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Multi-agent simulations and ecosystem management: a review

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Abstract

This paper proposes a review of the development and use of multi-agent simulations (MAS) for ecosystem management. The use of this methodology and the associated tools accompanies the shifts in various paradigms on the study of ecological complexity. Behavior and interactions are now key issues for understanding and modeling ecosystem organization, and models are used in a constructivist way. MAS are introduced conceptually and are compared with individual-based modeling approaches. Various architectures of agents are presented, the role of the environment is emphasized and some computer tools are presented. A discussion follows on the use of MAS for ecosystem management. The strength of MAS has been discussed for social sciences and for spatial issues such as land-use change. We argue here that MAS are useful for problems integrating social and spatial aspects. Then we discuss how MAS can be used for several purposes, from theorization to collective decision-making support. We propose some research perspectives on individual decision making processes, institutions, scales, the credibility of models and the use of MAS. In conclusion we argue that researchers in the field of ecosystem management can use multi-agent systems to go beyond the role of the individual and to study more deeply and more effectively the different forms of organization (spatial, networks, hierarchies) and interactions among different organizational levels. For that objective there is considerably more fruit to be had on the tree of collaboration between social, ecological, and computer scientists than has so far been harvested.

Keywords: Multi-agent systems; Simulation; Organization; Agent architectures; Decision-making process

1. Introduction

Recently, several researchers have started to use multi-agents systems, also called agent-based modeling, in different fields. Researchers in ecology or economics use this methodology and the associated tools for ecosystem management. If a history of multi-agent systems were to be written over the coming years, those authors would certainly situate the birth of this approach and its formative years in the rich breeding ground of the interdisciplinary movement. Originally, multi-agent systems came from the field of artificial intelligence (AI). At first, this field was called distributed artificial intelligence (DAI); instead of reproducing the knowledge and reasoning of one intelligent agent as in AI, the objective became to reproduce the knowledge and reasoning of several heterogeneous agents that need to coordinate to jointly solve planning problems. Some researchers have focused more on the agent and its autonomy (for instance, the definition of an agent proposed by Wooldridge (1999): "an agent is a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its design objectives"), while

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others, engaged in the field of multi-agent systems, have focused more on the organization of multiple agent interactions (Huhns and Stephens, 1999). Then, these later researchers met other researchers coming from other communities in social and life sciences. They also met groups from Artificial Life (Langton, 1988), a field which was developed more on the basis of physics and the general context of the sciences of complexity, which re-examined scientific questions by studying the interactions between elementary entities and their mode of organization. On the one hand, multi-agent systems provide a method to reformulate certain questions in the social and natural sciences. On the other hand, researchers in the field of computer sciences used several concepts from social sciences: cognitive psychology and game theory to rationalize the strategies used in establishing relations with other agents; sociology to define the modes of interaction between individuals and society, and linguistics to provide the agents with language and to organize communication protocols. Nowadays, one issue is that of the interactions of agents with a collective environment. Among the scientific disciplines mobilized to examine this problem, ecology, for which the environment is a fundamental notion, could play a key role in specifying concepts and developing appropriate tools.

Various groups have emerged from the rich breeding ground of the interdisciplinary movement and they use multi-agent systems in different ways. Multi-agent systems are now an umbrella term (Ferber, 1995, 1999) for (i) interacting hardware agents (collective robotics), (ii) systems of interactive software agents (softbots) used in distributing planning tasks, for example, for Telecom scheduling applications (program design), and (iii) simulations of multi-agents, also called multi-agent simulations. In this paper we will review and discuss on how multi-agent simulations (this is what MAS will stand for in this paper) concepts and techniques can be used in ecological modeling practices.

Fruitful relations have already been established in the past. References to ecology, in its broadest sense, appear rapidly in the work on MAS. The anthill metaphor provides a much-used illustration to represent the notions of reactive agents and emergence and was the subject of the first applications (Drogoul, 1993). Hogeweg and Hesper's work on bee colonies (Hogeweg and Hesper, 1983), and Craig Reynolds' "Boids" (Reynolds, 1987), which imitate the behavior of groups of migrating birds, even appear to precede the notions of MAS or Artificial Life. They were followed by a range of studies on animal behaviors and animal societies. MAS were also used for so-called environmental applications that is, applications involving interactions between natural and social dynamics such as water management (Lansing and Kremer, 1994) or fisheries (Bousquet et al., 1994). This paper is a review and discussion based on papers devoted to ecosystem and resource management, which may take into account these interactions between society and natural systems.

We first present how the use of a bottom-up approach comes from and leads to paradigm shifts. Second, we present MAS and their use in ecological and social research. Then we propose a classification of the kind of agent and interaction protocols used in the literature and the various software tools. We end with a discussion on the various uses of MAS.

2. MAS and ecosystem management: the paradigm shifts

2.1. From "dynamics under constraints" to Interactions

In the field of ecosystem management, the problems of access and use of natural and renewable resources are key issues. Scientists working in this area need to examine the interactions between ecological dynamics and social dynamics. Indeed, for many years, this question was examined either exclusively from the angle of "an ecological system subject to anthropogenic disturbance" or, from the angle of "a social system subject to natural constraints".

In the first case, scientists make a careful description of the dynamics of the resource, with management constituting a definition of the various forms of anthropogenic exploitation, which can be sustained over the long term by this resource. Social dynamics are summarized in terms of the type of resource exploitation they entail.

In the second case, researchers generally concentrate on the problem of resource usage, placing themselves in the position of an isolated economic agent who wishes to maximize the benefits obtained from a restricted resource and placing the collective use of common resources within a framework of competitive exploitation. Assuming the same decision-making model for every agent (the optimizing rationality), aggregation of behaviors is possible and the same model can be applied from micro to macro levels.

For 10 years now, the challenge has been to develop a new approach focusing more on the interactions between ecological and social components and taking into account the heterogeneity of these components.

2.2. From a systemic to an organizational point of view

In his paper on ecosystem complexity, Holling (1987) defines three concepts that have dominated causality in ecological systems and that define the principles for the management of ecosystems. The first one is based on the notion of equilibrium (balance of nature), the second one defines several states of stability (nature engineered or nature resilient). This second perception is interested in dynamics caused by variability, by events that occur at small scales. The third point of view is the one of organizational change (nature evolving). The system changes: external events lead to perturbation of the system, but also, especially when human beings are part of the system, the actors of the system may, by themselves, change the organization of the system. This third point of view corresponds to the approach adopted by the sciences of complexity: the general state of a set of interacting entities may converge toward attractors, may be disordered, or may exhibit patterns of organization that change from one to another in an unpredictable way (Wolfram, 1984; Langton, 1992). To study these systems, the observations focus on the connectivity of the ecosystem's elements, their interactions, and their organization across various scales.

2.3. Modeling tools: from stocks and flows to behavior and interactions

To take into account the links between the natural system and the socioeconomic system, researchers have integrated the two subsystems as modules of models (Costanza et al., 1993). This systemic research uses the tools and methods of the mathematicians who developed that methodology: system dynamics (Von Bertalanffy, 1968). Muller (1997) explains how ecosystem theory got inspiration from systems analytical sources and establishes the linkages among ecosystem theory and cybernetics and control theory, information theory, network theory, thermodynamics. Practically, modelers describe systems as a set of modules or compartments interlinked by flows and controls. User-friendly software such as Stella,[1] Vensim,[2] Simulink,[3] and others is available. Practically, with these tools, the compartments are used to represent the stocks (aggregated variables) and flows represent flows of matter, energy, or information. It is thus possible to model linked ecological and economic components in an integrated model. Each subsystem dynamic is controlled by other subsystems. For instance, stocks of a resource are controlled by the harvest, which in turn is controlled by capital. Researchers, who have tried to standardize the flows of both systems by means of energetic transformation, have proposed a stronger link (Jorgensen et al., 2000). The theoretical assumptions and the tools used by this approach led to studies of the equilibrium properties of a system. For Uchmanski and Grimm (1996), this systemic point of view represents ecological systems as stable states. System dynamics is a method for identifying the set of attractors and the properties of the system near the attractors.

Although the systemic approach has been proposed as an alternative to a reductionist approach, a new point of view is emerging. The individual is the central object of that ecology that focuses on problems of behavior and interactions. This approach based on the concept of the individual has developed its own tools and methods. In ecology these models are called individual-based models (IBM). But there are two schools of thought and thus two uses of the concept of the individual. According to researchers and applications, these models fit in with the second or the third approach presented by Holling. On the one hand, for several researchers, the representation of individuals introduces inter-individual variability and thus heterogeneity is not aggregated (Lomnicki, 1999). Models are called *i-state distribution models* (Maley and Caswell, 1993). This does not challenge the principles of a systemic point of view and its

[1] http://www.hps-inc.com/#.
[2] http://www.vensim.com/.
[3] http://www.mathworks.com/products/simulink/.

Table 1
Two systems of interpretation leading to two concepts of complexity (Villa, 1992)

	Dynamic view	Organizational view
System conceplualisation	State variables	Lower level process/entities
Suitable metaphores	Cybernatic system	Parallel computers
Specification of mechanism	Centralized	Distributed
Means of analysis	Differential equations	Computer simulations
Key behaviors	Equilibrium, dynamic complexity	Self-organization structural complexity
System organization	Fixed, single level	Variable, multilevel

major themes: equilibrium and control. On the other hand, for other researchers, the introduction of the individual in the organization corresponds to an alternative to the systemic approach. Models are called *i-state configuration models* (Maley and Caswell, 1993). The individual is given unique characteristics (Judson, 1994) and holds a specific history (Gross, 1998). Furthermore, taking into account the social aspects, the individuals perceive the system and decide to change the organization. While strengthening the importance of the autonomy of the individual and the organizational aspects, the researchers in ecology prepared themselves for the interdisciplinary encounter with computer scientists who were developing the multi-agent system methodology (this is discussed in Section 3.2). Villa (1992) refers to the use of new computer tools and architecture to enhance the development of this organizational point of view (Table 1) as an alternative to the dynamic point of view.

