

2
3 GOVERNING SOCIAL-ECOLOGICAL SYSTEMS

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10 Abstract 10

11
12 Social-ecological systems are complex adaptive systems where social and biophysical 12
13 agents are interacting at multiple temporal and spatial scales. The main challenge for 13
14 the study of governance of social-ecological systems is improving our understanding of 14
15 the conditions under which cooperative solutions are sustained, how social actors can 15
16 make robust decisions in the face of uncertainty and how the topology of interactions 16
17 between social and biophysical actors affect governance. We review the contributions 17
18 of agent-based modeling to these challenges for theoretical studies, studies which com- 18
19 bines models with laboratory experiments and applications of practical case studies. 19

20 Empirical studies from laboratory experiments and field work have challenged the 20
21 predictions of the conventional model of the selfish rational agent for common pool 21
22 resources and public-good games. Agent-based models have been used to test alter- 22
23 native models of decision-making which are more in line with the empirical record. 23
24 Those models include bounded rationality, other regarding preferences and heterogene- 24
25 ity among the attributes of agents. Uncertainty and incomplete knowledge are directly 25
26 related to the study of governance of social-ecological systems. Agent-based mod- 26
27 els have been developed to explore the consequences of incomplete knowledge and 27
28 to identify adaptive responses that limited the undesirable consequences of uncertain- 28
29 ties. Finally, the studies on the topology of agent interactions mainly focus on land use 29
30 change, in which models of decision-making are combined with geographical informa- 30
31 tion systems. 31

32 Conventional approaches in environmental economics do not explicitly include non- 32
33 convex dynamics of ecosystems, non-random interactions of agents, incomplete un- 33
34 derstanding, and empirically based models of behavior in collective action. Although 34
35 agent-based modeling for social-ecological systems is in its infancy, it addresses the 35
36 above features explicitly and is therefore potentially useful to address the current chal- 36
37 lenges in the study of governance of social-ecological systems. 37

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40 Keywords 40

41
42 social-ecological systems, agent-based computational models, commons dilemma, 42
43 cooperation, non-convex ecosystem dynamics 43

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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

1 common-pool resource experiments using several models of human decision-making. 1
2 It is important to realize that every method used to study social-ecological systems has 2
3 its methodological problems. We will therefore emphasize in this chapter the plurality 3
4 of approaches, which may unravel the complexity of the systems when findings are 4
5 consistent with all the types of approaches used. 5

6 The studies reviewed in this chapter differ from those most frequently addressed by 6
7 environmental economists. Conventional economic theory predicts that when agents 7
8 have free access to a common-pool resource they will consume ecosystem services to 8
9 the point where private costs equal the benefits, whereas externalities are imposed on the 9
10 rest of the community. This can lead to the well-known tragedy of the commons (Hardin, 10
11 1968). Traditionally, economists study the management of ecosystems in terms of har- 11
12 vesting ecosystem services from renewable resources. Substantial progress has been 12
13 made during the last 30 years. Prior to 1970, models were mainly static, such as the 13
14 seminal work on renewable resource harvesting by Gordon (1954). During the 1970s, 14
15 the trend shifted toward dynamic systems for the economics of renewable resources. The 15
16 resulting optimization problem was addressed by dynamic programming, game theory, 16
17 and equilibrium analysis (Clark, 1990; Dasgupta and Heal, 1979; Mäler, 1974). Irre- 17
18 versibility and uncertainty have been addressed since the early 1970s (Arrow and Fisher, 18
19 1974; Henry, 1974) and remain among the main foci of environmental economics (e.g., 19
20 Chichilnisky, 2000). Recently, economists have started to include non-convexities of 20
21 ecosystems into their analysis of optimal management of ecosystems (Dasgupta and 21
22 Mäler, 2003; Janssen et al., 2004). 22

23 In simple models in mainstream environmental economics, a representative agent 23
24 is presumed to have perfect knowledge (or knowledge on the probabilities of out- 24
25 comes) and to maximize utility of consumption for an infinite time horizon. Such an 25
26 approach results in interesting insights. Representing agents as maximizing known util- 26
27 ity functions is, however, of limited use when systems are characterized by non-convex 27
28 dynamics, structural uncertainty, heterogeneity among agents, multi-attribute utility, 28
29 and spatial heterogeneity. Evidence is accumulating that social-ecological systems fre- 29
30 quently do have complex, non-linear dynamics. This affects the type of governance that 30
31 may lead to sustainable outcomes (Scheffer et al., 2001). Initial steps have been taken 31
32 to include such non-linear dynamics in environmental economics (Dasgupta and Mäler, 32
33 2003). Furthermore, increasing evidence exists that agents are able to self-govern some 33
34 types of common-pool resources without external governmental intervention but do not 34
35 always succeed (Bromley et al., 1992; Ostrom, 1990; National Research Council, 2002; 35
36 Ostrom et al., 1994). The question is how to analyze ecosystem management problems 36
37 with spatially explicit, non-convex dynamics influenced by multiple stakeholders with 37
38 divergent interests and who consume different types of ecosystem services. We need 38
39 new tools. Agent-based modeling is a promising tool for the analysis of these complex 39
40 problems (Janssen, 2002a). 40

41 Several developments outside environmental economics during the last thirty years 41
42 have influenced the current state of agent-based modeling of social-ecological systems. 42
43 We will briefly discuss some of these developments. Since the early 1970s, scholars 43

1 from system dynamics have developed and used integrated models of humans and their 1
2 environment (Ford, 1999). Prime examples are the World 2 and 3 models of Forrester 2
3 (1971) and Meadows et al. (1972, 1974). The World 2 and 3 models simulated the long- 3
4 term interactions between population, industrial and agricultural production, resource 4
5 use, pollution and food supply at an aggregated global level. A core finding was that 5
6 continuing early 1970s' trends would lead to an overshoot and collapse in terms of pop- 6
7 ulation and economic development. The World 2 and 3 models were highly criticized for 7
8 the subjectivity of the assumptions and the lack of rationality of the decision-making ac- 8
9 tors within the model (Cole et al., 1973; Nordhaus, 1973). In fact, the actors, economic 9
10 sectors on a global level, reacted in a predetermined way. 10

11 The first type of agent-based model for governing social-ecological systems that we 11
12 were able to trace in the literature is Bossel and Strobel (1978). They developed a model 12
13 to address two lacunae in the World 2 and 3 models—namely, their failure to account 13
14 for cognitive processes and their usual neglect of normative criteria and changes in these 14
15 criteria. In fact, the Bossel and Strobel model is of a cognitive agent interacting with the 15
16 global system. Their agent bases its decisions on the state of the global system, using 16
17 indicators, so-called system's orientors, like existence needs, security, freedom of ac- 17
18 tion, adaptivity, and effectiveness. This agent receives information about the state of the 18
19 system and decides to change priorities or aspirations, which affect the investment de- 19
20 cisions of the agent. Inclusion of these "intelligent" agents prevents the preprogrammed 20
21 "pollution crisis" from occurring. It also leads to policies producing very satisfactory 21
22 overall results, provided the planning horizon and the control sensitivity are sufficiently 22
23 large. The current field of integrated modeling of humans and the environment still faces 23
24 similar problems, uncertainty, subjective assumptions and lack of behavioral models, to 24
25 those of the initial models (Janssen and de Vries, 1999). Core questions remain regard- 25
26 ing how to deal with uncertainty and subjective assumptions and how to include human 26
27 dimensions. 27

28 Another field that contributed to the development of agent-based modeling of social- 28
29 ecological systems is individual-based modeling in ecology, which really took off in the 29
30 late 1980s (Huston et al., 1988). Individual-based modeling refers to simulation models 30
31 that treat individuals as unique and discrete entities who have at least one property, in 31
32 addition to age, that changes during the life cycle, e.g. weight, rank in a social hierarchy, 32
33 etc. Often motivated by pragmatic reasons, individual-based models are used to study 33
34 systematically the behavior of organisms in complex (spatially explicit) environments 34
35 (Grimm, 1999). 35

36 In the artificial intelligence field since the late 1980s, scholars developed tools for 36
37 natural resource management (Coulson et al., 1987). Well known are geographic infor- 37
38 mation systems and expert systems, but also a number of models have been developed 38
39 that included intelligent agents interacting with their complex environment (Anderson 39
40 and Evans, 1994). An interesting early example is the PHOENIX model on fire manage- 40
41 ment (Cohen et al., 1989). The model simulates a forest fire and the actions of intelligent 41
42 agents, representing bulldozers and airplanes. The model is an event-driven simulation 42
43 model, meaning that the agents perform real-time tasks based on events that happen 43

1 in their local environment. Every five simulated minutes of the model, the agents are 1
2 synchronized to allow coordination among the agents. The model is aimed at evaluating 2
3 fire-fighting plans in various scenarios. 3

4 **Bousquet et al. (1994)** developed an objected-oriented model of natural resource man- 4
5 agement of fisheries in the central Niger delta. Based on fieldwork, an artificial world 5
6 was created where different scenarios of rules of when and where to fish in a wetland 6
7 area were analyzed for this impact on long term viability of the natural resources. The 7
8 existence of space-sharing rules was found to be essential to avoid overfishing. 8

9 **Deadman and Gimblett (1994)** constructed a system that handles the complexity of 9
10 goal-oriented autonomous human agents seeking recreational opportunities in natural 10
11 environments. The model simulates the behavior of three types of visitors and their 11
12 interactions in an event-driven GIS environment of a park environment using intelligent 12
13 agents: hikers; bikers; and visitors transported in tour vehicles. The results of hiker 13
14 interactions with other users have been used to provide feedback about the implications 14
15 for alternative recreation management planning. 15

