Chapter 30

# GOVERNING SOCIAL-ECOLOGICAL SYSTEMS

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* We gratefully acknowledge support from the Center for the Study of Institutions, Population, and Environmental Change at Indiana University through National Science Foundation grants SBR9521918 and SES0083511. We also want to thank the participants of the conference for the Handbook of Computational Economics, Vol II: Agent-Based Computational Economics, Ann Arbor, Michigan, May 21–23, 2004, as well as Marty Anderies, David Batten, François Bousquet, Matt Hoffmann, and several anonymous referees for their feedback on an earlier version of this chapter. We thank Leigh Tesfatsion for her careful reading of the manuscript and the editorial suggestions, and Joanna Broderick and Patty Lezotte for the editorial help in various stages of this project.

*Handbook of Computational Economics, Volume 2. Edited by Leigh Tesfatsion and Kenneth L. Judd*

*DOI: 10.1016/S1574-0021(05)02030-7*

## Abstract

Social-ecological systems are complex adaptive systems where social and biophysical agents are interacting at multiple temporal and spatial scales. The main challenge for the study of governance of social-ecological systems is improving our understanding of the conditions under which cooperative solutions are sustained, how social actors can make robust decisions in the face of uncertainty and how the topology of interactions between social and biophysical actors affect governance. We review the contributions of agent-based modeling to these challenges for theoretical studies, studies which combines models with laboratory experiments and applications of practical case studies.

Empirical studies from laboratory experiments and field work have challenged the predictions of the conventional model of the selfish rational agent for common pool resources and public-good games. Agent-based models have been used to test alternative models of decision-making which are more in line with the empirical record. Those models include bounded rationality, other regarding preferences and heterogeneity among the attributes of agents. Uncertainty and incomplete knowledge are directly related to the study of governance of social-ecological systems. Agent-based models have been developed to explore the consequences of incomplete knowledge and to identify adaptive responses that limited the undesirable consequences of uncertainties. Finally, the studies on the topology of agent interactions mainly focus on land use change, in which models of decision-making are combined with geographical information systems.

Conventional approaches in environmental economics do not explicitly include non-convex dynamics of ecosystems, non-random interactions of agents, incomplete understanding, and empirically based models of behavior in collective action. Although agent-based modeling for social-ecological systems is in its infancy, it addresses the above features explicitly and is therefore potentially useful to address the current challenges in the study of governance of social-ecological systems.

## Keywords

social-ecological systems, agent-based computational models, commons dilemma, cooperation, non-convex ecosystem dynamics

*JEL classification*: C70, C90, D70, D80, H41, Q20, Q30, Q57

# 1. Introduction

For millennia, human activities have affected their environment. In ancient times, the use of fire and tools enabled humans to learn to live outside their original environment—the savannah of eastern Africa. The development of agriculture about ten thousand years ago, and industrialization during the last two hundred years, have generated massive population increases and intense uses of natural resources. Now, we live on a human-dominated planet. Human activities have transformed the land surface, altered the major biogeochemical cycles, and added or removed species in most of Earth's ecosystems (Vitousek et al., 1997).

This chapter reviews the efforts by many scholars to use agent-based computational models to study the governance of social-ecological systems. This field is truly interdisciplinary. It will be difficult, if not impossible, therefore to restrict our focus solely to economics. Although economics will be our starting point, we will include studies from other disciplines. To facilitate communication across disciplines we will use an organizing framework in the second section of this chapter. To structure our chapter, we identify three main challenges for the study of the interactions between human activities and ecosystems.

- What conditions enhance the likelihood of cooperative solutions to the massive number of social dilemmas that confront social-ecological systems? This relates to the problem of preventing overharvesting of common-pool resources such as fish stocks, forests, and fresh water.
- How do economic agents make effective and robust decisions given the fundamental uncertainty of the complex dynamics of the social-ecological system?
- How can the topology of interactions among actors be explicitly included in the analysis of the first two questions given the importance of interactions to an understanding of natural resource dynamics?

The aim of this chapter is to show the contribution of agent-based computational economics to these challenges. We emphasize the linkages between field research, laboratory experiments, and agent-based modeling. Pure analytical models have proved to be essential tools for analyzing highly competitive markets and other settings with strong selection pressures (Ruttan, 2003). When trying to understand how and why individuals engage in collective action, however, analytical models have not proved as useful. In the field and in the experimental laboratory, we have observed many settings in which individuals overcome the incentives to free ride, increase the levels of inter-personal trust, produce public goods, and manage common-pool resources sustainably (Bromley et al., 1992; Gibson et al., 2000a; National Research Council, 2002; Ostrom and Walker, 2003; Dietz et al., 2003). Candidate theories for explaining these surprising empirical results are too complex to be usefully pursued using only analytical techniques. To understand these phenomena agent-based modeling has become an essential tool complementing empirical methods. Other chapters in this volume (Brenner, 2005; Duffy, 2005) also address the combination of laboratory experiments and agent-based modeling. Their contribution focuses more on learning models, while our focus is on public goods and common-pool resource experiments using several models of human decision-making. It is important to realize that every method used to study social-ecological systems has its methodological problems. We will therefore emphasis in this chapter the plurality of approaches, which may unravel the complexity of the systems when findings are consistent with all the types of approaches used.

The studies reviewed in this chapter differ from those most frequently addressed by environmental economists. Conventional economic theory predicts that when agents have free access to a common-pool resource they will consume ecosystem services to the point where private costs equal the benefits, whereas externalities are imposed on the rest of the community. This can lead to the well-known tragedy of the commons (Hardin, 1968). Traditionally, 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, models were mainly static, such as the seminal work on renewable resource harvesting by Gordon (1954). During the 1970s, the trend shifted toward 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 foci of environmental economics (e.g., Chichilnisky, 2000). Recently, economists have started to include non-convexities of ecosystems into their analysis of optimal management of ecosystems (Dasgupta and Mäler, 2003; Janssen et al., 2004).

In simple models in mainstream environmental economics, a representative agent is presumed to have perfect knowledge (or knowledge on the probabilities of outcomes) and to maximize utility of consumption for an infinite time horizon. Such an approach results in interesting insights. Representing agents as maximizing known utility functions is, however, of limited use when systems are characterized by non-convex dynamics, structural uncertainty, heterogeneity among agents, multi-attribute utility, and spatial heterogeneity. Evidence is accumulating that social-ecological systems frequently do have complex, non-linear dynamics. This affects the type of governance that may lead to sustainable outcomes (Scheffer et al., 2001). Initial steps has been taken to include such non-linear dynamics in environmental economics (Dasgupta and Mäler, 2003). Furthermore, increasing evidence exists that agents are able to self-govern some types of common-pool resources without external governmental intervention but do not always succeed (Bromley et al., 1992; Ostrom, 1990; National Research Council, 2002; Ostrom et al., 1994). The question is how to analyze ecosystem management problems with spatially explicit, non-convex dynamics influenced by multiple stakeholders with divergent interests and who consume different types of ecosystem services. We need new tools. Agent-based modeling is a promising tool for the analysis of these complex problems (Janssen, 2002a).

Several developments outside environmental economics during the last thirty years have influenced the current state of agent-based modeling of social-ecological systems. We will briefly discuss some of these developments. Since the early 1970s, scholars from system dynamics have developed and used integrated models of humans and their environment (Ford, 1999). Prime examples are the World 2 and 3 models of Forrester (1971) and Meadows et al. (1972, 1974). The World 2 and 3 models simulated the long-term interactions between population, industrial and agricultural production, resource use, pollution and food supply at an aggregated global level. A core finding was that continuing early 1970s' trends would lead to an overshoot and collapse in terms of population and economic development. The World 2 and 3 models were highly criticized for the subjectivity of the assumptions and the lack of rationality of the decision-making actors within the model (Cole et al., 1973; Nordhaus, 1973). In fact, the actors, economic sectors on a global level, reacted in a predetermined way.

The first type of agent-based model for governing social-ecological systems that we were able to trace in the literature is Bossel and Strobel (1978). They developed a model to address two lacunae in the World 2 and 3 models—namely, their failure to account for cognitive processes and their usual neglect of normative criteria and changes in these criteria. In fact, the Bossel and Strobel model is of a cognitive agent interacting with the global system. Their agent bases its decisions on the state of the global system, using indicators, so-called system's orientors, like existence needs, security, freedom of action, adaptivity, and effectiveness. This agent receives information about the state of the system and decides to change priorities or aspirations, which affect the investment decisions of the agent. Inclusion of these "intelligent" agents prevents the preprogrammed "pollution crisis" from occurring. It also leads to policies producing very satisfactory overall results, provided the planning horizon and the control sensitivity are sufficiently large. The current field of integrated modeling of humans and the environment still faces similar problems, uncertainty, subjective assumptions and lack of behavioral models, to those of the initial models (Janssen and de Vries, 1999). Core questions remain regarding how to deal with uncertainty and subjective assumptions and how to include human dimensions.

Another field that contributed to the development of agent-based modeling of social-ecological systems is individual-based modeling in ecology, which really took off in the late 1980s (Huston et al., 1988). Individual-based modeling refers to simulation models that treat individuals as unique and discrete entities who have at least one property, in addition to age, that changes during the life cycle, e.g. weight, rank in a social hierarchy, etc. Often motivated by pragmatic reasons, individual-based models are used to study systematically the behavior of organisms in complex (spatially explicit) environments (Grimm, 1999).

In the artificial intelligence field since the late 1980s, scholars developed tools for natural resource management (Coulson et al., 1987). Well known are geographic information systems and expert systems, but also a number of models have been developed that included intelligent agents interacting with their complex environment (Anderson and Evans, 1994). An interesting early example is the PHOENIX model on fire management (Cohen et al., 1989). The model simulates a forest fire and the actions of intelligent agents, representing bulldozers and airplanes. The model is an event-driven simulation model, meaning that the agents perform real-time tasks based on events that happen in their local environment. Every five simulated minutes of the model, the agents are synchronized to allow coordination among the agents. The model is aimed at evaluating fire-fighting plans in various scenarios.

Bousquet et al. (1994) developed an objected-oriented model of natural resource management of fisheries in the central Niger delta. Based on fieldwork, an artificial world was created where different scenarios of rules of when and where to fish in a wetland area were analyzed for this impact on long term viability of the natural resources. The existence of space-sharing rules was found to be essential to avoid overfishing.

Deadman and Gimblett (1994) constructed a system that handles the complexity of goal-oriented autonomous human agents seeking recreational opportunities in natural environments. The model simulates the behavior of three types of visitors and their interactions in an event-driven GIS environment of a park environment using intelligent agents: hikers; bikers; and visitors transported in tour vehicles. The results of hiker interactions with other users have been used to provide feedback about the implications for alternative recreation management planning.

