study regions have unexploited development opportunities, their agro-ecological conditions are relatively favorable, population density is high, and access to markets is fairly good. In this respect, they rather belong to the group of more favored rural areas than to the group of LFAs, at least if measured by the criteria proposed in Pender et al. (2004). Second, research is still underway; we cannot illustrate the nine questions posed in Table 1 for each study region. Yet, the purpose of this paper is to demonstrate the suitability of MAS rather than to present policy conclusions for a particular LFA. In the first subsection, we show on the basis of farm household data from Uganda, how a static bio-economic model specification without agent interactions can be applied to address questions 1-5. In the second subsection, we then show with Chilean data how a dynamic and connected model specification can be applied to address questions 6-9.

4.1 Assessing the feasibility and constraints to increasing agricultural productivity

The first group of research questions to be addressed deals with the feasibility of increasing agricultural productivity in a sustainable manner. We first give an overview of the model implementation and then show some simulation results. The study region comprises two communities in the Iganga district in Southeastern Uganda. The prospects of agricultural development are high, but current land productivity is very low and farmers extract large amounts of nutrients from their soils through unsustainable land management practices. This process of low productivity and high nutrient depletion could potentially be halted and reversed through the application of new fertilizer technologies (e.g., green manures and improved fallow). Such technologies were recently tested in field trials in the region; at present, however, their adoption is limited (Woelcke, 2003; Kayuki et al., 2004).

The bio-economic modeling system, developed for testing the feasibility and constraints to technology adoption, consists of three major components:

1. mathematical programming models at the farm household level to reflect agent decision-making under different scenarios;
2. artificial neural networks as yield estimators; and
3. nutrient balances for N, P, and K as indicators for ecological sustainability.

The modeling system is implemented as an aspatial, non-connected MAS; it consists of independent farm programming models without inter-agent linkages and is used for comparative-static analyses. The objective function of each agent maximizes the household income subject to consumption requirements and a number of financial and technical constraints. Additional nutritional constraints represent the food requirements and consumption preferences that the households articulated during in-depth interviews. Statistical tests with data from fertilizer experiments revealed that artificial neural networks could better capture the observed nonlinearities in fertilizer response than general linear models and multiple regressions. The yield estimations and nutrient balances are incorporated into the mathematical programming problem as coefficients and sustainability constraints. Model validation is conducted by measuring the “goodness of fit” between modeled and observed values in the baseline scenario; for details, the reader is referred to Woelcke (2003).

<< **Insert Table 2: Simulation experiments for the average commercial farm household in Iganga district, Uganda** >>

From a large sample of farm households, four household types are identified through cluster analysis taking into account the level of education, resource endowments, innovativeness, and market orientation. Here, we summarize the simulation experiments only for a single household type, namely the average commercial farm household. Results for this household type have high policy priority in Uganda because the commercialization of farm production is promoted by the government. The simulation results for questions 1-5 are depicted in Table 2. Negative nutrient balances in the current situation reveal a relatively high rate of nutrient depletion in the study region (S1a in Table 2). Imposing an additional sustainability constraint (non-negative nutrient balances) does not yield a feasible solution—meaning that, under current conditions, ecological sustainability is out of reach for the average commercial farm household (S1b). Even if new technologies (fertilizers), which could potentially increase agricultural productivity and preserve soil fertility, are made available, the negative nutrient balances still persist, and nutrient mining does not halt (S2). Making available new technologies and imposing the sustainability constraint simultaneously is still infeasible (S3). Only if cash constraints are relaxed, the commercial farm household may increase productivity and produce with non-negative nutrient balances (S4a). Without the sustainability constraint though (S4b), the profitable solution leads to higher nutrient losses for nitrogen and potassium, as compared to the baseline scenario. This implies a tradeoff between the private goal of increasing the farm household income in the short run and the social goal of ecological sustainability in the long run. These results are similar to those reported by Ruben et al. (2000).