16 Complexity science is still another foundation for the study of the governance of com- 16
17 plex social-ecological systems. Social-ecological systems can be viewed as complex 17
18 adaptive systems—systems in which the components, and the structure of interactions 18
19 between the components, adapt over time to internal and external disturbances (**Holland,** 19
20 **1992a**). Order in complex systems is emergent as opposed to predetermined. The sys- 20
21 tem's history is irreversible, and future behavior is path dependant. The system's future 21
22 is often unpredictable due to the non-linearity of many basic causal relationships. The 22
23 variables that affect performance are both fast and slow moving. If information about 23
24 slow-moving variables is not recorded for a long period of time, substantial surprises 24
25 can occur when a slow-moving variable reaches some threshold. In social-ecological 25
26 systems, the key components are individuals and institutions. With institutions we refer 26
27 to the formal and informal rules that shape human interactions. Individuals may change 27
28 their relations with other individuals, their strategies, and the rules they are using. In 28
29 fact, individual strategies and institutional rules interact and co-evolve, frequently in 29
30 unpredictable ways. For example, the peasants who were starting to drain the peat mires 30
31 on a local level more than 1000 years ago in the precursor of the Netherlands did not 31
32 foresee the large-scale consequences in the few hundred years on the larger-scale land- 32
33 scape (lowering of the surface by about 2 cm a year), leading to new institutions (like 33
34 waterboards), and different practices (livestock instead of agriculture). 34

35 From this perspective, the question arises of how to govern social-ecological systems. 35
36 In systems that are indeed complex, one needs to understand processes of organization 36
37 and reorganization including collapse and the likely processes that happen after col- 37
38 lapse. Does a system have one and only one equilibrium to which it returns after a major 38
39 shock and temporary collapse? Are there multiple equilibria with different characteris- 39
40 tics? How easy is it for a system to flip from a desirable equilibrium to an undesirable 40
41 one? These are crucial questions. 41

42 The complex adaptive systems perspective provides us the view of individuals within 42
43 a variety of situations structured by the biophysical world, the institutional rules, and 43

1 the community in which they interact. Within ongoing structures, individuals search out
2 perceived advantageous strategies given the set of costs and benefits that exist and the
3 strategies that others adopt. Boundedly rational individuals trying to do as well as they
4 can in uncertain situations continuously tinker with their strategies, including trying
5 to change the rules that affect particular situations. They may look for loopholes in
6 the law, particularly if they think others are doing the same. They may check out the
7 level of enforcement by occasionally breaking rules. Those who have responsibility for
8 changing the rules of an institution also experiment with new rules and try to learn from
9 others why other institutional arrangements appear to work better than their own.

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

- 12 • Agent decisions are based on internal decision rules; this fits very well with the
13 increasing insights from experimental social science that humans use various types
14 of heuristics in different situations (Gigerenzer et al., 1999; Gigerenzer and Selten,
15 2001).
- 16 • The explicit inclusion of agent interactions helps to integrate the increasing insight
17 of the importance of communication in managing social dilemmas (Ostrom et al.,
18 1994; Ahn et al. 2003, 2004).
- 19 • Agent-based modeling shares similarities with models used in ecology, such as
20 individual-based models, system theory, and the inclusion of space. Therefore,
21 agent-based modeling facilitates collaborative efforts of ecologists and social sci-
22 entists.
- 23 • Agent-based models are suitable for modeling complex adaptive systems, in which
24 the interactions of individual units lead to larger-scale phenomena.
- 25 • Agent-based modeling makes it possible to address the problem of scale explicitly
26 (Gibson et al., 2000b).

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

31 32 33 34 **2. A framework for social-ecological systems**

35
36 The social-ecological systems (SESs) to be examined in the rest of this chapter are (1)
37 systems composed of both biophysical and social components, (2) where individuals
38 self-consciously invest time and effort in developing forms of physical and institutional
39 infrastructure that affect the way the system functions over time in coping with (3)
40 diverse external disturbances and internal problems, and (4) that are embedded in a
41 network of relationships among smaller and larger components. In other words, humans
42 have designed *some parts* but not all of the overall SES. In most instances, the design has
43 evolved over time as feedback generated information about how the SES was operating

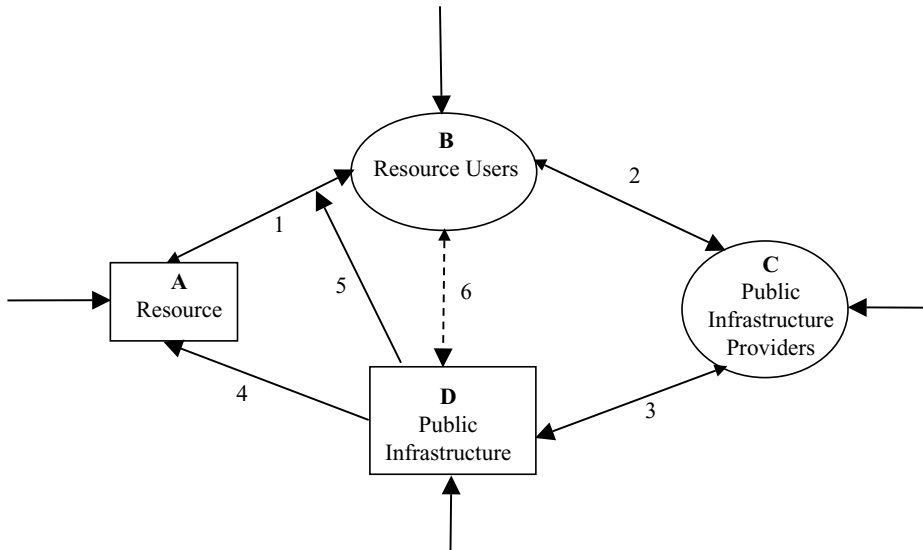


Figure 1. A conceptual model of a social-ecological system. Source: Anderies et al. (2004).

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.

1 The resource (A in Figure 1) is most frequently a biophysical system or a form of 1
2 natural capital that has been transformed for use by B through the efforts of C to invest 2
3 in D . We will focus on common-pool resources where it is difficult to exclude potential 3
4 beneficiaries from receiving the costs or benefits of governance strategies, and where the 4
5 resource flows withdrawn from the resource system subtract from the availability of re- 5
6 source flows for other users (Ostrom et al., 1994). If one is going to examine robustness 6
7 or resilience, one needs to include external disturbances (*incoming arrows* on Figure 1), 7
8 which can include biophysical disruptions (Linkages 7) including floods, earthquakes, 8
9 landslides, and climate change which impact on A and D or socioeconomic changes 9
10 (Linkages 8) including population increases, changes in economic opportunities, de- 10
11 pressions or inflations, and major political changes that impact on B , C and D . 11

12 A social-ecological system can be challenged in two ways: (1) by external distur- 12
13 bances; and (2) by fluctuations within internal entities and the links between them. The 13
14 internal fluctuations may result from the strategic interactions among the resource users 14
15 and among the participants in the process of providing the public infrastructure. Further, 15
16 strategic interactions exist among resource users regarding the harvesting rate from the 16
17 resource (Linkage 1 on Figure 1), the linkages among resource users and the public in- 17
18 frastructure providers (Linkage 2 on Figure 1), the public infrastructure providers and 18
19 the investments made in the infrastructure (Linkage 3), and potentially, the linkage be- 19
20 tween resource users and the public infrastructure (Linkage 6). Further, the linkages 20
21 among the ecological entities (Linkages 1, 4 and 5) are also sources of fluctuations that 21
22 may challenge the robustness of the overall SES at any particular point in time. 22

23 The simplest example of a social-ecological system consistent with the framework is 23
24 a small group of actors with relatively homogeneous interests who are in both positions 24
25 B and C . Without a medium of exchange other than labor and goods, cooperation must 25
26 be undertaken by direct interactions and transparent means. Such a system might be a 26
27 small irrigation system where farmers who own relatively similar plots of land meet 27
28 regularly to discuss how many days to work on maintenance and how to allocate the 28
29 water (see Tang, 1992; Lam, 1998; Ostrom, 1992). A social-ecological system becomes 29
30 more complex when task specialization occurs and most actors are either resource users 30
31 or public infrastructure providers. This might create incentives for rent seeking, corrup- 31
32 tion, and mismanagement due to incomplete or competing knowledge systems. So the 32
33 internal stability might become less robust when a system becomes more diverse and 33
34 specialized. 34

35 External threats may affect the various components and links within the SES. Natural 35
36 events, human induced impacts, and accidents can disrupt the resource system. External 36
37 sources may change the preferences of resource users as a consequence of new infor- 37
38 mation and inward and outward migration of people. The abilities to perform by public 38
39 infrastructure providers can be affected due to changes in higher level regulations, and 39
40 by the emergence or decline of local champions, those individuals who make a differ- 40
41 ence in making things happen. Finally, the public infrastructure can itself be affected 41
42 by natural events and accidents (physical infrastructure) and changes in higher level 42
43 regulations (institutional rules). These external disturbances interdependently affect the 43

1 activities within the social-ecological system. In fact, there might be interactions across 1
2 scales that make SES's become more or less robust to internal and external challenges. 2

3 This general framework lets us rephrase the three puzzles identified in the introduc- 3
4 tion. The first set of questions addresses social dilemmas: What kind of institutional 4
5 frameworks lead to robust governance of social-ecological systems? What is the influ- 5
6 ence of the ecological dynamics? What kind of information do resource users and public 6
7 infrastructure providers exchange? What are conflicting and compromising interactions 7
8 between the different agents involved? What is the effect of different levels of spatial 8
9 and temporal scale? How do institutional rules evolve? 9

10 The second type of question addresses uncertainty: What information do resource 10
11 users and public infrastructure providers have, and what is the asymmetry of this infor- 11
12 mation? How do resource users learn, and how do their learning processes differ from 12
13 how public infrastructure providers learn? How do different mental models of agents 13
14 affect the use and governance of the resource? Finally, social and biological agents in- 14
15 teract in a spatially explicit landscape formulated as maps or networks. How does spatial 15
16 heterogeneity affect the functioning of social-ecological systems? How does informa- 16
17 tion spread among nodes in a network? Who talks with whom, when and about what, 17
18 and how does this affect resource management? 18