Complexity science is still another foundation for the study of the governance of complex social-ecological systems. Social-ecological systems can be viewed as complex adaptive systems—systems in which the components, and the structure of interactions between the components, adapt over time to internal and external disturbances (Holland, 1992a). Order in complex systems is emergent as opposed to predetermined. The system's history is irreversible, and future behavior is path dependant. The system's future is often unpredictable due to the non-linearity of many basic causal relationships. The variables that affect performance are both fast and slow moving. If information about slow-moving variables is not recorded for a long period of time, substantial surprises can occur when a slow-moving variable reaches some threshold. In social-ecological systems, the key components are individuals and institutions. With institutions we refer to the formal and informal rules that shape human interactions. Individuals may change their relations with other individuals, their strategies, and the rules they are using. In fact, individual strategies and institutional rules interact and co-evolve, frequently in unpredictable ways. For example, the peasants who were starting to drain the peat mires on a local level more than 1000 years ago in the precursor of the Netherlands did not foresee the large-scale consequences in the few hundred years on the larger-scale landscape (lowering of the surface by about 2 cm a year), leading to new institutions (like waterboards), and different practices (livestock instead of agriculture).

From this perspective, the question arises of how to govern social-ecological systems. In systems that are indeed complex, one needs to understand processes of organization and reorganization including collapse and the likely processes that happen after collapse. Does a system have one and only one equilibrium to which it returns after a major shock and temporary collapse? Are there multiple equilibria with different characteristics? How easy is it for a system to flip from a desirable equilibrium to an undesirable one? These are crucial questions.

The complex adaptive systems perspective provides us the view of individuals within a variety of situations structured by the biophysical world, the institutional rules, and the community in which they interact. Within ongoing structures, individuals search out perceived advantageous strategies given the set of costs and benefits that exist and the strategies that others adopt. Boundedly rational individuals trying to do as well as they can in uncertain situations continuously tinker with their strategies, including trying to change the rules that affect particular situations. They may look for loopholes in the law, particularly if they think others are doing the same. They may check out the level of enforcement by occasionally breaking rules. Those who have responsibility for changing the rules of an institution also experiment with new rules and try to learn from others why other institutional arrangements appear to work better than their own.

Agent-based models are a suitable methodology to study these complex social-ecological systems in a formal manner for the following reasons:

- Agent decisions are based on internal decision rules; this fits very well with the increasing insights from experimental social science that humans use various types of heuristics in different situations (Gigerenzer et al., 1999; Gigerenzer and Selten, 2001).
- The explicit inclusion of agent interactions helps to integrate the increasing insight of the importance of communication in managing social dilemmas (Ostrom et al., 1994; Ahn et al. 2003, 2004).
- Agent-based modeling shares similarities with models used in ecology, such as individual-based models, system theory, and the inclusion of space. Therefore, agent-based modeling facilitates collaborative efforts of ecologists and social scientists.
- Agent-based models are suitable for modeling complex adaptive systems, in which the interactions of individual units lead to larger-scale phenomena.
- Agent-based modeling makes it possible to address the problem of scale explicitly (Gibson et al., 2000b).

The perspective of social-ecological systems as complex adaptive systems provides us a useful stepping stone for using agent-based modeling for the study of social-ecological systems. In the next section we discuss a general framework of social-ecological systems that we will use as a guideline to discuss the work done in this field.

## 2. A framework for social-ecological systems

The social-ecological systems (SESs) to be examined in the rest of this chapter are (1) systems composed of both biophysical and social components, (2) where individuals self-consciously invest time and effort in developing forms of physical and institutional infrastructure that affect the way the system functions over time in coping with (3) diverse external disturbances and internal problems, and (4) that are embedded in a network of relationships among smaller and larger components. In other words, humans have designed *some parts* but not all of the overall SES. In most instances, the design has evolved over time as feedback generated information about how the SES was operating

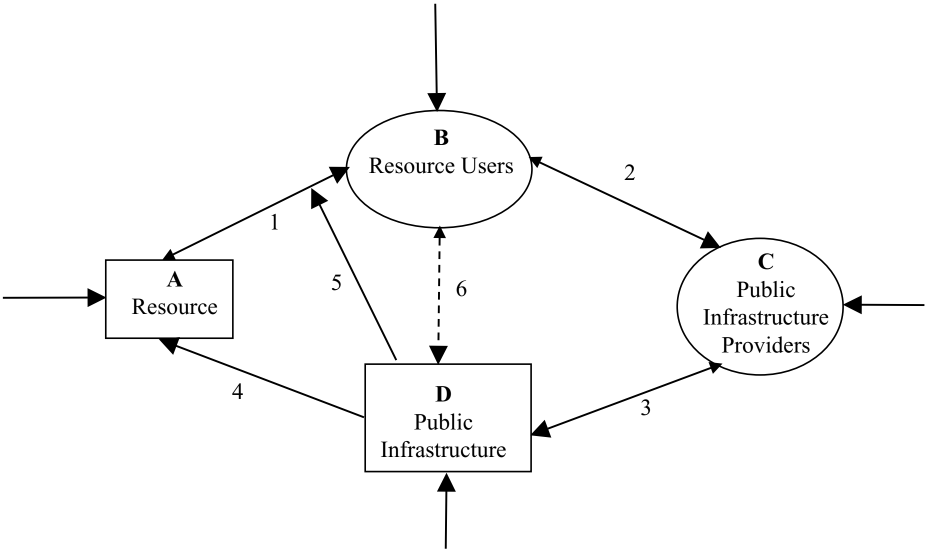



Figure 1. A conceptual model of a social-ecological system. Source: Anderies et al. (2004).

and participants in various positions try to improve the operation of the system—at least from their perspective.

We adopt the general framework proposed by Anderies et al. (2004) that identifies the relevant parts of a social-ecological system and how they are linked. In Figure 1, the elements of such a framework are presented. Given that most multi-level SESs are very complex, we start by focusing first on a single-level SES. We identify four "entities" that are normally involved in SESs utilized by groups of individuals over time. Two of these entities are composed of humans. First are the resource users (*B* in Figure 1), who are the population of those harvesting from the resource (*A* in Figure 1). Second are the public infrastructure providers (*C* in Figure 1), who receive monetary taxes or contributed labor and make policies regarding how to invest these resources in the construction, operation and maintenance of a public infrastructure. A substantial overlap may exist among the individuals in *B* and in *C* or they may be entirely different individuals depending on the structure of the social system governing and managing the SES.

The public infrastructure (*D* in Figure 1) combines two forms of capital: human-made capital (physical capital) and institutional capital (see Ostrom and Ahn, 2003; Costanza et al., 2001). The physical capital includes a variety of engineered works, for example the headworks and canals of an irrigation system and the constructed highways of a transportation system. The institutional capital includes the rules actually used by those governing, managing and using the system that create opportunities and constraints in the action-outcome linkages available to participants.

The resource ($A$ in Figure 1) is most frequently a biophysical system or a form of natural capital that has been transformed for use by $B$ through the efforts of $C$ to invest in $D$. We will focus on common-pool resources where it is difficult to exclude potential beneficiaries from receiving the costs or benefits of governance strategies, and where the resource flows withdrawn from the resource system subtract from the availability of resource flows for other users (Ostrom et al., 1994). If one is going to examine robustness or resilience, one needs to include external disturbances (*incoming arrows* on Figure 1), which can include biophysical disruptions (Linkages 7) including floods, earthquakes, landslides, and climate change which impact on $A$ and $D$ or socioeconomic changes (Linkages 8) including population increases, changes in economic opportunities, depressions or inflations, and major political changes that impact on $B$, $C$ and $D$.

A social-ecological system can be challenged in two ways: (1) by external disturbances; and (2) by fluctuations within internal entities and the links between them. The internal fluctuations may result from the strategic interactions among the resource users and among the participants in the process of providing the public infrastructure. Further, strategic interactions exist among resource users regarding the harvesting rate from the resource (Linkage 1 on Figure 1), the linkages among resource users and the public infrastructure providers (Linkage 2 on Figure 1), the public infrastructure providers and the investments made in the infrastructure (Linkage 3), and potentially, the linkage between resource users and the public infrastructure (Linkage 6). Further, the linkages among the ecological entities (Linkages 1, 4 and 5) are also sources of fluctuations that may challenge the robustness of the overall SES at any particular point in time.

The simplest example of a social-ecological system consistent with the framework is a small group of actors with relatively homogeneous interests who are in both positions $B$ and $C$. Without a medium of exchange other than labor and goods, cooperation must be undertaken by direct interactions and transparent means. Such a system might be a small irrigation system where farmers who own relatively similar plots of land meet regularly to discuss how many days to work on maintenance and how to allocate the water (see Tang, 1992; Lam, 1998; Ostrom, 1992). A social-ecological system becomes more complex when task specialization occurs and most actors are either resource users or public infrastructure providers. This might create incentives for rent seeking, corruption, and mismanagement due to incomplete or competing knowledge systems. So the internal stability might become less robust when a system becomes more diverse and specialized.

External threats may affect the various components and links within the SES. Natural events, human induced impacts, and accidents can disrupt the resource system. External sources may change the preferences of resource users as a consequence of new information and inward and outward migration of people. The abilities to perform by public infrastructure providers can be affected due to changes in higher level regulations, and by the emergence or decline of local champions, those individuals who make a difference in making things happen. Finally, the public infrastructure can itself be affected by natural events and accidents (physical infrastructure) and changes in higher level regulations (institutional rules). These external disturbances interdependently affect the activities within the social-ecological system. In fact, there might be interactions across scales that make SES's become more or less robust to internal and external challenges.

This general framework lets us rephrase the three puzzles identified in the introduction. The first set of questions addresses social dilemmas: What kind of institutional frameworks lead to robust governance of social-ecological systems? What is the influence of the ecological dynamics? What kind of information do resource users and public infrastructure providers exchange? What are conflicting and compromising interactions between the different agents involved? What is the effect of different levels of spatial and temporal scale? How do institutional rules evolve?

The second type of question addresses uncertainty: What information do resource users and public infrastructure providers have, and what is the asymmetry of this information? How do resource users learn, and how do their learning processes differ from how public infrastructure providers learn? How do different mental models of agents affect the use and governance of the resource? Finally, social and biological agents interact in a spatially explicit landscape formulated as maps or networks. How does spatial heterogeneity affect the functioning of social-ecological systems? How does information spread among nodes in a network? Who talks with whom, when and about what, and how does this affect resource management?

We will now discuss each of the three areas and dig in more deeply to discuss theoretical and applied agent-based models, and the relation of laboratory experiments with agent-based modeling.

