1. Introduction

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1.1 THE ISSUE

Our world view on the structure of systems is changing rapidly. According to the traditional Newtonian paradigm, we can assume a system is in equilibrium, and study it in isolated parts. Scholars in the field of complexity adopt a paradigm of complex adaptive systems, which assumes that systems are emergent structures on a macro scale due to interactions between micro-level agents who adapt themselves to their environment. Unlike the Newtonian paradigm, which assumes that systems have a predictable behavior, the behavior of complex adaptive systems cannot be predicted accurately. However, complex adaptive systems can provide us with insights under which circumstances simple local rules can lead to emergent macro-level structures.

Examples of complex adaptive systems are immune systems, nervous systems, economies and ecologies. These systems can be studied by a number of new computation-based modeling tools, including genetic algorithms, cellular automata, neural networks, multi-agent systems, and artificial life forms. In this volume the interactions between people and their environment is addressed. Both theoretical and practical examples are presented of developing and applying methodology of studying the management of complex adaptive social-ecological systems.

Economists study the management of ecosystems in terms of harvesting ecosystem services from renewable resources. Substantial progress has been made during the last 30 years. Prior to 1970, model analysis was mainly static, such as the seminal work on renewable resource harvesting by Gordon (1954). After 1970 the trend shifted towards dynamic systems for the economics of renewable resources. The resulting optimization problem was addressed by dynamic programming, game theory and equilibrium analysis (Clark, 1990; Dasgupta and Heal, 1979; Mäler, 1974). Irreversibility and uncertainty have been addressed since the early 1970s (Arrow and Fisher, 1974; Henry, 1974) and remain among the main focuses of environmental economics (e.g. Chichilnisky, 2000).

In mainstream environmental economics it is usual to analyse a representative agent who has perfect knowledge and maximize its utility of consumption for an infinitive time horizon. Such an approach resulted in interesting insights but is of limited use if systems are characterized by non-convex dynamics, structural uncertainty, heterogeneity among agents and spatial heterogeneity. The question is how to analyse ecosystem management problems with spatial explicit non-convex dynamics influenced by multiple stakeholders who consume different types of ecosystem services. We need new tools, and multi-agent systems are promising new tools in the toolkit for the social scientist.

Multi-agent systems, also referred to as agent-based (computational) modeling, consist of a number of interacting autonomous agents (Conte *et al.*, 1997; Epstein and Axtell, 1996; Gilbert and Troitzsch, 1999; Weiss, 1999). Agents can represent animals, people or organizations; can be reactive or proactive; may sensor the environment; communicate with other agents; learn, remember, move and have emotions. The main components of multi-agent systems are cellular automata, and models of the agents. Each agent is represented as a computerized independent entity capable of acting locally in response to stimuli or to communication from other agents. Therefore, the first task is to build architectures for intelligent agents and secondly to design an organization of interacting agents to accomplish a task.

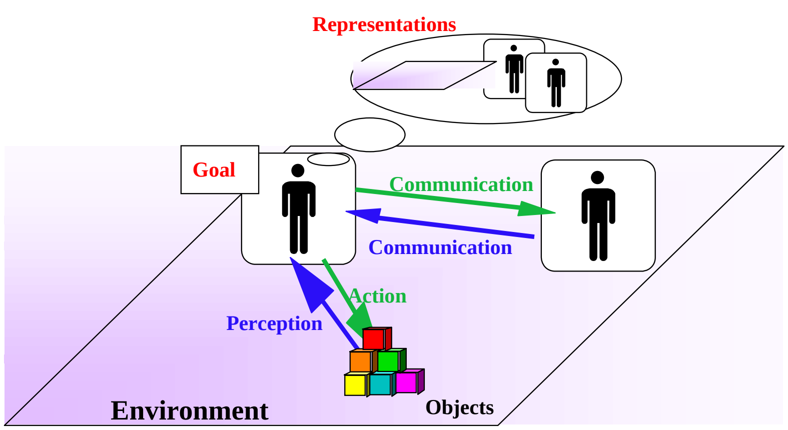

Figure 1.1: Multi-agent system general organization and principles (from Ferber, 1999)

A multi-agent system perspective of ecosystem management is essentially different from traditional environmental economic approaches. Three different types of agents can be distinguished: *humans* who differ in mental maps, goals, locations, and abilities; *non-humans* such as animals and plants; and *passive* agents such as non-living entities. We mainly focus on the human agents who are more complicated than other types of agents.

Wooldridge (1999) 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 balancing reactive and goal-directed behavior. Developing models with agents who have only reactive behavior is relatively simple. Individual-based ecological modeling addresses problems by simulating non-human agents as reactive objects (e.g. DeAngelis and Gross, 1992). Econophysics (www.econophysics.org), an emerging field that applies methods from statistical physics and non-linear dynamics to macroeconomic modeling and financial market analysis, approaches human behavior as behavior of particles.

