8. Agent-Based Modelling

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8.1 INTRODUCTION

Agent-based modelling (ABM)[2] is the computational study of social agents as evolving systems of autonomous interacting agents. ABM is a tool for the study of social systems from the complex adaptive system perspective. From this perspective, the researcher is interested in how macro phenomena are emerging from micro level behaviour among a heterogeneous set of interacting agents (Holland, 1992). By using ABM as computational laboratories, one may test different hypotheses related to attributes of the agents, their behavioural rules, and the types of interactions, and their effect on macro level stylized facts of the system.

An illustrative example of emergence in ecological economic systems and the use of ABM is the Bali irrigation system as studied by Lansing (1991). The irrigators have to solve a complex coordination problem. On the one hand, control of pests is most effective when all rice fields have the same schedule of planting rice. On the other hand, the terraces are hydrologically interdependent, with long and fragile systems of tunnels, canals, and aqueducts. To balance the need for coordinated fallow periods and use of water, a complex calendar system has been developed which states what actions should be done on each specific date. These actions are related to offerings to temples: from the little temples at the rice terrace level, to the temple at the village level; from the region level up to the temple of the high priest Jero Gde, the human representative of the Goddess of the Temple of the Crater Lake. This crater lake feeds the groundwater system which is the main source of water for irrigation. These offerings were collected as a counter performance for the use of water that belonged to the gods.

The function and power of the water temples were invisible to the planners involved in promoting the Green Revolution during the 1960s. They regarded agriculture as a purely technical process. Farmers were forced to switch to the miracle rice varieties that give three harvests a year, instead of the two of the traditional varieties. Farmers were stimulated by governmental programmes which subsidised the use of fertilizers and pesticides. The farmers continued to perform their rituals, but now they no longer coincided with the timing of rice farming activities. Soon after the introduction of the miracle rice, a plague of plant-hoppers caused huge damage of rice production. A new variety was introduced, but then a new pest plague hit the farmers. Furthermore, there were problems of water shortage.

During the 1980s an increasing number of farmers wanted to switch back to the old system, but the engineers interpreted this as religious conservatism and resistance to change. It was Lansing (1991) who unraveled the function of the water temples, and was able to convince the financers of the Green Revolution project on Bali that the irrigation was best coordinated at the level of the water temples. Lansing built an ABM of the interactions of subaks, groups of rice farmers having adjacent fields, management strategies and the ecosystem, and the local adaptation of subaks to strategies of neighbouring subaks, and showed that for different levels of coordination, from farmer level, up to central control, the temple level was the level of scale where decisions could be made to maximize the production of rice (see also Lansing and Kremer, 1994). He also showed how the coordination might have been evolved as a result of local interactions (Lansing, 2000).

The complex irrigation systems and the role of the temples have evolved over a long history of local adaptations, at different levels of scale. The water temples played a significant role in the coordination of the use of water. The problem of coordination and multi-level interaction is not unique to the Bali irrigation example. Such interactions of social agents and their environments can be found in many social systems. Since the early 1990s ABM has increasingly been used in most of the social sciences (e.g., Berry et al., 2002; Bousquet et al., 2001; Conte et al., 1997; Epstein and Axtell, 1996; Gilbert and Doran, 1994; Gimblett, 2002; Janssen, 2002; Kohler and Gumerman, 2000; Lomi and Larsen, 2001; Macy and Willer, 2002; Parker et al., 2003; Tesfatsion, 2001).

In this chapter I shall focus on the applications of ABM related to ecological economics. ABM of ecological economic systems can be defined as systems that are populated with heterogeneous population of agents, who determine their interactions with other agents and with their environment, on the basis of internalized social norms and mental models, internal behavioural rules and cognitive abilities, formal and informal institutional rules that affect how agents interact, individual and social learning, etc.

Three different types of agents can be distinguished: *humans* who differ in mental maps, goals, locations, and abilities, and also differ in scale from individuals, households up to organizations and nations; *non-humans* such as animals and plants; and *passive* agents such as non-living entities. We focus on the human agents, which can be represented by a rich pallet of possible behavioural rules varying from self rational agents up to agents behaving according to psychological heuristics. Agents may continually adapt their behaviour in response to agent-agent and agent-environment interactions in an attempt to satisfy their needs.

