PART I

State of the art

CHAPTER 1

Further Towards a Taxonomy of Agent-Based Simulation Models in Environmental Management

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Abstract

Agent-based simulation (ABS) is being increasingly used in environmental management. However, the efficient and effective use of ABS for environmental modelling is hindered by the fact that there is no fixed and clear definition of what an ABS is or even what an agent should be. Terminology has proliferated and definitions of agency have been drawn from an application area (Distributed Artificial Intelligence) which is not wholly relevant to the task of environmental simulation. This situation leaves modellers with little practical support for clearly identifying ABS techniques and how to implement them.

This chapter is intended to provide an overview of agent-based simulation in environmental modelling so that modellers can link their requirements to the current state of the art in the techniques that are currently used to satisfy them. Terminology is clarified and then simplified to two key existing terms, a*gent-based modelling* and m*ulti-agent simulation*, which represent subtly different approaches to ABS, reflected in their respective Artificial Life and Distributed Artificial Intelligence roots. A representative set of case studies are reviewed, from which a classification scheme is developed as a stepping-stone to developing a taxonomy. The taxonomy can then be used by modellers to match ABS techniques to their requirements.

1.1 Introduction

Agent-based simulation (ABS) is being used in environmental modelling for many reasons that have already been discussed in the literature (e.g. Bousquet and Le Page, 2004; Ferber, 1999; Judson, 1994; Taylor and Jefferson, 1994). ABS provides a framework in which tractable techniques can be implemented that meet various requirements of environmental management modelling. First of all, ABS permits the coupling of environmental models to the social systems that are embedded in them, such that the roles of social interaction and adaptive, disaggregated (micro-level) human decision-making in environmental management can be modelled. It also permits the study of the interactions between different scales of decision-maker, as well as the investigation of the emergence of adaptive, collective responses to changing environments and environmental management policies.

Whilst there are a number of practical problems associated with implementing ABS, such as dealing properly with floating point arithmetic and "ghosts in the model" (Polhill et al. 2006), we argue, however, that the efficient and effective application of ABS for environmental modelling is, at least for the beginner, more generally hindered by the fact that there is no fixed and clear definition of what an ABS is or even what an agent should be. Terminology has proliferated and definitions of agency have been drawn from an application area, Distributed Artificial Intelligence (DAI), which is not wholly relevant to the task of environmental simulation. This situation leaves modellers with little practical support for clearly identifying alternative ABS techniques and how to implement them. Those who are new to the field have no framework to guide their exploration of existing ABS applications.

This paper is intended to provide an overview of agent-based simulation in environmental modelling so that modellers can link their requirements to the current state of the art in the techniques that are currently used to satisfy these requirements. A selected set of case studies have been reviewed and from them a classification scheme has been developed as a steppingstone to developing a taxonomy. Taxonomies are widely used in the natural sciences to classify plants and animals. Such classification frameworks allow researchers to understand how different objects are related by defining the features that they have in common. By creating a taxonomy for ABS we hope to eventually provide a tool that helps modellers to understand the current state of research. Such a taxonomy can be used by modellers to match current ABS techniques to their own requirements.

Section 2 begins the process by clarifying terminology and explaining why current definitions of agency are unhelpful. Section 3 proposes a set of eleven case studies that are used to link six modelling requirements (*coupling social and environmental models; micro-level decision-making; social interaction; intrinsic adaptation of decision-making and behaviour; population-level adaptation and multiple scale-level decision-making*) to specific techniques implemented in these studies. Section 4 proposes a first classification scheme as a step towards a taxonomy. Since this paper represents a snapshot of ABS case studies from a specific point in time, it is intended that as further studies emerge in the literature, they can be incorporated into this classification scheme. Over time, the classification scheme itself can be modified so as to address changing directions and new developments within the ABS field.

1.2 Disentangling terminology

A review of the literature reveals many different terms being used to describe what, forwant of a neutral term, we have in this paper so far called agent-based simulation. These terms include agent-based modelling (Epstein and Axtell, 1996) agent-based simulation modelling (Polhill et al., 2001), multi-agent simulation (Ferber, 1999; Gilbert and Troitzsch, 2000), multi-agent-based simulation (Edmonds, 2001), agent-based social simulation (Doran, 2001; Downing et al., 2001) and individual-based configuration modelling (Judson, 1994)). Bousquet and Le Page (2004) also refer to such simulations as multi-agent systems.