19 We will now discuss each of the three areas and dig in more deeply to discuss theo- 19
20 retical and applied agent-based models, and the relation of laboratory experiments with 20
21 agent-based modeling. 21
22

23 3. Social dilemmas 23

24
25
26 A key theoretical and empirical puzzle in all of the social sciences is how individ- 26
27 uals overcome the strong temptation not to cooperate in social dilemmas, in which 27
28 individual contributions exceed individual returns, and instead attempt to achieve joint 28
29 benefits through cooperation (Axelrod, 2005). Both sets of human actors identified in 29
30 Figure 1 face multiple social dilemmas. Resources users (*B*) face common-pool re- 30
31 source dilemmas that can, if unresolved, lead to serious over-harvesting and potentially 31
32 the destruction of the resource. As one New England fisher recently put it, "I have no 32
33 incentive to conserve the fishery, because any fish I leave is just going to be picked up 33
34 by the next guy" (cited in Tierney, 2000, p. 38). Some users may develop trust (Ostrom 34
35 and Walker, 2003) and/or strong reciprocity even when they have heterogeneous inter- 35
36 ests (Bowles and Gintis, 2004). Without some agreed-upon and enforced rules, however, 36
37 resources users may simply race each other to use up the resource. Public infrastructure 37
38 providers (*C*) also face social dilemmas in their effort to develop effective institutions (a 38
39 public good) or efficient infrastructure (usually another common-pool resource). Sim- 39
40 ply authorizing some individuals to govern a resource does not guarantee that they will 40
41 overcome the temptations to engage in rent-seeking, to accept bribes, or simply to avoid 41
42 investing in costly information acquisition. 42
43

1 Cooperation in social dilemmas can be easily explained when the social agents are ge- 1
2 netically related (Frank, 1998) and/or interact repeatedly over a long indeterminate time 2
3 (Kreps et al., 1982). The question of why non-related social agents cooperate relates 3
4 to a number of important issues in ecological economics, especially to the question of 4
5 designing effective institutional configurations for common-pool resources and public 5
6 goods. Schlager (2004) reviews the extensive empirical cases where local communities 6
7 have developed institutions to deal with social dilemmas. These examples demonstrate 7
8 that people have the capacity to organize themselves to achieve much higher outcomes 8
9 than predicted by conventional economic theory. Capacity is not, however, sufficient to 9
10 ensure that resources are governed sustainably. 10

11 Empirical research stimulated in large part by a mid-1980s Committee of the National 11
12 Research Council (National Research Council, 1986) and synthesized by a more recent 12
13 committee (National Research Council, 2002) has demonstrated that no form of gov- 13
14 ernance is guaranteed to change the strong incentives of the pervasive social dilemmas 14
15 faced by resource users and public infrastructure providers so as to generate long-term 15
16 sustainability. Governing resources successfully is always a struggle (Dietz et al., 2003). 16
17 Empirical findings suggest that successful, adaptive governance of natural resources re- 17
18 quires: (1) generating substantial information about stocks, flows, and processes within 18
19 the resource (the arrows in Figure 1); (2) dealing with conflict that arises among mul- 19
20 tiple users and uses of a resource; (3) inducing rule compliance among all participants 20
21 so that each has confidence that the others are not cheating; (4) providing effective 21
22 physical and institutional infrastructure (*C* in Figure 1); and (5) preparing for the in- 22
23 evitable changes that occur due to external disturbances as well as internal changes in 23
24 resource and human dynamics (Dietz et al., 2003). A recent empirical study of over 200 24
25 forests located in Africa, Latin America, Asia, and the United States provides strong 25
26 evidence that regular rule enforcement is more important in achieving sustainable forest 26
27 conditions than the form of organization governing a forest, the level of social capital 27
28 existing among users, or the level of dependence of users on a forest (Gibson et al., 28
29 2005). 29

30 31 3.1. Theoretical models 31

32
33 Field research has thus generated substantial evidence that, contrary to earlier economic 33
34 theory, no optimal form of governance exists that can be imposed on all SESs with the 34
35 expectation that resource users and public infrastructure providers will accept the sys- 35
36 tem and make it work. On the other hand, field research has also shown that resource 36
37 users and public infrastructure providers have devised an ingenious array of rule con- 37
38 figurations that work effectively in specific ecological and social settings. Thus, there is 38
39 a lot for theory to explain! 39

40 As discussed in more detail by Dibble (2005), Axelrod (2005), Young (2005), and 40
41 Kollman and Page (2005), agent-based models are being intensely used to derive a 41
42 better theoretical understanding of the conditions that lead social agents to cooperate. 42
43 Axelrod (1984, 1987) pioneered in this field with his iterated prisoner's dilemma (IPD) 43

1 tournaments and with his simulation of the evolution of strategies using genetic algo- 1
2 rithms. This led to a vast number of human–subject experiments (summarized in [Davis](#) 2
3 [and Holt, 1993](#); [Colman, 1995](#)) and agent-based models on variations of the IPD game 3
4 focused on the effects of partner choice, tags, reputation symbols, spatial interactions, 4
5 noise, probabilistic choice, and so forth (see [Gotts et al., 2003](#)). Multiple theoretical 5
6 efforts have been made to provide a coherent, analytical framework for explaining the 6
7 repeated finding that cooperation levels in social dilemmas are frequently above the zero 7
8 contribution level predicted by non-cooperative game theory (see [Boyd and Richerson,](#) 8
9 [1992](#); [Bowles, 1998](#); [Gintis, 2000](#); [Camerer, 2003](#)). 9

10 [Axelrod \(1986\)](#) was among the first to tackle how norms supporting cooperative 10
11 strategies, that were not the strategies leading to a Nash equilibrium, could be sustained 11
12 over time. He posited that individuals could adopt norms—meaning that they usually 12
13 acted in a particular way and were often punished if they were not seen to be acting in 13
14 this manner. He posited that some individuals also developed a norm to punish those 14
15 who defected in social dilemmas as well as the concept of a meta norm—a norm that 15
16 “one must punish those who did not punish a defection” [Axelrod \(1986, p. 1109\)](#). With 16
17 punishment norms backing cooperative norms, and the meta norm of punishing those 17
18 who did not punish defectors, Axelrod was able to develop an evolutionary theory of 18
19 cooperation consistent with evidence from the field. 19

20 Recent evolutionary models by [Kameda et al. \(2003\)](#) have developed these ideas 20
21 even further. In a formal analysis of a set of simplified strategies, these authors ex- 21
22 plore the viability of a “communal sharing strategy” which cooperates when in the role 22
23 of resource acquisition and imposes sanctions on others if they engage in non-sharing 23
24 behavior. They establish that the communal-sharing strategy is a unique evolutionar- 24
25 ily stable strategy that blocks any other strategy from successfully invading for a wide 25
26 range of parameters. Kameda et al. also undertook a simulation of the performance 26
27 of multiple strategies when ten players are involved and their strategies could evolve 27
28 over time. Here they observed that free riding could become the dominate strategy 28
29 over multiple generations due to the problem of second-order free riding in regard to 29
30 norm enforcement. When they added an “intolerant” norm enforcer who is willing to 30
31 bear extra costs for excluding others who are second-order free riders on the enforce- 31
32 ment of cooperative norms, simulated ten-person games tended to sustain cooperative 32
33 sharing over very large number of generations. In field settings of robust SESs, one 33
34 does tend to find some members of self-organized groups who are “fired up” about 34
35 the need for everyone to follow the rules and norms they have evolved over time. 35
36 Some groups rotate the role of being the local enforcer among their membership, so 36
37 no one has to bear the cost of monitoring and enforcing at all times, while each of 37
38 them is “super-charged” with the responsibility for local monitoring on a rotating ba- 38
39 sis. 39

40 Many of the specific rules that empirical researchers have observed in the field have 40
41 puzzled theorists. In addition to rotating enforcement responsibilities, elaborate turn- 41
42 taking rules have, for example, been observed in robust institutions related to harvesting 42
43 fish from inshore fisheries (see [Berkes, 1986](#)) and obtaining water from farmer-governed 43

1 irrigation systems (Ostrom, 1992). Even subjects in repeated common-pool resource 1
2 experiments with opportunities to engage in face-to-face communication have devised 2
3 rotation systems enabling one set of subjects to gain more in one round and less in the 3
4 next (Ostrom et al., 1994). A recent paper by Lau and Mui (2003) has now provided a 4
5 strong game-theoretic analysis of how such complex rules can be sustained in a repeated 5
6 environment characterized by asymmetric payoffs in any one period. 6

7 Let us now turn to agent-based models of cooperation. Thébaud and Locatelli (2001), 7
8 for example, developed an agent-based model to address a puzzle initially proposed by 8
9 Sugden (1989). Sugden observed the emergence of property-right rules of those who 9
10 gather driftwood after a storm on the Yorkshire coast. Whoever found an item first 10
11 could take it and gather it into piles. By placing two stones on the top of each pile, the 11
12 gatherer could mark his property. If a pile had not been removed after two more high 12
13 tides, the ownership rights terminated. Thébaud and Locatelli were able to generate the 13
14 emergence of piles, whose existence varied with the range of vision (could the agent 14
15 steal without being caught?) and the threshold of the size of the pile before it is consid- 15
16 ered private property (lower threshold makes it easier to generate private piles). Another 16
17 aspect that was found important is the imitation rule. Agents compare their wood pile 17
18 with others they encounter and, if the observed pile is larger than their own (including 18
19 the wood they are currently carrying), they adopt the strategy of its owner with regard 19
20 to the property rule. 20
21