## 3. Social dilemmas

A key theoretical and empirical puzzle in all of the social sciences is how individuals overcome the strong temptation not to cooperate in social dilemmas, in which individual contributions exceed individual returns, and instead attempt to achieve joint benefits through cooperation (Axelrod, 2005). Both sets of human actors identified in Figure 1 face multiple social dilemmas. Resources users ($B$) face common-pool resource dilemmas that can, if unresolved, lead to serious over-harvesting and potentially the destruction of the resource. As one New England fisher recently put it, "I have no incentive to conserve the fishery, because any fish I leave is just going to be picked up by the next guy" (cited in Tierney, 2000, p. 38). Some users may develop trust (Ostrom and Walker, 2003) and/or strong reciprocity even when they have heterogeneous interests (Bowles and Gintis, 2004). Without some agreed-upon and enforced rules, however, resources users may simply race each other to use up the resource. Public infrastructure providers ($C$) also face social dilemmas in their effort to develop effective institutions (a public good) or efficient infrastructure (usually another common-pool resource). Simply authorizing some individuals to govern a resource does not guarantee that they will overcome the temptations to engage in rent-seeking, to accept bribes, or simply to avoid investing in costly information acquisition.

Cooperation in social dilemmas can be easily explained when the social agents are genetically related (Frank, 1998) and/or interact repeatedly over a long indeterminate time (Kreps et al., 1982). The question of why non-related social agents cooperate relates to a number of important issues in ecological economics, especially to the question of designing effective institutional configurations for common-pool resources and public goods. Schlager (2004) reviews the extensive empirical cases where local communities have developed institutions to deal with social dilemmas. These examples demonstrate that people have the capacity to organize themselves to achieve much higher outcomes than predicted by conventional economic theory. Capacity is not, however, sufficient to ensure that resources are governed sustainably.

Empirical research stimulated in large part by a mid-1980s Committee of the National Research Council (National Research Council, 1986) and synthesized by a more recent committee (National Research Council, 2002) has demonstrated that no form of governance is guaranteed to change the strong incentives of the pervasive social dilemmas faced by resource users and public infrastructure providers so as to generate long-term sustainability. Governing resources successfully is always a struggle (Dietz et al., 2003). Empirical findings suggest that successful, adaptive governance of natural resources requires: (1) generating substantial information about stocks, flows, and processes within the resource (the arrows in Figure 1); (2) dealing with conflict that arises among multiple users and uses of a resource; (3) inducing rule compliance among all participants so that each has confidence that the others are not cheating; (4) providing effective physical and institutional infrastructure (*C* in Figure 1); and (5) preparing for the inevitable changes that occur due to external disturbances as well as internal changes in resource and human dynamics (Dietz et al., 2003). A recent empirical study of over 200 forests located in Africa, Latin America, Asia, and the United States provides strong evidence that regular rule enforcement is more important in achieving sustainable forest conditions than the form of organization governing a forest, the level of social capital existing among users, or the level of dependence of users on a forest (Gibson et al., 2005).

### 3.1. Theoretical models

Field research has thus generated substantial evidence that, contrary to earlier economic theory, no optimal form of governance exists that can be imposed on all SESs with the expectation that resource users and public infrastructure providers will accept the system and make it work. On the other hand, field research has also shown that resource users and public infrastructure providers have devised an ingenious array of rule configurations that work effectively in specific ecological and social settings. Thus, there is a lot for theory to explain!

As discussed in more detail by Dibble (2005), Axelrod (2005), Young (2005), and Kollman and Page (2005), agent-based models are being intensely used to derive a better theoretical understanding of the conditions that lead social agents to cooperate. Axelrod (1984, 1987) pioneered in this field with his iterated prisoner's dilemma (IPD) tournaments and with his simulation of the evolution of strategies using genetic algorithms. This led to a vast number of human–subject experiments (summarized in Davis and Holt, 1993; Colman, 1995) and agent-based models on variations of the IPD game focused on the effects of partner choice, tags, reputation symbols, spatial interactions, noise, probabilistic choice, and so forth (see Gotts et al., 2003). Multiple theoretical efforts have been made to provide a coherent, analytical framework for explaining the repeated finding that cooperation levels in social dilemmas are frequently above the zero contribution level predicted by non-cooperative game theory (see Boyd and Richerson, 1992; Bowles, 1998; Gintis, 2000; Camerer, 2003).

Axelrod (1986) was among the first to tackle how norms supporting cooperative strategies, that were not the strategies leading to a Nash equilibrium, could be sustained over time. He posited that individuals could adopt norms—meaning that they usually acted in a particular way and were often punished if they were not seen to be acting in this manner. He posited that some individuals also developed a norm to punish those who defected in social dilemmas as well as the concept of a meta norm—a norm that "one must punish those who did not punish a defection" Axelrod (1986, p. 1109). With punishment norms backing cooperative norms, and the meta norm of punishing those who did not punish defectors, Axelrod was able to develop an evolutionary theory of cooperation consistent with evidence from the field.

Recent evolutionary models by Kameda et al. (2003) have developed these ideas even further. In a formal analysis of a set of simplified strategies, these authors explore the viability of a "communal sharing strategy" which cooperates when in the role of resource acquisition and imposes sanctions on others if they engage in non-sharing behavior. They establish that the communal-sharing strategy is a unique evolutionarily stable strategy that blocks any other strategy from successfully invading for a wide range of parameters. Kameda et al. also undertook a simulation of the performance of multiple strategies when ten players are involved and their strategies could evolve over time. Here they observed that free riding could become the dominate strategy over multiple generations due to the problem of second-order free riding in regard to norm enforcement. When they added an "intolerant" norm enforcer who is willing to bear extra costs for excluding others who are second-order free riders on the enforcement of cooperative norms, simulated ten-person games tended to sustain cooperative sharing over very large number of generations. In field settings of robust SESs, one does tend to find some members of self-organized groups who are "fired up" about the need for everyone to follow the rules and norms they have evolved over time. Some groups rotate the role of being the local enforcer among their membership, so no one has to bear the cost of monitoring and enforcing at all times, while each of them is "super-charged" with the responsibility for local monitoring on a rotating basis.

Many of the specific rules that empirical researchers have observed in the field have puzzled theorists. In addition to rotating enforcement responsibilities, elaborate turn-taking rules have, for example, been observed in robust institutions related to harvesting fish from inshore fisheries (see Berkes, 1986) and obtaining water from farmer-governed irrigation systems (Ostrom, 1992). Even subjects in repeated common-pool resource experiments with opportunities to engage in face-to-face communication have devised rotation systems enabling one set of subjects to gain more in one round and less in the next (Ostrom et al., 1994). A recent paper by Lau and Mui (2003) has now provided a strong game-theoretic analysis of how such complex rules can be sustained in a repeated environment characterized by asymmetric payoffs in any one period.

Let us now turn to agent-based models of cooperation. Thébaud and Locatelli (2001), for example, developed an agent-based model to address a puzzle initially proposed by Sugden (1989). Sugden observed the emergence of property-right rules of those who gather driftwood after a storm on the Yorkshire coast. Whoever found an item first could take it and gather it into piles. By placing two stones on the top of each pile, the gatherer could mark his property. If a pile had not been removed after two more high tides, the ownership rights terminated. Thébaud and Locatelli were able to generate the emergence of piles, whose existence varied with the range of vision (could the agent steal without being caught?) and the threshold of the size of the pile before it is considered private property (lower threshold makes it easier to generate private piles). Another aspect that was found important is the imitation rule. Agents compare their wood pile with others they encounter and, if the observed pile is larger than their own (including the wood they are currently carrying), they adopt the strategy of its owner with regard to the property rule.

Another set of papers discusses the effect of different models of human behavior on the management of common resources. Jager et al. (2000) discuss the harvesting by a population of agents of a fish stock and a gold mine (whose pollutants negatively affect the carrying capacity of the fish population). They tested two types of models of behavior. In the first model, the agents considered all possible actions. In the second, agents used heuristics mimicking repetition, deliberation, social comparison, and imitation. Which heuristic was active at a certain moment in time depended on the level of satisfaction and uncertainty. Jager et al. (2000) show that constant deliberation over all possible options leads to a faster decline of the resources, and an uneven transition from fishing to gold digging. Several social psychology-based agent-based models on the collective use of common resources have especially focused on including the effects of resource uncertainty (Jager et al., 2002; Mosler and Brucks, 2002). Jager et al. (2002), for example, show that overharvesting is more severe in periods of uncertainty, which is consistent with laboratory experimental and field evidence. Due to the use of agent-based models, Jager et al. were able to pin-point three different behavioral processes that may contribute to this overuse. Another relevant paper is by Janssen and Ostrom (2005), who study the conditions that are needed for a population of agents to voluntarily restrict their own behavior to avoid collapse of the 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 because the agents trust each other to follow the rules.

### *3.2. Laboratory experiments related to the governance of social-ecological systems*

Behavioral game theory has been instrumental in testing the effects of alternative models of decision-making on social dilemmas (see, for example, Erev and Roth, 1998; Camerer and Ho, 1999; Camerer, 2003; Duffy, 2005). With regard to the governance of social-ecological systems, the study of public goods and common-pool resources are important. The standard linear public-good provision experiment can be characterized by the number of individuals $(N)$, the marginal per capita return $(r)$, the number of repetitions $(T)$, and the initial endowment of token money for each player $(\omega)$. An experimental linear public-good provision game involves a free-rider problem if $r < 1$ and $N \times r > 1$. Suppose, in a given round, individual $i$ contributes $x_i$ of $\omega$ for the provision of the public good. The subject's payoff $(\pi_i)$ is:

$$\pi_i = \omega - x_i + r \sum_{j=1}^{N} x_j.$$

The equilibrium prediction, assuming individuals maximize own monetary payoffs, is that the public good will not be provided at all.

For the common-pool resource experiments with a quadratic production function, the experiments are formulated in the following way. The initial resource endowment $\omega$ of each participant consists of a given set of tokens that the participant needs to allocate between two markets: Market 1, which has a fixed return; and Market 2, which functions as a collective resource and which has a return determined in part by the actions of the other participants in the experiment. Each participant $i$ chooses to invest a portion $x_i$ of his/her endowment of $\omega$ in the common resource Market 2, and the remaining portion $\omega - x_i$ is then invested in Market 1. The payoff function as used in Ostrom et al. (1994) is:

$$u_i(\mathbf{x}) = \begin{array}{ll} 0.05 \cdot e & \text{if } x_i = 0 \\ 0.05 \cdot (\omega - x_i) + \left(x_i / \sum x_i\right) \cdot F\left(\sum x_i\right) & \text{if } x_i > 0 \end{array}$$

where

$$F\left(\sum x_i\right) = \left(23 \cdot \sum_{i=1}^{8} x_i - 0.25 \cdot \left(\sum_{i=1}^{8} x_i\right)^2\right) / 100.$$

According to this formula, the payoff of someone investing all $\omega$ tokens in market one $(x_i = 0)$ is $0.05 \times \omega$, thus 0.5 tokens. The return is like a fixed wage paid according to the hours invested. Investing a part or all of the tokens in market two $(x_i > 0)$ yields an outcome that depends on the investments of the other players. If the players behave according to the non-cooperative game theory, they would derive the Nash equilibrium, where each player maximizes payoff given the strategies chosen by the other players.