In this section, the objective is not to define new terminology for ABS in environmental modelling, but to reduce these terms to a smaller set of less ambiguous, more distinct terms. Key to understanding and differentiating between these terms is the knowledge that obscured in this morass of terms, there are two important conceptual distinctions in approaches. On the one hand, there is the belief that interactions are the most important phenomena to be modelled (agents can therefore be fairly simple in terms of cognition), and on the other, that deliberative social cognition is the most important (the deliberations of the agents spawn the interactions). This distinction in approaches derives from the three different heritages of agent-based simulation (Epstein and Axtell, 1996; Ferber, 1999):

- *Individual-based modelling (IBM)* - stipulates that populations of organisms should be disaggregated when modelled and thus represented in terms of discrete individuals which are unique only in terms of characteristics (Grimm, 1999);
- *Artificial Life (A-life) simulation* - refers to the simulation of life-like behaviours at the macro scale through the modelling of the behaviours of simple interacting micro scale components (Bonabeau, 1997; Langton, 1988)
- *DAI/Multi-Agent Systems* - refers to systems containing many agents which are: *autonomous* - they act independently of any controlling intelligence; *social* - they interact with other agents; *communicative* - they can communicate with other agents explicitly via some language; *reactive* - they observe and respond to changes in the environment and *pro-active* - they are goal-driven (Wooldridge and Jennings, 1995). Agents use these abilities to interact with and change other agents and objects within an environment (Ferber, 1999, p11), in order to solve group problems.

The A-life/IBM roots of agent-based modelling and the DAI roots of multi-agent simulation are clear in the following definitions:

"In multi-agent simulations, the agents are located in an environment… they will need 'sensors' to perceive their local neighbourhood and some means with which to affect the environment … agents will also need to be able to 'hear' messages … and send messages". (Gilbert & Troitzsch, 2000, p167).

"Agent-based modelling [is used to] discover fundamental local micro mechanisms that generate macro structure". (Epstein & Axtell, 1996).

"Agent-based modelling [is] the set of techniques [in which] relations and descriptions of global variables are replaced by an explicit representation of the micro-

scopic features of the system, typically in the form of microscopic entities ("agents") that interact with each other and their environment according to (often very simple) rules in a discrete space-time". (Gross & Strand, 2000, p27)

Of the other terms used, *multi-agent-based simulation* (MABS) is defined as the simulation of a multi-agent system, which mirrors Gilbert & Troitzsch's definition given above.

Individual-based configuration models are defined in terms of simpler interacting agents and thus fall into the category of ABM. Doran's definition of *agent-based social simulation* (ABSS) (Doran, 2001) is essentially the same as that used by Gilbert & Troitzsch (2000) and therefore is simply another term for a multi-agent simulation. Downing et al.'s (2001) definition of ABSS appears to be an umbrella term stretching across both ABM and MABS, for models which use heterogeneous agents, with bounded rationality that map to human actors in the real world. Figure 1.1, below, summarises how the terms would fit along a continuum according to the types of interaction modelled. From herein, the umbrella term agent-based simulation ABS (also used by Doran (1996)) will continue to be used. The ABSs we describe and classify in this paper would fit a number of the definitions listed above.

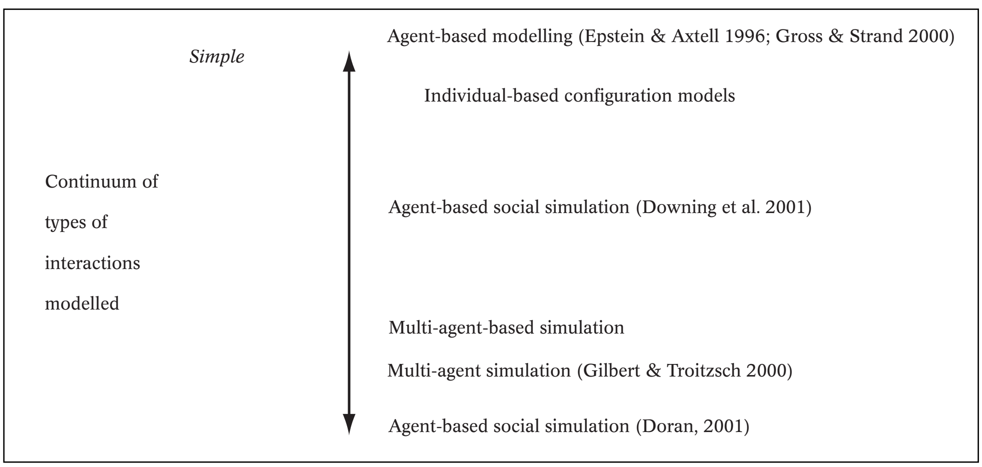

Figura 1.1. How the various terms fit along the continuum according to type of interaction modeled.

Having a clearer set of terms still does not help us to know how to best design an ABS. Looking up definitions of what an agent should be is also not very helpful. Most definitions of agency (e.g. Davidsson, 2001; Doran, 2001; Gilbert and Troitzsch, 2000) look to the field of DAI and use versions of the definition supplied by Wooldridge and Jennings (1995), above. The problem here is that this definition is used for a particular application, DAI, in which software agents operate in a real world, be they robots moving around a room or software agents moving in different parts of the internet. In this case, whether or not a prospective agent meets these criteria is a functional fact. If the agent cannot communicate explicitly using a language, then it is dumb and no amount of interpretation of its actions will prove the contrary.

When these criteria are applied to *simulations of agents*, however, whether a criterion is met or not can depend on the use of metaphor, not on functionality. For example, Moss et al. (2001) and Lansing & Kremer (1994), in their models set in the Thames region and Bali respectively, both implement social imitation as the copying of a behaviour from one neighbouring agent to another. However, whilst Moss et al. (2001) describe this imitation activity as agents “observing” their neighbours’ actions, Lansing & Kremer (1994) describe the process as one of “communication” between neighbours in group meetings. The former description meets the criteria of *reactivity* and the latter meets the criteria of *communication,* yet both implementations are equivalent.