Having identified the binding factors for the adoption of profitable and sustainable farming practices, the model can then be used to identify policy incentives that could induce the farm households to increase productivity while maintaining soil fertility. Through sensitivity analyses it is first estimated by how much the fertilizer price must be reduced to give an incentive for setting off the nutrient losses. Reduction in fertilizer price alone, however, is found to be insufficient. Only combinations of higher output prices, lower input prices, and provision of credit may induce the adoption of profitable and less depleting farming practices (S5).

4.2 Assessing the impacts of technology adoption and policy intervention

Until now, we have used the bio-economic modeling system for analyzing the constraints and policy incentives from a comparative-static point of view. The next group of questions put to a dynamic, connected model version focuses on the likely adjustment process and policy responses of farm households. Even if profitable and sustainable combinations of new technologies, credit and relative prices can be identified as incentives as in the Ugandan study region, there is still no guarantee that farm households eventually adopt these innovations and increase agricultural productivity. Often, farm households can select between multiple innovations and then—depending on their individual factor endowments, resource constraints and subjective risk behavior—adopt only the most suitable ones. The interaction of farm households in communication networks is, especially in developing countries, an integral part of the adoption decision process since interpersonal communication lowers the uncertainty of innovation (Rogers, 1995: 304). Other types of interactions that may be decisive for technology adoption are land markets and population migrations (Berger, 2005). Furthermore, the goals of farm households are not necessarily compatible with the goals of policymakers. A model of policy response must therefore include the farm households' objective functions (Hazell and Norton, 1986: 135). Both, interactions and heterogeneity of policy responses, can be captured by adding three more components to the static, non-connected specification of MAS:

1. rules of interactions between agents as, for example, the exchange of information in communication networks and the exchange of land parcels on land markets;

2. specification of the agent decision-making, especially for inter-temporal decision problems such as consumption versus investment;
3. sequencing of the agents' actions, for example, when agents make investment decisions, when they engage in land markets, and when they harvest their crops.

We will here discuss results of a model application to Chile. The Chilean model employs standard crop water production functions instead of artificial neural networks, and water balances instead of nutrient balances. But the basic model component, the mathematical programming models at farm household level, has the same structure as the model for Uganda in the previous section. For implementation, validation and more empirical results of the Chilean model, the reader is referred to Berger (2001).

In the Chilean study region—the Melado River catchment, 300 km south of the country's capital Santiago—ten farm household types were identified according to farm size, communication networks and innovativeness. Again, we summarize scenario results for the household type that receives most attention of policymakers and change agencies, which in this case are the clients of the Chilean extension service. The extension clients belong to the group of small-scale holdings, the network of *campesino* farms, and to the late majority in terms of innovativeness.

<< Insert Table 3: **Simulation experiments for farm households in the Melado River catchment, Chile >>**

Table 3 depicts the simulation results related to the second group of research questions in Table 1. The columns 'EXT' provide indicators for the group of extension clients only; the columns 'ALL' provide additional information for all households at catchment level. The first three scenarios (S6a/b and S7 in Table 3) show that the extension clients will likely adopt much less innovations than were made available through change agencies (column 1). Fourteen basic innovations with high yield potentials for different technology levels and soil types were tested both at the experimental station and in farm trials. According to the gross margin analyses, all innovations are profitable. But even under ideal technical conditions with *a priori* complete information sets —i.e., technology adoption occurs independent of the communication process in farm agent networks (Berger, 2001)—, only 27% of the opportunities for innovation are taken advantage of. Under market conditions (S7), if we consider the communication process in farm agent networks, this indicator even goes down to 4%.