22 Another set of papers discusses the effect of different models of human behavior on 22
23 the management of common resources. Jager et al. (2000) discuss the harvesting by a 23
24 population of agents of a fish stock and a gold mine (whose pollutants negatively af- 24
25 fect the carrying capacity of the fish population). They tested two types of models of 25
26 behavior. In the first model, the agents considered all possible actions. In the second, 26
27 agents used heuristics mimicking repetition, deliberation, social comparison, and imi- 27
28 tation. Which heuristic was active at a certain moment in time depended on the level of 28
29 satisfaction and uncertainty. Jager et al. (2000) show that constant deliberation over all 29
30 possible options leads to a faster decline of the resources, and an uneven transition from 30
31 fishing to gold digging. Several social psychology-based agent-based models on the 31
32 collective use of common resources have especially focused on including the effects of 32
33 resource uncertainty (Jager et al., 2002; Mosler and Brucks, 2002). Jager et al. (2002), 33
34 for example, show that overharvesting is more severe in periods of uncertainty, which 34
35 is consistent with laboratory experimental and field evidence. Due to the use of agent- 35
36 based models, Jager et al. were able to pin-point three different behavioral processes 36
37 that may contribute to this overuse. Another relevant paper is by Janssen and Ostrom 37
38 (2005), who study the conditions that are needed for a population of agents to voluntar- 38
39 ily restrict their own behavior to avoid collapse of the resource in the longer term. They 39
40 show that when agents are able to evolve mutual trust relationships, a proposed rule on 40
41 restricted use of the resource will be accepted because the agents trust each other to 41
42 follow the rules. 42
43

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 (ω). 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 ω for the provision of the public good. The subject's payoff (π_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 ω 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 ω 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:

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

where

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

According to this formula, the payoff of someone investing all ω 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,

1 1988; Marwell and Ames, 1979, 1980, 1981; Ostrom et al., 1994). Depending on the
2 return rate from investments in the public good, the initial contribution rate remains the
3 same or decreases with the number of rounds. Laboratory experiments have consistently
4 shown that communication is a crucial factor for achieving cooperative behavior (Sally,
5 1995; Brosig, 2002).

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

12 13 3.3. *Agent-based models of laboratory experiments* 14

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

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

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

40 Like Deadman (1999), Jager and Janssen (2002) used agent-based models to provide
41 a possible explanation of observed patterns in common-pool experiments without com-
42 munication. The agents in Jager and Janssen are based on a meta-theoretical framework
43 of psychological theories. An agent is assumed to have different type of needs, includ-

1 ing subsistence, identity and exploration. Depending on whether the needs of the agent 1
2 are satisfied or not, and whether the agent is uncertain or not, an agent uses one of four 2
3 decision rules: deliberation; social comparison; repetition; and imitation. An unsatis- 3
4 fied agent spends more cognitive energy (e.g., deliberation or social comparison) than 4
5 a satisfied agent (who relies more on repetition and imitation). An uncertain agent uses 5
6 information from other agents (social comparison or imitation) instead of relying on 6
7 individual information (deliberation or repetition). The difference between social com- 7
8 parison and imitation is that during social comparison an agent checks whether copying 8
9 the strategy of another agent leads to an expected improvement of the utility. 9

10 Jager and Janssen found that agent-based models of individual behavior in common- 10
11 pool resource settings needed to include 11

- 12 ● social value orientation, 12
- 13 ● preferences one has for a particular distribution of outcomes for oneself and others, 13
- 14 ● satisfying behavior, 14
- 15 ● exploratory behavior when payoffs of an agent remain the same for a number of 15
16 rounds, and 16
- 17 ● heterogeneity of needs among the agents. 17

18 All five individual characteristics are needed in the analysis to derive token investment 18
19 patterns at the group level similar to those resulting in the human–subject experiments. 19
20 The investment patterns were evaluated by taking into account the average investment 20
21 level, the differences between the agents in a group, and the changes of investment levels 21
22 across rounds. 22

23 **Castillo (2002)** investigates the decision rules individuals used during field experi- 23
24 ments of common-pool resources conducted by (Cárdenas among coastal communities 24
25 in the Colombian Caribbean Sea (Cardenas et al., 2000). The model is based on the 25
26 theory of collective action of **Ostrom (1998)** and implemented from a systems dynam- 26
27 ics perspective. As in previous studies, Castillo simulates the experiments describing 27
28 the actions of individual agents. By using response functions, Castillo is able to esti- 28
29 mate the theoretical framework of **Ostrom (1998)** without describing the mechanisms 29
30 of reputation, trust, and reciprocity explicitly. 30

31 We are aware of two additional papers that use agent-based model to understand the 31
32 behavior of agents in public-good experiments. **Iwasaki et al. (2003)** examined a rein- 32
33 forcement learning model to explain patterns of behavior observed in their threshold 33
34 public-good experiments. In such an experiment, a minimum threshold of investments 34
35 in the public good must be contributed before the public good is provided. Their model 35
36 of reinforcement learning was only partly able to explain the observed data. It did 36
37 reproduce cooperative patterns, but was not able to reproduce non-cooperative pat- 37
38 terns. 38

39 **Janssen and Ahn (2005)** compare the empirical performance of two decision mak- 39
40 ing models to explain the outcomes in a large set of public-good experiments without 40
41 communication (Isaac and Walker, 1988; Isaac et al., 1994), namely, the experienced 41
42 weighted attraction learning model of **Camerer and Ho (1999)**, and the best-response 42
43 model with signaling based on **Isaac et al. (1994)**. In contrast with the previous studies, 43

1 Janssen and Ahn focus on the problems on parameter calibration and the evaluation of 1
2 the model performance on individual and group level statistics. Both models outperform 2
3 the selfish rational actor model as an explanation of observed behavior. Furthermore, the 3
4 learning model was found to give the best performance using the individual level cal- 4
5 ibration, while the best response model was found to calibrate best at the group level. 5
6 The essential elements of the model that enhances its performance is the inclusion of 6
7 other regarding preferences and satisficing behavior, similar to Jager and Janssen (2002) 7
8 for common-pool resources. 8
9

10 The strategy method, where human subjects develop strategies based on their exper- 10
11 ience in laboratory experiments, is an interesting method which links agent-based 11
12 models and experiments (Selten et al., 1997). Keser and Gardner (1999) apply the strat- 12
13 egy method to common-pool resources. Their common-pool resource game consisted of 13
14 a constituent game played for twenty periods. Sixteen students, all experienced in game 14
15 theory, were recruited to play the game over the course of six weeks. In the first phase of 15
16 the experiment, they played the common-pool resource game on-line three times. In the 16
17 second phase of the experiment, the tournament phase, they designed strategies which, 17
18 after implementation as agents, were then played against each other. As for human sub- 18
19 jects, a Nash equilibrium was found at the aggregate level, but at the individual level, 19
20 fewer than 5% of subjects played in accordance with the game equilibrium prediction. 20
21

22 Combining agent-based modeling and laboratory experiments of complex dynamic 22
23 social dilemmas has just started (see Duffy, 2005 for a more general discussion on 23
24 agent-based modeling and laboratory experiments). The current publications demon- 24
25 strate considerable potential to test alternative theories of human behavior. Huge 25
26 methodological challenges still exist, however, in regard to parameter estimation and 26
27 model comparison. For example, Salmon (2001) showed that identification of the cor- 27
28 rect learning models using econometrics techniques leads to potential problems. Salmon 28
29 generated experimental data by simulation of normal-form games using a number of 29
30 learning models so that he could test four different econometric approaches in their ac- 30
31 curacy of distinguishing the individual models by which the data was generated. Wilcox 31
32 (2003) did a similar experiment to test the implication of the assumption of homogene- 32
33 ity of the subjects. If the agent population is heterogeneous in parameter values, serious 33
34 problems in accuracy of parameter estimation are created. 34
35

36 Model selection is an important line of research in cognitive science (Pitt and Myung, 36
37 2002). Various approaches have been developed to test models in regard to goodness of 37
38 fit and generalizability. These approaches penalize models with increasing complexity. 38
39 Approaches based on maximum likelihood depend on the assumption that the obser- 39
40 vations are statistically independent. This is not the case when multiple actors interact 40
41 over time in experiments with public goods and common-pool resources. Interdepend- 41
42 ence in a complicated fashion definitely exists when communication, monitoring, and 42
43 sanctioning are allowed. 43

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 financiers 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

1 farming system links these two externalities in such a way that cooperation, rather than
2 chaos, results. The reason for this, depending on the underlying ecological parameters
3 in the system, is that regimes exist in which the farmers would like to coordinate their
4 cropping patterns (in particular, have identical fallow periods) so as to control pest pop-
5 ulations. In other regimes, coordination is not an equilibrium, even though coordinated
6 farming would result in greater aggregate crop output. Lansing and Miller identified
7 two indirect mechanisms by which the system can reach cooperation. The first is to
8 have the upstream farmers share their water with the downstream farmers. The second
9 is that increases in pest damage can drive the system into a coordinated equilibrium,
10 enhancing aggregate output. The Balinese rice temples would have played a facilitat-
11 ing role in deriving coordination in this complex system. In an earlier game-theoretical
12 paper, Ostrom (1996) also examined how differences between head-end and tail-end
13 farmers could be the foundation for extensive mutually productive coordination in the
14 maintenance of irrigation infrastructure.