Such flexible use of metaphor to describe the behaviour of agents can also make it difficult to compare simulations which claim the same behavioural criterion for their agents. For example, it is unclear how Lansing & Kremer’s implementation of “communication” can be compared, with respect to the “criteria of communication”, with a simulation that actually uses a language for communication between agents (e.g. in MAGIC (Legeard, 1999)). A final problem is that it is unclear how many of the criteria need to be passed for a prospective agent to be deemed an actual agent. A different approach is required for helping modellers design the right agent-based simulation for their needs. Such an approach needs to articulate a common framework through which agent-based simulations can be described and compared.

1.3 The Case Studies

The approach taken in this paper is, therefore, to start from problem requirements, not terminology, in providing a key to choosing a suitable agent-based simulation design. A number of ABS models have been selected to both provide examples of how different ABS technologies have been applied, and to populate the taxonomic tree outlined in the last section. The ABS models selected here focus on current environmental management and/or assessment issues. They are also focussed on representing the interactions between human and natural systems, whereby the agents represent some sort of a human entity (individual people, families, or other groups) and the environment with which the agents interact represents some sort of natural resource or landscape. Within the scope of this paper, it is not possible to include all the existing ABS models that fit the above description. We provide only a representative sample taken from environmental applications that span from urban and rural water resource management to land use change and tourism, as well as the various European and North American “schools” of agent-based simulation practice. Indeed, numerous effective and interesting ABS models exist within other disciplines such as Economics (Tesfatsion, 2002), Anthropology (Kohler and Gumerman, 2000), Ecology (Booth, 1997; Duke-Sylvester and Gross, 2002), and Biology (Kreft et al., 1998). While these models represent effective examples of ABS that could eventually be incorporated into the taxonomy presented here, they are beyond the scope of this paper. Furthermore, the intention of this exercise is not to evaluate or compare the effectiveness of the ABS models included here, but simply to describe and classify them so as to illustrate different approaches to ABS.

In this section, the different requirements for environmental management models identified in the introduction are matched to different techniques used in a representative set of cases of ABS found in a variety of different literature. Within this framework, prospective environmental modellers will be able to match their modelling requirements to existing techniques.

The exemplar applications represent a range of application areas in environmental modelling:

- Rural water resource management (Lansing and Kremer, 1994) - from hereon referred to as the "Bali" model - this model seeks to investigate whether or not a specific Balinese system of water temple networks managing irrigation practices could have self-organised. A simulation is developed to test the theory. Agents: subaks (groups of farmers). No. of agents: 172.
- Rural water resource management (Barreteau and Bousquet, 2000) - "SHADOC" - investigation of the viability of current irrigation practices in the Senegal river valley through the development and interactive use of an agent-based model. Agents: individual farmers, pumping station manager, water course manager. No. of agents: 40-60.
- Rural water resource management (Becu et al., 2002) -"CATCHSCAPE"- investigation of the viability of irrigation practices in Thailand with respect to future changes in drought conditions, commodity prices and farmer behaviour. Agents: individual farmers, water manager. No. of agents: 327.
- Rural water resource management (Janssen, 2001) - the "Lake" model - this exploratory model assesses farmers' adaptive responses to policy measures (i.e. taxation) for reducing phosphorus levels in a hypothetical lake. Agents: individual farmers. No. of agents: 100.
- Urban water demand management (Downing et al., 2001; Moss et al., 2001) - the "Thames" model - this model investigates how social structure and learning affects the efficacy of a regulator's exhortations for consumers to save water as part of a drought management policy. Agents: households, policy agent. No. of agents: 80-100.
- Flood mitigation decision support (Legeard, 1999) -"MAGIC"- this is a tool in which various "expert agents" cooperate with each other in order to come up with decision support advice for real-world flood catastrophe response teams. Agents: individual expert decision agents. No. of agents: <10.
- Animal waste management (Guerrin et al., 1999) -"Biomas"- this model explores possible negotiating strategies and outcomes used by simulated actors involved in managing the removal, transportation and processing of animal wastes. Agents: eleveur, cultivateur, transporteur, transformateur. No. of agents: <10.
- Rangeland resources management (Janssen et al., 2000) - the "Rangeland" model - this model explores the range of possible collective responses of hypothetical pastoralists to regulators' policies for sustainability. Agents: pastoralists, regulator. No. of agents: 100.
- Agricultural land use change (Polhill et al., 2001) -"FEARLUS"- this conceptual model investigates how well different social learning strategies employed

by farm decision makers compete against each other in the face of a changing, heterogeneous environment. Agents: farmer households. No. of agents: 40+.

- Agricultural land use change (Lim et al., 2002) -"LUCITA"- this model explores how the characteristics of frontier families influence changing agricultural land use, and secondary succession, in the Amazon rainforest near Altamira, Brazil. Agents: farmer households. No. of agents: 236.
- Recreation management (Gimblett et al., 2002) - the "Grand Canyon" model - assesses the impacts of river rafting trip management scenarios, where agents represent individual trips on the Colorado River through Grand Canyon National Park. Agents: rafting trips. No. of agents: 50+.