3. Multi-agent systems, ecology, social sciences, and ecosystem management

3.1. A definition of multi-agent systems

There are various definitions of an agent (among them, the one given by Wooldridge referred to in the introduction of this paper) and multi-agent systems. We present here the definition given by Ferber (1995, 1999) because it seems to be the more meaningful for researchers in ecology and environmental sciences.

A multi-agent (Fig. 1) system is composed of:

- An environment E, that is usually a space.
- A set of objects, O. These objects are situated, that is to say, it is possible at a given moment to associate any object with a position in E.
- An assembly of agents, A, which are specific objects (a subset of O) and represent the active entities in the system.

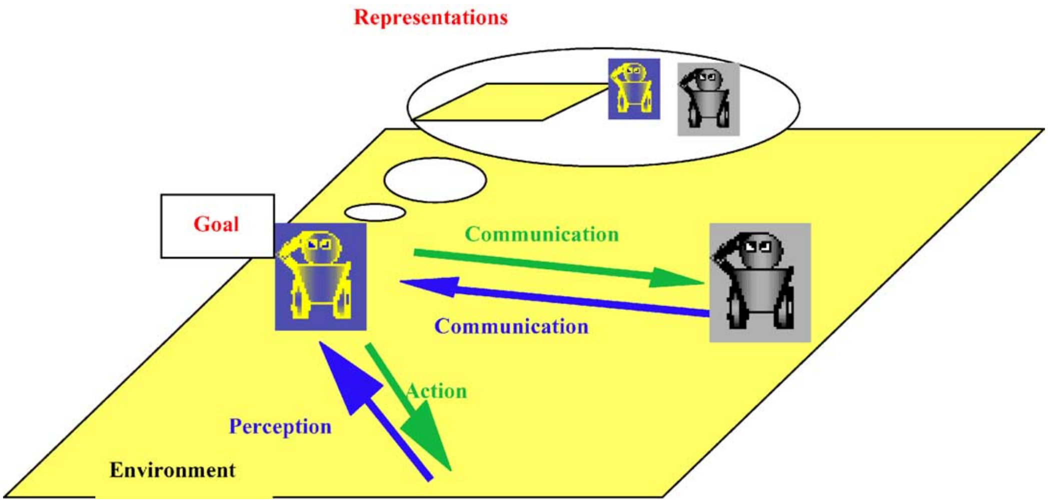

Fig. 1. A multi-agent system (Ferber, 1999).

- An assembly of relations, R, that link objects (and therefore agents) to one another.
- An assembly of operations, Op, making it possible for the agents of A to perceive, produce, transform, and manipulate objects in O.
- Operators with the task of representing the application of these operations and the reaction of the world to this attempt at modification, which we shall call the laws of the universe.

The key issue is formalizing the necessary coordination among agents. The questions are related to:

- *Decision-making*: What decision-making mechanisms are available to the agent? What are the links among their perceptions, representations, and actions?
- *Control*: What are the hierarchical relationships among agents? How are they synchronized?
- *Communication*: What kinds of message do they send each other? What syntax do these messages obey?

Various elaborate formulas are put forward for all these elements.

Multi-agent systems simplify problem-solving by dividing the necessary knowledge into subunits, by associating an intelligent independent agent to each subunit, and by coordinating the agents' activity. Thus, this refers to distributed artificial intelligence. This theory can be applied to monitoring an industrial process (Van Dyke Parunak et al., 1998), for example, the coordination of several specialized monitors rather than a single omniscient one. Fundamental research is being conducted on the problems associated with the representation of agents' decisions and protocols for communication. The main applications for multi-agent systems are in telecommunications, the Internet and physical agents, such as robots (Weiss, 1999). A group of scientists specializes in the simulations of agents' societies in ecology and social sciences.

3.2. MAS and IBM

In ecology, individual-based models (IBM) were developed at the end of the 1980s. The article written by Huston et al. (1988) is the most frequently quoted. These authors argue that there are two reasons for developing this approach: first, the need to take into account the individual because of his or her genetic uniqueness and, second, the fact that each individual is situated and his or her interactions are local.

These arguments were well received since a very large number of publications now refer to this approach. Shortly after this publication, Hogeweg and Hesper (1990) published a similar article on "individual-oriented modeling", which synthesized research that started 10 years before and influenced more particularly the community of Artificial Life researchers. In 1990, a conference titled "Individual-based models and approaches in ecology" was held in Knoxville, Tennessee, the proceedings of which now constitute the fundamental literature on this question (DeAngelis and Gross, 1992).

Wide-ranging studies have been carried out by researchers in theoretical ecology. In 1994, Durett and Levin (1994) published an article entitled "The importance of being discrete and spatial". In this article, the authors compare four approaches for modeling the dynamics of spatially distributed systems: (i) the average field (ordinary differential equations) in which each individual has an equal probability of interacting with other individuals; (ii) "patch models" in which individuals are grouped on a set of sites with no connection structure; (iii) reaction–diffusion models where a population of individuals diffuses in space; and (iv) particulate approaches in which the individuals are "discretized". Durett and Levin (1994) demonstrate the conditions in which these models are equivalent or otherwise. Various other studies (McCauley et al., 1993; Wilson et al., 1993; Wilson, 1996) have pursued this approach, comparing results of mathematical models and simulations centered on the individual.

During the 1990s, several individual-based models were published. See the work of Roese et al. (1991), Silvert (1993), and Derry (1998). Several models are models of forests (Deutschman et al., 1997). Numerous ongoing applications can also be seen on the Web site of C. Reynolds.[4] Dedicated simulators (Carter, 1996; Risenhoover, 2002) also exist. The most striking application is doubtless the ATLSS model (across trophic level system simulation), which seeks to simulate the ecological functioning of the Everglades region in Florida (Abott et al., 1995). This model repre-

[4] http://www.red3d.com/cwr/ibm.html.

sents abiotic factors such as hydrology, fire and hurricanes, and the various trophic levels. Inside these models, which may be multi-compartment mathematical models, different animal populations are simulated (deer, felines) using IBM models. For models truly distributed on the individual (*i*-configuration models), the object approach has generally been applied.

A special issue of *Ecological Modeling* (Grimm, 1999; Grimm et al., 1999) presented a discussion on what conclusions can be drawn after 10 years of development and use of IBM. Mainly, two ideas are expressed on the need for a consolidation phase. The biologists–computer scientists have to examine classical modelers' questions: how to describe the structure of a model and how to present the results? The consolidation is also theoretical. Too many applications were presented without any concern about the generic nature of the results. Grimm (1999) proposed favoring models closer to theoretical issues, usually represented in mathematical terms.

There are some differences between MAS and IBM. IBM were developed by ecologists who tried to introduce the notion of the individual to understand the role of heterogeneity. MAS are more influenced by computer sciences and the social sciences. MAS give more emphasis to the decision-making process of the agents and to the social organization in which these individuals are embedded. Furthermore, an agent is not necessarily an individual. An agent can represent any level of organization (a herd, a cohort, a village, etc.).

3.3. MAS, artificial societies and computational economics

MAS are developing rapidly in the field of social sciences. Social simulation is the subject of numerous conferences, for example, "*multi-agent systems and agent-based simulation*" (MABS) (Sichman et al., 1998) and "*simulating societies*" (Gilbert and Doran, 1994), among others. Research on the subject is published in the electronic journal *JASSS* (*Journal of Artificial Societies and Social Simulation*) or in specialized journals. In addition, a group called agent-based computational economics (ACE) (Tesfatsion, 1997) has been set up, publishing on environmental issues in various economic journals.

In social sciences, the use of MAS to simulate social phenomena is generally associated with the methodological individualism in which the singular individual is considered as the elementary unit or the atom of society (Weber, 1971). The overlap is, in fact, in the bottom-up approach that characterizes MAS. However, the equivalence between individuals from a society and agents from a MAS can be misleading: it is possible for social groups, institutions, and even opinions (Bura, 1994) to be considered as agents with their own standards and rules for functioning. The agents are directed by constraints or rules that are expressed on a group level, that is, they are no more than entities that act and are placed in a dynamic environment.

This straightforward comment—which is natural when MAS are used for modeling—shows how the simple duality that exists between individualism and holism can be called into question. This is a major preoccupation for researchers working on ecosystem management and MAS:

(i) individuals, products of history are driven by collective values and rules;
(ii) collective values and rules evolve because of the interaction between individuals and groups;
(iii) the individuals are neither similar nor equal but have their own specific roles and social status.

How do individuals make up a group? How is an institution created? The individual cannot be considered as an autonomous entity that is independent of its social environment. How are individuals constrained by collective structures that they themselves have set up and how do they make these structures evolve (Gilbert, 1995)? What degrees of freedom are given to the definition of individual practices? Here are just some of the questions that can be explored using MAS and that can be expressed as follows: "How are collective structures set up and how do they function when they are based on agents with different capacities of representation, that exchange information, goods, or services, etc., draw up contracts, and are thrust into a dynamic environment that responds to their actions?"

3.4. MAS and ecosystem management

Parallel to the scientific dynamics presented above, and despite limited interaction (only a few authors publish in both communities) many developments have been achieved by computer scientists invoking a reference to ecology. Our review shows that, in most cases, the method used is that of simulation. A few studies examine the question of problem solving, called collective problem solving in the context of MAS. On the basis of ethological studies on the problem-solving capacities of social insects (Deneubourg and Goss, 1989), numerous studies have been performed involving processes that can be transposed to the domain of computer programming and robotics. Drogoul (1993) provides an excellent review and develops with Ferber an original approach called eco-resolution. This approach involves modeling agents that must seek a state of satisfaction by avoiding a state of displeasure. One of the most well-known examples is that of the sliding squares puzzle: by seeking to satisfy themselves individually, the agents accomplish the collective task of defining a particular spatial configuration. Born out of the collaboration between computer scientists and ethologists, this method could be useful in dealing with problems of ecosystem management: for example, the problems of spatial organization of a landscape on the basis of the different roles allocated to the interacting portions of landscape. An initial example, concerning the spatial organization of agricultural land, is found in the work of Le Ber et al. (1999). Land use is represented by groups of agents seeking to occupy plots to satisfy production objectives. The performances of the system are comparable to those of the simulated annealing algorithm. The work of Baejs (1998) and Ferrand et al. (1997) can be placed in the same category. In this context of land development, the interactive agents are responsible for finding a spatial configuration that optimizes a global criterion. One application, for example, concerns the routing of a high-voltage power line across a landscape filled with constraints.