The rest of the chapter is build up as follows. In section 8.2 the use of ABM in context of other modelling approaches will be discussed. A brief overview of the main methodology is given in section 8.3. In section 8.4 a number of applications in ecological economics are presented and in section 8.5 the question of the degree of complexity in modelling is discussed, and future challenges of ABM within ecological economics are mentioned. Section 8.6 closes the chapter with some conclusions.

8.2 MOTIVATIONS FOR AGENT-BASED MODELLING

Some readers may question why we need complex approaches such as ABM. Are equation-based models not sufficient? Other readers may argue that ABM is now new. My response to these queries is that it all depends on the type of questions one is interested in. For many problems, equation-based models are excellent tools to study the problem of concern, as illustrated by other chapters in this book. However, for a problem like coordination or strategic interaction, multiple agents need to be distinguished.

Traditional game theory has been very successful in addressing strategic interaction by a small number (mainly two) (types of) players, using equation-based models. Unfortunately, traditional game theory is rather restrictive: Agents are required to have high cognitive abilities, the rules of the game are fixed, and the structure of the interactions is on a rigid lattice or fully random. But from empirical studies it is known that humans are boundedly rational, the rules of the game change, and social interactions have complex social structures (e.g., Gigerenzer and Selten, 2001; Janssen and Ostrom, in press). It is no surprise that ABM has been widely applied to games since the early 1980s (e.g., Axelrod, 1984).

Indeed, models of individual units were developed long ago, such as statistical mechanics and micro-simulations. But these methods assume no interaction, or random interaction, between the agents. A key element in ABM is the possibility of complex structures of social interactions. In some systems, the macroscale properties are sensitive to the structure of interactions between agents and social networks. In equation-based models, the agents are frequently, implicitly, assumed to be well mixed, the mean-field assumption, and thus these approaches miss the opportunity to investigate the sensitivities of the structure of interactions.

Finally, within integrated modelling of ecological economic systems, one of the key problems is how to match the scale of social and ecological dynamics (Levin, 1992; Gibson et al., 2000). By the use of agents, we derive tools that make it possible to integrate processes and interactions at different levels of scale, for agent-agent and agent-environment interactions.

8.3 ABM METHODOLOGY

Most ABMs applied within ecological economics consist of two elements: cellular automata and agents. I will now discuss briefly both elements.

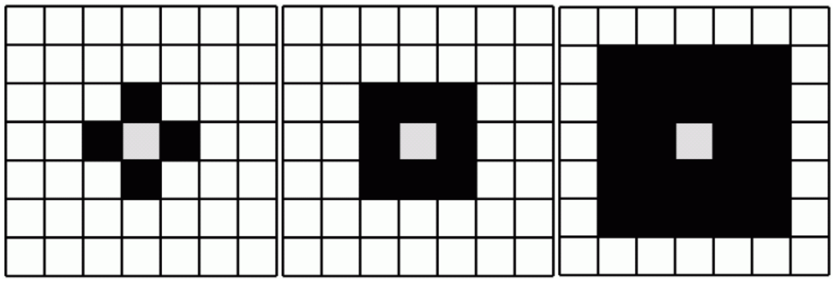
8.3.1 Cellular Automata

Originally, the cellular automata (CA) approach was introduced by John von Neumann and Stanislaw Ulam at the end of the 1940s, mainly to give a reductionist model of life and self-reproduction. The *Game of Life*, invented by John Conway in 1970, popularized the CA approach (Gardner, 1970). This game consists of cells on a checkerboard, which can have two states, ‘alive’ and ‘dead’. Time goes by in discrete steps. According to some deterministic rules, which are the same for each cell, the state of a cell in the next time step depends on its own present state and the states of all its surrounding cells in the present period. The resulting surprising complex dynamics which evolved from this simple game, attracted the attention of many people. Since the early 1970s, CA have been used by many disciplines to study complex dynamic behaviour of systems. The essential properties of a CA are:

- a regular *n*-dimensional lattice (*n* is in most cases of one or two dimensions), where each *cell* of this lattice has a discrete state,
- a dynamical behaviour, described by so called *rules*. These rules describe the state of a cell for the next time step, depending on the states of the cells in the *neighbourhood* of the cell.