1.3.1 Requirement One: Coupling Social and Environmental Models

In environmental modelling, having an environment in which to embed agents is the first priority. Space can be represented either as spatially non-explicit or as spatially explicit. Typically, if spatial patterns or processes are not an important aspect of the modelling application, then a spatially non-explicit representation of space should be adopted. For example, a spatially non-explicit representation of space can be a database of characteristics of that space.

However, in certain applications, such as modelling land use patterns, if the landscape spatial pattern is of interest, then clearly a spatially explicit representation of the environment is required. Such a representation can be in the form of a GIS or a simple grid. Note, that the existence of neighbourhood rules does not necessarily dictate the need for a spatially explicit environment, since neighbourhood associations can be modelled non-spatially in a database. Care should be given to this topic as each representation can affect the computational performance of a simulation model. For example, the choice of a spatial resolution, or cell size, in a grid representing a natural environment will directly affect the computational intensity of the simulation.

A spatially non-explicit representation is used in the Lake model, the Rangeland model, SHADOC, Biomas and in the Thames model. In these cases, the environment can be simply a spatially abstract mathematical model linked in some way to the agents. In SHADOC, for example, each farmer has simply a link to a "Plot" object, which represents the land upon which he/she works. This plot object, among other things, calculates the water level in the farmer's plot according to global, hence non-spatially explicit, environmental parameters representing evapo-transpiration and infiltration.

In this case, making the link between the agents and the environmental model requires recognition that the environmental model and agents may be at different scale levels. The output from the environmental model may therefore have to be distributed in some way to individual agents. Conversely, the individual agents' decisions affecting the environmental model may have to be aggregated. In the Lake model, all agents interact with the same lake, in its entirety. Each agent's decision about phosphorous use is therefore aggregated and an aggregate figure for phosphorous inputs is applied to the whole lake. Similarly, each agent therefore perceives the same overall figure for lake water quality calculated by the environmental model. In contrast, in the Rangeland model, each agent has its own model representing their own area of the environment.

A spatially explicit environmental space can represent a theoretical environment, as in FEARLUS, or an actual environment based upon data from a specific location, such as the Mae Uam catchment, in Northern Thailand, modelled in CATCHSCAPE. The issue then arises as to whether the environment is represented using a raster grid or a set of vector polygons or a vector network. A raster grid contains a uniform grid of cells (usually square cells) in which all the cells are the same size. Vector layers, on the other hand, represent a collection of polygons, in which the shape and sizes of the individual elements can vary. In a raster model a lake would be represented as a collection of contiguous cells, each one designated as "lake". In a vector model, the lake would be represented as a single polygon with associated attributes. CATCHSCAPE, LUCITA, Grand Canyon, and FEARLUS all use raster grids of some kind.

The desire to accurately model a specific location is normally the driving factor in choosing the high-cost approach of embedding agents in such spatially-referenced grid. For example, the Grand Canyon model and LUCITA, both seek to model environmental impacts in specific areas, i.e. the Amazon rainforest and the Grand Canyon respectively. Mobility is another motivation for spatially-referenced grids. In the Grand Canyon model, agents need to be mobile; they traverse the grid (move down the river) at a rate that is dependent upon their current status and internal schedules.

The purpose of the model also influences the amount of detail in which the environmental data is represented. In MAGIC, a GIS is incorporated into the model which provides precise information on the location of buildings, people and the degree of inundation affecting these buildings. This design is useful for providing detailed flood support for a region in Southern Europe. In FEARLUS, on the other hand, each grid cell contains simple attribute information pertaining to a fictitious land parcel, e.g. yield and land use. This design is appropriate to the model's more exploratory goals of investigating how spatial factors, such as proximity to likeminded farmers, affect farmer strategies.

The same problems of scale, encountered with non-spatially explicit approaches, have to be considered when linking agents to explicit environmental models.

1.3.2 Requirement Two: Micro-Level Decision-Making

Of equal importance, in environmental modelling is to be able to explicitly represent human decision-making. This is particularly the case, with regards to being able to apply, to agent design, psychological and sociological knowledge of actual decision-making, that contrasts with the rational *homo-economicus* of classical economics. Decision-making, in the context of this criterion refers to the ability of an agent, in isolation, to decide on its behaviour at any one point in time. Social interaction and adaptation are considered later.

The range of decision making-models used in the exemplars in this paper represents a continuum from sophisticated knowledge-based rule inferencing (e.g. MAGIC) to simple single behaviour agents (the Bali model). Decisions about complexity usually stem from the number of agents being modelled and the goal of the model. MAGIC uses distributed agents to come up with decision support for mitigating flood catastrophes. There are only three agents, each of which have a responsibility for generating recommendations for a particular flood situation. The issue is complicated, the numbers of agents are low, and each agent has to flexibly support the other with appropriate information, thus the agent design is complex. The agents have explicit perception and communication modules that are used to update a knowledge base. The knowledge base is then used by an inference engine to decide on a possible course of action. A similar approach is used for assessing land use change from satellite imagery (Skelsey, 1997).