The environmental impacts at the catchment level are measured by the frequency of water-saving irrigation methods adopted by all households in twenty years, at the end of the last simulation period (column 2). Under ideal technical conditions, almost half of the irrigated area is irrigated with modern, water-saving methods; under market conditions only 12%. The socioeconomic impacts of technology diffusion at the catchment and extension group level are here measured by indicators for migration and household incomes. Without innovation, slightly more than 1% of the farm household agents *per annum* decide to abandon their plots (column 4). Under ideal technical conditions, in contrast, the farm household incomes can almost be doubled (column 6) and by this means provide a strong incentive to stay; out-migration slows down to 0.1% per year. But technical change, and thus higher income, does not reach all households under market conditions because the communication of information slows down ideal adoption rates (for more details on the underlying network threshold model see Berger, 2001). As scenario S7 reveals, the extension client incomes fall by 14% and migration rises to nearly 2% *per annum*. Other interactions between agents, in the Chilean context the exchange of land parcels and water rights, do not play a major role. Empirically, land and water sales hardly occur and rental contracts are only informal and short-term in the study region. Accordingly, there should be little incentives for additional investments in new technologies in order to expand farm sizes. The simulation experiment without rental markets and 'pull' factors for migration confirms this hypothesis as it does not lead to significant changes in income under ideal technical conditions (S8 compared with S6b).

Finally, the model simulations shed light on the response to policy programs that aim at promoting the diffusion of innovations. The first program as proposed by the Chilean farmers association is comprehensive and non-targeted; it is intended for all farm holdings and includes credit schemes for all available technologies, public investments in irrigation facilities as well as fertilizer subsidies (S9a). In contrast, the second program of the Chilean extension service is much smaller in scope and therefore less costly. It targets exclusively at extension clients and mainly involves micro-finance and intensified extension (S9b). The simulation experiments suggest that both policy programs may give incentives to take more advantage of agricultural development opportunities than under market conditions (see indicators for all farm households in columns 2, 4, and 6). They also show that well targeted extension programs are cost-effective because both the non-targeted and the targeted policy programs have similar environmental and socioeconomic impacts. The key success factor of the targeted program, however, is a smoothly functioning extension service that enables extension clients to innovate and actually links them to high-value markets.

5. Discussion

The simulation experiments demonstrate the suitability of multi-agent simulations in disentangling the complexity of human-environment interactions and policy responses. The

MAS implementation captures more fully than conventional modeling approaches the social and spatial heterogeneity of farm households and their biophysical environment. This is especially important for policy modeling in LFAs, which, by definition, face a multitude of biophysical and socioeconomic constraints and interactions. The MAS experiments allow for a stepwise isolation of partial and combined effects to parameter changes and can thus identify the binding factors at farm household level. Through sensitivity analyses it is possible to identify ideal policy incentives leading to the internalization of environmental externalities. The model structure is also flexible and rich enough to test actual policy interventions over time at disaggregated and aggregated level. By exploring the socio-economic and environmental impacts of different policy options, MAS may therefore provide useful information for the targeting of policy interventions in LFAs.

The model case studies represent the situation typical of LFAs where farm technologies with high yield potentials do not automatically translate into high adoption rates. Although improved and sustainable technologies are potentially available, low land productivities and relatively high rates of resource depletion can be observed. The first group of MAS simulations shows that a number of technical and financial constraints might compel the farm households to employ poor farming practices and to deplete their natural resource base. From a normative point of view, policy interventions should be targeted at those factors constraining adoption. The computer experiments may then reveal whether the market environment is too distorted to provide economic incentives for a productive and sustainable land management, even if new technologies were made available through ideal policy interventions. The second group of MAS simulations illustrates that the diffusion of technologies takes considerable time under market conditions. Policy programs can help to speed up the diffusion of innovations by giving incentives to technology adoption. The MAS experiments demonstrate that targeted policy programs have potentially a cost advantage over non-targeted programs but their success relies on the well functioning of hardly manageable factors such as knowledge networks and agricultural extension services.