The basic element of a CA is the *cell* that is represented by *states.* In the simplest case, each cell can have the binary states 1 or 0. In more complex simulations, the cells can have more different states. These cells are arranged in a lattice. The most common CAs are built in one or two dimensions. The cells can change state by transition rules, which determine the state of the cells for the next time step. In cellular automata, a rule defines the state of a cell in dependence of the *neighbourhood* of the cell. The most common neighbourhoods for two-dimensional CA are given in Figure 8.1.

Figure 8.1 Examples of Cellular Automata



von Neumann Neighbourhood

Moore Neighbourhood

Extended Moore Neighbourhood

The grey cell is the centre cell, the black cells are the neighbourhood cells. The states of these cells are used to calculate the next state of the (grey) center cell according to the defined rule.

With regard to our interest for ecological economics, the application of CA can be rather straightforward. In fact, CA can be used to produce a dynamic Geographical Information System (GIS)[3]. The lattice represents a map of a certain area, with each possible state of a cell representing a possible land use. Due to physical restrictions, cells on some locations may be restricted to a limited number of states; for example, a secondary forest cannot turn back into a primary forest. Transition rules determine when a certain land use of a cell changes into another land use. Cell changes can be influenced by local rules; for example, if the cell is a forest-cell, and if one of the neighbour cells is on fire, then the cell turns to fire. However, global rules are also possible, since land use changes can be influenced by demand for certain land on a higher level of scale. For example, demand for extra agricultural land can be translated as changing those cells to agriculture that are the most suitable.

It must be noted that social agents can also be represented as CA. One of the earliest and best known cellular automata models of social processes is the Schelling (1971) model of neighbourhood segregation. Two types of agents are randomly distributed on a lattice and move to empty locations if the number of in-group neighbours falls below a certain threshold. The model show how extreme segregation tends to arise in a population that prefers diversity, as agents relocate to avoid being in the minority. In the CA approach for social processes each cell represents an agent, which interacts with its neighbours. The state of the cells relates to different characteristics of the agents such as social class, attitude, social orientation, etc.

A drawback of using CA for representing social agents is its simplicity. For example, social networks are more complex than the local neighbours on a lattice. The number of possible states in which a social agent can be might be too large to be efficiently represented as a CA. Within land use models, landowners may own multiple cells and make decisions on the land use of their cells. Thus a cell-based rule that ignores parcel boundaries is inadequate. The study of agents has been a topic of research for a long time in computer science, which has developed its own tools and frameworks.

8.3.2 Agents

The architecture of agents in ABM has been much influenced by work on multi-agent systems in Artificial Intelligence (AI). Multi-agent systems research studies the behaviour of adaptive autonomous agents in the physical world (robots) or in cyberspace (software agents). The agents often consist of sensors, to derive information from the environment, and intelligent functions such as perception, planning, learning, etc.

Distributed artificial intelligence is a relatively recent development of artificial intelligence studies (Bond and Gasser, 1988). It concerns the properties of sets of intercommunicating agents coexisting in a common environment. The aim may be to study the properties of such systems in an abstract way, or to design systems of immediate practical use, or to use such a programmed multi-agent system as a model of a human or other real-world system.

Wooldridge (2002) argues that intelligent agents are able to act flexibly and autonomously. By flexibility we mean that agents are goal-directed (satisfying or maximizing their utility), reactive (responding to changes in the environment) and capable of interacting with other agents. One of the difficulties is in balancing reactive and goal-directed behaviour. Developing models with agents who have only reactive behaviour is relatively simple, and individual-based ecological modelling addresses problems by simulating non-human agents as reactive objects (e.g., DeAngelis and Gross, 1992).