15 Bousquet and his colleagues (Bousquet et al., 1998) developed a modeling plat-
16 form, CORMAS, dedicated to the study of common-pool resources through agent-based
17 modeling. They have performed many applications and work together with local stake-
18 holders, often in Africa and Asia, to develop agent-based models for practical natural
19 resource management problems.¹ Barreteau and Bousquet (2000), for example, study
20 the underutilization of irrigated systems in the Senegal River Valley in North Sen-
21 gal. An agent-based model was developed to simulate an archetypal irrigation sys-
22 tem. The agents represent farmers, credit access, and water allocation groups. The
23 processes represented deal with the circulation of water and credit and with interac-
24 tions about their allocation and access to them. The model was used in role-playing
25 experiments to test its potential as a negotiation support tool and to test the model with
26 the agents they try to simulate (Barreteau et al., 2001). The use of a role-playing game
27 was found very useful for testing the model and interacting with local stakeholders.
28 This led Bousquet et al. (2002) to the idea of *companion modeling*, which interac-
29 tively combines agent-based modeling and role-playing games and uses the latter to
30 acquire knowledge, build and validate the agent-based model, and use the model in
31 the decision-making process. This has been applied to a number of case studies, as re-
32 viewed in Bousquet et al. (2002). We come back to role-playing games later in this
33 chapter.

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

41
42
43 ¹ See <http://cormas.cirad.fr>.

1 for the cheapest spots; or (3) they make offers to the villages with the best friendship 1
2 relations that take into account past refusals of offers. Rouchier et al. found that choices 2
3 based on costs lead to the lowest number of animals that the simulated system could 3
4 sustain, because considerable resources are lost by negotiation and refusals when all 4
5 herdsmen try to enter cheapest village. Since the herdsmen do not learn in this model, 5
6 they continue losing productivity by aggregating around the same village every time 6
7 period. Other applications of the CORMAS group include collaborative forest manage- 7
8 ment in East Kalimantan in Indonesia (Purnomo et al., 2003) and the management of 8
9 livestock effluents in Réunion, France (Farolfi et al., 2002). 9
10

11 3.5. What have we learned? 11

12
13
14 In regard to the governance of common-pool resources, agent-based modeling has been 14
15 able to draw on a foundation of extensive fieldwork and laboratory experiments as well 15
16 as extending our theoretical understanding of cooperation in social dilemma settings. 16
17 Since both forms of empirical research had already challenged the capacity of simple, 17
18 analytical theory based on non-cooperative game theory to explain empirical results, 18
19 the field was ripe for the use of agent-based models. We have learned from agent-based 19
20 models of the processes linking resource users, public infrastructure providers, and their 20
21 resources and infrastructures that much of the data reported by field researchers is con- 21
22 sistent with a complex, adaptive systems view of social dilemmas. 22

23 From the combination of research methods examining factors enhancing levels of 23
24 cooperation, we have learned that devising rules that allocate benefits to resource users 24
25 in a legitimate, fair, and enforceable way is essential to overcome incentives to free 25
26 ride. Rarely can external authorities devise rules that are well tailored to a local ecol- 26
27 ogy and culture and also invest substantial resources in monitoring patterns of resource 27
28 use and sanctioning those who do not follow rules. Thus, the repeated finding that in- 28
29 dividuals can devise agreed-upon norms for governing a resource that they themselves 29
30 can monitor and enforce has changed our scientific understanding of these processes. 30
31 Unfortunately, public policies have all too frequently relied on simple panaceas that 31
32 either recommend government, private property, or decentralized governance of SESs. 32
33 We have strong evidence that simplistic solutions that are imposed by external agen- 33
34 cies on resource users rarely work (National Research Council, 2002; Dietz et al., 34
35 2003). And, fortunately, we now have methods—agent-based models—that facilitate 35
36 the analysis of complex SESs by stakeholders and officials. No longer do we need to 36
37 throw up our hands in despair because the system is so complex! We do, however, need 37
38 to continue a sense of modesty. Even with agent-based models of complex SESs, we 38
39 rarely can prescribe “the” optimal solution for any complex setting. Those involved 39
40 have to learn over time by experimenting with local ideas, with what they can learn 40
41 from others and with ideas from the literature describing what has worked well in other 41
42 settings. 42
43

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

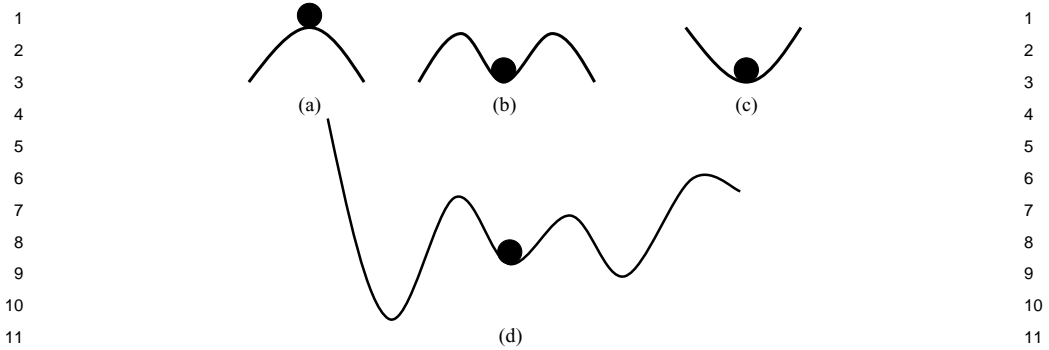


Figure 2. Perspectives of nature: (a) nature is unstable; (b) nature is stable within limits; (c) nature is stable; (d) nature has different stability domains (after Janssen, 2002b).

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 oligotrophic 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

1 human-induced perturbations are recommended in order to learn from the system over
2 time.

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

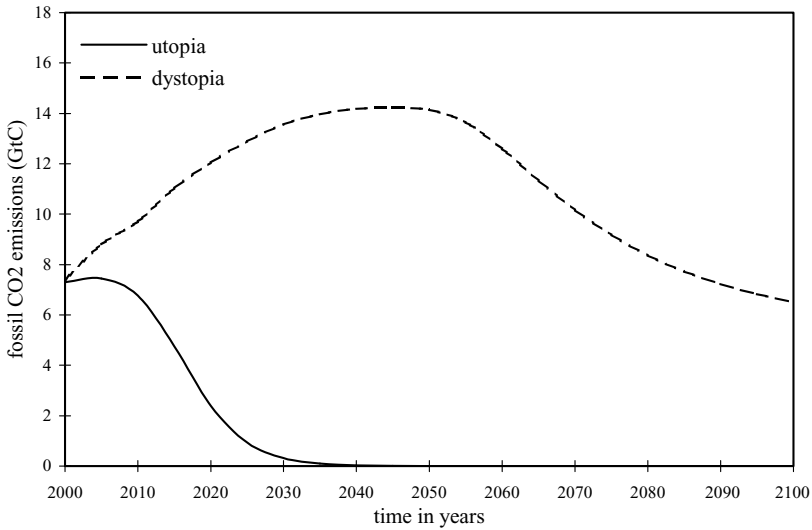
12 The three main worldviews in Cultural Theory are:

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

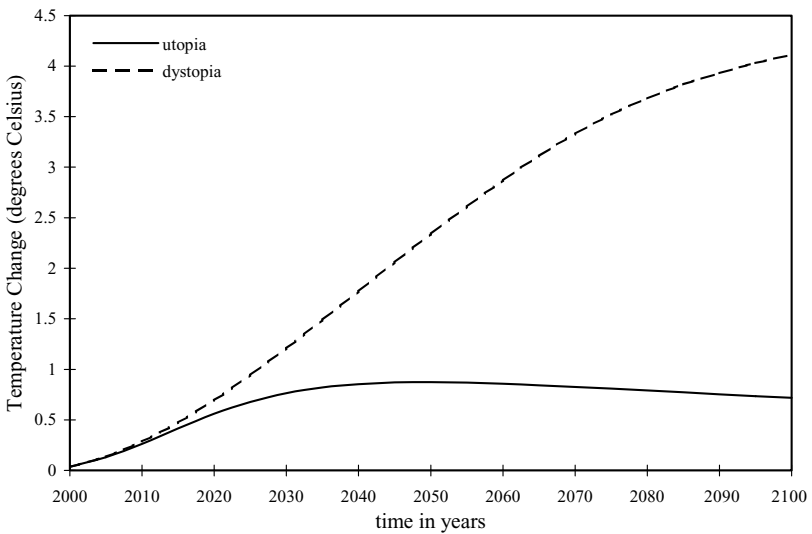
21 Human-induced climate change is a topic surrounded with many uncertainties and is
22 therefore an excellent example to illustrate how worldviews can be quantified to sim-
23 ulate alternative futures based on different perceptions of reality. Such an analysis was
24 made by Janssen and de Vries (1998),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

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

42 By introducing a population of agents with heterogeneous worldviews, a complex
43 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 and 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).