A series of laboratory experiments during the last twenty years have shown that subjects do invest in public goods and are able to govern common-pool resources more sustainably than predicted by theory (Isaac et al., 1984, 1985, 1994; Isaac and Walker, 1988; Marwell and Ames, 1979, 1980, 1981; Ostrom et al., 1994). Depending on the return rate from investments in the public good, the initial contribution rate remains the same or decreases with the number of rounds. Laboratory experiments have consistently shown that communication is a crucial factor for achieving cooperative behavior (Sally, 1995; Brosig, 2002).

In the common-pool resources, the average harvest approaches the Nash equilibrium when no communication or sanctioning is allowed, but decreases to a cooperative level when participants do communicate (cheap talk) or are able to penalize (impose costs on) those who harvest more than agreed upon. The ability of participants to determine their own monitoring and sanctioning system is critical for sustaining efficient cooperative behavior (Ostrom et al., 1994).

### *3.3. Agent-based models of laboratory experiments*

Since the behavior of subjects is not consistent with predictions using a rational choice model of individual behavior, an important question is what types of models of human behavior explain the observations. A recent development is the use of agent-based models to test alternative models that replicate the patterns of the subjects in the laboratory experiments. Peter Deadman (1999) defined agents who chose a certain strategy and could update these strategies in an environment that is similar to the common pool experiments run at Indiana University (Ostrom et al., 1999). He modeled their updating process to be based on the expected and experienced performance of strategies in previous rounds. The types of strategies he used were based on exit interviews conducted after a session of common-pool resource experiments had ended (Ostrom et al., 1994).

One strategy attempts to maximize the individual return received in each round by comparing investments in Market 2 in previous rounds with the resulting returns. If returns on tokens are increasing, then more tokens are placed in Market 2. If returns on tokens invested in Market 2 are decreasing, then fewer tokens are placed in Market 2. Another strategy mentioned by subjects is to compare average returns between Market 1 and Market 2, increasing the tokens allocated to the market that performs better. The last type of strategy directly compares an individual agent's investment with the investments of the group as a whole. The agent-based model showed similar fluctuations in aggregated token investment levels in Market 2 as in the laboratory experiments reported in (Ostrom et al., 1994).

Deadman et al. (2000) introduce communication between agents in their agent-based model. During communication, agents are assumed to pool their experience in regard to the various strategies they have used. In this way, all agents derive a similar map of which strategies work well. As in the laboratory experiments where communication was allowed, investment levels moved closer to the optimal level of full cooperation.

Like Deadman (1999), Jager and Janssen (2002) used agent-based models to provide a possible explanation of observed patterns in common-pool experiments without communication. The agents in Jager and Janssen are based on a meta-theoretical framework of psychological theories. An agent is assumed to have different type of needs, including subsistence, identity and exploration. Depending on whether the needs of the agent are satisfied or not, and whether the agent is uncertain or not, an agent uses one of four decision rules: deliberation; social comparison; repetition; and imitation. An unsatisfied agent spends more cognitive energy (e.g., deliberation or social comparison) than a satisfied agent (who relies more on repetition and imitation). An uncertain agent uses information from other agents (social comparison or imitation) instead of relying on individual information (deliberation or repetition). The difference between social comparison and imitation is that during social comparison an agent checks whether copying the strategy of another agent leads to an expected improvement of the utility.

Jager and Janssen found that agent-based models of individual behavior in common-pool resource settings needed to include

- social value orientation,
- preferences one has for a particular distribution of outcomes for oneself and others,
- satisfying behavior,
- exploratory behavior when payoffs of an agent remain the same for a number of rounds, and
- heterogeneity of needs among the agents.

All five individual characteristics are needed in the analysis to derive token investment patterns at the group level similar to those resulting in the human–subject experiments. The investment patterns were evaluated by taking into account the average investment level, the differences between the agents in a group, and the changes of investment levels across rounds.

Castillo (2002) investigates the decision rules individuals used during field experiments of common-pool resources conducted by (Cárdenas among coastal communities in the Colombian Caribbean Sea (Cardenas et al., 2000). The model is based on the theory of collective action of Ostrom (1998) and implemented from a systems dynamics perspective. As in previous studies, Castillo simulates the experiments describing the actions of individual agents. By using response functions, Castillo is able to estimate the theoretical framework of Ostrom (1998) without describing the mechanisms of reputation, trust, and reciprocity explicitly.

We are aware of two additional papers that use agent-based model to understand the behavior of agents in public-good experiments. Iwasaki et al. (2003) examined a reinforcement learning model to explain patterns of behavior observed in their threshold public-good experiments. In such an experiment, a minimum threshold of investments in the public good must be contributed before the public good is provided. Their model of reinforcement learning was only partly able to explain the observed data. It did reproduce cooperative patterns, but was not able to reproduce non-cooperative patterns.

Janssen and Ahn (2005) compare the empirical performance of two decision making models to explain the outcomes in a large set of public-good experiments without communication (Isaac and Walker, 1988; Isaac et al., 1994), namely, the experienced weighted attraction learning model of Camerer and Ho (1999), and the best-response model with signaling based on Isaac et al. (1994). In contrast with the previous studies, Janssen and Ahn focus on the problems on parameter calibration and the evaluation of the model performance on individual and group level statistics. Both models outperform the selfish rational actor model as an explanation of observed behavior. Furthermore, the learning model was found to give the best performance using the individual level calibration, while the best response model was found to calibrate best at the group level. The essential elements of the model that enhances its performance is the inclusion of other regarding preferences and satisficing behavior, similar to Jager and Janssen (2002) for common-pool resources.

The strategy method, where human subjects develop strategies based on their experience in laboratory experiments, is an interesting method which links agent-based models and experiments (Selten et al., 1997). Keser and Gardner (1999) apply the strategy method to common-pool resources. Their common-pool resource game consisted of a constituent game played for twenty periods. Sixteen students, all experienced in game theory, were recruited to play the game over the course of six weeks. In the first phase of the experiment, they played the common-pool resource game on-line three times. In the second phase of the experiment, the tournament phase, they designed strategies which, after implementation as agents, were then played against each other. As for human subjects, a Nash equilibrium was found at the aggregate level, but at the individual level, fewer than 5% of subjects played in accordance with the game equilibrium prediction.

Combining agent-based modeling and laboratory experiments of complex dynamic social dilemmas has just started (see Duffy, 2005 for a more general discussion on agent-based modeling and laboratory experiments). The current publications demonstrate considerable potential to test alternative theories of human behavior. Huge methodological challenges still exist, however, in regard to parameter estimation and model comparison. For example, Salmon (2001) showed that identification of the correct learning models using econometrics techniques leads to potential problems. Salmon generated experimental data by simulation of normal-form games using a number of learning models so that he could test four different econometric approaches in their accuracy of distinguishing the individual models by which the data was generated. Wilcox (2003) did a similar experiment to test the implication of the assumption of homogeneity of the subjects. If the agent population is heterogeneous in parameter values, serious problems in accuracy of parameter estimation are created.

Model selection is an important line of research in cognitive science (Pitt and Myung, 2002). Various approaches have been developed to test models in regard to goodness of fit and generalizability. These approaches penalize models with increasing complexity. Approaches based on maximum likelihood depend on the assumption that the observations are statistically independent. This is not the case when multiple actors interact over time in experiments with public goods and common-pool resources. Interdependence in a complicated fashion definitely exists when communication, monitoring, and sanctioning are allowed.

### *3.4. Applications to social-ecological systems*

An early application of agent-based modeling to study the coordination among resource users is the study of the irrigation systems of Bali (Lansing and Kremer, 1993). The irrigators have to solve a complex coordination problem (Lansing, 1991). On one hand, control of pests is most effective when all rice fields in a watershed 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 that details what actions should be done on each specific date in each organized group of farmers—called a *subak*. These actions are related to offerings to temples, ranging from the little temples at the rice terrace level to the temples at the regional level and all the way up to the temple of the high priest Jero Gde, the human representative of the Goddess of the Temple of the Crater Lake. Crater Lake feeds the groundwater system, which is the main source of water for irrigating in the entire watershed. These offerings were collected as a counter gift 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, which were predicted to lead to three harvests a year, instead of the two of the traditional varieties. Farmers were stimulated by governmental programs that subsidized the use of fertilizers and pesticides. After the governmental incentive program was started, the farmers continued performing their rituals, but 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 to the rice crop. 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 subaks with their water temples. Lansing built an agent-based model of the interactions of subak management strategies and the ecosystem, and the local adaptation of subaks to strategies of neighboring 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, 1993). He also showed how the coordination might have been evolved as a result of local interactions (Lansing, 2000).

In Lansing and Miller (2003), a simple game-theoretic model is used to provide a compact explanation for many of the most salient features observed in the system. While externalities caused by either water scarcity or pests in isolation would be expected to cause a serious failure in the system, they find that the ecology of the rice farming system links these two externalities in such a way that cooperation, rather than chaos, results. The reason for this, depending on the underlying ecological parameters in the system, is that regimes exist in which the farmers would like to coordinate their cropping patterns (in particular, have identical fallow periods) so as to control pest populations. In other regimes, coordination is not an equilibrium, even though coordinated farming would result in greater aggregate crop output. Lansing and Miller identified two indirect mechanisms by which the system can reach cooperation. The first is to have the upstream farmers share their water with the downstream farmers. The second is that increases in pest damage can drive the system into a coordinated equilibrium, enhancing aggregate output. The Balinese rice temples would have played a facilitating role in deriving coordination in this complex system. In an earlier game-theoretical paper, Ostrom (1996) also examined how differences between head-end and tail-end farmers could be the foundation for extensive mutually productive coordination in the maintenance of irrigation infrastructure.

Bousquet and his colleagues (Bousquet et al., 1998) developed a modeling platform, CORMAS, dedicated to the study of common-pool resources through agent-based modeling. They have performed many applications and work together with local stakeholders, often in Africa and Asia, to develop agent-based models for practical natural resource management problems.[1] Barreteau and Bousquet (2000), for example, study the underutilization of irrigated systems in the Senegal River Valley in North Senegal. An agent-based model was developed to simulate an archetypal irrigation system. The agents represent farmers, credit access, and water allocation groups. The processes represented deal with the circulation of water and credit and with interactions about their allocation and access to them. The model was used in role-playing experiments to test its potential as a negotiation support tool and to test the model with the agents they try to simulate (Barreteau et al., 2001). The use of a role-playing game was found very useful for testing the model and interacting with local stakeholders. This led Bousquet et al. (2002) to the idea of *companion modeling*, which interactively combines agent-based modeling and role-playing games and uses the latter to acquire knowledge, build and validate the agent-based model, and use the model in the decision-making process. This has been applied to a number of case studies, as reviewed in Bousquet et al. (2002). We come back to role-playing games later in this chapter.