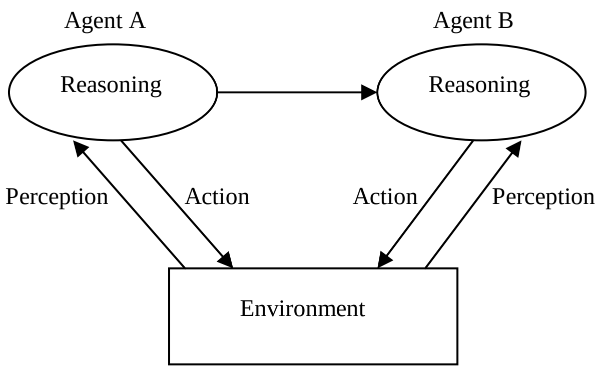
However, humans combine reactive and goal-directed behaviour. Conventional economics assumes the selfish rational actor to describe individual behaviour. Although this agent model provides a good description of human behaviour in highly competitive markets, as is confirmed in experimental studies, it is not satisfactory for the description of behaviour in various decision situations of importance for ecological economics (Gintis, 2000). For decision situations such as economic valuation and collective action, motivation, fairness and preferences play an important role, and the characteristics may vary within the population of human agents. Furthermore, decision problems related to environmental management are often so complex that it is not likely that one has full information and understanding of the problem and is able evaluate all possible options. Models of bounded rationality have been used as an alternative in economics (Simon, 1955). Furthermore, using concepts from psychology, we are able to include dimensions of economic agents such as emotions, motivations, and perceptions. A problem is that loosening the tight framework of the selfish rational actor leads to many possible frameworks. Within behavioural economics, there is mainly attention to models of learning that explain observed behaviour in experiments (Camerer, 2003). Others focus on fast and frugal heuristics, of how individuals make a choice in simple problems under time pressure (Gigerenzer et al., 1999).

An important agent-architecture within the multi-agent systems community is the belief-desire-intention (BDI) approach, in which decision-making depends upon the manipulation of data structures representing the beliefs, desires, and intentions of the agent. The BDI architecture is based on practical reasoning (Bratman et al., 1988), and involves two key processes: deciding what goals an agent wants to achieve (deliberation), and how an agent is going to achieve these goals (means-ends reasoning). The main idea is that an agent has limited resources to make decisions, in terms of time and knowledge. The beliefs represent information on the agent's current environment, and together with desires filter in a deliberation process the range of possible options to a set of intentions. The intentions represent the focus on actions of the agents, though due to changes in the environment (affecting beliefs) the intentions may change.

Another important integrated approach in ABM for simulating decision-making is the consumat approach (Jager et al. 2000; 2002). The consumats, artificial consumers, may engage in different cognitive processes in deciding how to behave, depending on their level of need satisfaction and degree of uncertainty. Consumats having a low level of need satisfaction and a low degree of uncertainty are assumed to deliberate, that is: to determine the consequences of all possible decisions given a fixed time-horizon in order to maximize the level of need satisfaction. Consumats having a low level of need satisfaction and a high degree of uncertainty are assumed to socially compare. This implies the comparison of own previous behaviour with the previous behaviour of consumats having about similar abilities, and selecting that behaviour which yields a maximal level of need satisfaction. When consumats have a high level of need satisfaction, but also a high level of uncertainty, they will imitate the behaviour of other similar consumats. Finally, consumats having a high level of need satisfaction and a low level of uncertainty simply repeat their previous behaviour. After the consumption of opportunities, a new level of need satisfaction will be derived, and changes will occur regarding their abilities, opportunities and the social and physical environment, which will affect the consumption in succeeding time steps. As a consequence, agents may switch between heuristics in a dynamic environment that affects their satisfaction and uncertainty, and may mimic the behaviour of others only when they are uncertain.

A scheme of a simple model of two agents interacting with each other and their environment is given in Figure 8.2, which provides the simplest description of ABM applied to ecological economics. Agents derive information from the environment that informs the perception they have about the state of the environment. Based on the goals and attributes of the agents they make decisions what actions to perform and these actions affect the environment. The agents can interact indirectly, for example by affecting the common resource, or directly by communication. This communication might be used to exchange information about possible strategies, knowledge about the resource and agreements how to solve collective action problems.

Figure 8.2 A Scheme of Cognitive Interactions between Two Agents and their Environment



The main dilemma concerning the architecture of agents with regard to the study of ecosystem management is the degree of complexity embodied in the agent. Since the roots of agent research lie in computer science, the agents are often designed for certain tasks (smart software agents to assist the limited human agent) but do not necessary represent theoretical insights from behavioural science. Within ecological economics, the techniques of multi-agent systems are combined, together with concepts from sociology, psychology and economics, to design more comprehensive agents from a social science point of view.