However, humans combine reactive and goal-directed behavior. Conventional economics makes use of fully rational actors to study human behavior. The rational actors are self-regarding individuals maximizing their own wellbeing. However, the powerful concept of the rational actor seems to be invalid according to experimental research in economics and psychology (e.g. Thaler, 1992; Gintis, 2000b).

Deliberation about an economic decision is a costly activity in terms of time and cognitive effort, and many social scientists argue that people often employ simpler decision rules, aimed at satisfying rather than optimizing (see Chapter 6). Models of bounded rationality have been used as an alternative in economics (Simon, 1955; Sargent, 1993). Still other important dimensions of the economic agents have been excluded, such as emotions, motivations, and perceptions. In order to include this dimension of behavior we have to enter the domain of psychology.

Psychology and many other social sciences were originally focused on experimental research of individual and group behavior. Since the early 50s social scientists have used computers to simulate behavioral and social processes, although the real breakthrough became in the late 80s due to the development of new simulation techniques like cellular automata, genetic algorithms and neural networks, and the widespread availability of personal computers. Computers became laboratories, allowing simulating behavior theories in virtual environments. Those multi-agent systems are used to study the stock-market dynamics (Palmer *et al.*, 1994), evolution of cooperation (e.g., Axelrod, 1984), evolution of language (Cangelosi and Parisi, 2001), rise and fall of (ancient) societies (Kohler and Gumerman, 2000), pedestrian behavior (Jiang, 1999), land use and land cover change (Parker *et al.*, 2001), etc. Simulation of multi-agent systems is now recognized as a promising methodology for social science as shown by the colloquium on this topic organized in October 2001 by the National Academy of Sciences of the USA.

In this book we apply multi-agent systems to study the interactions between humans and ecosystems. Until recently nature was being seen by most individuals as an infinite resource of materials and energy to satisfy human needs, as well as an infinite sink for human wastes and pollutants. In the last century humankind became aware of its large domination of the Earth by transforming land surface, by altering biogeochemical cycle, and by adding or removing species and genetically distinct populations in most of the earth's ecosystems (Vitousek *et al.*, 1997). The expected growth of the human population and its associated economic activities are likely to accelerate the scale and intensity of human-induced changes.

The concept of ecosystem management was introduced during the last ten years as an approach to focus on long-term sustainability of ecosystems. Various interpretations on ecosystem management are being used and are discussed in, amongst others, Grumbine (1994, 1997) and Christensen *et al.* (1996). Key elements of ecosystem management are the focus on long-term sustainability, inclusion of humans as ecosystem components, the inherent change and evolution of ecosystems, the importance of structural complexity and connectedness to maintain resilience of systems, and the acknowledgement of our incomplete knowledge of ecosystems which require adaptive management (Christensen *et al.*, 1996).

We are living in a world with fast-changing ecological and social systems. Our current institutional arrangements are based on past experience. Change is too fast to depend on learning by doing alone. Computational laboratories can explore possible futures. The resulting better understanding of the functioning of institutions can contribute to a more sustainable co-evolution of people and nature.

1.2 MULTI-AGENT MODELING

Most multi-agent models applied to ecosystem management consist of two elements: agents and cellular automata. We discuss briefly both elements. For a more detailed discussion on the methodology of multi-agent modeling we refer to Ferber (1999), Weiss (1999) and Parker *et al.* (2001).

1.2.1 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 behavior of systems.

The basic features of a CA are (Hegselmann, 1998):

- There is a D-dimensional lattice.
- Time is advancing in *discrete* steps.
- There are a *finite* number of states. At each site of the lattice we have a cell, which is in one of the possible states.
- The cells change their states according to *local* rules, both in space and in time.
- The transition rules usually used are deterministic, but non-deterministic rules are allowed too.
- The system is *homogeneous* in the sense that the set of possible states is the same for each cell and the same transition rule applies to each cell.
- The updating procedure can consist of applying the transition rule to all cells *synchron* or *asynchron*.

With regard to our interest for ecosystem management, the application of CA can be rather straightforward. In fact, CA can be used to produce a dynamic GIS. The lattice represents a map of a certain area. Each possible state of a cell represents 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 to 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 neighbor 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 which are the most suitable. Note that we do not have to use CA for representing the environment, since not all problems are spatially explicit, or different spatial explicit models can be used.

One of the main drawbacks of the attention to CA only is the limited inclusion of social processes. It must be noted that social agents can also be represented as CA. Within the field of social simulation CA are used to simulate social phenomena. One of the first papers in the field is the analysis of segregation processes by Schelling (1971). In the CA approach for social processes each cell represents an agent, which interacts with its neighbors. The state of the cells relates to different characteristics of the agents such as social class, attitude, social orientation, etc. An overview of this field is given in Hegselmann (1998).