6. Conclusions

By the very definition of LFAs, their agricultural development is constrained by the abundance of biophysical and socioeconomic factors. If policy interventions are desired, they should be targeted at the most binding constraints at farm household level and provide economic incentives for technology adoption and preservation of natural resources. The policy problem, however, involves a relatively high degree of complexity and cannot be solved straightforwardly without additional scientific information. This again poses difficulties for bio-economic modeling research because computer simulation approaches are needed that capture more fully the spatial and temporal interactions at farm household level. We advocate the use of MAS because this methodology is well-suited to represent the heterogeneity of farm households in an environment characterized by many biophysical and socioeconomic constraints and interactions. By means of computer simulations, the impact of policy options and alternative technologies can be assessed *ex ante* to inform strategic investment decisions in LFAs.

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Table 1: Sequence of MAS experiments for policy simulations in LFAs

Scenario	Research question
#1	What are the impacts of current agricultural practices on household incomes, food security, and the conditions of natural resources?
#2	Are innovations available to the farm households that are technically feasible and profitable?
#3	If such innovations are available, does the adoption of these innovations enable farm households to increase land productivity without depleting the natural resource base?
#4	If current adoption levels are sub-optimal, what constrains the adoption at the farm household level?
#5	What policy incentives can induce the change of farming practices? What policy instruments lead to the profitable adoption of innovations?
#6	What will be the speed of technology diffusion and what types of farm households will be reached?
#7	What are the potential economic and environmental impacts of these innovations over time?
#8	Are there future constraints emerging from inter-household linkages? (For example informal land markets, local arrangement for labor exchange, flow of information in communication networks, management of common pool resources.)
#9	How can different policy options best be implemented over time?

Table 2: Simulation experiments for the average commercial farm household in Iganga district, Uganda

Scenario (see Table 1)		Profitability	Nutrient balance [kg/ha]		
			Nitrogen	Phosphorus	Potassium
S1a	Baseline	0	-77	-15	-71
S1b	+ Sustainability		#infeasible		
S2	+ Innovation	8	-96	58	-100
S3	+ Innovation + Sustainability		#infeasible		
S4a	+ Innovation + Credit + Sustainability	-30	0	47	53
S4b	+ Innovation + Credit	9	-104	56	-106
S5	+ Innovation + Credit + Price changes	33	-15	72	-14