8.4 AGENT-BASED MODELLING IN ECOLOGICAL ECONOMICS

I shall now describe the main areas within ecological economics where ABM has been applied and provide some of the key references.

8.4.1 Evolution of Cooperation

One of the key problems in science is the evolution of cooperation. Cooperation has been explained when the social agents are generically related, and/or interact repeatedly. The question when social agents cooperate relates to a number of important issues in ecological economics, especially to the question of institutional configurations for common resources and public goods. Ostrom (1990) shows that there are many empirical cases where local communities have developed institutions to deal with social dilemmas. These examples show that people have the capacity to organize themselves to achieve much better and more cooperative outcomes than is predicted by conventional theory (Ostrom, 1990). Furthermore, laboratory experiments have been performed which show that communication is a crucial factor to stimulate cooperative behaviour, and the ability of the participants to determine their own monitoring and sanctioning system is critical for sustaining cooperative behaviour (Ostrom et al., 1994). Note that the experiments show that the type of communication can have significant effects on the results.

The reasons why these factors are important are not precisely known, but the hypothesis is that it relates to the development of mutual trust during interactions between resource appropriators. ABM can contribute to a better understanding of the factors that stimulates such self-governance. The irrigation system of Bali, as discussed in the beginning of this chapter, is an example of the use of ABM to understand self-governance. Another relevant paper is Janssen and Ostrom (in press), who study the conditions that are needed for a population of agents to voluntarily restrict their own behaviour, to avoid the collapse of a resource in the longer term. They show that when agents are able to evolve mutual trust relationships, a proposed rule on restricted use of the resource will be accepted, since they trust others will, in general, also follow the rules.

There is a substantial literature on the use of ABM on the management of common-pool resources. Bousquet et al. (1998, 2001, 2002) developed a modelling platform, CORMAS, dedicated to the study of common-pool resources by ABM, and performed many applications[4]. In their application they work together with the local stakeholders, often in Africa and Asia, to develop ABM for practical natural resource management problems. Deadman (1999) compared his ABM with experimental data of common-pool resource experiments and Jager et al. (2000) tested how different theories of decision making affect the state of the common resource.

8.4.2 Diffusion Processes

Diffusion processes are important for understanding what determines the spread of innovations in a population. Such innovations might be the use of a new environmentally friendly product, a technology to reduce waste, or norms about green consumption. Diffusion processes often replicate the observed stylized fact of an S-shaped curve of cumulated adopters of the innovation. In fact, the increasing number of adopters is in essence the diffusion process. The growth of new products is a complex process, which typically consists of a large body of agents interacting with each other over a long period of time. Traditional analytical models described diffusion processes at the market level, but in recent years ABM has become used as an alternative model. One approach is based on cellular automata, where the individuals interact with their neighbours and transition rules determine how neighbours affect the awareness or adoption of an innovation (e.g., Weisbuch, 2000; Goldenberg and Efroni, 2001); others address more realistic network structures (e.g., Valente, 1995; Abrahamson and Rosenkopf, 1997).

Applications of ABM to diffusion problems within ecological economics are rare. An interesting example is Berger (2001), who studied the diffusion of agricultural technologies based on the concept of different types of adapters (early and late) applied to an agricultural region in Chile. Another application is of Deffuant et al. (2002) who simulate adoption of organic farming practices as a consequence of governmental policy, for an agricultural region in France. In a more theoretical study, Janssen and Jager (2002) study the diffusion of green products in a coevolution of consumers and firms, where firms try to make products that fit the demand of the consumers, and consumers have to make a choice between a limited number of products.

Within the field of evolutionary economics (e.g., Nelson and Winter, 1982), simulation models are used to simulate innovation, diffusion and learning of firms and organizations. An interesting application of ABM for ecological economics related to industrial organizations might be the area of industrial ecology where different type of agents process material and energy flows in their economic activities (Axtell et al., 2002).