Numerous publications claim a purely metaphorical link with biology and ecology. For example, this article does not cover the studies that apply to problems of agents within electronic networks and that refer to ecological processes. This is an emerging field and interested readers may refer to Maes and Schneiderman (1997) for further information.

Several authors have been using MAS in the field of ecosystem management for several years. This kind of application was begun by Lansing and Kremer who studied water management in Bali (1994), Bousquet et al. (1993) for fisheries management, Deadman and Gimblett (1994) for park management, and Kohler and Carr (1996) for archeological issues. These authors were followed by several researchers such as Janssen and Carpenter (1999) for lake management and Dean et al. (2000) and Balmann (1997) for agricultural land management.

If we view ecosystems in terms of people and management problems, Epstein and Axtell (1996) study the structuring of networks and their effect on the management and distribution of resources. In a more applied context, we note the studies of Antona et al. (1998) on the organization of economic exchanges between harvesters of renewable resources and consumers. In this context, the use of economic management tools is suggested, such as quotas, taxes, permits (Kozlack et al., 1999) and their influence is tested according to the level in the supply chain at which they apply.

Barreteau and Bousquet (2000), Feuillette et al. (2003) and Mathevet et al. (2003), among others, propose models and simulations that involve relations among one or more natural resources, agents who can individually exploit the common land and act on the common resource, and sets of interactions between agents who coordinate their actions or exchange information. A good overview of work by the research community from the United States is given in a book published by Kohler and Gumerman (2000). Janssen (2003) also edited a book composed of several papers on the topic of MAS for ecosystem management.

4. MAS: computer tools for ecosystem modeling

MAS relies on a bottom-up approach. Through the modeling of agents' behaviors and interactions, properties emerge that can be observed at the level of the system. Although a model conceptualized in terms of agents can be implemented with mathematical equations (Janssen and de Vries, 1998), it seems more natural to implement the agents with computer agents. The field of computer science proposes various architectures for the agents' decision-making and several protocols of interaction.

4.1. Agents architectures

Although the notion of multi-agents involves interaction among many agents, the literature shows that most studies focus on the internal mechanisms of the agent, either in terms of deliberation for intentional agent, or in terms of adaptation for reactive agents. Several types of architecture are proposed. Most are architectures for reactive agents, although when human actions are considered in the ecosystem, architectures place more emphasis on deliberation. Production rules are very often used to simulate the deduction process of an agent facing environmental stimuli. However, most frequently, production rules are mixed with other kinds of formalizations such as parameterized functions, or are organized in a specific internal architecture of the agent such as competitive tasks or belief–desire–intention architectures. We start here with agent architectures based on evolutionary and connectionist principles.

4.1.1. Architectures based on the evolutionary metaphor

Many applications of MAS to ecosystems have been developed by the Artificial Life community. These researchers, who seek to understand complexity through a bottom-up approach, use a range of techniques, including MAS. Seeking to understand life as it could have been rather than as it is (Langton, 1988), they often use approaches based on the theory of evolution to understand adaptation. The most well-known method is that of genetic algorithms (Holland, 1975), which make use of what Oppenheimer (1988) calls numerical genes. As part of his research on adaptive systems, Holland (1975) has produced a class of algorithms which code for the potential solution to a problem in the form of a series of numbers or a chain of characters (chromosomes). The algorithm attributes an adaptation or "fitness" value to each chromosome. A periodic selection process, a function of "fitness", causes the population to evolve by favoring the fittest individuals. Cross-breeding and mutations also occur. Numerous applications have been proposed with evolutionary agents of this kind (Lindgren and Nordahl, 1994, for example). Certain authors see each chromosome as a situated agent rather than as a set of probabilistic interactions. The coding of a chromosome within the agent often involves associating different behaviors (movement, transport, communication, etc.) with chromosome portions (genes) to obtain the "fittest" behavior combinations. One of the first applications of this approach, relating to foraging problems, was presented by Collins and Jefferson (1992). Krebs and Bossel (1996) focus on the emergence of objectives for agents who are required to use an environment. Nishimura and Takashi (1997) present an application of these evolutionary approaches and demonstrate the emergence of collective movement and congregation behaviors. A handful of applications have been proposed, showing how the control structure (the program) of an agent looking for food evolves and adapts over time. Holland suggested an agent architecture based on this approach, which led to the creation of the Echo platform (Hraber et al., 1997). These ideas also led to the use of the concept of tag, again a kind of numerical gene that codes the skills or the behavior: agent interactions are driven through the comparison of their tags. This is used to simulate the emerging social organizations of societies of agents (Epstein and Axtell, 1996; Riolo et al., 2001).

4.1.2. Architectures for competitive tasks

Various architectures have been proposed to represent the choices made by an agent when it receives several stimuli which activates different tasks. There are many links in this area with robotics and with the community working on animats (Guillot, 1999). Taking the problem of finding food as a basis, Tyrell (1993) proposes an architecture where behavior systems are activated in parallel. Taking the idea of intelligence without representation to its limits, certain authors create agents whose decisions are based directly on stimulus perception (behaviorism). Examples include a MANTA architecture proposed by Drogoul and Ferber (1994), which attributes an activation level to each competing task. This activation level a_i of a task i is calculated as follows:

$$a_i(t) = \frac{w_i(t)}{\sum_{j=1}^{n} w_j(t)} x_i(t)$$

where w_i is the weight of the task and x_i the stimulus intensity. A task is selected if a_i is greater than a given threshold. To select the tasks, Brooks has proposed a subsumption architecture (Brooks, 1991). The activities are represented by different levels. Control is based on mechanisms of inhibition and suppression. The upper levels are capable of suppressing the inputs of the lower levels and inhibiting their outputs. Though it is still referenced in theory and appears well adapted to ethological problems, this architecture has few applications in ecology.

4.1.3. Architectures based on neural networks

Emphasis is placed on the learning capacity of agents. The perception–action relation is modeled by a network whose connections evolve. Collins and Jefferson (1992) endow their ants with neural networks so that they are capable of learning. To deal with the wide range of tasks to be accomplished, the agent ant possesses several neural networks (one to learn to explore, one to learn to transport). Jefferson et al. also propose neural networks for their Genesys agents (Jefferson et al., 1991). An application of these methods is found in the thesis by Dagorn et al. (2000), who seeks to understand the movements of tuna fish within their environment. In the Creature model (Grand and Cliff, 1998), a commercially available computer game, the agent's metabolism interacts with a neural network to simulate the agent's development: it acquires a language. A handful of applications couple neural networks with genetic algorithms that cause the network to evolve.

4.1.4. Parameterized functions

The agent's decision may be expressed in terms of additions of physical forces. For example, the work on bird flight by Reynolds (1987) applies vector calculations in force fields resulting from the attraction or repulsion of other agents. This type of modeling, where agents represent elementary particles, is undergoing major developments in a range of fields related to fluid dynamics, be it for modeling of water flow (Perrier and Cambier, 1997), crowd dynamics, urban traffic flow, or mass animal movements (Mechoud et al., 1998; Ramat et al., 1998; Lambert et al., 1999).

For certain resource management applications, sometimes referred to as agro-ecosystems, the decision-making processes of economically rational agents are simulated. To decide what action to take, these agents use models based on operational research (gradient calculation, for example) or microeconomics (such as the maximization of utility) to obtain an optimal solution in the presence of constraints. This is the case in the work of Weisbuch et al. (1997) and Balmann (1997), who simulate the optimization of a farmer by means of linear programming. This process of optimization can be more or less bounded and thus the calculation of an optimum is often combined with a set of production rules (Polhill et al., 2001; Becu et al., 2003). Other applications (Deffuant, 2001) endow their agents with decision-making methods based on multi-criteria analysis. The agent may even be represented by a matter or energy flow model (Guerrin et al., 1999). The application of these techniques often raises the question of how to link or choose an individual rationality, for which numerous methods are available, with collective decision-making.

4.1.5. BDI (belief–desire–intention) architectures

The cognitive agents involved in ecosystems made an early appearance in the MAS community (Bousquet et al., 1993; Doran and Palmer, 1993). They were not based on neural network architectures but on what have been defined and called afterward belief–desire–intention architectures (Fig. 2). The proposed architectures comprise objectives, representation, and involvement in individual or collective actions. However, most applications for ecological problems use simple agents and attention focuses on understanding their coordination or their relations with the environment. There is nevertheless a cognitive dimension that is primordial for all ecological systems, i.e., spatial representation. A few initial studies (Saarenma et al., 1988) looked at the spatial representation of animals. The most widely used method is the memorization of space and re-

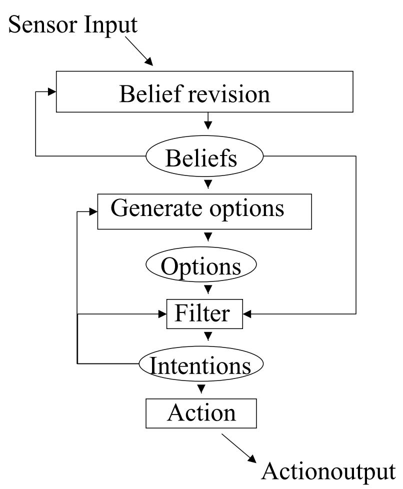

Fig. 2. Belief–desire–intention architecture (Woolridge, 1999).

sources via a set of objects corresponding to a mental map. The pioneering work of Folse et al. (1989) is an example of this. Another cognitive dimension is used when modeling agent interactions is the notion of reputation. Agents may have beliefs about other agents, coming from their individual experience or as a result of social reputation, that are used to guide their level of commitment to collective resource management (Doran and Palmer, 1993; Rouchier et al., 2001a; Mathevet et al., 2003).

4.2. Interactions: the role of environment

In the case of MAS applied to ecology, there are three major types of interactions: interactions by communication among agents, physical interactions (grow, push, eat), and interactions mediated by the environment.