A drawback of using CA for representing social agents is its simplicity. For example, social networks are probably more complex than the local neighbors on a lattice. The possible states in which a social agent can be might be too large to be efficiently represented as a CA. 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.

1.2.2 Agents

The architecture of agents in multi-agent systems has been much influenced by work in Artificial Intelligence (AI). In this field a popular wave is the autonomous agents research or behavior-based AI, which studies the behavior of adaptive autonomous agents in the physical world (robots) or in the cyberspace (software agents). This field in AI is highly inspired by biology. The phenomena of interest are those traditionally covered by ethnology and ecology (in the case of animals) or psychology and sociology (in the case of humans). The agents often consist of sensors to derive information from the environment and intelligent functions such as perception, planning, learning, etc. Behavior is defined as regularity observed in the interaction dynamics between characteristics and processes of a system and the characteristics and processes of an environment. Examples include: a theory at the behavior level that explains the formation of paths in an ant society in terms of a set of behavioral rules without reference to how they are neurophysiologically implemented. Another example is the study of behavioral rules implemented in robots who have to survive (they need to reload energy every now and then) in a physical environment with other robots as a way to explore emergent behavior in such a group. An overview of this field can be found in, for example, Steels (1995) and Maes (1995).

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-agents system as a model of a human or other real-world system.

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 designed for certain tasks but do not necessary represent theoretical insights from behavioral science. The fields of social simulation (e.g. Conte *et al.*, 1997) and agent-based computational economics (e.g. Tesfatsion, 2001) use the techniques of multi-agent systems together with concepts from sociology, psychology and economics to design more comprehensive agents from a social science point of view. Nevertheless, empirical validation of the agent architecture remains an activity which receives too little attention. More cooperation with experimental research and computational experimentalists is necessary to improve the construction of the agents.

1.3 APPLYING MULTI-AGENT SYSTEMS FOR ECOSYSTEM MANAGEMENT

In this section I briefly discuss what type of questions can be addressed by multi-agent systems, and what the possible problems are. As Roger Bradbury clearly discusses in Chapter 4, accepting the paradigm of complexity also means the recognition that the future cannot be predicted. Using multi-agent systems as a tool for the study of complex social ecological systems implies that we are not interested in predicting the state of the system in a certain moment in the future, like Newtonian science can for the orbits of the planets and stars in our universe. The focus of multi-agent systems is to understand persistent emergent phenomena. Emergence arises from the context-dependent, non-linear interaction of the objects and the rules (Holland, 1998). Non-linear interaction means that the behavior of the system cannot be obtained by summing or averaging the behavior of the constituents.

An example is an ant colony where ants with limited individual capabilities are able to construct comprehensive societies. A colony of a million army ants is a sophisticated ‘super-organism’ (Gordon, 1999). The colony carries out its raids and can even keep nest temperatures constant to within a degree. An ant colony seems endowed with intelligence far beyond that of any individual ant: It seems that intelligence, natural or artificial, is an emergent property of collective communication. Camazine *et al.* (2001) provide a state of the art volume on self-organization in biological systems.

They show that the combination of laboratory research, field experiments and modeling provide a fruitful combination to understand which micro-level behavior leads to emerging patterns at the macro-level.

An example of an emergent property in economics is the equilibrium of demand and supply. In conventional economics it is assumed that the economic system is in equilibrium, but within agent-based computational economics, the economic agents are simulated from the bottom up (Tesfatsion, 2001).

A prominent example of using multi-agent systems for ecosystem management is the Bali irrigation system studied by Lansing (2000). A large number of subaks, and each subak consists of about 50 farmers, have to coordinating planting and irrigation. Synchronous planting has the benefit of effectively controlling rice pests, but leads to water bottleneck, since they all use the water from the same river. Lansing equipped the agents with simple heuristics. Each year a subak compares its yields with the yield of its closest neighbors, and copies the cropping pattern of its (best) neighbor. The model, using real data of a watershed in southern Bali, produces similar spatial cropping patterns as observed in the field.

The Bali example shows the fruitful use of a multi-agent system perspective for the study of ecosystem management. Lansing (2002) discusses the role of 'artificial societies' in a historical debate in social science on methodology. It is clear that the mainstream statistical approach is confronted with an alternative, and this alternative is criticized. It is therefore necessary that models of multi-agent systems are applied to real case studies. This volume shows that there is progress in that respect by presenting a number of real-world case studies, and a number of methodological challenges such as validation, experimental research and the use of models in a participatory process.