8.4.3 Mental Models and Learning

If agents do not have perfect knowledge of the complex ecological system, how does their mental model of the system affect their actions, and how can they learn to derive a more accurate mental representation? This problem refers to the general problem in ABM, that agents do not have perfect knowledge of the system and make their decisions based on the perception they have on the problem. These perceptions do not have to include correct representations of reality and may vary among agents.

A number of ABMs in the field of ecological economics have addressed this problem. Janssen and de Vries (1998) developed an ABM where agents have different mental models of the climate change problem. They simulate a learning process where agents may adjust their mental models when they are surprised by observations, and make adjustments in their decisions according to their new perception of the problem. This approach has been also applied to lake management (Carpenter et al., 1999), and rangeland management (Janssen et al., 2000).

Carpenter et al. (1999) developed a simulation model with different type of agents to explore the dynamics of social-ecological systems. The ecosystem is a lake subject to phosphorus pollution, which flows from agriculture to upland soils, to surface waters, where it cycles between water and sediments. The ecosystem is multistable, and moves among domains of attraction depending on the history of pollutant inputs. The alternative states yield different economic benefits. Agents form expectations about ecosystem dynamics, markets, and/or the actions of managers, and choose levels of pollutant inputs accordingly. Agents have heterogeneous beliefs and/or access to information and their aggregate behaviour determines the total rate of pollutant input. As the ecosystem changes, agents update their beliefs and expectations about the world they co-create, and modify their actions accordingly. Carpenter et al. (1999) analyze a wide range of scenarios and observe irregular oscillations among ecosystem states and patterns of agent behaviour, which resemble some features of the adaptive cycle of Holling (1986).

8.4.4 Land Use and Land Cover Change

ABM for land-use and land-cover change combine a cellular model representing the landscape of interest, with an ABM that represents decision-making entities (Parker et al., 2003). Due to the digitalization of land use/cover data (i.e., remotely sensed imagery) and the development of Geographic Information Systems (GIS), cellular maps can be derived for analysis, and since the 1980s, cellular automata have became used to model land use/cover over time. Human decision-making was implicitly taken into account in the transition rules, but not expressed explicitly. Sometimes the cells represent the unit of decision-making but, in most applications, the unit of decision making and the cell do not match. The desire to include more comprehensive decision rules, and the mismatch between spatial units and units of decision making, led to the use of ABM for land use and land cover change. By including agents, one can explicitly express ownership, or the property about which an agent can make decisions. An agent can make decisions on the land use in a number of cells, for example by allocating cells for deriving a portfolio of crops.

Applications on land use and land cover change include impact of innovations and policy on agricultural practices (Balmann, 1997; Berger, 2001; Deffuant et al., 2002), reforestation and deforestation (Hoffman et al. 2002) and urban sprawl (Torrens and Benenson, 2004). I refer to Gimbett et al. (2002) and Parker et al. (2003) for recent reviews of this area.

8.4.5 Participatory Approaches

In the spirit of adaptive management (Holling, 1978), various researchers have developed their ABMs together with the stakeholders of the problem under concern. Bousquet et al. (2002) have developed an approach, which they call ‘companion modelling’, that uses role games to acquires knowledge, build an ABM, validate the ABM and use it in the decision making process (see also Barrateau, 2003). As for the participatory modelling approach, such as in practiced in systems dynamics (e.g., Costanza and Ruth, 1998), they use the model as a tool in the mediation process with stakeholders. Within the system dynamic model, agents are represented at an aggregate level, and the use of ABM makes it possible to include a broader set of interactive autonomous agents. These autonomous agents may respond to the decisions of the stakeholders in the participatory process in unexpected ways. A non-scientific example of this is the computer game SimCity where the player, the virtual mayor, has to make decisions to satisfy the citizens, the Sims.

8.5 DEGREES OF COMPLEXITY

One of the crucial questions in the field of ABM is how much model complexity is necessary to derive an understanding of the emergent properties. This can be illustrated by the ‘flocking fallacy’. The visually interesting flocking ‘boids’ that appear often on screen savers are based on three simple rules for each agent (Reynolds, 1987):

- avoid collisions with nearby flock mates,
- attempt to match velocity with nearby flock mates, and
- attempt to stay close to nearby flock mates.