Direct interactions through the exchange of messages are relatively rare in ecological applications. A few metaphorical applications are mentioned, such as that of the prey–predator model studied by Bouron or Baray (1998): predators communicate to surround a prey. The most pertinent examples concern negotiations and exchanges of contracts, goods, or services among agents that represent humans forming part of the ecosystem. For example, Franchesquin (1995) implements the Sian protocol to simulate negotiations among Bolivian farmers.

The physical interactions through which agents exert a physical action on others such as pushing, pulling or exerting a pressure are not used for ecological applications, as far as we know. These kinds of interactions have been used in physical applications such as hydrology or physics of soil. On the contrary, a physical interaction such as predation is often used in models.

The third type (mediation by the environment) is a response to what Kawata and Toquenaga (1994) define as one of the two key questions of Artificial Life, namely, the relation between organisms and their environment. The environment cannot simply be taken to mean all other agents; the environment can be seen as the physical space and the resources. This type of interaction ties in with the concept of externality used by economists. The results of an agent's action transform the common environment, with a retroactive effect (positive or negative) on the other agents. In certain studies, the dynamics of the environment and its heterogeneity are used as a medium for collective adaptation. In this case, we speak of dynamic co-adaptation. Many applications use the environment as a set of signals for movement, for reproduction, or for the choice of tasks. The algorithms are often based on the concept of "swarm intelligence", which originated in the ethology of social insects. The key idea is that "the structure of the environment and the organization of the group of agents are mutually co-determining" (Théraulaz, 1994). There are many applications of this approach (swarm intelligence, co-evolution, world model, etc.) (Bonabeau et al., 1999).

4.3. Tools

The applications presented are generally developed with an object-oriented language. Some of them use platforms. They can be divided into three types:

- Generic platforms are used for many purposes, such as telecommunications and networks. Some of them are regularly cited in environmental applications. These tools are based on a principle that is not necessarily resource management. Swarm (Minar et al., 1996) is the favored tool of many researchers, especially in the U.S. StarLogo (NetLogo) is also one often mentioned tool: it is much-more user friendly but has less potential than Swarm. SDML features a declarative modeling language and is useful for focusing on the cognitive aspects of the agents.
- Platforms for social and ecological simulations provide utility programs to simulate ecosystems or resource management problems. These tools, which include spatial representation, simulation utilities for Monte-Carlo-type methods, and links to other software (GIS, databases), are complete tools for the implementation of different social or ecological systems. Algorithms or structures are provided to implement the link between agents and their environment and elements are provided to organize societies of agents (markets, auctions, predation mechanisms, etc.). Ecosim (Lorek and Sonnenschein, 1999) is more oriented towards ecology, whereas Repast (based on Swarm) or Cormas (Bousquet et al., 1998) are more open to the implementation of social dynamics in interaction with natural resource dynamics.

- Dedicated platforms are tools concerned more with specific applications. For example, Manta (Drogoul, 1994) focuses on problems of foraging or task allocation in a society of insects. Arborscape (Savage and Bell, 2000) models forest dynamics with emphasis on diversity. BacSim (Kreft et al., 1998) models microbiological dynamics. Mobydic models the dynamics of fish populations (Ginot et al., 2002). Users gain valuable insights into dimensionality, relations of predation or competition, and standard biological functions (mortality, growth, etc.).

5. Discussion on the use of MAS for ecosystem management

5.1. Coupling spatial and social dimensions

As presented briefly in Section 3, the purpose of MAS is to study the interactions between autonomous agents and their organization. Is the organization constitutive of the MAS or is it the result of the MAS? The emergence debate is less simplistic today and is based on a study of micro–macro circularity. Though organization is simultaneously a product, a context, and a constraint for the agents, its characterization is nevertheless limited. Though agent structures and interactions are categorized and described, organizations are less clearly formalized. In MAS dedicated to ecosystems, two elements of organization can be found: spatial organization and networks.

The spatial dimension is the most frequently mentioned, with descriptions of the organization of agents spread over space. Most problems associated with the search for food involve the organization of agents and their environment. Studies also focus on an important question in ecology, that of regulation. In the context of agents' relations with their environment, the question of the number of animals capable of surviving and reproducing is often raised (Pepper and Smuts, 1999). This directly affects the calculation of how many of these animals can be harvested by the society and how the environment should best be adapted to this requirement. In an integrative cybernetic vision, and taking inspiration from demography, numerous studies have been carried out on the theme of density dependence. The concept of a maximum carrying capacity used to be the cornerstone of ecosystem management. MAS have been used to test organizational hypotheses other than density dependence. For example, Le Page and Cury (1997) test the theory of "obstinate nature", according to which agents tend to reproduce under environmental conditions equivalent to those in which they were born. By combining the movement behavior linked to this theory with the structuring of space, the authors describe a population dynamic regulated without density dependence. Several researchers are now turning toward the characterization of spaces in which agents move and coordinate their actions (Pepper and Smuts, 1999). The landscape itself can be a MAS comprising different areas of space interacting on several levels (Le Page et al., 1999). The spatial representation of the agents is also of importance (Dumont and Hill, 2001). The organization of the agents' space and of the resources within it can also be the driving force of a dynamic that leads to task allocation mechanisms. Drogoul (1993) thus shows how agents (ants) are able to specialize in different tasks to ensure that the anthill functions successfully.

The second type of organization that can be studied with MAS is that of an interaction network structure. Many studies have been conducted in the field of food webs and species diversity. The relations of causality between the stability of an ecosystem and its degree of connectivity have been tested in this way (May, 1973). This question was theoretically treated by Lindgren and Nordahl (1994). A similar question has been raised, in a very applied manner, with regard to fishing. Two experiments conducted at IRD (Institute for Research and Development, France) were seeking to determine the link among predation, competition dynamics and ecosystem indicators. In the first experiment, a food web comprising three fish species whose behaviors are assumed to represent the diversity of strategies encountered in the Niger River was simulated (Bousquet et al., 1994). The environment is a river–floodplain system represented by several habitats offering quantities of food that vary over time. The implemented agents present behaviors that express different adaptation mechanisms (adaptive strategies): different types of reproduction and movements in space and time. One species eats the plankton brought in by high waters. The second is heterotrophic: it consumes plankton or small fish. The third is a pure predator. The agents in this system are not models of individuals but rather models of groups. Starting with this food web, increasing exploitation pressure (fishing intensity) is simulated. It is thus possible to observe the impact of this pressure on the food web, notably the decline in species populations and the overall response in terms of catches. This response takes the form of a plateau in the population curve, illustrating the ecosystem's resistance to the stress of intensive fishing. This type of plateau is well known in resource ecology (Welcomme, 1989): indeed it reflects the response pattern of all organisms subjected to a stress. We thus move on from knowledge of species behaviors to the characteristics of the system's dynamics. A similar experiment was conducted by Shin (2000). Agents modeled on the basis of fish species database information and positioned on a spatial grid interact through predatory behavior. The result of these numerous interactions is observed via a global indicator, the size spectrum, widely used by managers to analyze the biological situation. In the case of these two experiments, the aim was to establish a link between data at different levels: behaviors and interactions at the micro level and patterns observed at the ecosystem level.

If we include the human dimension in the ecosystem, social scientists model and simulate interaction networks among agents to analyze the effects of different rationalities and exchanges. For example, Rouchier et al. (2001a) show how various hypotheses of relations between agents engaged in transhumance (migration) and sedentary agents in the Sahel produce very different resource dynamics.

The most productive option is to combine the structure of a network and its position in space. Networks of interaction between species take on more importance if they are structured in space. In one of the original models, Hogeweg (1988) simulates agents based on social insects. Through interactions between TODO agents (behavior: do whatever activities come along) and DODOM agents (behavior: establish relations of dominance), social groups are formed and a rhythm is created. The influence of space structuring on the creation of hierarchies is demonstrated. In the same type of simulation, Doran and Palmer (1993) study the social networks that are formed to capture resources located in space. This work is based on a classic BDI approach with recruitment of agents to accomplish a task. Hierarchies appear and their functionality is studied. Epstein and Axtell (1996) present a set of simulations based on the theme of spatial exchanges.

5.2. *From theorization to collective decision making*

MAS simulations are developed in the field of ecosystem management for several purposes.

The first type of possible use of these simulations complies with the principles of Artificial Life: investigating "life as it might be rather than life as it is" (Langton, 1988). The modeler sets up mechanisms and observes the emerging responses. These forms may actually exist. This research is founded on the results and approach adopted in physics (Weisbuch, 1991): it is the transitions between phases of a system that are studied. The aim is thus to build very simple interaction models and to find the critical coefficients that characterize the transitions. One assumes that the model and system under study belong to the same class of universality whose qualitative properties have thus been described. Although they do not explicitly refer to physics, many publications use MAS for theoretical purposes (Doran and Palmer, 1993; Hales, 1997; Pepper and Smuts, 1999; Rouchier et al., 2001b; Thébaud and Locatelli, 2001).

Another more empirical use comes from the community of modelers working in life sciences and social sciences, who are either directly or indirectly involved in resource management problems. The underlying idea, which is to produce a system that behaves like reality, is always present, with the aim of using the simulator to ask the question "and what if . . . ?". By adapting the model to reality the aim is not to make the model into a prediction tool, but rather to understand the dynamics that exist or have existed. The authors examine behavior and identify parameters not to provide an explanation but to simulate observations of reality: the hypothesis tested can be used to simulate these observations, but other hypotheses could also simulate this reality. This method is used, for example, in archaeology (Kohler et al., 2000) and history. One example of an application is that of Dean et al. (2000) who reconstitute the history of the Anasazi indians and simulate scenarios that examine population movements in response to environmental crises. Another famous example is the work of Lansing and Kremer (1994) on the coordination for water management in Bali. MAS are also used to understand the traditional management of renewable resources (Bousquet et al., 2001) and agricultural practices (Balmann, 1997).

