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Agent Based Modeling in Land-Use and Land-Cover Change Studies

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Agent Based Modelling in Land Use and Land Cover Change Studies

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Agent Based Modelling in Land Use and Land Cover Change Studies

Marco G. A. Huigen

1 Introduction

Land has multiple economic, ecological and cultural functions and land uses are the result of human actions and decisions. Much research has already been conducted focusing on the change of land use/cover (LUCC). These studies have their origin in various scientific disciplines and interdisciplinary approaches and resulted in, inter alia, a multitude of LUCC-frameworks and -models. The term land cover denotes the natural or artificial objects on the earth's surface. It is closely related to land use, which refers to why and how people work the land and how vegetation and soils are affected during this process. Land-use/cover changes alter how the earth's system functions by modifying: the bio-geo-chemical cycles, the radiation balance and the ecological complexity (Fischer 1999). Changes in land use and land cover are among the issues central to the study of global environmental change. In addition to their cumulative long-term global dimensions, such changes can have profound regional environmental implications during the life span of current generations, such as reduced bio-diversity, reduced land productivity due to soil degradation, problems of land and water contamination, and the lowering of groundwater tables. Thus, a better understanding of the dynamics in land and water use over the next 30 to 50 years is central to the debate of sustainability" (Fischer 2000).

Human activities, arising from a multiplicity of social objectives, are considered the immediate source of land cover change (Schimel et al. 1991; Hobbs et al; Turner 1989 in Turner 1993). To understand these social objectives one must analyse the underlying driving forces that motivate and constrain human activities. There are also biophysical driving forces and shocks (e.g. geomorphic processes, global and local climate changes and variability) responsible for changes in land cover, and ultimately land use (Turner et al., 1995). Each of these interacting driving forces operates over a range of scales in space and time. The term scale refers to the spatial and temporal dimensions used to measure and study objects and processes. For each process a range of scales may be defined over which it has a significant influence on the land use pattern (Meentemeyer 1989; Dovers 1995 in Verburg 2003 et al.).

Basically two directions of research exist to get a better understanding of this causality between human activities and land use change. The first is "spatially based", where we analyse the land use change patterns and relate these to social drivers. The second is "socially based", where we analyse the behavioural and decisional processes of land use and often connect them to a spatial context. The first type of analysis is based upon spatial comparison studies in which remote sensing images are compared via GIS and statistics. In this GIS and statistics approach, first the possible driving factors of land use are identified. Then, patterns of driving factor changes are conceptualised into models with multivariate analysis. The second type of analysis is based upon either an equation based model (EBM) which is sometimes transposed to a spatial grid or an agent based model (ABM) often linked to a spatial grid.

In EBM modelling, the relation between variables is considered known at a certain time t, or the subject of investigation (e.g. in regression techniques). In agent based modelling, that has its origin in complexity theories (cf. Minar et al. 1996), a mechanistic linear causality is not applied; causality is not one way directed. Everything relates to everything else in a tangled dynamic web of interdependent relationships. The modelling approach in complexity theories is holistic and not deterministic. (Langton et al. 1992). In agent based modelling, individual agents, representing social actors, communicate and interact according to a pre-determined or evolving rationale among themselves and with their environment. The concepts agent and environment will be explained in detail in the next section.

ABM and EBM differ in two ways: (1) the fundamental relationships among entities that they model, and (2) the level at which they focus their attention. EBM begins with a set of equations that express relationships among observables (measurable characteristics of interest). The evaluation of these equations produces the evolution of the observables over time. These equations may be algebraic, or they may capture variability over time (as used in system dynamics) or over time and space (partial differential equations). Oppositely, agent based modelling begins with behaviours through which individuals interact with one another. The starting point of modelling is the representation of the behaviour of each actor. Then, within a simulation run, these behaviours may interact. Direct relationships among the observables are an output of the process, not its input. The second fundamental difference between agent based modelling and EBM is the level at which the model focuses. EBM tends to make extensive use of system-level observables, since it is often easier to formulate parsimonious closed-form equations using such quantities. In contrast, the natural tendency in agent based modelling is to define agent behaviours in terms of observables accessible to the individual agent, which leads away from reliance on system-level information (Van Dyke Parunak et al. 1998).