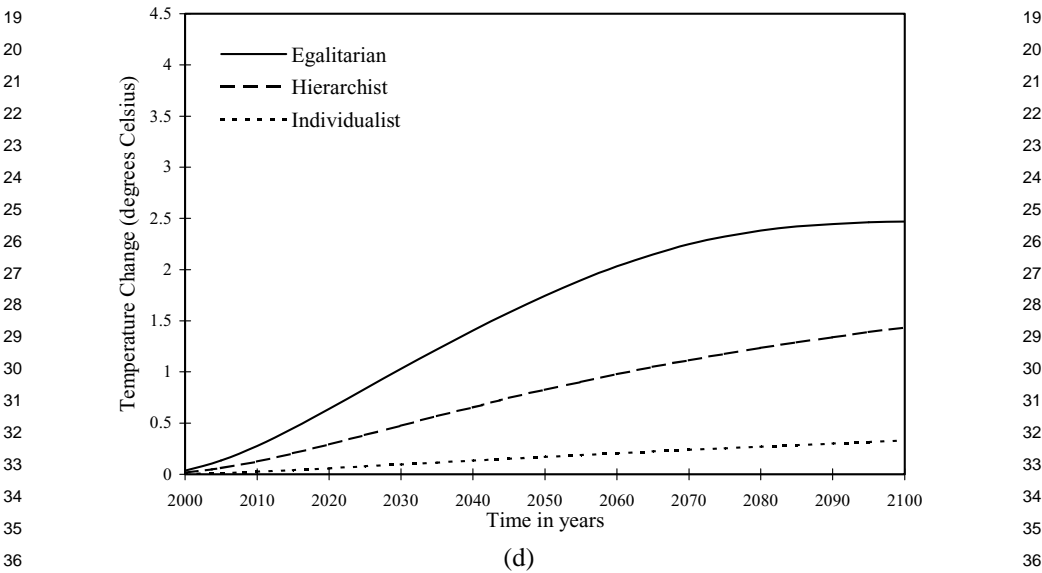
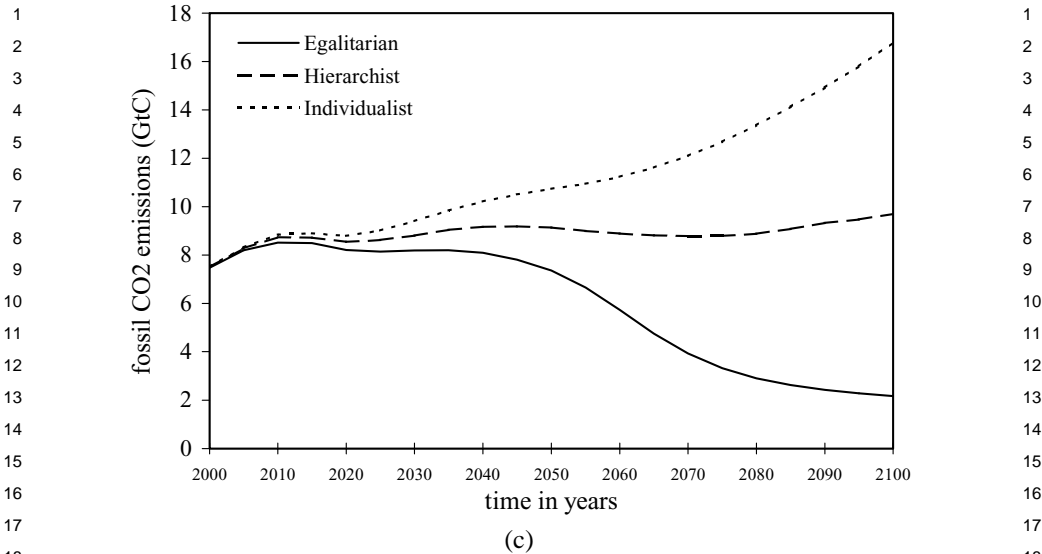


Figure 3. (Continued.)

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

1 adjust their mental models when they are surprised by observations, and may make ad- 1
2 justments in their decisions according to their new perceptions of the problem. Agents 2
3 tolerate some level of error, however, before they change their worldviews. The initial 3
4 distribution of worldviews is therefore important for the long-term evolution of the 4
5 social-ecological system. On aggregate, worldviews tend to change to the worldview 5
6 that explain the observations in the most convincing way. Suppose that reality is one of 6
7 the three possible worlds, and an agent obtains information over time that causes it to 7
8 adjust (or not) its perspective on the problem of climate change. Three sets of projec- 8
9 tions are derived in which agents adapt to climate change (Figures 3c and 3d). Prior to 9
10 year 2040, the observed climate change does not lead to domination of one of the world- 10
11 views. After 2040, the climate signal becomes clear enough that one of the worldviews 11
12 begins to dominate. In the event of the world functioning according to the egalitarian 12
13 worldview, the emissions growth stabilizes in the coming decades and decreases to a 13
14 level below half of the present amount of emissions. However, this reduction cannot 14
15 avoid a global mean temperature increase of about 2.5°C in the coming century. 15

16 The explicit inclusion of subjective perceptions of reality has led to a rich variety of 16
17 possible futures. This approach has also been applied to lake management (Carpenter 17
18 et al., 1999a, 1999b; Janssen and Carpenter, 1999; Janssen, 2001; Peterson et al., 2003) 18
19 and rangeland management (Janssen et al., 2000). Lakes are a favorite ecosystem for the 19
20 study of social-ecological systems, because the multiple stable states are well studied 20
21 and simple, empirically based models are available (Carpenter et al., 1999b). The typi- 21
22 cal lake model focuses on phosphorus pollution. Phosphorus flows from agriculture to 22
23 upland soils, and then on to surface waters where it cycles between water and sediments. 23
24 The lake ecosystem has multiple locally stable equilibria and moves among basins of 24
25 attraction depending on the history of pollutant inputs. Lakes are often classified as 25
26 oligotrophic or eutrophic depending on their productivity. Oligotrophic lakes are char- 26
27 acterised by low nutrient inputs, low to moderate levels of plant production, relatively 27
28 clear water, and relatively high economic value of ecosystem services. Eutrophic lakes 28
29 have high nutrient inputs, high plant production, murky water with problems including 29
30 anoxia and toxicity, and relatively low value of ecosystem services. When mitigating 30
31 eutrophication, lakes can respond differently to reduced phosphorus inputs, which is 31
32 mainly related to recycling of phosphorus from sediments to the overlying water. 32

33 In Carpenter et al. (1999a), an agent-based model is developed in which agents form 33
34 expectations about ecosystem dynamics, markets, and/or the actions of managers, and 34
35 they choose levels of pollutant inputs accordingly. Agents have heterogeneous beliefs 35
36 and/or access to information. Their aggregate behavior determines the total rate of pol- 36
37 lutant input. As the ecosystem changes, agents update their beliefs and expectations 37
38 about the world they co-create. They modify their actions accordingly. For a wide range 38
39 of scenarios, Carpenter et al. observe irregular oscillations among ecosystem states and 39
40 patterns of agent behavior. These oscillations resemble some features of the resilience 40
41 of complex adaptive social-ecological systems. Janssen and Carpenter (1999) applied 41
42 the same framework of worldviews as used in Janssen and de Vries (1998) to the man- 42
43 agement of lakes. The agents learn and adapt to unexpected changes in the state of the 43

1 lake, and a mix of perspectives is required to manage the resilience of the system. Al- 1
2 though low levels of phosphorus in the lake will not be reached, the lake is prevented 2
3 from flipping to catastrophically high phosphorus levels. 3

4 The agents are always learning, but never get it exactly right. They come close 4
5 enough, however, to sustain the social-ecological system. In Janssen (2001), the agents 5
6 were enriched with a mix of various cognitive processes, such as imitation, deliberation, 6
7 and repetitive behavior, in their decisions about how much phosphorus to use. Analyses 7
8 with the model showed that the dominating type of cognitive processing was a relevant 8
9 factor in the response to uncertainty and policy measures. When agents are easily unsat- 9
10 isfied with their economic performance, it leads to a more intensive use of phosphorus 10
11 and to higher levels of phosphorus in the lake. Simulated farmers used phosphorus more 11
12 intensively in situations with high natural variability. A tax on phosphorus had little ef- 12
13 fect on the behavior of the farmers when they felt uncertain and were easily satisfied. 13

14 Peterson et al. (2003) describe the management of a lake as a learning process. The 14
15 agents consider two management models of the lake, one for an oligotrophic lake and 15
16 the other for a eutrophic lake. As agents observe the lake varying from year to year, 16
17 they estimate how well each of the two management models is supported by the ob- 17
18 served data. Management policies maximize the expected net present value of the lake. 18
19 Even under optimistic assumptions about environmental variation, learning ability, and 19
20 management control, conventional decision theory and optimal control approaches fail 20
21 to stabilize ecological dynamics. Rather, these methods drive ecosystems into cycles of 21
22 collapse and recovery. 22

23 Weisbuch and Duchateau-Nguyen (1998) study fisheries where fishers do not have 23
24 complete understanding of the underlying (logistic) resource dynamics. Historical in- 24
25 formation about catches, capital amounts, and the fraction of the income used for 25
26 consumption, are used by the agents to predict future catches. Incremental learning is 26
27 used to update the weights on the various sources of information. The agents were able 27
28 to learn to manage the system and could cope with sudden shocks to the system. 28

29 In the rangeland model of Janssen et al. (2000), agents do not learn but may go bank- 29
30 rupt, leave the system, and be replaced by a random, new pastoralist. The agents have 30
31 incomplete understanding of the complex rangeland system. They tend to overgraze 31
32 their property by putting too many sheep on their land, and suppress fire too much so 32
33 woody shrubs can start dominating. Janssen et al. analyzed the consequence of different 33
34 government regulations on the evolution of types of agents. Agents who evolve under 34
35 a regime of limited grazing do not have a proper understanding of the dynamics of the 35
36 system. Agents who evolve without regulations, experience the whole spectrum of pos- 36
37 sible events. In the latter case, many properties are unproductive for a longer period, 37
38 but those agents who evolve have a good understanding of the system. This example 38
39 shows the importance of exploring the possible dynamics of a regime and the effects of 39
40 precautionary policies to avoid overuse of the resource. 40

41 Bodin and Norberg (2005) examine the principal impact of information sharing in 41
42 (social) networks of artificial natural resource managers capable of experimenting, sim- 42
43 ple information processing, and decision-making. All managers adaptively manage their 43

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.