The vocation of a model is generally to serve as a decision support tool. The domain of the distributed problem solving will likely be applied widely to propose solutions for configuring an area of space, for example (Le Ber et al., 1999). But simulation can also be used and can contribute to decision-making processes. Take the work of Gimblett et al. (1998), for example, who suggested that a natural park be redesigned to prevent competing users (mountain bikes, walkers, jeeps) from crossing each other's paths by simulating the movement and field of vision of agents. Other methods are proposed, such as companion modeling (Bousquet et al., 1999). This method proposes to use MAS to deal with problems of common property management as part of a constructivist approach with the players of the system. The model becomes a shared representation and can become, as the social process moves forward, a tool for dynamic co-adaptation between one or more social groups and their environment. This circular approach of model presentation and model construction with the players involved has been proposed and tested in several different field situations. The role-playing method is used (Barreteau et al., 2001). Role playing can be used to present a MAS or to construct it with the players: bottom-up modeling for bottom-up decision-making (Aquino (d') et al., 2002; Hare and Pahl-Wostl, 2002; Lynam et al., 2002; Bousquet et al., 2003).

Likewise, applications in ecology offer many points of interest for computer scientists. In the community of Artificial Life, Bonabeau and Theraulaz (1994) mentions several, including algorithm design and theorization.

- *The metaphor for algorithm design*. Relations modeled for an application serve to conceptualize algorithms, protocols, systems of visualization (Hutzler, 2000), and even architectures. Genetic algorithms and eco-resolution are initial examples, though many others should emerge now that MAS are raising questions of common resource sharing and the ecologist and environmentalist vogue gives the stamp of acceptability to all environmental labels attached to new computational ideas.
- *Theorization*. The points raised with regard to IBM are relevant here too: MAS can be created from mathematical models with a view to making them more complex, and it is possible to use MAS to develop new theoretical constructions. Cazoulat (1995), Keitt (1997), Weisbuch et al. (1997), Van Dyke Parunak et al. (1998), among others, produced initial studies comparing an MAS with mathematical models that already exist or have been created for an application. In general, the mathematical model is first created (the methods of statistical physics are widely used) and its properties are studied. MAS then serve to introduce heterogeneity, anisotropy and local histories. But MAS models are also very powerful methods for directly developing new theories, "more theory building than modeling" (Doran and Palmer, 1993). They thus contribute to efforts to theorize relations. This theorization does not rule out comparison with field data. Alongside the Artificial Life approach, the idea of the virtual laboratory has emerged. It involves building a model of the world and observing its dynamics via indicators based on the same protocols as those used to observe the real world. Classical validation methods used in simulation (Hill, 1995) can even be used. These comparisons with mathematical models and with observed data can validate the architectures and protocols proposed by computer scientists.

6. Some perspectives

MAS for ecosystem management is still a recent research field. However, after the first set of applications and theoretical papers one can propose a set of research questions to be examined in the future, as has (Parker et al., 2003). These are themes for which the interdisciplinary encounter between computer scientists and social scientists and ecologists will be necessary. Not surprisingly, we classify these questions on the basis of individual decision-making, collective decision-making, the problem of scales, the credibility of the model, and the use of the model.

6.1. Individual decision-making

Interesting questions are emerging on the modeling of the decision-making process of an agent.

First is the question regarding whether the research should concentrate on the testing of theoretical models or work on the elicitation of decision models from the observation of the real world. On the one hand, some researchers (Parker et al., 2003) suggest that researchers be wary of accumulating too many specific cases or too many applied models of decision. For them, preference is to be given to models close to theory and a challenge is to decide among the number of these. The aim is to test which model is appropriate for decision-making situations. On the other hand, some other researchers (Aquino (d') et al., 2002) are more interested in the elicitation of local decision-making models and, in an inductive way, they try to determine which are the common elements of these models.

Second, there should be new interdisciplinary research on the learning process. In most papers presenting MAS for ecosystem management, the learning process of the agents is poorly represented. As this is one of the main research themes for computer scientists working on agents, this should be improved in the near future. For example, there is the question of the spatial representation of agents: How does an agent decide to leave a place where resources are scarce and make a long journey to supposedly better zones? This question is particularly relevant for herd modeling (Bah, 1997; Dumont and Hill, 2001). A lot of papers are proposed by computer scientists working in the field of robotics and common work between the communities should be fruitful.

6.2. Institutions for regulation

MAS are already used to study food webs, hierarchies, commodity subsectors, economic regulation tools, auctions, etc. The general institutional domain offers a framework for studying the management of common property and social regulation mechanisms (Janssen and Ostrom, 2001). It should also provide inspiration for MAS: computer scientists should soon be turning to the corpus of literature on the management of common property. The institutional domain proposes solutions other than economic (*market-oriented*) solutions, as proposed by Wellman (1996). If this happens, as it happened for electronic markets and virtual markets, one can expect from the computer scientists new architectures of agents and interaction protocols built to facilitate the modeling of resource-sharing issues. For example, a common problem is the one of open systems: how can a society of agents, sharing a common resource, adapt its organization to face the problem of migration of agents?

6.3. Scale and organizational levels

One important reference in ecology is the theory of hierarchy introduced by Allen and Starr (1982). Complex systems are presented as intermediate between large-number systems for which a statistical approach is adapted and small-number systems for which mathematical approaches such as differential equations are suitable. Intermediate systems are opaque unless they are modeled as hierarchical organizations. The use of hierarchies is a conceptual and practical tool to observe the world and better understand it: scales are defined by the observer of the system. In their book, Allen and Hokstra (1992) explain that the understanding of a complex system in ecology implies the understanding of interactions not only at a given level but also among various levels (organisms, populations, communities, ecosystems, landscapes, biome, and biosphere). A nested hierarchy is the simplest system, in which the upper level contains the elements of the lower level. By adopting the "layer cake" metaphor for ecosystem scales presented by Allen and Hokstra (1992), analysis can be performed horizontally (across a level), vertically (across scales) or diagonally (both the type of system and the level are changed): "there is plenty of room for entities from almost any type of ecological system to be contained within an entity belonging to any other class of systems". The authors give the example of rumination, which involves an ecosystem under the control of an organism (the ruminant).

MAS is an interesting method for the questions examined by the theory of hierarchy because it proposes solutions for the modeling of agents interacting at various levels. First, agents representing different levels, and acting at different speeds, may interact in a simulation. Several platforms (see Section 4.3) propose different schedulers for the activation of agents, and also propose tools to model groups of agents that have their own behavior and may interact with other groups or agents. Second, some MAS researchers are interested in the dynamic creation of groups. Agents may decide to form a group and give the control to it. Alternatively, groups may cede the control of the dynamics to the lower entities. Servat et al. (1998) proposes an example for hydrology: at one level, water bowls have their own dynamics, and at the upper level agents represent ponds or rivers. The use of MAS based on the evolutionary metaphor can also give very interesting results on the emergence and dynamics of hierarchies (see Section 4.1.1). Evolutionary simulations are used to create artificial worlds, which are used to define theoretical properties. Although MAS present a promising potential to be used for better understanding of hierarchies, we are not aware of applications in ecosystem management.

6.4. The use of models: from positivism to constructivism

The principles of MAS are principles of collective decision-making of societies of agents that have different representations. Here, we argue that it is consequently not possible to use this kind of model for decision-making processes in a positivist stance.

Under the paradigm of natural sciences, the role of researchers is to discover the truth and to unravel natural laws that drive the system (Castella et al., 1999). Definitions of sustainability emphasize biophysical attributes of ecosystems and often focus on calculable thresholds below which land becomes unsustainable. Hard sciences can show that an ecosystem is endangered but the sustainable land use is defined as the outcome of human interactions and agreement, learning, conflict resolution, and collective action (Roling, 1996). Soft systems (Checkland, 1981) are based on the assumption that people construct their own realities through learning in social processes. The role of interdisciplinary teams including natural and social scientists is to understand and strengthen the collective decision-making process through platforms of interactions. The different stakeholders, including scientists, should work out in an interactive fashion a common vision on resource management that would lead to new indicators, shared monitoring procedures, information systems and concrete alternatives for action. The scientist's role is partly to feed this platform with "objectively true" knowledge on the biophysical subsystem, and the ways to compare, assess, and realize the concrete alternatives are collectively decided. Thus, adaptive management not only consists of the objective of increasing the adaptiveness of the ecosystem but also deals with the social process that leads to this ecological state.

In other words, what are important are solutions that emerge from interaction. And with them comes a different portfolio of interventions, including mediation to resolve conflicts, facilitation of learning, and participatory approaches that involve people in negotiating collective action. Computer-enhanced modeling becomes a tool for collective learning (Bousquet et al., 1999), instead of tools for piloting the system. Within that framework, a lot of work has to be done to improve the methodologies and to establish methods to assess the impact of such modeling exercises.

6.5. Credibility of the model

In the assessment of progress made by researchers within the IBM community (Grimm, 1999), various conclusions are drawn that can also be drawn for MAS. The general idea is that, after several years of enriching innovation, a period of consolidation is necessary. This consolidation must apply first to the method. How should the results of a model be expressed? How should its structure be presented? The stages of experimental science must be reapplied. Within the MAS community (Axtell, 2000) it is also widely recognized that one weakness of MAS is the impossibility of establishing a mathematical proof of the obtained results. However, the use of several techniques and methods may enhance the credibility of MAS and this is the subject of some research. We do not discuss here sensitivity analysis, which is a classical step in simulation methodology. Although approaches for the sensitivity analysis of complex models are not very often used, they are documented (Kleijnen, 1998) and we are not aware of research specific for MAS.

The first strategy is to provide rigorous presentations of the structure of the model. For that purpose, many authors document their model using graphic language such as Unified Modeling Language. Research is being done on a language more adapted to agents called AUML (Agent UML). Others graphic languages may be used, such as Petri Nets (Bakam et al., 2001), from which it is possible to derive mathematical properties at the cost of severe simplification of the model. The presentation of models using a graphic language also allows the replication of models as proposed by Axelrod (1997), which is made easier by the availability of platforms and their similarity (for instance, Cormas, Ascape, Repast).

The second strategy is to compare the results of the MAS with other types of models, such as differential equations. MAS can be simplified or parameterized in order that they can be formulated with equations that are explicitly solvable. The equivalence of the simulated results with the analytical results enhances the credibility of the model, although it does not validate the results of MAS when the model is simulated in more complex situations.