Further along the continuum are decisions making agents whose behaviours are decided by sets of rules (e.g. the Thames model and Biomas). In Biomas, agents are closer in style to those in MAGIC, but less complex. They are greater in number and their rules are designed to control their negotiations over waste carriage and processing. The agents in the Thames model use rules to determine consumers' water use in response to climate and exhortations from a water regulator. The latter model represents a move towards simulations representing many agents (80+). In the SHADOC model, farmer agents determine their behaviour using a complex set of Petri nets, which are equivalent to a series of sequenced rules.

Agents in the Grand Canyon model utilize a schedule that influences the decisions they make at specific points in time. In addition, these agents utilize a viewshed operator, similar to those of a raster GIS, to create viewsheds from their location within the raster landscape and to determine if other agents are within their view. The time of day, position of the agent relative to its schedule, attributes of the nearby environment, and position of other agents all influence the decisions made by the rafting agents with regards to their movement down the river.

Other simulation models with large number of agents reduce the complexity of their agent decision-making by creating agents that make use of objective functions. For example, in the Rangeland model, 100 pastoralist agents are simulated and the goal of the simulation exercise is to assess their aggregate response to management policies. Each agent is designed to decide on a stocking level by finding the stocking level that results in reaching a minimum level of utility as calculated by the objective function. Similarly, FEARLUS uses agents which calculate the financial returns from the adoption of each possible particular land use and choose the land use that maximises these returns. The Lake model uses the same approach in its deliberation algorithm for selecting a farmer's phosphorus usage.

Finally, at the other end of the continuum, in the case of Bali model, agents simply have a fixed behaviour, in their case a cropping pattern. Social interaction is needed for behaviour to adapt and change.

1.3.3 Requirement Three: Social Interaction

Of increasing importance in environmental modelling is to be able to explicitly represent social interactions (Downing et al., 2001); interactions that may make a difference to environmental policy effectiveness. In the exemplars in this paper, social interaction is explicitly modelled in a number of different ways: either as part of a process of social adaptation or as part of a group-based task, such as group decision-making and negotiation.

However, it is important to note that not all agent-based simulations use social agents. Depending upon the application, social interaction may or may not be appropriate. As already mentioned, the Rangeland model represents none. The assumption has been made that pastoralist behaviour is not socially mediated. Out of the spatially explicit models, LUCITA and CATCHSCAPE also do not involve social interaction.

Simulations reviewed in this paper perceive social interaction as useful for either group-based tasks (MAGIC, Biomas) or social adaptation (FEARLUS, SHADOC, Bali, Lake, Grand Canyon, and Thames models). The former two tend to use smaller amounts of agents than the latter. Choice of social interaction technique implemented determines which agents can interact with which and the choice depends on the role of the interaction, and whether the interactions to be modelled are local or global. It does not necessarily depend on the metaphor beging used to describe social interactions.

Group-based tasks - With the decision-making agents in MAGIC, and the negotiation agents in Biomas, there is a need for explicit message communication protocols to share knowledge, deliberations and in the latter case, offers. Both models represent distributed tasks, hence social interaction is task-centred whereby each agent interacts with only the agents it needs to perform the task. This is more in line with the older notion of a Distributed Artificial Intelligence application.

Local social adaptation - In this case, agents are adapting their behaviour in response to other agents in their spatial locality or social network. In the Thames model, the mechanism by which agents adapt and learn new behaviours is derived from the psychological principle of consistency. The agents tend to imitate other agents that are visible to them and who have similar patterns of water usage to themselves. The agents' social network is represented by a grid and knowledge of another agent depends on them being "near" that agent on this social network. The social network in SHADOC is made up of several "friendship networks" of farmers. Membership of a particular friendship network allows the farmer to learn from and imitate the "good" behaviour of other farmers in it. The Bali, FEARLUS, and Grand Canyon models, on the other hand, have concentrated on the importance of representing the effect of spatial proximity on the spread of behaviours. The agents in the Bali and FEARLUS models imitate neighbours who are spatially close in the environment. In FEARLUS, this means that land managers must have land parcels that border each other on the environmental grid. As mentioned above, in the Grand Canyon model the mobile agents must use their *viewshed* operator to determine who their neighbours are (those within their view) at any point in time.

Note that, although the metaphor is different, both social networks and physical proximity can be modelled in the same way, e.g. by grids. However, because of this, it is important for the model designer not to confuse metaphors by setting up a grid-based social network and then treating it as a spatial network. This would happen, for example, by having a feedback loop between activities of the agents and particular parts of the environment as if the relationship between agents' social grid locations were the same as the relationship between agents' geographical locations.

Global social adaptation - The Lake model incorporates two types of socially adaptive agent behaviour. The first, referred to in the model as "imitation", is the copying of whatever behaviour is currently done by the majority of the other agents. The second, "social comparison", makes use of social comparison theory and allows an agent to copy the behaviour adopted by other agents which have "comparable abilities", i.e. have similar phosphorus usage and returns. In both cases, no network or space is represented. Rather, the agents can copy the behaviour of particular agents anywhere in the population.