1 Goldstone and Ashpole (2004) performed experiments where a large number of hu- 1
2 man participants interacted in real time within a shared virtual world. Two resource 2
3 pools were created with different rates of replenishment. The participants' task was to 3
4 obtain as many resource tokens as possible during an experiment. Besides variation in 4
5 the rate at which consumed tokens were replaced, Goldstone and Ashpole manipulated 5
6 whether agents could see each other and the entire token distribution, or had their vi- 6
7 sion restricted to tokens in their own location. The optimal solution for participants is to 7
8 distribute themselves in proportion to the distribution of resources. The human subjects 8
9 did not to distribute themselves in this optimal fashion. Rather, they systematically al- 9
10 located themselves more to the relative scarce resource, leading to an underutilization 10
11 of the resources. Furthermore, especially when the vision of the subjects was restricted, 11
12 oscillations in the harvesting rates of the resources across time were observed. Per- 12
13 ceived underutilization of a resource resulted in an influx of agents to that resource. 13
14 This sudden influx, in turn, resulted in an excess of agents, which then led to a trend 14
15 for agents to depart from the resource region. Thus, uncertainty about the availability of 15
16 resources increased instability of the distribution of the subjects, which itself enhanced 16
17 uncertainty. 17
18

19 4.3. Applications 19

20
21 In the spirit of adaptive management (Holling, 1978), various researchers develop their 21
22 agent-based models together with the stakeholders of the problem. Like the participa- 22
23 tory modeling approach, such as practiced in systems dynamics (e.g., Costanza and 23
24 Ruth, 1998), they use the model as a tool in the mediation process with stakeholders 24
25 and as a way for the stakeholders to learn strategies that might solve the dilemmas they 25
26 face in complex environments. In Bousquet et al.'s (Bousquet et al., 2002) companion 26
27 modeling, the role-playing games are meant to reveal some aspects of social relation- 27
28 ships by allowing the direct observation of interactions among players, the stakeholders. 28
29 Barreteau et al. (2003) argue that such role-playing games are good communication 29
30 tools among stakeholders, but it is difficult to reproduce the results. Systematic compar- 30
31 ison of the results is difficult since many factors are uncontrolled. When players play 31
32 again, they may change the context of the game due to their learning experience in the 32
33 previous experiment. 33

34 In Etienne et al. (2003), for example, an agent-based model was developed to simu- 34
35 late strategies of natural resource management in the Causse Méjan, a limestone plateau 35
36 in southern France dominated by a rare grassland-dominated ecosystem endangered by 36
37 pine invasion. To facilitate discussion of alternative long-term management strategies 37
38 for the sheep farms and the woodlands, contrasting perspectives on land resources from 38
39 foresters, farmers, and rangers of the National Park of Cévennes were designed at differ- 39
40 ent spatial scales. A series of exercises with different stakeholder groups was performed 40
41 to confront the consequences of their viewpoints, and that of the other stakeholders. As 41
42 a result of this iterative process it was possible to select a set of feasible scenarios 42
43 stemming from the current actors' perceptions and practices and to suggest alterna- 43

1 tive sylvopastoral management based on innovative practices. D'Aquino et al. (2003) 1
2 describe their project on irrigation systems in Senegal. Since 1997 they have experi- 2
3 mented at an operational level (2500 km²) in the Senegal River valley with agent-based 3
4 modeling intertwined with role-playing games. Their self-design approach is aimed to 4
5 include as much as possible the knowledge of the local participants. This develop- 5
6 ment of methodology may contribute to additional tools of resource users and public 6
7 infrastructure providers to self-govern their common resources. 7

8 Pahl-Wostl (2002) discusses a similar development that she calls participatory agent- 8
9 based social simulation. This modeling technique inputs social processes into integrated 9
10 models that are developed in participatory settings. Hare and Pahl-Wostl (2002) illus- 10
11 trate in a Swiss case study how card-sorting can be used to categorize stakeholders to 11
12 inform the design of agent-based models. 12

13 An interesting application of learning models to natural resource management is the 13
14 work of Dreyfus-Leon on fisheries. Dreyfus-Leon (1999) presents a basic model to 14
15 mimic the search behavior of fishers. It is built on two neural networks to cope with 15
16 two separate decision-making processes in fishing activities. One neural network deals 16
17 with decisions to stay in current fishing grounds or move to new ones. The other is 17
18 constructed for the purpose of finding prey within the fishing grounds. Reinforcement 18
19 learning is used to derive expectations of catches from previous neural network-based 19
20 decisions. Feedback about catches is used to update the weights of the neural networks. 20
21 Some similarities with the behavior of real fishers were found: the concentrated local 21
22 search once a prey has been located to increase the probability of remaining near a prey 22
23 patch and the straightforward movement to other fishing grounds. Also, they prefer ar- 23
24 eas near the port when conditions in different fishing grounds are similar or when there 24
25 is high uncertainty in their world. 25

26 The observed behavior of the artificial fisher in uncertain scenarios can be described 26
27 as a risk-aversion attitude. In Dreyfus-Leon and Kleiber (2001), the model of fishers' 27
28 behavior was applied to yellow-fin tuna fishing in the eastern Pacific Ocean. In contrast 28
29 to Dreyfus-Leon (1999)—where the schools of fish were located at fixed points—in 29
30 this study, movements of schools of fish were simulated with artificial neural networks, 30
31 based on relative habitat comfort. Like Dreyfus-Leon (1999), the individual fishing ves- 31
32 sels were represented with artificial neural networks. The tuna vessels searched for the 32
33 tuna schools during a fishing trip. An interesting Turing experiment was performed to 33
34 test the performance of the model by asking experts, fishers, and tuna researchers to 34
35 identify which tracks were simulated and which were real. The experts were not able to 35
36 provide the correct answer more frequently than random choice. This provided the mod- 36
37 elers some confidence in their results. Two scenarios were considered in the analysis: 37
38 one with no fishing regulation and another with an area closure during the last quarter 38
39 of the year. In the scenario without regulation, fishing effort was allocated, particularly 39
40 in higher levels nearer the coast and where high concentrations of tuna were detected. In 40
41 the scenario with regulation, redistribution of effort was uneven but increased in neigh- 41
42 boring areas or in areas relatively near the closure zone. Decrease in effort was evident 42
43 only in the closed area. Effort redistribution when regulations were implemented is not 43

1 well understood, but this modeling approach can help fishery managers to envisage 1
2 some regulation effects in the fishery. 2

3 4 *4.4. What have we learned?* 4

5
6 Uncertainty and limited knowledge about ecological processes are crucial elements in 6
7 the study of social-ecological systems. Agent-based modeling provides us a tool to 7
8 test the consequences of the limitations of knowledge of various actors in decision- 8
9 making processes on the governance of natural resources. Theoretical models focused 9
10 on mental models match very well the applications that use role-playing games and 10
11 the participatory approach. These applications provide stakeholders instruments to test 11
12 the consequences of different perceptions of the systems, which enable them to identify 12
13 compromises and conflicts. The participatory use of models, such as systems-dynamics, 13
14 already existed. Agent-based models enable researchers to be more explicit about the 14
15 behavioral and spatial aspects of social-ecological systems. 15

16 The experimental work related to natural resource management and uncertainty re- 16
17 lates primarily to heuristics and learning models. In that respect there is a mismatch 17
18 with the theoretical and applied agent-based models. A considerable challenge remains 18
19 to develop experimental work to test the consequences of various mental models for the 19
20 management of natural resources. 20

21 22 23 **5. Topology of interactions** 23

24
25 The importance of non-random and non-uniform topologies of interactions between 25
26 agents can be an important reason to use agent-based models. As discussed by [Dibble](#) 26
27 [\(2005\)](#), [Wilhite](#) [\(2005\)](#), and [Vriend](#) [\(2005\)](#), the role of the structure of interactions has 27
28 been found important in various areas of agent-based computational economics. In this 28
29 chapter we mainly focus on exogenous structures of interactions, especially as they are 29
30 caused by ecological processes. In fact, when we include space, many questions arise 30
31 related to the structure of interactions. 31

32 Explicit inclusion of space in the analysis of environmental economic problems leads 32
33 to the questions of how to allocate a scarce amount of space, how to manage land given 33
34 uncertainty of the dynamics of the system, how to deal with spatial externalities and re- 34
35 sulting spatial conflicts, and how information spreads in a spatially explicit system. The 35
36 area of land-use and land-cover change addresses these issues, and agent-based mod- 36
37 eling has been applied in this area. Agent-based modeling for land-use and land-cover 37
38 change combines a cellular model representing the landscape of interest with an agent- 38
39 based model that represents decision-making entities ([Parker et al., 2003](#)). Due to the 39
40 digitalization of land-use/cover data, i.e. remotely sensed imagery, and the development 40
41 of geographic information systems, cellular maps can be derived for analysis. 41

42 Since the 1980s, cellular automata have been used to model land use/cover over time 42
43 ([Couclelis, 1985](#)). Human decision-making was taken implicitly into account in the 43

1 transition rules, but not expressed explicitly. Sometimes the cells represent the unit of 1
2 decision-making. In most applications, however, the unit of decision-making and the 2
3 cell are not the same. The desire to include more comprehensive decision rules, and 3
4 the mismatch between spatial units and units of decision-making, led to the use of 4
5 agent-based modeling for land-use and land-cover change. By including agents, one 5
6 can express ownership explicitly, as the property about which an agent can make deci- 6
7 sions. An agent can make decisions on the land use in a number of cells—for example, 7
8 by allocating cells to derive a portfolio of crops. 8

9 Another rapid development is the study of the structure of networks (Watts and Stro- 9
10 gatz, 1998; Barabasi and Albert, 1999). Since agent-based models are characterized by 10
11 the interactions of agents, it is important to understand the consequences of the effects of 11
12 different network structures on the collective behavior in social-ecological systems. We 12
13 will review some of this literature from the perspective of governing social-ecological 13
14 systems. 14

15 5.1. Theoretical models 15

16 In a number of examples, Axtell (2000) shows that changes in the interaction topology 16
17 can have important consequences for the outcomes in agent-based simulations, since 17
18 the topology affects the speed at which information is processed among agents. For 18
19 example, having X interactions in each time step, or on *average*, may lead to different 19
20 aggregated results, depending on the nonlinear behavior of the agent-based model. In 20
21 a similar vein, Flache and Hegselmann (2001) investigated the sensitivity of two main 21
22 processes in social science, migration dynamics and influence dynamics, to different 22
23 spatial relationships among the agents. They concluded that most of the insights are 23
24 robust to alternative spatial patterns, but some interesting differences do exist. Irregular 24
25 grids, for example, result in path-dependent processes, leading to lock-ins of certain 25
26 patterns. 26
27 27
28 28

29 Within the theoretical studies of social dilemmas, the paper of Nowak and May 29
30 (1992) simulated the study of social dilemmas in a spatial context. In their study, agents 30
31 play a Prisoner's Dilemma game with their nearby neighbors in a rectangular cellular 31
32 automata environment. The players defect or cooperate, and update their strategy each 32
33 round, by imitating the strategy with the highest payoff in their neighborhood. The de- 33
34 terministic model led to spatially chaotic patterns of cooperation and defection. Thus, 34
35 without memory, patterns of cooperation can be derived in a spatial context. 35

36 We will not review the comprehensive literature on spatial games here, but focus on 36
37 public-good games because of their relevance for natural resource management. Hauert 37
38 and colleagues study the evolution of cooperation in spatial public-good games (Hauert 38
39 et al., 2002; Brandt et al., 2003; Hauert and Szabo, 2003). They show that when agents 39
40 are able to leave a game, defectors, cooperators, and non-players co-exist in a dynamic 40
41 environment (Hauert et al., 2002). The possibility of costly punishment of defectors 41
42 significantly increases the level of cooperation (Brandt et al., 2003). Hauert and Szabo 42
43 (2003) tested the consequence of different geometries of interactions. Cooperation is 43

1 higher on honeycomb versus square interactions. Also, larger neighborhoods, and thus
2 larger groups who share the public good, reduce the level of cooperation.