An example of the GIS statistics type of LUCC research is the CLUE model by the Wageningen University. Logistic regression techniques, are used in the Conversion of Land Use and its Effects –model –(CLUE), to extract patterns of land cover. These patterns are used to predict future development of the land. Except for areas with minimal human influence, these patterns are the result of a long history of land-use change, and contain, therefore, valuable information about the relations between land use and its driving factors (Veldkamp and Fresco 1996; Verburg et al. 1999).

A good example of land use research of the EBM type is the work by the IIASA LUC section.

IIASA LUC has engaged in a range of activities geared towards providing a biophysical / ecological basis for the representation of land-based economic sectors in modelling land and water-use decisions. Changes in land and water use are viewed as dependent on how these resources are transformed and managed by human activity. The underlying decision problem is cast in the form of a welfare optimum model to elaborate socially desirable and economically efficient trajectories of resource uses and transformations (Fischer 2000).

In this paper we present the agent based computer modelling technique (ABM) and discuss the possibilities, limits and benefits of applying these techniques in LUCC studies. The paper is based upon extensive literature research on human behaviour models, environmental sciences, land use sciences and computer sciences. In chapter 2 the concept of agent based modelling is explained, the basic concepts of agent based techniques are listed and the theoretical and technical implications for agent based modelling in LUCC are analysed. In chapter 3 the strengths and limitations of agent based in LUCC modelling are analysed. The final chapter tries to answer questions like: What can we do with agent based modelling in LUCC? What should we focus on in the future? What are the main hindrances in exploiting the powers of agent based modelling in LUCC and how can we tackle those?

2 Agent based modelling in LUCC

2.1 Introduction

Agent based modelling has its roots in the science of Artificial Intelligence and stems from the field of multi agent system (MAS) modelling. Agent based modelling refers to a modelling concept which is closely linked to the modelling techniques of object orientation (OO). Object-orientation is the use of objects and classes in analysis, design, and programming. In OO, the world is modelled by identifying the classes and objects that shape the vocabulary of the problem domain (the artificial world). Furthermore, this artificial world contains abstractions and mechanisms that provide the behaviour that this model requires. In object-oriented programming, the data is stored in so-called `slots' within the object and the procedures are called `methods'. A method implements the behaviour of the object. A method is a function or procedure, and can access the internal state of an object of that object to perform some operation (cf. Booch 1991, Coad 1991).

Nowadays, agent based modelling is applied in many scientific disciplines. The agents' conceptual model is dependent on the research question (e.g. behavioural theory in household economics, cognitive science in Artificial Intelligence). Hence, the conceptual model of the agent is a function of the system under investigation (e.g. information search on the internet, flight control, simulation of social activities) and of the scientific approaches used to study this system. The technique does not force the modeller to a certain conceptual agent model and may be used for a variety of scientific research objectives. Because the agent's conceptual model is not dependent on one scientific field it facilitates interdisciplinary approaches.

The agents or component parts "live" in some topological space (e.g. farmers, political institutions, predators and prey may live in a two or three dimensional world). Agents perform their activities in this environment. Agents communicate among each other and can cooperate in fulfilling their activities. The communication and actions of the autonomous agents is rule-based. Every agent possesses rules that enable it to deal with specific situations. For example, if an agent is approached by another agent and is asked whether it wants to participate in an exchange, the agent will search for a rule within its "register" that applies to the proposed exchange. If the agent has selected a rule, this rule allows the agent to negotiate in the exchange. A rule is a method of the agent.