Computer scientist Reynolds was interested to simulate certain patterns, and for him it was important that '… many people who view these animated flocks immediately recognize them as a representation of a natural flock, and find them similarly delightful to watch' (Reynolds, 1987, p. 26). One might derive the impression that we have now a better understanding of flocking behaviour. However, research on schooling of fish illustrates that we lack a good understanding of the micro-behaviour of fish in relation to schooling (Camazine et al., 2001, Chapter 11). Indeed, information about the behaviour of nearby neighbours is found to be a crucial factor in empirical studies, but which behavioural rules are in use is a puzzle.

Camazine et al. (2001) show that the puzzles in biology have recently successfully been approached by combining field work, controlled laboratory experiments and models. They stress that the models 'should be developed solely based on observations and experimental data concerning subunits of the system and their interactions' (Camazine et al., 2001, p. 70).

If we look at ABM for the study of social phenomena, we have to conclude that the fruitful combination of fieldwork, laboratory data and modelling is lacking. Looking at most formalizations of 'bounded rationality' in agent rules, they leave the impression of being developed in a rather 'ad hoc' manner, from the perspective of programming rules rather than reflecting a formalization on the basis of theoretical considerations. Bounded rationality is not an excuse for using sloppy decision rules. For example, it is very interesting to study the effects of introducing an 'imitation' strategy in agents within a system. However, not considering the issues of the conditions under which the agents are likely to imitate, and which other agents they are most likely to start imitating, may yield results that do not originate from the 'psychological laws' on imitative behaviour. Key publications in social simulation, such as segregation by Schelling (1971), and the evolution of cooperation by Axelrod (1984), could explain macro-phenomena, by assuming simple logical rules for the behaviour of the agents. However, like the flocking 'boids', the behavioural rules are not validated by empirical research. I do not want to reduce the importance of the contributions of Schelling and Axelrod, which are evidently milestones and stimulated much work to test variations of the models. Instead, I wish to argue that the use of ABMs should more often be based on empirically tested theoretical models of human decision making, combined with rigorous empirical research in the field and in the laboratory. Due to the rapid growth of the use of experimental research in social science, there is a potential to develop more micro-level validated decision rules of agents.

In economics this is successfully happening with the testing of alternative learning models on relatively simple games, where the participants converge in many rounds towards a unique mixed equilibrium (Camerer, 2003). Janssen and Ahn (2003) test different ABMs on a large set of public good and common-pool resources, which are more complex since the participants do not reach an equilibrium. Janssen and Ahn (2003) find that motivational heterogeneity and satisficing are explanatory factors that lead to a reasonable fit with the observations.

Within psychology there is an effort to test alternative, theoretically sound, heuristics on laboratory experiments of decision-making (Gigerenzer et al., 1999). Other psychologists develop ABM that combines findings of many theories in a kind of meta-theoretical framework (Jager et al., 2002; Mosler and Brucks, 2003).

Another approach is the participatory one, as described above. By playing role games, and confronting the stakeholders with the simulations, the scientists derive valuable insights into the possible rules in use. An important question is how to design role games such that the stakeholders behave during role-playing as they do normally.

8.6 CONCLUSIONS

In this chapter a brief overview has been given of ABM and its application to ecological economics. ABM applied so far has been successfully used in various social sciences, but has been limited within ecological economics. There is a great potential of the use of ABM, especially for problems related to common use of resources, land use and land cover change, integrated modelling and participatory processes.

Due to the rapid developments of ABM in other disciplines, ecological economics can 'piggyback', by using theory and experimentally tested models of agents who interact with their complex environment. This might provide ecological economics with a promising tool for integrated modeling, and for testing different theories of behaviour and organization at different levels of scale.

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NOTES

1 The author gratefully acknowledges support from the Center for the Study of Institutions,

Population, and Environmental Change at Indiana University through National Science Foundation grants SBR9521918 and SES0083511.

2 Also referred to as multi-agent systems, multi-agent based systems or agent-based computational economics.

3 A Geographic Information System is a computer system for capturing, storing, checking, integrating, manipulating, analyzing and displaying data related to positions on the Earth's surface.

4 See http://cormas.cirad.fr