3 4 5.2. *Laboratory experiments*

5
6 Laboratory experiments with regard to the importance of the structure of interactions are
7 rare, especially with respect to the governance of social-ecological systems. This may
8 change in the near future since new laboratories for experimental studies have been
9 established at the University of Rhode Island and Indiana University. Both laboratories
10 will focus on spatially explicit experiments with human subjects.

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

30 31 5.3. *Applications*

32
33 [Balmann \(1997\)](#) studied structural change in agricultural activities. He developed a
34 model that was based on a number of individually acting farms located at different
35 points in an agricultural region. Like a cellular automaton, the region was subdivided
36 into a number of spatially ordered plots. The farms competed for these plots and
37 competed in different markets. Farms were allowed to engage in different production
38 possibilities and could use several investment alternatives. They optimized their activi-
39 ties with respect to their objective function by considering their expectations, financial
40 state, and existing assets. The model was applied to a hypothetical region and studied
41 how agricultural development was path dependent. In [Balmann et al. \(2002\)](#), an ap-
42 plication of the model is presented with data from a region in Germany. The model
43 consists of approximately 2600 farms, distinguishing twelve farm types, as observed in

1 the data. In their application of the model, heterogeneity among the agents resulted in 1
2 diversity of adjustment costs to policy interventions. The model provides insights into 2
3 the distribution and dynamics of the impacts of policy changes on incomes. 3

4 Building on the work of [Balmann \(1997\)](#), [Berger \(2001\)](#) developed an agent-based 4
5 model for an agricultural region in Chile. The farm-household decision-making was 5
6 represented as a linear programming problem solved for each simulated year. Berger 6
7 analyzed the adoption of new export-oriented agricultural activities using a network- 7
8 threshold framework ([Valente, 1995](#)). Empirical studies provided the foundation for the 8
9 type of networks and the heterogeneity of threshold values. The analysis showed that a 9
10 governmental policy to stimulate export-oriented agricultural activities was effective to 10
11 double the income from agriculture in a twenty-year period, compared to a stabilization 11
12 of the income level if the policy intervention was not implemented. 12

13 [Deffuant et al. \(2002\)](#) present another agent-based model of innovation among farm- 13
14 ers. Their model is based on an in-depth survey and interviews with farmers in various 14
15 locations in Europe. The empirical model presented about Allier, France, tried to under- 15
16 stand how organic farming was diffused. A positive attitude toward organic farming 16
17 was necessary but not sufficient to get adoption started. Positive information in the press 17
18 stimulated farmers to exchange opinions, and stimulated adoption of organic farming. 18

19 [Allen and McGlade \(1987\)](#) developed a spatially explicit model of fishers. These 19
20 fishers could have different strategies, based on the information available to them, such 20
21 as fishing only at the location from which they expected the highest catch, or moving 21
22 around randomly. Inclusion of stochastic behavior for some fishers was necessary to 22
23 discover the location of fish stocks and to maintain the fish industry. 23

24 [Hoffmann et al. \(2002\)](#) present a pilot study of land-use change in south-central Indi- 24
25 ana, USA. This part of the state was primarily forested prior to the arrival of settlers from 25
26 Europe in the early 1800s. These settlers cleared substantial areas of land for agricultural 26
27 production (crops and pasture) and for forest products used for construction materials. 27
28 The process of clearing land continued until the early 1900s, at which time areas marginal 28
29 for agricultural production were gradually abandoned, resulting in a pattern of 29
30 forest regrowth in areas of low agricultural suitability. The agents (private landowners) 30
31 made decisions regarding their portfolio of land-use products that affected their utility. 31
32 The utility depended on components such as income from timber, income from farm- 32
33 ing, and aesthetic enjoyment of the forests. Using scenarios of prices for agricultural 33
34 commodities, Hoffmann et al. were able to reproduce land-cover dynamics in line with 34
35 observed stylized facts (agriculture on the flat land, reforestation on the slopes). 35

36 [Evans and Kelley \(2004\)](#) tested an elaborated version of the Hoffmann et al. model on 36
37 Indian Creek Township, located in southwest Monroe County, Indiana. This area is ap- 37
38 proximately 10×10 km, with private landholders as the primary actors in the landscape. 38
39 Indian Creek Township is characterized by a series of rolling hills with bottomland areas 39
40 suitable for agricultural production interspersed between ridges/hills that are largely 40
41 forested. Landowners are a mix of households that derive a portion of their household 41
42 income from extraction practices (agriculture, farming, haying, timber harvesting) and 42
43 other households that derive all their income from non-farm activities. Evans and Kel- 43

1 ley analyzed the consequences of using different scales of modeling the decisions of the 1
2 private landowners. The best fit of the calibrated model was derived at the highest reso- 2
3 lution, and declined non-monotonically with scale. The authors argue that agent-based 3
4 models of land use need to be analyzed at different levels of scale. 4

5 Parker and Meretsky (2004) focus on externalities of land use, and their affect on 5
6 land-use composition and pattern. Their model was used to analyze interactions be- 6
7 tween urban use and agricultural use, and how externalities of the use of the property 7
8 affected spatial patterns if agents made rational decisions to maximize their utility. The 8
9 assumption was that when agents adopt NIMBY (not in my back yard) strategies related 9
10 to urban activities, inefficient urban sprawl results. 10

11 Brown et al. (2005) present a model of urban sprawl applied to Washtenaw County, 11
12 Michigan, USA. The agents entering the county weigh aesthetics, distance to the service 12
13 center, and neighborhood density to make decisions about where to live. In addition to 13
14 their empirical landscape, Brown et al. used artificial landscapes to test the ability of 14
15 the model to predict certain spatial patterns generated by a known model. It was not 15
16 always possible to predict settlement patterns with the model, illustrating the difficulty 16
17 of getting a good fit in spatially explicit models. Nevertheless, they were able to derive 17
18 good fits with *aggregated* spatial metrics. 18

19 The study areas of Brown et al. (2005) and Evans and Kelley (2004) are similar in 19
20 some aspects (agents are households making decisions on a detailed, real landscape), but 20
21 differ in others (urban vs. rural, residential choice vs. allocation of land-use activities). 21
22 It is important to note the difference between the two modeling approaches as applied. 22
23 Brown et al. developed an extremely stylized model. By keeping it as simple as possible, 23
24 they were able to explore the parameter space in a comprehensive way. The agents and 24
25 decision-making processes in the Evans and Kelley model were more sophisticated, and 25
26 the model was calibrated on the observed detailed pattern of land-cover changes. Both 26
27 approaches are defended as being more appropriate to understanding the underlying 27
28 processes. More work definitely needs to be done to define the right type of model for 28
29 the research question at stake. 29
30

31 5.4. What have we learned? 31

32 32
33 33
34 Agent-based models offer various new aspects to spatially explicit modeling. By ex- 34
35 plicitly including decision-making processes we may be able to test the consequences 35
36 of various behavioral theories on spatial processes, such as land-use change and urban 36
37 sprawl. We recognize a lacuna in the availability of laboratory experiments that may 37
38 inform the choice of behavioral theories, but new laboratories at Indiana University and 38
39 the University of Rhode Island are currently conducting such experiments. 39

40 Spatially explicit processes in landscapes and networks of interactions are important 40
41 to investigate, since agent-based models are defined by the topology of interactions 41
42 among agents. Much more work needs to be done to address how the structures of 42
43 interactions and networks affect aggregated outcomes. 43

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

1 shown that such a top-down perspective is often ill-suited and can stimulate unsus- 1
2 sustainable use of the resource. Empirical studies also have shown that complex, nested 2
3 governance systems operating at multiple levels can govern similarly complex ecologi- 3
4 cal systems at multiple scales more efficiently than single, large units lacking knowledge 4
5 of many specific structures and processes. Social-ecological systems are complex, adap- 5
6 tive systems in which heterogeneity, multiple scales, multiple domains of attraction, 6
7 surprise, and fundamental uncertainty of the functioning of the ecosystem need to be 7
8 explicitly considered. Agent-based modeling may provide new tools to address impor- 8
9 tant questions of how to govern our common resources now that we have a better 9
10 appreciation of the complexity of social-ecological systems and the multiple dilemmas 10
11 facing resource users and public infrastructure providers at multiple scales. However, 11
12 the development of agent-based modeling is in its infancy. Whatever the future may 12
13 bring, agent-based models need to be used as one of the tools in a pluralistic toolbox of 13
14 concepts, frameworks, and methods in understanding and improving the governance of 14
15 social-ecological systems. 15
16
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