Rouchier et al. (2001) discuss a coordination problem of nomad herdsmen securing their access to the rangelands in Cameroon. Herdsmen who need the grass and water from the villages negotiate with village leaders to get access to the land of the farmers. The herdsmen choose which leaders to approach. Those leaders may reject offers if they are lower than a minimum acceptance level. Herdsmen need to sell some of their animals to derive the resources to pay the fee. Three types of choice processes are simulated: (1) herdsmen make offers to place their animals on random spots; (2) they make offers

[1] See http://cormas.cirad.fr.

for the cheapest spots; or (3) they make offers to the villages with the best friendship relations that take into account past refusals of offers. Rouchier et al. found that choices based on costs lead to the lowest number of animals that the simulated system could sustain, because considerable resources are lost by negotiation and refusals when all herdsmen try to enter cheapest village. Since the herdsmen do not learn in this model, they continue losing productivity by aggregating around the same village every time period. Other applications of the CORMAS group include collaborative forest management in East Kalimantan in Indonesia (Purnomo et al., 2003) and the management of livestock effluents in Réunion, France (Farolfi et al., 2002).

### 3.5. *What have we learned?*

In regard to the governance of common-pool resources, agent-based modeling has been able to draw on a foundation of extensive fieldwork and laboratory experiments as well as extending our theoretical understanding of cooperation in social dilemma settings. Since both forms of empirical research had already challenged the capacity of simple, analytical theory based on non-cooperative game theory to explain empirical results, the field was ripe for the use of agent-based models. We have learned from agent-based models of the processes linking resource users, public infrastructure providers, and their resources and infrastructures that much of the data reported by field researchers is consistent with a complex, adaptive systems view of social dilemmas.

From the combination of research methods examining factors enhancing levels of cooperation, we have learned that devising rules that allocate benefits to resource users in a legitimate, fair, and enforceable way is essential to overcome incentives to free ride. Rarely can external authorities devise rules that are well tailored to a local ecology and culture and also invest substantial resources in monitoring patterns of resource use and sanctioning those who do not follow rules. Thus, the repeated finding that individuals can devise agreed-upon norms for governing a resource that they themselves can monitor and enforce has changed our scientific understanding of these processes. Unfortunately, public policies have all too frequently relied on simple panaceas that either recommend government, private property, or decentralized governance of SESs. We have strong evidence that simplistic solutions that are imposed by external agencies on resource users rarely work (National Research Council, 2002; Dietz et al., 2003). And, fortunately, we now have methods—agent-based models—that facilitate the analysis of complex SESs by stakeholders and officials. No longer do we need to throw up our hands in despair because the system is so complex! We do, however, need to continue a sense of modesty. Even with agent-based models of complex SESs, we rarely can prescribe “the” optimal solution for any complex setting. Those involved have to learn over time by experimenting with local ideas, with what they can learn from others and with ideas from the literature describing what has worked well in other settings.

## 4. Dealing with uncertainty

Understanding of the processes of social-ecological systems is incomplete and is likely to remain incomplete. Given the persistent uncertainty facing resource users and public infrastructure providers in the field, researchers need to incorporate uncertainty explicitly in their analyses (Ludwig et al., 1993). Agent-based models can address uncertainty by analyzing the consequences of how people make decisions under uncertainty and by assessing the impact of different types of hypotheses about these processes in social-ecological systems.

Models of human decision-making under uncertainty have traditionally been approached from a probabilistic standpoint: human performance was compared to probabilistic prescriptions. Any divergence was interpreted as a deviation from the optimal behavior. Laboratory experiments of human decision-making, however, show that frequently people do not make decisions under uncertainty that are consistent with the probabilistic perspective (Kahneman and Tversky, 1979). Further, many decision problems cannot be characterized by a closed set of probabilities (Ludwig et al., 1993).

If agents do not have complete knowledge of a complex ecological system, how do their mental models of the system affect their actions? How can they learn to derive a more accurate mental representation? These questions refer to the general problem in agent-based modeling that agents do not have perfect knowledge of the system. They make their decisions based on the perceptions they have of the problem. These perceptions do not have to include correct representations of reality and may vary among agents. The focus in this section is on the uncertainty of agents about the ecological dynamics.

### *4.1. Theoretical models*

An important source of uncertainty in the governance of social-ecological systems is the fundamental uncertainty of the functioning of the biophysical system. One of the uses of agent-based models is to explore the consequences of agents who have incomplete perceptions of reality. Different perceptions of reality can be visualized by different perspectives of stability (Figure 2). According to the equilibrium perspective, systems are in equilibrium. External effects can push the system briefly out of equilibrium, but it automatically returns to the previous equilibrium situation. This perspective corresponds very well with the Newtonian-modeling paradigm. The perspective of stability can be represented graphically as a ball at the bottom of a valley (Figure 2c). Perturbations only temporarily knock the ball away from the bottom of the valley. An implicit assumption of this perspective is that systems have the capacity to dampening all kinds of disturbances.

An alternative perspective is the obverse: namely, the perspective of instability. Systems are assumed to be very sensitive to disturbances. Every disturbance can lead to a catastrophe. Applied to environmental issues, the perspective of instability explains why some people argue that human activities are not supposed to disturb the natural

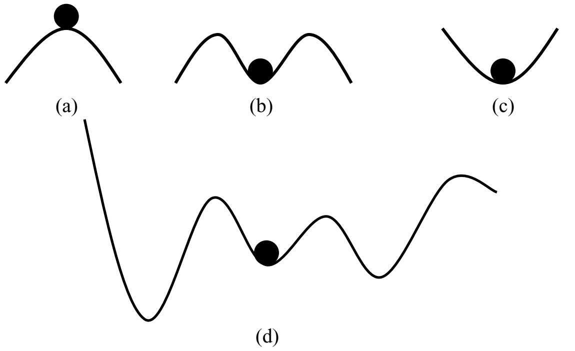



Figure 2. Perspectives of nature: (a) nature is unstable; (b) nature is stable within limits; (c) nature is stable; (d) nature has different stability domains (after Janssen, 2002b).

system. Any degree of pollution or increase of extractions can lead to a collapse of the system. This perspective can be visualized by a ball on a peak (Figure 2a). Any perturbation can cause the ball to roll down the slope. A third perspective is in-between the perspectives of stability and instability: namely, a system is assumed to be stable within limits. When the system is managed well, the system can absorb small perturbations. This perspective can be visualized as a ball in a valley between two peaks (Figure 2b).

A more advanced framework is to consider multiple stable states (Scheffer et al., 2001). As depicted in Figure 2d, this perspective can be represented as a number of peaks and valleys. The ball is resting in a valley and is able to absorb a certain degree of disturbance. However, a severe disturbance can push the ball over a peak such that it will rest in another valley, an alternative equilibrium. Examples of these multiple states are lakes that can flip from an oligotropic state to a eutrophic state due to inputs of phosphates, and rangelands that can flip from a productive cattle-grazing system into unproductive rangeland dominated by woody vegetation, triggered by variability in rainfall.

A perspective of systems that is more advanced, and lies in line with the complex adaptive system modeling paradigm, is the perspective of resilience. The perspective of resilience not only considers the balls moving up and down the peaks and valleys, but also considers possible movements of the peaks and valleys themselves. In this evolutionary picture, stability domains can shrink, and disturbances that previously could be absorbed might now dislodge the system. This view has important implications for managing systems. In the previously discussed perspective, systems could be known perfectly. Surprises could lead to changes of management, because the balls move into another valley; but, in principle, management is simply a matter of controlling the system. From the perspective of an evolving 'landscape,' however, one has to manage a system in the face of fundamental uncertainty about the functioning of the system. One continually needs to observe the system in order to respond adequately. Moreover, small human-induced perturbations are recommended in order to learn from the system over time.

Various concepts called worldviews are designed to classify different perceptions of reality. Michael Thompson and his colleagues give a general description of perspectives on natural and human systems and social relations in their Cultural Theory (Thompson et al., 1990). This theory was used during the 1990s to classify different types of institutional designs in relation to global environmental change. Cultural Theory is even used in various mathematical models, when suitable, because it includes perspectives on human and natural systems that claim generality and includes the determinism of explaining the rationality of each perspective. Cultural Theory combines anthropological and ecological insights, and results in multiple types of culture.

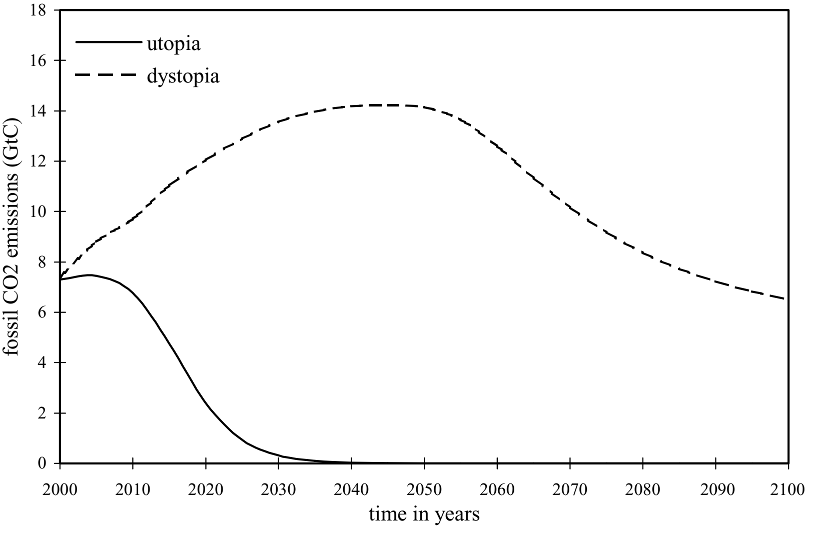
The three main worldviews in Cultural Theory are:

- Hierarchists assume that nature is stable in most circumstances but can collapse if it crosses the limits of its capacity. Therefore, central control is advocated as a management style.
- Egalitarians assume that nature is highly unstable and that the least human intervention could lead to its complete collapse. A preventive management style is preferred.
- Individualists assume that nature provides an abundance of resources and believe it is stable with human interventions. A responsive management style is advocated.

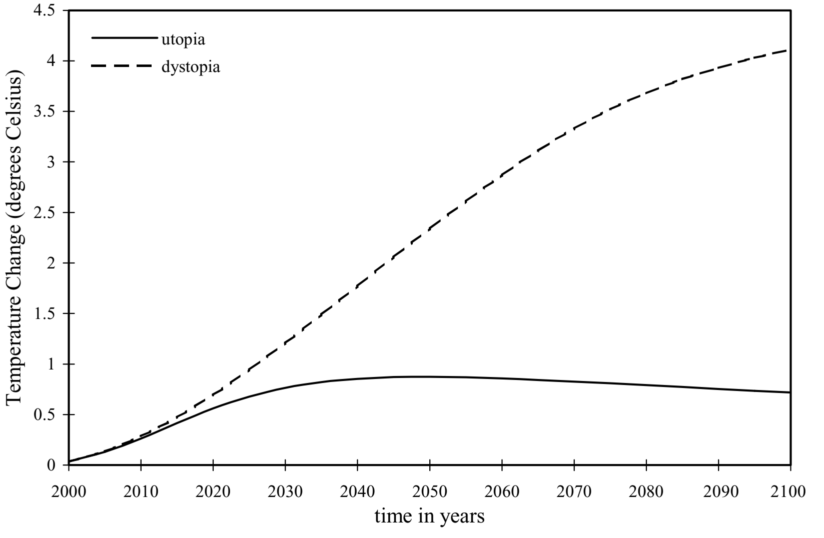
Human-induced climate change is a topic surrounded with many uncertainties and is therefore an excellent example to illustrate how worldviews can be quantified to simulate alternative futures based on different perceptions of reality. Such an analysis was made by Janssen and de Vries (1998), who developed three versions of a simple model of a social-ecological system based on alternative assumptions about climate sensitivity, technological change, mitigation costs, and damage costs due to climate change. Egalitarians, for example, assume high climate sensitivity, high damage costs, low technological development, and low mitigation costs. For management styles, they assume different strategies for investments and reductions of emissions of carbon dioxide. The individualist, for example, assumes a strategy that maximizes economic growth and assumes emissions are reduced only if a certain threshold of economic damage is exceeded.