The applications that use agent based modelling vary widely. The techniques are both used for scientific as well as commercial purposes. Within scientific fields the applications also vary widely. They range from experimental and explorative to empirical and explanatory. Besides a classification based upon the research objectives, we can also make a distinction based on how the 'behaviour' of an agent is specified, or in other words, what the agent architecture and the agent formalism are. At one side of a continuum we distinguish a declarative type of agent modelling and on the other side, an imperative type of agent modelling. In the imperative modelling of agents, behaviour and thus the rules are often a behavioural aggregation or process-description. In the declarative modelling, the rules are based on simple behavioural premises (cf. Sycara 1998, Moss and Edmonds 1998). An example of imperative modelling would be to include a Cost Benefit function as the rationale of the agent. Declarative modelling exploits and aims more at the reasoning of the agent, which looks like:

My neighbor plants corn in winter.
My neighbor is rich,
I want to be rich.

THUS: I will plant corn in winter.

A multi agent system often uses an agent design that is closely linked to psychological models and/or behaviour models such as Fishbein and Ajzen's theory of rational expectations (Fibein and Ajzen, 1975). The agent designs in contemporary agent based modelling in LUCC differ from the agent design in an multi agent system; the contemporary scientific field of LUCC (Parker et al, 2001, Berger 2001, Gotts et al. 2003) uses the more imperative types of agent conceptual models, while the cognitive sciences and Artificial Intelligence work with more declarative programming techniques and agent conceptual models. In such a declarative type of modelling the agents reason and come to concluding actions.

As has been said, the agents' conceptual model is dependent on the objectives of the research. These objectives in LUCC range from understanding complex interactions (like strategies in land use) with relatively simple agents to modelling complex interactions with complex agents. Besides the objectives of the model and its theoretical foundations, also the spatial and temporal scales are significant elements determining the agents' conceptual model. If a model aims at understanding agent behaviour over a long period of time, then it can be expected that the level of detail in the agent behaviour is coarse. On the opposite, if the time-steps within an agent based model are small, then the level of agent' behavioural detail is high. The more a time-scale in a simulation approaches "real-time", the more likely it is that the rules become behavioural and declarative (agents reason themselves). The same reasoning is applicable for the level of detail of agent behaviour and the spatial scale. The coarser the spatial scale, the lesser detail will be held in the decisional structure of the agent. Of course, besides adjusting the level of detail of the agent behaviour when dealing with larger time and/or spatial scales, agents can be aggregated. In a model dealing with a spatial scale corresponding to a national level, it seems unwise to model agents that represent individuals. At such a large spatial scale an agent representing a group of individuals seems to be more appropriate.

Besides the temporal and spatial issues in agent based modelling in LUCC that will be discussed in the next section, also the object oriented and rule-based essence of agent based modelling contains in itself several theoretical and technical questions. This chapter deals with these questions, such as:

- What are the basic concepts in designing an agent based model?
- How is an agent constructed?
- How are rules derived and how should they be implemented?
- What is the role of the 'environment' in an agent based model?

These questions are answered while exploring the core components of an agent-based model: the agents, the world and their communication within a multi-agent model.

2.2 Agents

Agents are a representation and a simplification of complex (including human) behaviour. This representation is established by defining rules, which the agent uses to pursue a goal (or multiple goals). The rules together represent the ‘rational’ behaviour of the agent. In order to simulate an agent model we let the agents communicate with each other. Communication in agent simulation is how an agent modeller intuitively sees the interactions between real-life (e.g. other agents, but also the environment) entities. Agents must be able to communicate among each other, dependent on the behaviour-rules one applies in the model; also agents communicate with the simulated environment.

If the modeller constructs the conceptual model, he defines the way an agent perceives a communication message, how an agent deals with the message and how an agent responds to a message. This conceptual model of how an agent communicates may again be based upon a scientific discourse. For example, an agent can have a conceptual model based upon a “homo economicus” discourse; see for example the work by Berger (2001) who has an agent-based household model in which each agent has a separate objective function and individual resource constraints and updates its expectations for prices and water availability. But, instead of this objective function aiming at profit maximization being the core of the communication of the agent with its environment, the agent based modelling techniques allows also for agents communicating with their environment and with other agents differently.