1.3.4 Requirement Four: Intrinsic Adaptation of Decision-Making and Behaviour

A further interest to environmental modellers is how to explore the change in or emergence of agent behaviour over time in response to management policies and / or environmental change. In addition to the adaptation that can occur through social interaction, it can also be a requirement that agents are able to adapt intrinsically, i.e. adapt their own behaviour through their own cognizance. From the case studies, the *multiple strategy* and *fine tuning* approaches have been identified.

Multiple Strategies - A modeller might want to introduce into their model the fact that humans have more than one means of making decisions and the one they adopt will depend on environmental and personal circumstances that will change during the simulation. One possible approach to this is the *consumat* approach (Jager et al.,1999) as used in the Lake model. In the latter, the agent has a variety of decision making methods at their disposal (imitation, social comparison, repetition, and deliberation) and switches between them depending upon their levels of uncertainty and financial returns (satisfaction). An alternative method is provided by endorsements (Cohen, cited by Downing et al., (2001)). In the Thames model endorsement values are attached to particular rules which control whether or not the agent imitates, deliberates, or obeys authority. The endorsements thus function as a conflict resolution device; the rule with the currently highest endorsement is used. Similarly, in LUCITA, agents employ a non-evolving form of a classifier system to evaluate a collection of land use strategies. Each strategy has a strength value that is adjusted in response to the performance of that rule in the past. Rules with high strength values are more likely to be selected for use in the future. Unlike other classifier systems, new strategies do not evolve over time.

Fine Tuning – These techniques are used to adjust the decision making, rather than the overall behavioural strategy of an agent. Agents can update their mental models of parameter values when a particular satisfaction criterion is not met (e.g. in the Lake and Rangeland models); they can update their expectations of how the world should operate (e.g. in CATCHSCAPE), or else they can update their knowledgebase used for decision-making, based on new information gathered from the environment or other agents (MAGIC, Grand Canyon, SHADOC).

1.3.5 Requirement Five: Population Level Adaptation – searching for optimal management

This requirement represents the desire to use the ABS to identify optimal management strategies through the elimination of weaker management agents and the promotion of fitter ones. In these approaches, over time, certain management behaviours or strategies become dominant with respect to a particular state of the environment. The modeller can then go on to claim that these behaviours are the most optimal for that environmental state. Unlike in social interaction, where behaviours are imitated and thus pushed into a dominant position amongst the population, the analogy in this case is one of evolutionary selection. A suboptimal agent is removed whilst more optimal ones are allowed to replicate and to replace it. Such “replacement” algorithms can be local or global in nature. For example, in the Rangeland model, a global replacement algorithm is used and unfit agents are replaced by the best pastoral agents out of the whole population. In FEARLUS, local replacement is used, in which only farmers who are in the physical neighbourhood can move on to replace the owner of less successful land. The activity, that is being modelled is the buying up of bankrupt properties by neighbouring farmers.

When using these approaches, it is important to bear in mind the relevance of the evolutionary metaphor to the application problem and in particular to recognise that evolutionary mechanisms are principally search mechanisms. In the FEARLUS model, there is a clear analogy between what happens in reality (the buying up of bankrupt farms) and the “evolutionary” replacement algorithm implemented in the model. However, in the Rangeland model, this link to reality is not so clear. Do unfit pastoralists necessarily get replaced by the fittest ones, even ones that are not locally positioned? When replacement (or even social imitation) is carried out non-locally, the process approximates to a global search for the fittest behaviours. It is important therefore to consider whether or not humans collectively decide on management policy through such a process of search. Search might be useful for finding the hypothetically optimal set of management decisions for a particular environment, but not necessarily for modelling what really happens. Chattoe (1998) further explores the potential dangers of using evolutionary algorithms, such as genetic algorithms and genetic programming, to model social processes.

1.3.6 Requirement Six: Multiple Scale Level Decision-Making

The use of agents to represent different scales of decision-making is claimed to be an important benefit to understanding systems (Downing et al., 2001). However, sophisticated modelling of multiple scales of agents is not being dealt with yet. There are two ways that this can be done: a) multiple scale agency - the modelling of agents at different scale levels in the same model and b) multiple scale rules - the modelling of agents who rely on decision-making rules which are operational at different scale levels.

Multiple scale agency – In models such as the Thames and Rangeland models, a single higher scale regulator agent is represented to oversee the activities of the individual agents. These agents are currently very simple reactive agents with no capacity for devising new strategies of intervention. Slightly more complicated is the hierarchy of agents in SHADOC: the pumping station manager agent who oversees the water going to the water courses which are themselves looked after by water course manager agents who oversee the distribution of water to farmers.

Multiple scale rules – In SHADOC, farmers’ decision-making is determined by a mixture of individual rules, reflecting their own goals, and collective rules, which reflect the will of the community, e.g. the limits to permitted water extraction with respect to water allocation rotas. Similarly, but more ambitiously, Guerrin et al. (1999) refer to a future version of the Biomas model in which groups of individual agents will be able to organise in order to generate group level constraints regarding individual decisions.