Suppose the agents in a model world are all hierarchists, all egalitarians, or all individualists. If agents are assumed to have perfect knowledge of their world, their utopia can be simulated. If their worldview is incorrect and they still apply their preferred management style, their dystopia can be simulated. An example is presented in Figures 3a and 3b. In the egalitarian utopia, emissions of carbon dioxide will be reduced to zero within a few decades, leading to a modest temperature change. However, if the individualistic worldview manages a world that actually operates according to the egalitarian worldview, emissions increase until climate change causes such an economic disaster that an emission reduction policy is unavoidable.

By introducing a population of agents with heterogeneous worldviews, a complex adaptive system is produced. It is assumed that the better an agent's worldview ex-




(a)




(b)

Figure 3. (a, b) Expected carbon dioxide emissions and temperature increase according to the egalitarian utopia an a possible dystopia (individualistic management style in an unstable global system). (c, d) Expected carbon dioxide emissions and temperature increase according to different views on the functioning of the global system. (Based on Janssen and de Vries, 1998).

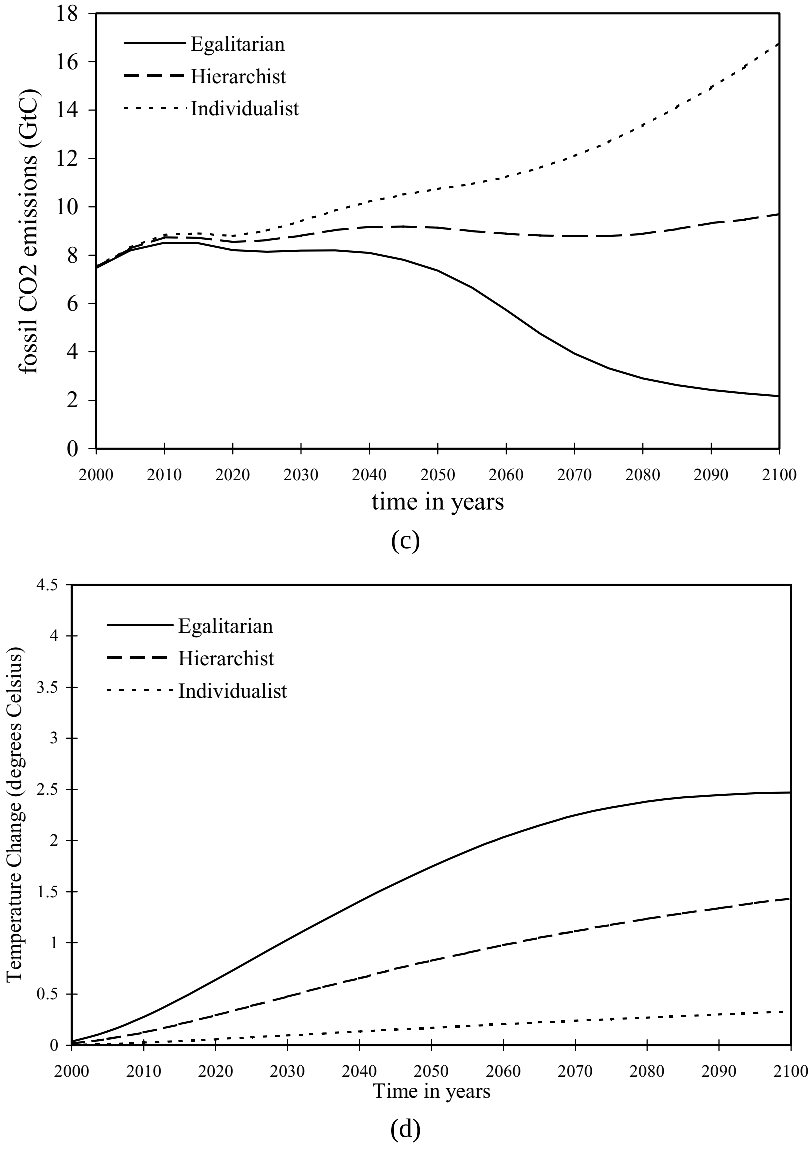



Figure 3. (*Continued.*)

plains the world's observed behavior, the greater is the chance that it will be stable. A genetic algorithm is used to simulate a battle between perspectives (Holland, 1992b). The better a worldview explains observations, the more it is likely to be followed by a larger proportion of the population. They simulate a learning process where agents may adjust their mental models when they are surprised by observations, and may make adjustments in their decisions according to their new perceptions of the problem. Agents tolerate some level of error, however, before they change their worldviews. The initial distribution of worldviews is therefore important for the long-term evolution of the social-ecological system. On aggregate, worldviews tend to change to the worldview that explain the observations in the most convincing way. Suppose that reality is one of the three possible worlds, and an agent obtains information over time that causes it to adjust (or not) its perspective on the problem of climate change. Three sets of projections are derived in which agents adapt to climate change (Figures 3c and 3d). Prior to year 2040, the observed climate change does not lead to domination of one of the worldviews. After 2040, the climate signal becomes clear enough that one of the worldviews begins to dominate. In the event of the world functioning according to the egalitarian worldview, the emissions growth stabilizes in the coming decades and decreases to a level below half of the present amount of emissions. However, this reduction cannot avoid a global mean temperature increase of about 2.5°C in the coming century.

The explicit inclusion of subjective perceptions of reality has led to a rich variety of possible futures. This approach has also been applied to lake management (Carpenter et al., 1999a, 1999b; Janssen and Carpenter, 1999; Janssen, 2001; Peterson et al., 2003) and rangeland management (Janssen et al., 2000). Lakes are a favorite ecosystem for the study of social-ecological systems, because the multiple stable states are well studied and simple, empirically based models are available (Carpenter et al., 1999b). The typical lake model focuses on phosphorus pollution. Phosphorus flows from agriculture to upland soils, and then on to surface waters where it cycles between water and sediments. The lake ecosystem has multiple locally stable equilibria and moves among basins of attraction depending on the history of pollutant inputs. Lakes are often classified as oligotrophic or eutrophic depending on their productivity. Oligotrophic lakes are characterised by low nutrient inputs, low to moderate levels of plant production, relatively clear water, and relatively high economic value of ecosystem services. Eutrophic lakes have high nutrient inputs, high plant production, murky water with problems including anoxia and toxicity, and relatively low value of ecosystem services. When mitigating eutrophication, lakes can respond differently to reduced phosphorus inputs, which is mainly related to recycling of phosphorus from sediments to the overlying water.

In Carpenter et al. (1999a), an agent-based model is developed in which agents form expectations about ecosystem dynamics, markets, and/or the actions of managers, and they choose levels of pollutant inputs accordingly. Agents have heterogeneous beliefs and/or access to information. Their aggregate behavior determines the total rate of pollutant input. As the ecosystem changes, agents update their beliefs and expectations about the world they co-create. They modify their actions accordingly. For a wide range of scenarios, Carpenter et al. observe irregular oscillations among ecosystem states and patterns of agent behavior. These oscillations resemble some features of the resilience of complex adaptive social-ecological systems. Janssen and Carpenter (1999) applied the same framework of worldviews as used in Janssen and de Vries (1998) to the management of lakes. The agents learn and adapt to unexpected changes in the state of the lake, and a mix of perspectives is required to manage the resilience of the system. Although low levels of phosphorus in the lake will not be reached, the lake is prevented from flipping to catastrophically high phosphorus levels.

The agents are always learning, but never get it exactly right. They come close enough, however, to sustain the social-ecological system. In Janssen (2001), the agents were enriched with a mix of various cognitive processes, such as imitation, deliberation, and repetitive behavior, in their decisions about how much phosphorus to use. Analyses with the model showed that the dominating type of cognitive processing was a relevant factor in the response to uncertainty and policy measures. When agents are easily unsatisfied with their economic performance, it leads to a more intensive use of phosphorus and to higher levels of phosphorus in the lake. Simulated farmers used phosphorus more intensively in situations with high natural variability. A tax on phosphorus had little effect on the behavior of the farmers when they felt uncertain and were easily satisfied.

Peterson et al. (2003) describe the management of a lake as a learning process. The agents consider two management models of the lake, one for an oligotrophic lake and the other for a eutrophic lake. As agents observe the lake varying from year to year, they estimate how well each of the two management models is supported by the observed data. Management policies maximize the expected net present value of the lake. Even under optimistic assumptions about environmental variation, learning ability, and management control, conventional decision theory and optimal control approaches fail to stabilize ecological dynamics. Rather, these methods drive ecosystems into cycles of collapse and recovery.

Weisbuch and Duchateau-Nguyen (1998) study fisheries where fishers do not have complete understanding of the underlying (logistic) resource dynamics. Historical information about catches, capital amounts, and the fraction of the income used for consumption, are used by the agents to predict future catches. Incremental learning is used to update the weights on the various sources of information. The agents were able to learn to manage the system and could cope with sudden shocks to the system.

In the rangeland model of Janssen et al. (2000), agents do not learn but may go bankrupt, leave the system, and be replaced by a random, new pastoralist. The agents have incomplete understanding of the complex rangeland system. They tend to overgraze their property by putting too many sheep on their land, and suppress fire too much so woody shrubs can start dominating. Janssen et al. analyzed the consequence of different government regulations on the evolution of types of agents. Agents who evolve under a regime of limited grazing do not have a proper understanding of the dynamics of the system. Agents who evolve without regulations, experience the whole spectrum of possible events. In the latter case, many properties are unproductive for a longer period, but those agents who evolve have a good understanding of the system. This example shows the importance of exploring the possible dynamics of a regime and the effects of precautionary policies to avoid overuse of the resource.