Agents can be equipped with rules that allow them to learn, to copy their neighbours, to innovate and even to have a decisional structure made of multiple rules that originate from multiple “frames of references” (e.g. homo socialis, homo economicus, homo honoris) at the same time (cf. Huigen 2003). The agents equipped with a single objective function can be considered to be of a highly imperative type, while the agents with multiple frames of references are closer to the declarative type. Both the work of Berger (2001) and Huigen (2003) as well as most other agent based modelling LUCC studies (Gotts et al. 2003, Deadman and Schlager 2002) combine object orientation and agent modelling techniques with the more traditional programming techniques such as knowledge based systems (logic programming using rules) or mathematical methods (heuristic programming, mathematical programming, functional programming). The used programming language and techniques determine the model’s “degree of imperativeness”.

The agent formalisms, programming techniques and languages used in Artificial Intelligence are more declarative than the contemporary agent based LUCC models. The research objectives in Artificial Intelligence are quite different from those in LUCC and demand the use of the more declarative programming techniques (belief networks, fuzzy set theory, machine learning). As for now, such techniques are not much used within the field of LUCC.

If LUCC research wants to incorporate the social, behavioural aspects, there are, following Turner II et al. (1995), basically two paths to proceed. Either the spatially oriented sciences incorporate the social sciences (socialize the pixel) or the social sciences incorporate the spatial component (pixelize the social). Hence, there are two starting points, both with their own traditions and expertise. As it is shown in contemporary agent based LUCC, the GIS based fields of science that incorporate social elements often base their models on the mathematical and functional programming techniques. In these works, the economic elements of human behaviour are likely candidates for the “socializing the pixel” element due to its quantitative character. At the moment, not many agent based modelling LUCC models start from a more behavioural, cognitive angle or “pixelizing the social” starting point. In the social sciences agent based modelling is known and in several scientific fields achievements are published (Gilbert (1996), Gilbert, N. and Troitzsch, K. G. (1999), Edmonds (1997), Gilbert and Conte (1995) and Epstein and Axtell (1996) Doran J. and Palmer, M. (1993), Doran, J. (1996) Doran, J.E. (1997)). Many of the agent architectures used in these works extend an agent conceptualisation closer to the behavioural, cognitive theories.

The contemporary agent based LUCC models tend to have complex spatial components and simplify the social component. Within the agent based modelling LUCC, the social agent structures implement only few behavioural elements. In this paper we want to explore the agent structures that are used in the social sciences and Artificial Intelligence in order to come to a judgement on applicability of more declarative agent conceptual models.

In such an exploration, we should start with the most discussed topic in the field of Artificial Intelligence: rationality. Scholars with different disciplinary backgrounds (economy, philosophy, cognitive science, biology, etc.) tend to have different representations of rationality. The different views of rationality and how rationality should be approached come together, when implementing the behavioural rules of an agent. In Russell and Norvig (1995), a rational agent is defined as acting in such a way so as to achieve its goals based on its beliefs. According to them, rationality is dependent, at any given time, on four elements, namely, on

1. An ‘objective’ performance measure,
2. On an agent’s perception of its history (or the perceptual sequence),
3. On what the agent knows about the world, and finally
4. On the actions that the agent can perform.

This definition has a high level of abstraction and is therefore independent of scientific discipline. Such a definition is helpful when scientific discourses need to come together. For example, the definition supports the translation from an economic discourse into agent-based modelling terms. Doyle (1992) defines a rational agent by using an approach that focuses upon internal agent logic. Logic plays a descriptive role in developing the formulation of a problem and logic serves to describe the possibilities for reasoning and action. Although he starts from a highly declarative conceptual agent model, he ends up with a rather imperative conceptual agent model when he claims that economics can serve to prescribe choices among these possibilities for reasoning and action. For example, in the Bayesian decision theory, every rational agent maximizes the expected subjective utility of an action/decision. The utility of an action is usually some function of its cost, benefit, risks and other properties of the action; utility is an aggregate multi-dimensional measure of worth (the performance measure), with regard to the agent and its situation (Doyle 1992). Hence, the agent accepts the principle of maximizing the expected subjective utility, when this agent value-orders decisions so that decision X is preferred over Y, when EV (X) > EV (Y). The perception of the agents' history and its information and knowledge about the world are translated into this function. An agent is called perfectly rational when the agent always obeys the principle of maximizing expected utility. An agent that has no decision rule other than the principle of maximizing expected utility, is called hyperrational (Boman, 1995). Such hyperrational agents have been used much in economic models, which assume actors are perfectly rational optimizers with unfettered access to information, foresight, and infinite analytical ability.