1.4 A GUIDE TO THIS BOOK

This section provides a brief outline about the different contributions, and how they are linked together. Chapters 2 and 3 discuss multi-agent systems as rule-based systems. Marty Anderies proposes in Chapter 2 a general framework to describe each system in terms of rules and agents. The proposed framework can provide a common language for multi-agent systems, and Anderies applies his framework to the several contributions of this volume. In Chapter 3 the evolution of institutional rules is discussed. How are they coded, created, selected and remembered? Marco Janssen argues that linguistics and immunology provide interesting metaphors and computational tools to improve the methodology of simulating institutional rules.

The difference between Newtonian and complexity paradigms as mentioned at the start of this chapter are also the starting points for Chapters 4 and 5. Roger Bradbury describes clearly in Chapter 4 why we cannot predict the future of social-ecological systems, and argues that we can only study under which conditions emergent phenomena hold. In Chapter 5, Steve Manson discusses the problem of validating multi-agent systems. He presents a number of practical guidelines and tools, and discusses how differently applied studies in this volume address validation.

One of the crucial problems in multi-agent modeling is the validity of the design of the agents. Chapter 6 by Wander Jager and Marco Janssen is an attempt to test their artificial agents to experimental data. Their artificial agents provide new explanations of observed behavior of subjects in laboratory experiments. A next step would be to test these new hypotheses in the laboratory. This chapter illustrates that more interaction between experimental and modeling research is needed.

A traditional differential equation model of an Australian rangeland system is the starting point in Chapter 7 by Janssen *et al.* In the original model, space explicit dynamics were ignored, but by using a multi-agent system approach, it is shown that spatial heterogeneity of grazing pressure can lead to quite different conclusions compared to the original model.

The rest of this volume presents applications of multi-agent models. Applications vary from agricultural systems to forests and rangelands. Chapters 8 and 9 analyse the effects of agricultural policies in Europe. Balmann *et al.* developed an agent-based model that includes spatial interaction of some 2600 individually behaving heterogeneous farms. They apply this model to analyse the effects of a limitation of livestock density per hectare on a selected intensive production region in the southwest of Germany.

In Chapter 9, Deffuant *et al.* study the dynamics of organic farming practices in the Allier département in France. The agent-based model is the result of an iterative process between modeling researchers and specialists of agri-environment. It represents explicitly the propagation of information and the dynamics of discussions among farmers, as well as its impact on the farmers' decision process. Deffuant *et al.* found that the initial heterogeneity in perceptions of farmers towards organic farming was a crucial factor to explain observed adoption rates.

Tim Lynam, Chapter 10, uses spatially explicit, multi-agent simulation to study the relation of household characteristics and long-term production of the Masoka agro-ecosystem in Zimbabwe. Field research provided statistics of the households which were used to generate characteristics of the population in the model. Assuming different types of decision-making strategies, such as income maximizers and need satisfaction variance minimizers, and rainfall variability, a detailed sensitivity analysis was performed. Lynam concludes that although the model is incomplete, better understanding of the relation of natural resources and the wellbeing of households was derived.

Matthew Hoffmann *et al.* present in Chapter 11 a first version of a multi-agent model to study deforestation and reforestation patterns in Indiana (USA). Prior to European colonization, Indiana was nearly entirely forested. By 1900, only 5–10% of the state was forested, but since then forestland has rebounded to approximately 20% of the state's land cover. The multi-agent model of land cover change simulates the observed process of deforestation and afforestation in Indiana over time.

The last two chapters deal with interactions with stakeholders in order to solve collective-action problems. Bousquet *et al.* provide an overview of the work of CIRAD on their use of multi-agent systems for ecosystem co-management by performing role games. By using role games the required knowledge can be obtained, the model can be validated and used in decision-making processes. The discussion of the different applications shows how models can be used in support of collective decision-making processes in natural resource management.

In the last chapter, Nick Abel and colleagues discuss a large project in the rangelands of New South Wales, Australia. Participatory analysis of the land-use values of five stakeholder groups showed a great potential for multiple land-use as an efficient way of reducing land-use conflicts and satisfying stakeholders' needs, but legal and administration hurdles prevented the system change. Participatory policy making generated 160 proposals for legal, policy and administrative changes designed to simplify the complexity, realize win–win opportunities, resolve conflicts and promote regional resilience. The project has been influential within the region, but at State level there has been little change so far.

In sum, the contributions in this volume show that models of multi-agent systems can be applied for the study of ecosystem management. Applications focused on diffusion processes, explaining puzzling historical observations, and using models together with stakeholders in an attempt to solve contemporary management problems. The continuation of this endeavor can be improved when a number of methodological issues are addressed, notably validation, and the link between the behavioral rules of agents and experimental data.