Bodin and Norberg (2005) examine the principal impact of information sharing in (social) networks of artificial natural resource managers capable of experimenting, simple information processing, and decision-making. All managers adaptively manage their own local ecological resources. All properties are close to a threshold at which the ecological system flips into an unproductive state. Aggregate properties of the coupled social-ecological system are analyzed in relation to different network structures. Bodin and Norberg find that the network structures have a profound effect on the system's behavior. Networks of low- to moderate-link densities significantly increase the sustainability of the ecological resource. However, networks of high-link densities contribute to a highly synchronized behavior of the managers, which causes occasional large-scale ecological crises between meta-stable periods of high production. It is demonstrated that in a coupled social-ecological system the system-wide state transition occurs not because the ecological system flips into the undesired state, but because the managers loose their capacity to reorganize back to the desired state.

### *4.2. Laboratory experiments*

We will discuss the work of scholars who test different types of heuristics to explain experimental observation of decision-making in different situations (Gigerenzer et al., 1999). In a similar vein, we will analyze the comparative analysis of quantitative learning models on experimental data of subjects learning to find good solutions for allocation problems in complex environments (Rieskamp et al., 2003). For a broader discussion on agent-based models, laboratory experiments, and learning we refer to Brenner (2005) and Duffy (2005) in this volume.

Gigerenzer et al. (1999) argue that humans use fast and frugal heuristics to make satisfying decisions about a set of alternatives that respect the limitations of human time and knowledge. Complexity and uncertainty of the environment have led in the evolution of the brain to smart solutions that are "ecologically rational." The authors discuss a large number of experiments in which they test simple heuristics such as one-reason decision-making (e.g., "take the last," "take the best"), elimination heuristics, or recognition heuristics. A drawback of this research program, so far, is that the decision-making experiments are very simple, like what city has the largest population, compared to the more dynamic decision environments with social interactions as is characteristic of social-ecological systems.

Rieskamp et al. (2003) used experiments to compare two learning models related to long-term decisions made under uncertainty. One learning model is reinforcement learning, a global search model that assumes that decisions are made probabilistically based on the experience aggregated across all past decisions. The other learning model is hill-climbing, a local search model that assumes a new decision is made by comparing the preceding decision with the most successful decision up to that point. One application of their model is explaining the decisions made by resource users about diverse strategies of land use. In the laboratory experiment, participants were asked to allocate three financial assets in a repeated session of two hundred rounds. The optimal allocation was often not found, but a learning effect was still measurable. Rieskamp et al. (2003) conclude that the hill-climbing model best describes their observations.

Goldstone and Ashpole (2004) performed experiments where a large number of human participants interacted in real time within a shared virtual world. Two resource pools were created with different rates of replenishment. The participants' task was to obtain as many resource tokens as possible during an experiment. Besides variation in the rate at which consumed tokens were replaced, Goldstone and Ashpole manipulated whether agents could see each other and the entire token distribution, or had their vision restricted to tokens in their own location. The optimal solution for participants is to distribute themselves in proportion to the distribution of resources. The human subjects did not to distribute themselves in this optimal fashion. Rather, they systematically allocated themselves more to the relative scarce resource, leading to an underutilization of the resources. Furthermore, especially when the vision of the subjects was restricted, oscillations in the harvesting rates of the resources across time were observed. Perceived underutilization of a resource resulted in an influx of agents to that resource. This sudden influx, in turn, resulted in an excess of agents, which then led to a trend for agents to depart from the resource region. Thus, uncertainty about the availability of resources increased instability of the distribution of the subjects, which itself enhanced uncertainty.

### *4.3. Applications*

In the spirit of adaptive management (Holling, 1978), various researchers develop their agent-based models together with the stakeholders of the problem. Like the participatory modeling approach, such as practiced in systems dynamics (e.g., Costanza and Ruth, 1998), they use the model as a tool in the mediation process with stakeholders and as a way for the stakeholders to learn strategies that might solve the dilemmas they face in complex environments. In Bousquet et al.'s (Bousquet et al., 2002) companion modeling, the role-playing games are meant to reveal some aspects of social relationships by allowing the direct observation of interactions among players, the stakeholders. Barreteau et al. (2003) argue that such role-playing games are good communication tools among stakeholders, but it is difficult to reproduce the results. Systematic comparison of the results is difficult since many factors are uncontrolled. When players play again, they may change the context of the game due to their learning experience in the previous experiment.

In Etienne et al. (2003), for example, an agent-based model was developed to simulate strategies of natural resource management in the Causse Méjan, a limestone plateau in southern France dominated by a rare grassland-dominated ecosystem endangered by pine invasion. To facilitate discussion of alternative long-term management strategies for the sheep farms and the woodlands, contrasting perspectives on land resources from foresters, farmers, and rangers of the National Park of Cévennes were designed at different spatial scales. A series of exercises with different stakeholder groups was performed to confront the consequences of their viewpoints, and that of the other stakeholders. As a result of this iterative process it was possible to select a set of feasible scenarios stemming from the current actors' perceptions and practices and to suggest alternative sylvopastoral management based on innovative practices. D'Aquino et al. (2003) describe their project on irrigation systems in Senegal. Since 1997 they have experimented at an operational level (2500 $km^2$) in the Senegal River valley with agent-based modeling intertwined with role-playing games. Their self-design approach is aimed to include as much as possible the knowledge of the local participants. This development of methodology may contribute to additional tools of resource users and public infrastructure providers to self-govern their common resources.

Pahl-Wostl (2002) discusses a similar development that she calls participatory agent-based social simulation. This modeling technique inputs social processes into integrated models that are developed in participatory settings. Hare and Pahl-Wostl (2002) illustrate in a Swiss case study how card-sorting can be used to categorize stakeholders to inform the design of agent-based models.

An interesting application of learning models to natural resource management is the work of Dreyfus-Leon on fisheries. Dreyfus-Leon (1999) presents a basic model to mimic the search behavior of fishers. It is built on two neural networks to cope with two separate decision-making processes in fishing activities. One neural network deals with decisions to stay in current fishing grounds or move to new ones. The other is constructed for the purpose of finding prey within the fishing grounds. Reinforcement learning is used to derive expectations of catches from previous neural network-based decisions. Feedback about catches is used to update the weights of the neural networks. Some similarities with the behavior of real fishers were found: the concentrated local search once a prey has been located to increase the probability of remaining near a prey patch and the straightforward movement to other fishing grounds. Also, they prefer areas near the port when conditions in different fishing grounds are similar or when there is high uncertainty in their world.

The observed behavior of the artificial fisher in uncertain scenarios can be described as a risk-aversion attitude. In Dreyfus-Leon and Kleiber (2001), the model of fishers' behavior was applied to yellow-fin tuna fishing in the eastern Pacific Ocean. In contrast to Dreyfus-Leon (1999)—where the schools of fish were located at fixed points—in this study, movements of schools of fish were simulated with artificial neural networks, based on relative habitat comfort. Like Dreyfus-Leon (1999), the individual fishing vessels were represented with artificial neural networks. The tuna vessels searched for the tuna schools during a fishing trip. An interesting Turing experiment was performed to test the performance of the model by asking experts, fishers, and tuna researchers to identify which tracks were simulated and which were real. The experts were not able to provide the correct answer more frequently than random choice. This provided the modelers some confidence in their results. Two scenarios were considered in the analysis: one with no fishing regulation and another with an area closure during the last quarter of the year. In the scenario without regulation, fishing effort was allocated, particularly in higher levels nearer the coast and where high concentrations of tuna were detected. In the scenario with regulation, redistribution of effort was uneven but increased in neighboring areas or in areas relatively near the closure zone. Decrease in effort was evident only in the closed area. Effort redistribution when regulations were implemented is not well understood, but this modeling approach can help fishery managers to envisage some regulation effects in the fishery.

### 4.4. What have we learned?

Uncertainty and limited knowledge about ecological processes are crucial elements in the study of social-ecological systems. Agent-based modeling provides us a tool to test the consequences of the limitations of knowledge of various actors in decision-making processes on the governance of natural resources. Theoretical models focused on mental models match very well the applications that use role-playing games and the participatory approach. These applications provide stakeholders instruments to test the consequences of different perceptions of the systems, which enable them to identify compromises and conflicts. The participatory use of models, such as systems-dynamics, already existed. Agent-based models enable researchers to be more explicit about the behavioral and spatial aspects of social-ecological systems.

The experimental work related to natural resource management and uncertainty relates primarily to heuristics and learning models. In that respect there is a mismatch with the theoretical and applied agent-based models. A considerable challenge remains to develop experimental work to test the consequences of various mental models for the management of natural resources.

## 5. Topology of interactions

The importance of non-random and non-uniform topologies of interactions between agents can be an important reason to use agent-based models. As discussed by Dibble (2005), Wilhite (2005), and Vriend (2005), the role of the structure of interactions has been found important in various areas of agent-based computational economics. In this chapter we mainly focus on exogenous structures of interactions, especially as they are caused by ecological processes. In fact, when we include space, many questions arise related to the structure of interactions.

Explicit inclusion of space in the analysis of environmental economic problems leads to the questions of how to allocate a scarce amount of space, how to manage land given uncertainty of the dynamics of the system, how to deal with spatial externalities and resulting spatial conflicts, and how information spreads in a spatially explicit system. The area of land-use and land-cover change addresses these issues, and agent-based modeling has been applied in this area. Agent-based modeling for land-use and land-cover change combines a cellular model representing the landscape of interest with an agent-based model 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, cellular maps can be derived for analysis.

Since the 1980s, cellular automata have been used to model land use/cover over time (Couclelis, 1985). Human decision-making was taken implicitly into account in the transition rules, but not expressed explicitly. Sometimes the cells represent the unit of decision-making. In most applications, however, the unit of decision-making and the cell are not the same. The desire to include more comprehensive decision rules, and the mismatch between spatial units and units of decision-making, led to the use of agent-based modeling for land-use and land-cover change. By including agents, one can express ownership explicitly, as 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 to derive a portfolio of crops.

Another rapid development is the study of the structure of networks (Watts and Strogatz, 1998; Barabasi and Albert, 1999). Since agent-based models are characterized by the interactions of agents, it is important to understand the consequences of the effects of different network structures on the collective behavior in social-ecological systems. We will review some of this literature from the perspective of governing social-ecological systems.

### *5.1. Theoretical models*

In a number of examples, Axtell (2000) shows that changes in the interaction topology can have important consequences for the outcomes in agent-based simulations, since the topology affects the speed at which information is processed among agents. For example, having $X$ interactions in each time step, or on *average*, may lead to different aggregated results, depending on the nonlinear behavior of the agent-based model. In a similar vein, Flache and Hegselmann (2001) investigated the sensitivity of two main processes in social science, migration dynamics and influence dynamics, to different spatial relationships among the agents. They concluded that most of the insights are robust to alternative spatial patterns, but some interesting differences do exist. Irregular grids, for example, result in path-dependent processes, leading to lock-ins of certain patterns.

Within the theoretical studies of social dilemmas, the paper of Nowak and May (1992) simulated the study of social dilemmas in a spatial context. In their study, agents play a Prisoner's Dilemma game with their nearby neighbors in a rectangular cellular automata environment. The players defect or cooperate, and update their strategy each round, by imitating the strategy with the highest payoff in their neighborhood. The deterministic model led to spatially chaotic patterns of cooperation and defection. Thus, without memory, patterns of cooperation can be derived in a spatial context.