Contemporary developments in computer hardware and programming software, and especially agent based modelling, allow scholars more and more to explore sophisticated models that include different utility functions (e.g. bounded rationality) or other paradigms of decision making. Agent based models have the strength to vary the rationale of agents and create a heterogeneous field of rationales. This complexity has resulted in a movement towards agent-based models that employ some variant of bounded rationality.

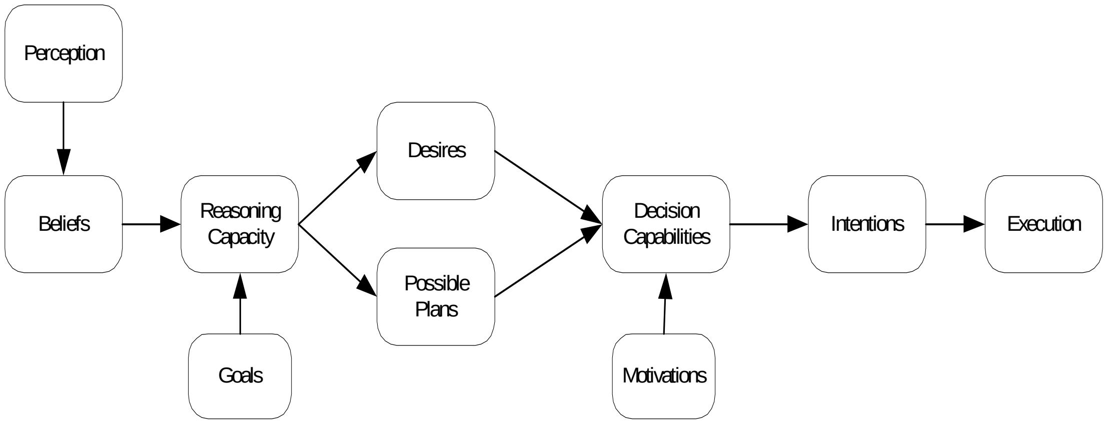
Alongside these developments that stem from the economic sciences, several approaches have been used in order to develop an agent with 'cognitive abilities'. These 'Agent theories' address such questions as:

1. How should agents be conceptualized?
2. What properties should agents have?
3. How to formally represent and reason about these properties?

Two important, theoretical agent architectures that formalize rational agents, namely the deliberative agents (Rao and Georgeff 1991 in Sycara 1998) and the reactive agents (Brooks 1992 in Sycara 1998) need to be mentioned here. These theoretical architectures introduce several mentalistic behavioural attributes of an agent. The deliberative agent architecture is also known as a Belief-Desire-Intention type (BDI). In short, an agent has beliefs containing the current facts or its perception of the facts about its world. It has a set of current desires (or goals) and long term goals to be realized. It has a set of plans describing how certain sequences of actions and tests may be performed to achieve given goals or to react to particular situations; and an intention structure containing those plans that have been chosen for [eventual] execution. In Figure 3 a BDI structure according to Rao and Georgeff(1991), Rao and Georgeff (1995) is given. For a detailed overview of the functionality of this scheme we refer to the work by Rao and Georgeff (1991) and Rao and Georgeff (1995).

The formalism of the BDI is particularly concerned with the notion of realism - the question of how the beliefs about the future of an agent affect its desires and intentions. The BDI architecture is highly comparable with human behavioural models and human decision and action models (cf. Fishbein and Ajzen 1975, De Groot 1992). This equality is not surprising, if we realise that Artificial Intelligence and the cognitive sciences are tightly coupled.