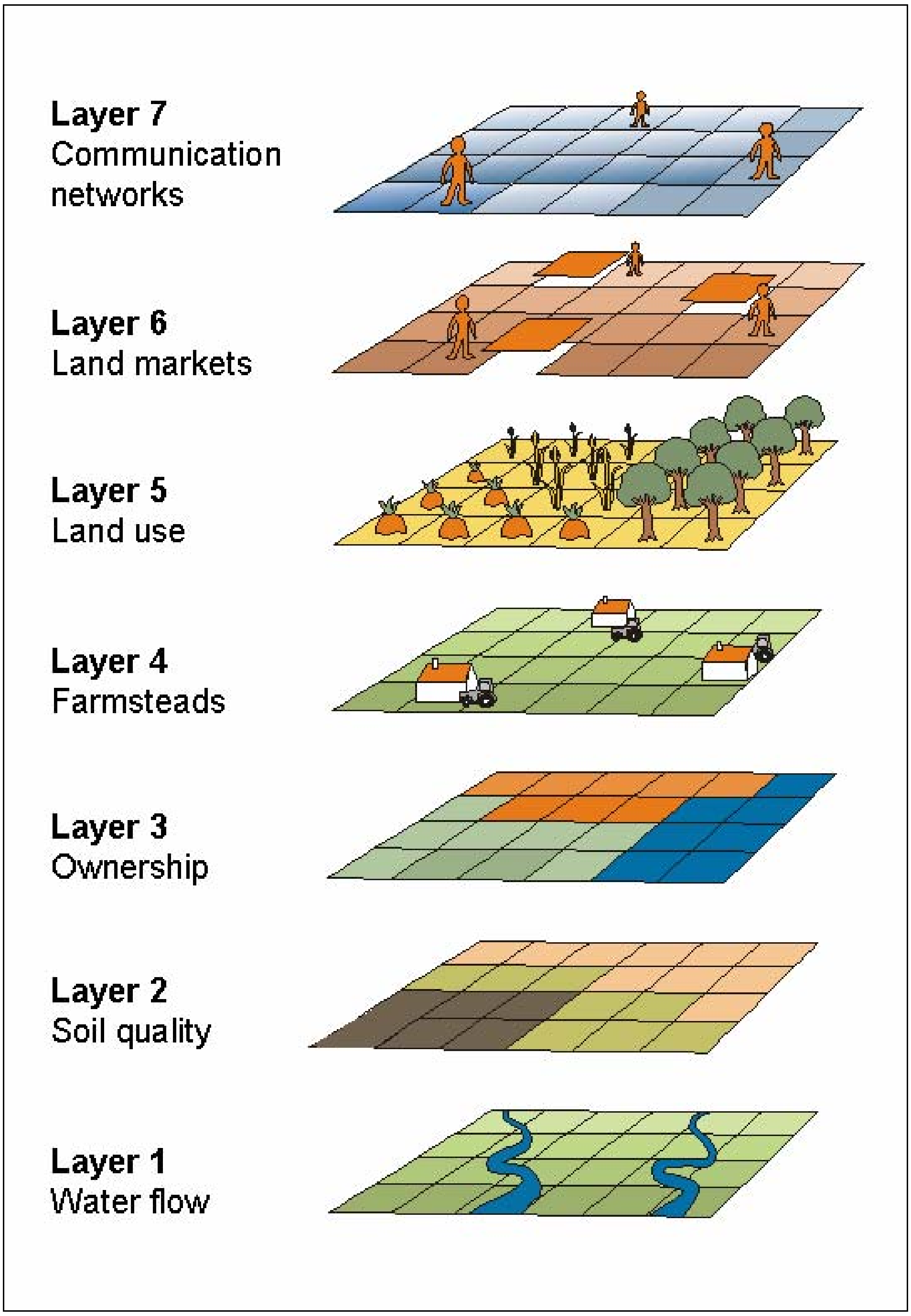
Notes: Simulation experiments for the most frequent soil type; profitability is measured in terms of percentage change of household income. New fertilizer technologies are only available for the cultivation of maize. The price changes in S5 include a 50 percent increase in output price and an 80 percent decrease in input price.

Table 3: Simulation experiments for farm households in the Melado catchment, Chile (all values in percent)

Scenario (see Table 1)		Adoption of available innovations	Frequency of water-saving irrigation	Annual change in number of farms		Incremental household income	
		EXT	ALL	EXT	ALL	EXT	ALL
(S6a)	Without technical change	0	0	-0.4	-1.2	0	0
(S6b)	Ideal technical change	27	49	-0.1	-0.1	86	110
(S7)	Market solution	4	12	-1.8	-1.3	-14	8
(S8)	Without rental markets and 'pull' factors	n/a	50	0.0	0.0	84	111
(S9a)	Non-targeted policy intervention	24	27	-0.1	-1.0	93	53
(S9b)	Targeted policy intervention	20	33	-0.2	-1.1	90	52

Notes: EXT refers to extension farm households; ALL refers to all farm households. 'Adoption of available innovations' is measured as the ratio of years of actual adoption and years of availability for adoption, summed over all innovations. 'Frequency of water-saving innovations' is measured as the proportion of non-traditional irrigation methods in irrigated agriculture at the end of the twentieth simulation period. 'Incremental household income' is calculated as the Net Benefit Increase (NBI), i.e. the discounted average income compared to the baseline income.

Figure 1: Spatial data representation of empirical Multi-Agent Systems (##please convert to black and white)



Layout: C. Block, ZEF-Bonn. First published in Berger and Ringler (2000).