The classical procedure for validation is to compare simulated data and observed data. This can also be done in the field of MAS. As MAS models for ecosystem management are often spatial models, particular methods are being developed in interaction with the field of landscape ecology. Several landscape indices exist to evaluate the performance of simulation models (Turner et al., 1989) and many papers are being published on the validation of land-use change models (Vedkamp and Lambin, 2001).

Another strategy is to assess the relevance of the hypotheses of the model. The assumptions of a MAS model lie in the representation of the behavior of agents and interactions. Some researchers propose to test the accuracy of these assumptions through experimental approaches (Deadman et al., 2000) or role-playing games (Barreteau et al., 2001).

Validation can be perceived as the search for consistency among different points of view. Authors use a set of approaches and methods to enhance the credibility of the model. New methods are under development and will be added to the available set; there is also a need for the emergence of a consensus on protocols for the use of this set of methods.

7. Conclusions

In this paper, we have reviewed the field of MAS and ecosystem management. We have presented a historical perspective on the emergence of this field of research through a set of interdisciplinary interactions. Among the disciplines involved, computer science has played a key role. We would like to use this conclusion as a call for the strengthening of this interdisciplinary encounter.

Since the mid-1980s, various research communities have been working on distributed models and ecosystems. Researchers in ecology and social sciences have introduced the notion of the individual in their models of dynamics to gain a clearer understanding of how ecosystems work. Computer scientists have developed ecosystem models both to find new conceptual models of behavior and interaction and to test the architectures they have imagined. After several exciting years, many applications are in progress. Nowadays, as the number of researchers using MAS for simulation of ecosystems has increased, it seems that there are fewer interactions with computer scientists. MAS platforms are available and several computer scientists do not consider the applications as useful advances for their discipline. However, there is still plenty of room for interdisciplinary interactions. Researchers in ecology and social sciences can use MAS to better model the decision-making and learning processes and to study more deeply and more effectively the different forms of organization (spatial, network, hierarchical) and interactions among different levels. Computer scientists can exploit the concepts of natural and social sciences, not only on the behavior of individuals but above all on the systems of interaction between agents and their environment (relations between organizations or institutions and properties of stability, resilience, hierarchies, etc.). These insights into regulation mechanisms can favor progress in the computer science discipline. Though each community can benefit from the other, it is together that real progress will be achieved in methodologies and in the use of these models as methods for observing artificial worlds, for experimentation, and for problem solving, and as tools aiding participation in the decision-making process.

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References

Abott, C.A., Berry, M.W., Dempsey, J.C., Comiskey, E.J., Gross, L.J., HK, L., 1995. Computational models of white tailed

deer in the Florida everglades. UTK-CS, http://www.cs.utk.edu/~berry/deer/deer.html.
Allen, T.F.H., Starr, T.B., 1982. Hierarchy: Perspectives for Ecological Complexity. University of Chicago Press.
Allen, T.F.H., Hokstra, T.W., 1992. Toward a Unified Ecology. Columbia University Press.
Antona, M., Bousquet, F., Le Page, C., Weber, J., Karsenty, A., Guizol, P., 1998. Economic theory of renewable resource management: a multi-agent system approach. Lecture Notes Artif. Intel. 1534, 61–78.
Aquino (d'), P., Le Page, C., Bousquet, F., Bah, A., 2002. A novel mediating participatory modelling: the 'self-design' process to accompany collective decision making. Int. J. Agric. Resources, Governance Ecol. 2, 59–74.
Axelrod, R., 1997. Advancing the art of simulation in the social sciences. Lecture Notes Econ. Math. Syst. 456, 21–40.
Axtell, R., 2000. Why agents? On the varied motivations for agent computing in the social sciences. The Brookings Institution Center on Social and Economic Dynamics Working Paper 17, http://www.brookings.edu/dybdocroot/es/dynamics/papers/agents/agents.html.
Baejs, C., 1998. Fonctionnalité emergente dans une société d'agents autonomes. Etude des aspects organisationnels dans les multi-agents réactifs. PhD these de l'INP Grenoble.
Bah, A., 1997. Simulation multi-agents des modes d'utilisation des ressources en propriété commune le cas de la mobilité pastorale en zone intertropicale sèche. Masters thesis, Ecole Supérieure Polytechnique de Dakar.
Bakam, I., Kordon, F., Le Page, C., Bousquet, F., 2001. Formalization of a spatialized multi-agent system using coloured petri nets for the study of a hunting management system. Lecture Notes Comput. Sci. 1871, 123–132.
Balmann, A., 1997. Farm based modelling of regional structural change. A cellular automata approach. Eur. Rev. Agric. Econ. 24, 85–108.
Baray, C. 1998. Effects of population size upon emergent group behavior. Complex. Int. 6, http://life.csu.edu;au/complex/ci/vol6/baray.
Barreteau, O., Bousquet, F., 2000. Shadoc: a multi-agent model to tackle viability of irrigated systems. Ann. Operat. Res. 94, 139–162.
Barreteau, O., Bousquet, F., Attonaty, J.-M., 2001. Role-playing games for opening the black box of multi-agent systems: method and lessons of its application to senegal river valley irrigated systems. J. Artif. Soc. Social Simul. 4, http://www.soc.surrey.ac.uk/JASSS/4/2/5.html.
Becu, N., Perez, P., Walker, B., Barreteau, O., Le Page, C., 2003. Agent-based simulation of a small catchment water management in northern thailand. Description of the catchscape model. Ecol. Model. 170, 319–331.
Bonabeau, E., Dorigo, M., Theraulaz, G., 1999. Swarm Intelligence. From Natural to Artificial Systems. Oxford University Press.
Bonabeau, E., Theraulaz, G., 1994. Why do we need artificial life? Artif. Life 1, 303–325.
Bousquet, F., Cambier, C., Morand P., Quensière J., Mullon, C., A., P., 1993. Simulating the interaction between a society and a renewable resource. J. Biol. Syst. 1, 199–214.
Bousquet, F., Cambier, C., Morand, P., 1994. Distributed artificial intelligence and object-oriented modelling of a fishery. Math. Comput. Model. 20, 97–107.
Bousquet, F., Bakam, I., Proton, H., Le Page, C., 1998. Cormas: common-pool resources and multi-agent systems. Lecture Notes Artif. Intel. 1416, 826–837.
Bousquet, F., Barreteau, O., Le Page, C., Mullon, C., Weber, J., 1999. An environmental modelling approach. The use of multi-agents simulations. In: Blasco, F., Weill, A. (Eds.), Advances in Environmental and Ecological Modelling. Elsevier, Paris, pp. 113–122.
Bousquet, F., LePage, C., Bakam, I., Takforyan, A., 2001. Multi-agent simulations of hunting wild meat in a village in eastern Cameroon. Ecol. Model. 138, 331–346.
Bousquet, F., Barreteau, O., Aquino (d'), P., Etienne, M., Boissau, S., Aubert, S., Le Page, C., Babin, D., Castella, J.-C. 2003. Multi-agent systems and role games: collective learning processes for ecosystem management. In: Janssen, M. (Ed.), Complexity and Ecosystem Management: The Theory and Practice of Multi-Agent Approaches. Edward Elgar Publishers, pp. 248–285.
Brooks, R., 1991. Intelligence without representation. Artif. Intel. 47, 139–159.
Bura, S., 1994. Minimeme: of life and death in the noosphere. In: Meyer J., Wilson, S. (Eds.), From Animals to Animats. MIT Press.
Carter, J., 1996. Moab: a generalizable artificial intelligence model for simulating duck nest depredation in the northern Paririe region of north America. Ph.D. thesis, University of Massachusets.
Castella, J.-C., Husson, O., Doanh, L.Q., Ha Dinh Tuan I., 1999. Implementing the ecoregional approach in the red river basin uplands, vietnam. In: Kinh, N.N. (Ed.), Towards an Ecoregional Approach for Natural Resource Management in the Red River Basin of Vietnam. The Agricultural Publishing House, Hanoi, pp. 75–94.
Cazoulat, R., 1995. Modélisation et simulation de la dynamique de population d'agents. Ph.D. thesis, Université de Caen.
Checkland, P., 1981. Systems Thinking, Systems Practice. John Wiley, Chichester.
Collins, R.J., Jefferson, D.R., 1992. Antfarm: towards simulated evolution. In: Langton, C., Taylor, C., Doyne Farmer, J., Rasmussen, S. (Eds.), Artificial Life II. Addison-Wesley, pp. 579–602.
Costanza, R., Wainger, L., Folke, C., Maler, K., 1993. Modelling complex ecological economic systems: toward an evolutionary, dynamic understanding of humans and nature. BioScience 43, 545–555.
Dagorn, L., Menczer, F., Bach, P., Olson, R.J., 2000. Co-evolution of movement behaviours by tropical pelagic predatory fishes in response to prey environment: a simulation model. Ecol. Model. 134, 325–341.
Deadman,
P., Gimblett, H.R., 1994. A role for goal-oriented autonomous agents in modeling people–environment interactions in forest recreation. Math. Comput. Model. 20, 121–133.
Deadman, P.J., Schlager, E., Gimblett, R., 2000. Simulating common pool resource management experiments with

adaptative agents employing alternate communication routines. J. Artif. Soc. Social Simul. 3, http://www.soc.surrey.ac.uk/JASSS/3/2.2.html.

Dean, J., Gumerman, G., Epstein, J., Axtell, R., Swedlund, A., Parker, M., McCaroll, S., 2000. Understanding anasazi culture change through agent-based modeling. In: Kohler, T., Gumerman, G. (Eds.), Dynamics in Human and Primate Societies. Oxford University Press, pp. 179–206.

DeAngelis, D.L., Gross, L.J. (Eds.), 1992. Individual-Based Models and Approaches in Ecology. Chapman and Hall.

Deffuant, G., 2001. Final report, "improving agri-environmental policies: a simulation approach to the cognitive properties of farmers and institutions". Cemagref, http://wwwlisc.clermont.cemagref.fr/ImagesProject/FinalReport/references_list.htm.