We will not review the comprehensive literature on spatial games here, but focus on public-good games because of their relevance for natural resource management. Hauert and colleagues study the evolution of cooperation in spatial public-good games (Hauert et al., 2002; Brandt et al., 2003; Hauert and Szabo, 2003). They show that when agents are able to leave a game, defectors, cooperators, and non-players co-exist in a dynamic environment (Hauert et al., 2002). The possibility of costly punishment of defectors significantly increases the level of cooperation (Brandt et al., 2003). Hauert and Szabo (2003) tested the consequence of different geometries of interactions. Cooperation is higher on honeycomb versus square interactions. Also, larger neighborhoods, and thus larger groups who share the pubic good, reduce the level of cooperation.

### *5.2. Laboratory experiments*

Laboratory experiments with regard to the importance of the structure of interactions are rare, especially with respect to the governance of social-ecological systems. This may change in the near future since new laboratories for experimental studies have been established at the University of Rhode Island and Indiana University. Both laboratories will focus on spatially explicit experiments with human subjects.

An interesting set of experiments that is of particular interest for this chapter seeks to understand how information from other agents affects decision-making. Kameda and Nakanishi (2002, 2003) performed experiments to analyze the consequences when human subjects had the choice to solicit information on the choices of other participants in the experiment. The experiment was called "Where is the rabbit?" and simulated a fluctuating uncertain environment in a laboratory setting. In this game, participants were asked to judge in which of two nests a rabbit was currently located based on stochastic information. Participants played the game for a total of sixty rounds. They were instructed that the rabbit (environment) had a tendency to stay in the same nest over time, but this tendency was not perfect: The rabbit might change its location between any two consecutive rounds with a probability of 20%. Thus, the location of the rabbit in a given round corresponded to the current state of the fluctuating environment. In one half of the experiments, subjects did not derive information from the choices of other participants. In the other half of the experiments, subjects in six-person groups derived information of three others (randomly chosen) in their group. In both cases, the subject could derive information about the location of the rabbit by a costly information search. Kameda and Nakanishi showed that the subjects who were able to derive information from others in their group derived a higher payoff than those who could only learn individually. A simulation was developed that mimicked the observed findings.

### *5.3. Applications*

Balmann (1997) studied structural change in agricultural activities. He developed a model that was based on a number of individually acting farms located at different points in an agricultural region. Like a cellular automaton, the region was subdivided into a number of spatially ordered plots. The farms competed for these plots and competed in different markets. Farms were allowed to engage in different production possibilities and could use several investment alternatives. They optimized their activities with respect to their objective function by considering their expectations, financial state, and existing assets. The model was applied to a hypothetical region and studied how agricultural development was path dependent. In Balmann et al. (2002), an application of the model is presented with data from a region in Germany. The model consists of approximately 2600 farms, distinguishing twelve farm types, as observed in the data. In their application of the model, heterogeneity among the agents resulted in diversity of adjustment costs to policy interventions. The model provides insights into the distribution and dynamics of the impacts of policy changes on incomes.

Building on the work of Balmann (1997), Berger (2001) developed an agent-based model for an agricultural region in Chile. The farm-household decision-making was represented as a linear programming problem solved for each simulated year. Berger analyzed the adoption of new export-oriented agricultural activities using a network-threshold framework (Valente, 1995). Empirical studies provided the foundation for the type of networks and the heterogeneity of threshold values. The analysis showed that a governmental policy to stimulate export-oriented agricultural activities was effective to double the income from agriculture in a twenty-year period, compared to a stabilization of the income level if the policy intervention was not implemented.

Deffuant et al. (2002) present another agent-based model of innovation among farmers. Their model is based on an in-depth survey and interviews with farmers in various locations in Europe. The empirical model presented about Allier, France, tried to understand how organic farming was diffused. A positive attitude toward organic farming was necessary but not sufficient to get adoption started. Positive information in the press stimulated farmers to exchange opinions, and stimulated adoption of organic farming.

Allen and McGlade (1987) developed a spatially explicit model of fishers. These fishers could have different strategies, based on the information available to them, such as fishing only at the location from which they expected the highest catch, or moving around randomly. Inclusion of stochastic behavior for some fishers was necessary to discover the location of fish stocks and to maintain the fish industry.

Hoffmann et al. (2002) present a pilot study of land-use change in south-central Indiana, USA. This part of the state was primarily forested prior to the arrival of settlers from Europe in the early 1800s. These settlers cleared substantial areas of land for agricultural production (crops and pasture) and for forest products used for construction materials. The process of clearing land continued until the early 1900s, at which time areas marginal for agricultural production were gradually abandoned, resulting in a pattern of forest regrowth in areas of low agricultural suitability. The agents (private landowners) made decisions regarding their portfolio of land-use products that affected their utility. The utility depended on components such as income from timber, income from farming, and aesthetic enjoyment of the forests. Using scenarios of prices for agricultural commodities, Hoffmann et al. were able to reproduce land-cover dynamics in line with observed stylized facts (agriculture on the flat land, reforestation on the slopes).

Evans and Kelley (2004) tested an elaborated version of the Hoffmann et al. model on Indian Creek Township, located in southwest Monroe County, Indiana. This area is approximately $10 \times 10$ km, with private landholders as the primary actors in the landscape. Indian Creek Township is characterized by a series of rolling hills with bottomland areas suitable for agricultural production interspersed between ridges/hills that are largely forested. Landowners are a mix of households that derive a portion of their household income from extraction practices (agriculture, farming, haying, timber harvesting) and other households that derive all their income from non-farm activities. Evans and Kelley analyzed the consequences of using different scales of modeling the decisions of the private landowners. The best fit of the calibrated model was derived at the highest resolution, and declined non-monotonically with scale. The authors argue that agent-based models of land use need to be analyzed at different levels of scale.

Parker and Meretsky (2004) focus on externalities of land use, and their affect on land-use composition and pattern. Their model was used to analyze interactions between urban use and agricultural use, and how externalities of the use of the property affected spatial patterns if agents made rational decisions to maximize their utility. The assumption was that when agents adopt NIMBY (not in my back yard) strategies related to urban activities, inefficient urban sprawl results.

Brown et al. (2005) present a model of urban sprawl applied to Washtenaw County, Michigan, USA. The agents entering the county weigh aesthetics, distance to the service center, and neighborhood density to make decisions about where to live. In addition to their empirical landscape, Brown et al. used artificial landscapes to test the ability of the model to predict certain spatial patterns generated by a known model. It was not always possible to predict settlement patterns with the model, illustrating the difficulty of getting a good fit in spatially explicit models. Nevertheless, they were able to derive good fits with *aggregated* spatial metrics.

The study areas of Brown et al. (2005) and Evans and Kelley (2004) are similar in some aspects (agents are households making decisions on a detailed, real landscape), but differ in others (urban vs. rural, residential choice vs. allocation of land-use activities). It is important to note the difference between the two modeling approaches as applied. Brown et al. developed an extremely stylized model. By keeping it as simple as possible, they were able to explore the parameter space in a comprehensive way. The agents and decision-making processes in the Evans and Kelley model were more sophisticated, and the model was calibrated on the observed detailed pattern of land-cover changes. Both approaches are defended as being more appropriate to understanding the underlying processes. More work definitely needs to be done to define the right type of model for the research question at stake.

### 5.4. *What have we learned?*

Agent-based models offer various new aspects to spatially explicit modeling. By explicitly including decision-making processes we may be able to test the consequences of various behavioral theories on spatial processes, such as land-use change and urban sprawl. We recognize a lacuna in the availability of laboratory experiments that may inform the choice of behavioral theories, but new laboratories at Indiana University and the University of Rhode Island are currently conducting such experiments.

Spatially explicit processes in landscapes and networks of interactions are important to investigate, since agent-based models are defined by the topology of interactions among agents. Much more work needs to be done to address how the structures of interactions and networks affect aggregated outcomes.

## 6. Challenges ahead

The use of agent-based computational modeling to understand the governance of social-ecological systems is rapidly developing. We identify a number of challenges for the coming years that are fundamental to the further development of this field.

- Throughout this chapter we have discussed theoretical and applied models in relation to laboratory experiments. Such a triangular approach is an exception within most research groups. We stress the importance of using multiple methods to analyze a common set of puzzles. No one method guarantees the right answer. When similar answers are derived from methodological triangulation, we can have more confidence in our findings.
- The Internet provides us new opportunities to study social-ecological systems from an agent perspective. Users need to make decisions in a complex, interlinked environment. Most of the information used during this process can be recorded. This leads to interesting opportunities to perform experiments in cyberspace, such as the experiment of Dodds et al. (2003) to identify social networks at a global scale.
- Significant progress has been achieved to understand the evolution of strategies and norms in collective-action situations, given a fixed set of commonly understood rules. What is currently lacking is a formal model of the process of rule change and the evolution of institutional rules, although some initial models have been developed (Janssen, 2005; Janssen and Ostrom, 2005).
- During the last few years considerable progress has been achieved in understanding the structure of networks. This has also been explored by those who are interested in the governance of social-ecological systems. An interesting development is the formal modeling of co-evolving networks, such as the work of Börner et al. (2004) in information science. From the perspective of social-ecological systems, it would be interesting to explore the co-evolution of social and ecological networks.

Agent-based models often have a tendency to become complicated and detailed, which reduces the ability for rigorous analysis of the model. How to find a balance between detail and simplicity is an important question. Therefore, evaluation techniques for the balance between complexity of the model and explanation of the empirical phenomena need to be developed. In a broader sense, we need to develop appropriate methodologies for model testing, model selection, and model validation (Durlauf, 2003).

## 7. Discussion and conclusions

The governance of social-ecological systems has been dominated during the last century by a top-down control paradigm. Concepts and tools from environmental economics generate the maximum sustainable yield of fish stocks, the optimal time to harvest forests, and the optimal allocation of water in irrigation systems. Empirical studies have shown that such a top-down perspective is often ill-suited and can stimulate unsustainable use of the resource. Empirical studies also have shown that complex, nested governance systems operating at multiple levels can govern similarly complex ecological systems at multiple scales more efficiently than single, large units lacking knowledge of many specific structures and processes. Social-ecological systems are complex, adaptive systems in which heterogeneity, multiple scales, multiple domains of attraction, surprise, and fundamental uncertainty of the functioning of the ecosystem need to be explicitly considered. Agent-based modeling may provide new tools to address important questions of how to govern our common resources now that we have a better appreciation of the complexity of social-ecological systems and the multiple dilemmas facing resource users and public infrastructure providers at multiple scales. However, the development of agent-based modeling is in its infancy. Whatever the future may bring, agent-based models need to be used as one of the tools in a pluralistic toolbox of concepts, frameworks, and methods in understanding and improving the governance of social-ecological systems.

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