1.3.7 Do all environmental ABS model at the scale of the human individual?

It is pertinent at this stage to digress somewhat in order to also highlight what scale is being used for the agents in the models in these case studies. As can be seen from the overviews of the case studies given at the beginning of Section 3, there is a difference with respect at which scale level agents are being modelled. Despite the emphasis on modelling human individuals in ABS, in these examples, only the SHADOC, Rangeland, CATCHSCAPE and Lake models explicitly model agents at the scale of individuals. Equally common are models such as FEARLUS, which represents land manager families, the Thames model with its "representative households" and the Bali model representing subaks, i.e. groups of farmers.

Of particular interest, too, is that Biomas not only represents human agents, it also represents physical objects as agents ("agents physiques"), such as "vehicles", and "breeding farms"[1]. The physical agents are allowed to take an active part in the negotiation process involving the human agents. This process of representing non-individuals as agents has been referred to as *agentification* (Gaumé et al., 1999). It is in the case of agentification that strict criteria for defining agency completely break down. In one sense, Wooldridge & Jennings' (1995) professed goal of providing criteria (see Section 2) in order to prevent the term agent becoming a meaningless "noise" term has failed. In another, the loss of the criteria brings some reality into the discussion of agents in simulation in that makes it clear that agents should be designed to fit simulation needs rather than to meet criteria, developed for another field such as DAI.

1.4 Towards a taxonomy: Classification of case studies

Organizing these requirements into an efficient taxonomic structure that makes sense to both experienced modellers and newcomers is a non-trivial task that will require continued debate. Creating such a taxonomy requires the development of a classification scheme for models that utilizes hierarchically arranged sets of characteristics. The more characteristics that are shared by two models, the closer they will be on the branches of a taxonomic tree.

The development of such a taxonomy requires that these characteristics be first defined and then hierarchically arranged to form the taxonomic tree. Even this exercise is fraught with potential pitfalls that will require continued debate to resolve. Simple questions, related to the characteristics that should be chosen and their hierarchical relationship will raise futher questions. Franklin and Graesser (1996) point

[1] Authors' translations of "moyen de transports" and "élevages".

out that agents could be classified according to a subset of properties that they possess, the tasks they perform, their control architecture, or the programming language.

Here, we offer a simple, preliminary, taxonomic structure that classifies models by three of the requirements described in earlier sections. We believe this is an approach that is well suited to environmental modelling because it allows the classification of a wide range of models into general categories in a way that is informative to those who are new to the field or may be in the early stages of model development.

The taxonomic structure has three basic levels that differentiate models on the basis of requirements 1, 3 & 4 in the previous section (coupling social and environmental models; social interaction and intrinsic adaptation). While not exhaustive, focussing on these three requirements allows us to present a preliminary taxonomy complex enough to foster a discussion. The arrangement we offer here places the most potentially complex undertakings towards the base of the taxonomic tree.

The basic structure of this taxonomy, including the model examples we have utilized, is presented in Figure 1.2. The highest branch on the taxonomic tree differentiates between models which couple social and environmental models using spatially explicit environments from those that do not. This is one of the fundamental decisions that must be made at the beginning of model development, and a decision that can influence the architecture of the agents that populate the environment. The next level of the taxonomic tree focuses on levels of agent social interaction, from less complex models with no interaction, through social adaptation, to the most complex models involving group decision-making. The highest node on the tree differentiates between models which implement different levels of intrinsic adaptation: none, multiple strategy adaptation and fine tuning.

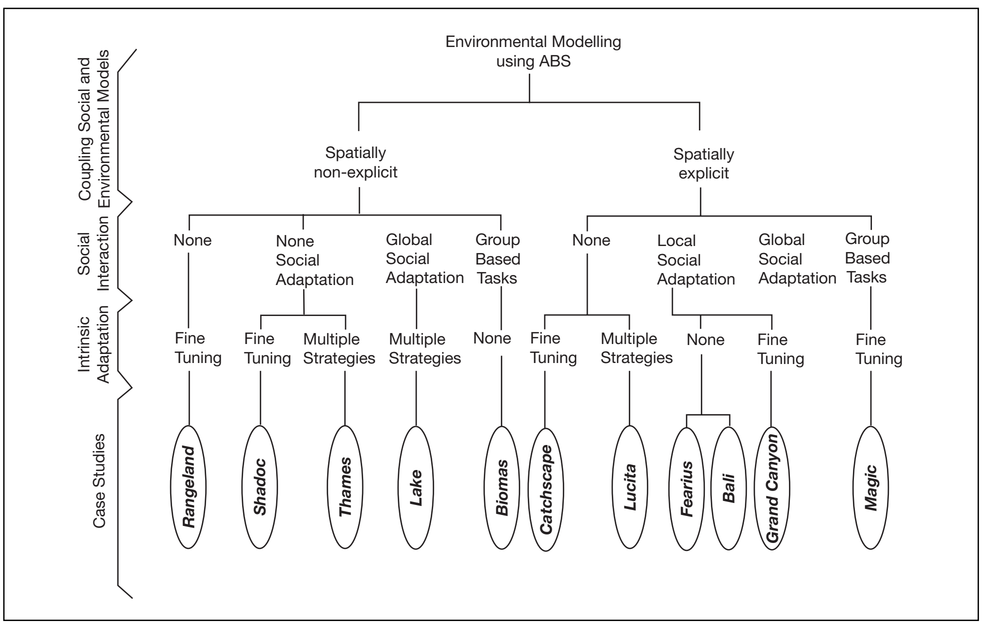

Figure 1.2. The basic taxonomic structure and the positions of the 11 case studies.