Deneubourg, J.L., Goss, S., 1989. Collective patterns and decision making. Ethol. Ecol. Evol. 1, 295–311.

Derry, J., 1998. Modelling ecological interaction despite object-oriented modularity. Ecol. Model. 107, 145–158.

Deutschman, D.H., Levin, S., Devine, C., Buttel, L., 1997. Scaling from trees to forests: analysis of a complex simulation model. http://www.sciencemag.org/feature/data/deutschman/abstract.

Doran, J., Palmer, M., 1993. The EOS project: integrating two models of paleolithic social change. In: Gilbert, N., Conte, R. (Eds.), Artificial Societies. UCL Press.

Drogoul, A., 1993. De la simulation multi-agent à la résolution collective de problèmes. Une étude de l'émergence de structures d'organisation dans les systèmes multi-agent. Ph.D. thesis, l'Université Paris VI, Paris.

Drogoul, A. 1994. La mémoire collective dans les sma réactifs: l'exemple de manta. In: Mémoire Collective, Dialogue Entre les sma Artificiels et les Sciences Humaines et Biologiques. Centre de Recherche de Royallieu, Compiègne.

Dumont, B., Hill, D., 2001. Multi-agent simulation of group foraging in sheep: effects of spatial memory, conspecific attraction and plot size. Ecol. Model. 141, 201–215.

Durett, R., Levin, S., 1994. The importance of being discrete (and spatial). Theor. Popul. Biol. 46, 363–394.

Epstein, J., Axtell, R., 1996. Growing Artificial Societies. Social Science from the Bottom up. Brookins Institution Press/MIT Press.

Ferber, J., 1995. Les Systèmes Multi-Agents. Vers une Intelligence Collective. InterEditions, Paris.

Ferber, J., 1999. Multi-Agent Systems: An Introduction to Distributed Artificial Intelligence. Addison-Wesley, Reading, MA.

Ferrand, N., Demazeau, Y., Baejs, C., 1997. Systèmes multi-agents réactifs et résolution de problèmes spatialisés. Revue d'Intelligence Artificielle 12, 37–72.

Feuillette, S., Bousquet, F., Le Goulven, P., 2003. Sinuse: a multi-agent model to negotiate water demand management on a free access water table. Environ. Model. Software 18, 413–427.

Folse, L., Packard, J., W., G. (1989). AI modelling of animal movements in a heterogenous habitat. Ecol. Model. 46, 57–72.

Franchesquin, N., 1995. Modélisation des négociations aboutissant à une prise de décision collective au sein d'une assemblée communautaire. DEA de l'Université Paris 6.

Gilbert, N., Doran, J. (Eds.), 1994. Simulating Societies. UCL Press.

Gilbert, N., 1995. Emergence in social simulation. In: Conte, R., Gilbert, N. (Eds.), Artificial Societies. The Computer Simulation of Social Life. UCL Press, pp. 144–156.

Gimblett, H., Richards, M., Itami, R., 1998. A complex systems approach to simulating human behaviour using synthetic landscapes. Complex. Int. 6.

Ginot, V., Le Page, C., Souissi, S., 2002. A multi-agents architecture to enhance end-user individual-based modelling. Ecol. Model. 157, 23–41.

Grand, S., Cliff, D., 1998. Creatures: entertainment software agents with artificial life. Auton. Agents Multi-Agent Syst. 1, 39–57.

Grimm, V., 1999. Ten years of individual-based modelling in ecology: what have we learned and what could we learn in the future? Ecol. Model. 115, 129–148.

Grimm, V., Wyszomirski, T., Aikman, D., Uchmanski, J., 1999. Individual-based modelling and ecological theory: synthesis of a workshop. Ecol. Model. 115, 275–282.

Gross, L.J., 1998. Behavioral ecology and individual-based modelling, lecture notes for Beijer institute. http://www.tiem.utk.edu/∼gross/behav.txt.

Guerrin, F., Courdier, R., Calderoni, S., Paillat, J.M., Soulié, J.C., Vally, J.D., 1999. Biomas: un modèle multi-agentspour aider à la gestion négociée d'effluents d'élevage. In: Ferrand, N. (Ed.), Modèles et Systèmes Multi-Agents pour la Gestion de l'Environnement et des Territoires. Cemagref Editions.

Guillot, A. 1999. Pour une approche dynamique des animats. In: Drogoul, A., Meyar, J.A. (Eds.), Intelligence Artificielle Située. Hermès.

Hales, D., 1997. Modelling meta-memes. Lecture Notes Econ. Math. Syst. 456, 365–384.

Hare, M., Pahl-Wostl., C., 2002. Stakeholder categorisation in processes of participatory integrated assessment. Integrat. Asses. 50–62.

Hill, D. (Ed.), 1995. Verification and Validation of Ecosystem Simulation Models. Ottawa, Ontario.

Hogeweg, P., Hesper, B., 1983. The ontogeny of the interaction structure in bumble bee colonies: a mirror model. Behav. Ecol. Sociobiol. 12, 271–283.

Hogeweg, P., 1988. Mirror beyond mirror: puddles of life. In: Langton, C. (Ed.), Artificial Life. Addison-Wesley.

Hogeweg, P., Hesper, B., 1990. Individual-oriented modelling in ecology. Math. Comput. Model. 13, 83–90.

Holland, J., 1975. Adaptation in Natural and Artificial Systems. University of Michigan Press.

Holling, C.S., 1987. Simplifying the complex: the paradigms of ecological function and structure. Eur. J. Operation. Res. 30, 139–146.

Hraber, P., Jones, T., Forest, S., 1997. The ecology of echo. Artif. Life 3, 165–190.

Huhns, M., Stephens, L., 1999. Multiagent systems and societies of agents. In: Weiss, G. (Ed.), Multiagent Systems. A Modern Approach to Distributed Artificial Intelligence. MIT Press, pp. 79–122.

Huston, M., DeAngelis, D., Post, W., 1988. New computer models unify ecological theory. Bioscience 38, 682–691.

Hutzler, G., 2000. Du jardin des hasards au jardin des données: une approche artistique et multi-agent des interfaces homme/systèmes complexes. Thèse de l'Université Paris 6.

Janssen, M., Ostrom, E., 2001. Critical factors that foster local self-governance of common-pool resources. In: Annual Meeting of the Resilience Alliance, Chiang Mai, Thiland, August, 16–18 and Conference on "Inequality, Collective Action, and Environmental Sustainability," Santa Fe Institute, September 21–23.

Janssen, M.A., de Vries, H.J.M., 1998. The battle of perspectives: a multi-agent model with adaptive responses to climate change. Ecol. Econ. 26, 43–65.

Janssen, M.A., Carpenter, S.R., 1999. Managing the resilience of lakes: a multi-agent modeling approach. Conserv. Ecol. 3.

Janssen, M., (Ed.), 2003. Complexity and Ecosystem Management: The Theory and Practice of Multi-agent Approaches. Edward Elgar Publishers, Chettenham (UK).

Jefferson, D., Collins, R., Cooper, C., Dyer, M., Flowers, M., Korf, R., Taylor, C., Wang, A., 1991. Evolution as a theme in artificial life: the genesys/tracker system. In: Lanton, C., Taylor, C., Farmer, J., Rasmussen, S. (Eds.), Artificial Life II. Addison-Wesley, pp. 549–578.

Jorgensen, S., Patten, B., Straskraba, M., 2000. Ecosystems emerging: 4. Growth. Ecol. Model. 126, 249–284.

Judson, O.P., 1994. The rise of the individual-based model in ecology. TREE 9, 9–14.

Kawata, M., Toquenaga, Y., 1994. From artificial individuals to global patterns. TREE 11, 417–421.

Keitt, T., 1997. Stability and complexity on a lattice: coexistence of species in an individual-based food web model. Ecol. Model. 102, 243–258.

Kleijnen, J., 1998. Experimental design for sensitivity analysis, optimization, and validation of simulation models. In: Banks, J. (Ed.), Handbook of Simulation. Wiley, New York, pp. 177–223.

Kohler, T., Kresl, J., Van West, C., Carr, E., Wilshusen, R., 2000. Be there and then: a modeling approach to settlement determinants and spatial efficiency among late ancestral pueblo populations of the mesa verde region, us southwest. In: Kohler, T., Gumerman, G. (Eds.), Dynamics in Human and Primate Societies. Oxford University Press, pp. 145–178.

Kohler, T.A., Carr, E. (Eds.), 1996. Swarm Based Modelling of Prehistoric Settlement Systems in Southwestern North America. Forli, Italy.

Kohler, T.A., Gumerman, G.J. (Eds.), 2000. Dynamics in Human and Primate Societies. Agent-Based Modeling of Social and Spatial Processes. Oxford University Press. Santa Fe Institute Studies in the Sciences of Complexity.

Kozlack, J., Demazeau, Y., Bousquet, F. (Eds.), 1999. Multi-Agent System to Model the Fishbank Play Process. Varsovie.

Krebs, F., Bossel, H., 1996. Emergent value orientation in self-organization of an animat. Ecol. Model. 96, 143–164.

Kreft, J.U., Booth, G., Wimpenny, J.W.T., 1998. Bacsim, a simulator for individual-based modelling of bacterial colony growth. http://www.eeb.yale.edu/ginger/bacillus/node1.html.

Lambert, P., Rochard, E., Masse, J., 1999. Environnement des poissons migrateurs dans les modèles individus-centrés. In: Ferrand, N. (Ed.), Modèles et Systèmes Multi-Agents pour la Gestion de l'Environnement et des Territoires. Cemagref Editions.

Langton, C., 1988. Artificial life. In: Langton, C. (Ed.), Artificial Life. Addison-Wesley, pp. 1–47.

Langton, C.G., 1992. Life at the edge of chaos. In: Langton, C.G., Taylor, C., Farmer, J.D., Rasmussen, S. (Eds.), Artificial Life II. Addison-Wesley, pp. 41–91.

Lansing, J.S., Kremer, J.N. (Eds.), 1994. Emergent Properties of Balinese Water Temple Networks: Coadaptaion on a Rugged Fitness Landscape. In: Langton C. (Ed.), Artificial Life III. Addison-Wesley, Santa Fe.