The order of the taxonomic levels represents the relative importance of the requirements in terms of ABS design. As Bousquet and Le Page (2004) indicate, the capability to model space and social interactions is one of the main purposes and benefits of ABS. Thus they should be foremost in the mind of the ABS designer and foremost in the taxonomy. Also, design decisions at one level of the taxonomy are likely to affect decisions made at a level lower. For example, although it is not an exhaustive set of cases upon which to base a judgement, it is still plausible to suggest that the lack of global social adaptation amongst the spatially explicit models is no coincidence. Designing a model in which your agents can be seen to be part of a spatially explicit environment will tend to draw to the model designer's attention to the role of location in determining agent behaviour. The value of implementing local, rather than global, social adaptation then becomes more apparent. Additionally, decisions about social interaction, perhaps, can affect how much intrinsic adaptation there needs to be modelled. Since another benefit of ABS is that they permit the modelling of adaptive decision making and behaviour in response to environmental change, wherever there is no social interaction, there will tend to be some form of intrinsic adaptation in order to maintain some sort of co-evolutionary interaction between agent behaviours and environment.

1.5 Conclusions

This chapter has introduced and discussed the roots and terminology behind the complex concept that is Agent-Based Simulation. It has tried to provide a context in which the proliferation of the terms in this burgeoning field can be explained, and it rejects the notion that the standard criteria for defining agency, as applied in Distributed Artificial Intelligence applications, is appropriate for environmental simulation. The main reason for the rejection is that the criteria are much too open to individual interpretation to be useful guides for environmental modellers interested in designing ABS and getting the best out of them. Instead the paper has adopted the approach of asking what the requirements are that modellers have from ABS. These requirements, quite naturally, are based on the perceived benefits that ABS brings to environmental modelling: the ability to couple social and environmental models and the ability to model social interaction, adaptation, and multiple scales of decision-making. Using these requirements, a set of 11 representative models have been categorised and the beginnings of a taxonomic structure developed that can be used to guide first-time ABS designers.

Clearly, the taxonomy presented here is a first step, designed to provoke discussion and feedback. A number of questions will require further development of the taxonomy before they can be addressed. For example, additional model requirements, such as those related to types of decision-making and scales of decision-making could have a place in a taxonomic tree.

Already, the taxonomy can provide salutary information. It shows, for example, how the Lake model differs from other case studies since it uses a social learning technique based upon global, rather than local agent interactions. Part of the reason, as already discussed, is possibly due to the decision to make the model non–spatially explicit. This design decision also, however, overlooks the roots and one of the claimed benefits of ABS, namely that local interactions can be investigated to explore the emergence of complex global behaviour (Cariana, 1991). This does not necessarily make the Lake model a poorer model, but the design does deprive the modeller and the model users of at least one possible benefit of this modelling approach.

Despite its preliminary nature, the goal of the taxonomy is to initiate a discussion that could eventually lead to the development of a tool that will both foster continued discussion of environmental ABS design, while serving as an educational tool for those interested in taking up modelling in response to specific environmental management questions. The debate surrounding the development of such a taxonomy could be very useful, by forcing researchers in this field to isolate and describe the key elements of such models, while identifying useful approaches to a particular design problem. While there are many types of agent-based simulation, the design choices a modeller makes can limit whether these simulations fully exploit the potential power of this simulation methodology. Future versions of this taxonomy could be used as a checklist by which modellers can confirm that their model designs meet their modelling requirements.

To end on a more general note, the case studies investigated in this paper also highlight some of the popular trends in ABS. Namely that social interaction tends to be implemented in terms of neighbour/friend imitation algorithms; that decision-making models based on simple sets of heuristic rules are the most popular, despite the existence of a myriad other possible cognitive architectures, and that the modelling of multiple scale decision-making is still in its infancy and needs to be further developed. Some of the case studies also bring to attention issues that the ABS community should bear in mind when designing their models. The main problem to recap on (as introduced in Section 2) is of the metaphorical and theoretical plasticity of some ABS implementations. By this it is meant that the same implementation can be explained or justified by the use of more than one metaphor or theory. The examples in this paper include the functionally equivalent implementation of social imitation that is described metaphorically, on the one hand, as agents "observing" each other (Thames) and, on the other hand, as agents "communicating" with each other (Bali). Also, the copying of behaviour between "similar" or "comparable" agents implemented in the Thames and Lake models claim the support of the social psychological principle of "consistency" and the theory of "social comparison", respectively. If the metaphorical and theoretical plasticity of ABS implementations becomes too great than it can weaken the confidence with which qualitative and theoretical validation can be carried out on agent-based simulations.

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