Le Ber, F., Dury, A., Chevrier, V., Benoit, M., 1999. Simuler l'organisation spatiale d'un territoire agricole: différentes approches. In: Ferrand, N. (Ed.), Modèles et Systèmes Multi-Agents pour la Gestion de l'Environnement et des Territoires. Cemagref Editions.

Le Page, C., Cury, P., 1997. Population viability and spatial fish reproductive strategies in constant and changing environments: an individual-based modelling approach. Can. J. Fish. Aquat. Sci. 54, 2235–2246.

Le Page, C., Lardon, S., Bommel, P., Baron, C., Bousquet, F., 1999. Entités spatiales génériques et modèles de simulation multi-agent. pp. 341–342. In: Gleizes, M.-P., Marcenac, P., (Eds.), Jfiadsma'99. Ingénierie des systèmes multi-agents. Hermès, St-Gilles (La Réunion).

Lindgren, K., Nordahl, M., 1994. Artificial food webs. In: Langton, C. (Ed.), Artificial Life III. Addison-Wesley.

Lomnicki, A., 1999. Individual-based models and the individual-based approach to population ecology. Ecol. Model. 115, 191–198.

Lorek, H., Sonnenschein, M., 1999. Modelling and simulation software to support individual-based ecological modelling. Ecol. Model. 115, 199–216.

Lynam, T., Bousquet, F., D'Aquino, P., Barreteau, O., Le Page, C., Chinembiri, F., Mombeshora, B., 2002. Adapting science to adaptive managers: spidergrams, belief models, and multi-agent systems modeling. Conserv. Ecol. 5, 24, http://www.consecol.org/vol5/iss2/art24.

Maes, P., Schneiderman, B., 1997. Direct manipulation vs. Interface agents: a debate. Interactions 4, 42–61.

Maley, C., Caswell, H., 1993. Implementing *i*-state configuration models for population dynamics: an object-oriented programming approach. Ecol. Model. 68, 75–89.

Mathevet, R., Bousquet, F., Le Page, C., Antona, M., 2003. Agent-based simulations of interactions between duck population, farming decisions and leasing of hunting rights in the camargue (southern France). Ecol. Model. 165, 107–126.

May, R., 1973. Stability and Complexity in Model Ecosystems. Princeton University Press.

McCauley, E., Wilson, W.G., de Roos, A., 1993. Dynamics of age-structured and spatially structured predator–prey interactions: individual-based models and population-level formulation. Am. Natur. 142, 412–442.

Mechoud, S., Hill, D., Campos, A., 1998. Simulation multi-agents de l'entretien des paysages par des herbivores en moyenne montagne. In: Ferrand, N. (Ed.), Modèles et Systèmes Multi-Agents pour la Gestion de l'Environnement et des Territoires. Cemagref Editions.

Minar, N., Burkhart, R., Langton, C., Askenazi, M., 1996. The swarm simulation system: a toolkit for building multi-agent simulations. http://www.santafe.ed/project/swarm.

Muller, F., 1997. State of the art in ecosystem theory. Ecol. Model. 100, 135–161.

Nishimura, S.I., Takashi, I., 1997. Emergence of collective strategies in a prey–predator game model. Artif. Life 3, 243–260.

Oppenheimer, P., 1988. The artificial menagerie. In: Langton, C. (Ed.), Artificial Life. Addison-Wesley, pp. 251–275.

Parker, D., Manson, S., Janssen, M., Hoffmann, M., Deadman, P., 2003. Multi-agent systems for the simulation of land-use and land-cover change: a review. Ann. Assoc. Am. Geogr. 93, 314–337.

Pepper, J., Smuts, B., 1999. The evolution of cooperation in an ecological context: an agent based-model. In: Kohler, T., Gunnerman, G. (Eds.), Dynamics of Human and Primate Societies: Agent Based-Modelling of Social and Spatial Processes. Oxford University Press, New York.

Perrier, E., Cambier, C., 1997. Une approche multi-agents pour simuler les interactions entre des acteurs hétérogènes de l'infiltration et du ruissellement d'eau sur une surface de sol. In: Blasco, F. (Ed.), Tendances Nouvelles en Modélisation pour l'Environnement. Elsevier, pp. 233–242.

Polhill, G., Gotts, N., Law, A., 2001. Imitative versus non-imitative strategies in a land use simulation. Cybernet. Syst. 32, 285–307.

Ramat, E., Preux, P., Seuront, L., Lagadec, Y., 1998. Modélisation multi-agents de systèmes naturels—réflexions générale et application en biologie marine. In: Ferrand, N. (Ed.), Modèles et Systèmes Multi-Agents pour la Gestion de l'Environnement et des Territoires. Cemagref Editions.

Reynolds, C., 1987. Flocks, herds and schools: a distributed behavioral model. Comput. Graph. 21, 25–34.

Riolo, R., Cohen, M., Axelrod, R., 2001. Cooperation without reciprocity. Nature 414, 441–443.

Risenhoover, K., 2002. Deer management simulator. http://lutra.tamu.edu/dms/dms.htm.

Roese, H., Risenhoover, K., Folse, J., 1991. Habitat heterogenity and foraging efficiency: an individual-based model. Ecol. Model. 57, 133–143.

Roling, N., 1996. Towards an interactive agricultural science. Eur. J. Agric. Educ. Extension 2, 35–48.

Rouchier, J., Bousquet, F., Requier-Desjardins, M., Antona, M., 2001a. A multi-agent model for transhumance in north Cameroon. J. Econ. Dyn. Control 25, 527–559.

Rouchier, J., Martin O'Connor, Bousquet, F. 2001b. The creation of a reputation in an artificial society organised by a gift system. J. Artif. Soc. Social Simul. 4, http://www.soc.surrey.ac.uk/JASSS/4/2/8.html.

Saarenma, H., Dtone, N., Packard, J., Grand, W., Folse, L., Makela, M., Coulson, R., 1988. Artificial intelligence approaches to modelling animal/habitat interactions. Ecol. Model. 44, 125–141.

Savage, M., Bell, R., 2000. Arborgames. http://margay.sscnet.ucla.edu∼reb/arborweb/arbormain.html.

Servat, D., Perrier, E., Treuil, J.P., Drogoul, A., 1998. When agents emerge from agents: introducing multi-scale viewpoints in multi-agent simulations. In: Sichman, C.A.G.E. (Ed.), Multi-Agent Systems and Agent-Based Simulation. Springer-Verlag, Berlin, pp. 183–198.

Shin, Y., 2000. Interactions trophiques et dynamiques des populations dans les écosystèmes marins exploités. Approche par modélisation individus-centrée. Ph.D. thesis, Paris-7, Paris.

Sichman, J., Conte, R., Gilbert, N. (Eds.), 1998. Multi-Agent Systems and Agent Based Simulation. Springer, p. 1534.

Silvert, W., 1993. Object-oriented ecosystem modelling. Ecol. Model. 68, 91–118.

Tesfatsion, L., 1997. How economists can get alife. In: Arthur, W., Durlauf, S., Lane, S. (Eds.), The Economy as an Evolving Complex System II. Addison-Wesley, Santa Fe, pp. 533–564.

Thébaud, O., Locatelli, B., 2001. Modelling the emergence of resource-sharing conventions: an agent-based approach. J. Artif. Soc. Social Simul. 4. http://www.soc.surrey.ac.uk/JASSS/4/2/3.html.

Théraulaz, G., 1994. Du super organisme à l'intelligence en essaim: modèles et représentations du fonctionnement des sociétés d'insectes. In: Bonabeau, E., Theraulaz, G. (Eds.), Intelligence Collective. Hermes, Paris, pp. 29–109.

Turner, M., Costanza, R., Sklar, F., 1989. Methods to evaluate the performance of spatial simulation models. Ecol. Model. 48, 1–18.

Tyrell, T., 1993. Computational mechanism for action selection. Ph.D. thesis, University of Edinburgh.

Uchmanski, J., Grimm, V., 1996. Individual-based modelling in ecology: what makes the difference? TREE 11, 437–441.

Van Dyke Parunak, H., Savit, R., Riolo, R., 1998. Agent based modelling vs equation based modelling: a case study and user's guide. In: Sichman, J., Conte, R., Gilbert, N. (Eds.), Multi-Agent Systems and Agent Based Simulation (Lecture Notes in Computer Science). Springer, pp. 10–25.

Vedkamp, A., Lambin, E., 2001. Predicting land-use change. Agric., Ecosyst. Environ. 85, 1–6.

Villa, F., 1992. New computer architectures as tools for ecological thought. TREE 7, 179–183.

Von Bertallanffy, L., 1968. Théorie Générale des Systèmes. Editions Dunod, Paris.

Weber, M., 1971. Economie et Société. Plon, Paris.

Weisbuch, G., 1991. Complex Systems Dynamics. Perseus Book.

Weisbuch, G., Kirman, A., Herreiner, F., 1997. Market organization. Lecture Notes Econ. Math. Syst. 456.

Weiss, G. (Ed.), 1999. Multiagent Systems: A Modern Approach to Distributed Artificial Intelligence. MIT Press.

Welcomme, R., 1989. Fisheries Ecology of Foodplain Rivers. Longman, London.

Wellman, M., 1996. Market-oriented programming: some early lessons. In: Clearwater, S. (Ed.), Market-Based Control: A Paradigm for Distributed Resource Allocation. World Scientific.

Wilson, W., de Roos, D., McCauley, S., 1993. Spatial instabilities within the diffusive Lotka-Volterra system: individual-based simulation results. Theor. Popul. Biol. 43, 91–127.

Wilson, W.G., 1996. Lotka's game in predator–prey theory: linking populations to individuals. Theor. Popul. Biol. 50, 368–393.

Wolfram, S., 1984. Cellular automata as models for complexity. Nature 311, 419–424.

Wooldridge, M., 1999. Intelligent agents. In: Weiss, G. (Ed.), Multiagent Systems. A Modern Approach to Distributed Artificial Intelligence. MIT Press, pp. 27–78.