Figure 1: BDI Architecture (Rao and Georgeff (1995))



Reactive agents have their roots in Brooks' (1991 in Sycara 1998) criticism of deliberative agents and his assertions that intelligence is the product of the interactions of an agent and its environment and intelligent behaviour emerges from the interaction of various simpler behaviours organised in a layered way through a master-slave relationship of inhibition (Sycara 1998).

Although this architecture has shown its worth, (e.g. MANTA system, simulating ants (Ferber 1996 in Sycara 1998)), it is not primarily applicable to human behaviour simulations and hence not for agent based modelling for LUCC. A reactive agent only reacts based on stimuli from the environment, while human decisions often need a more complex conceptualisation of stimuli. Reactive agents do not have representations of their environment. Human actions, however, are more than reactions only, they are deliberate, involve learning (e.g. based on historical knowledge or myopic behaviour) Furthermore, human actions may include inferences, strategies, negotiations, collaborations and social (or intra-agent) models. These concepts, recognised by the Artificial Intelligence community, are implemented in various agent-models and architectures.

Wooldridge and Jennings (1995) note that computer agents typically have the following properties:

Autonomy: agents operate without others having direct control of their actions and internal state;

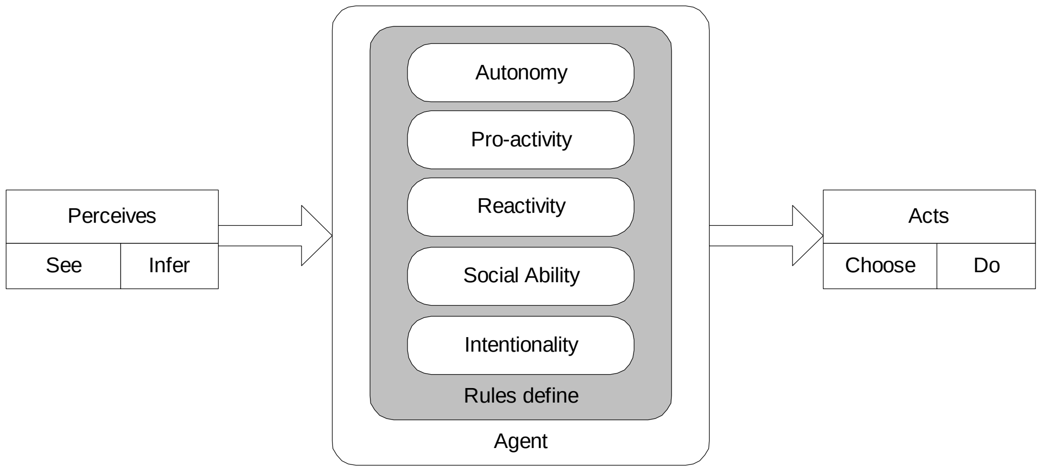
Social ability: agents interact with other agents through some kind of `language';

Reactivity: agents are able to perceive their environment and respond to it;

- Pro-activity: as well as reacting to their environment, agents are also able to take the initiative, engaging in goal-directed behaviour.

In addition, agents are often attributed a degree of intentionality. That is, their behaviour is interpreted in terms of a metaphorical vocabulary of belief, desires, motives, and even emotions, concepts that are more usually applied to people rather than to computer programs. In Figure 2, a schematic overview of the Wooldridge and Jennings description of an agent is given.

Figure 2: A first notion of an agent



We may think of an agent to be a computer system that, in addition to having the properties identified above, is either conceptualised or implemented using features that are usually ascribed to humans. For example, it is quite common in the Artificial Intelligence community to characterise an agent using mentalistic notions, such as knowledge, belief, intention, and obligation. Wooldridge and Jennings (1995) mention several other attributes in the context of agency, especially the attributes mobility and rationality. They consider ‘mobility’ the ability of an agent to move around an electronic network (White 1994 in Wooldridge and Jennings 1995). Especially in so called cyberspaces (e.g. the Internet), one considers this aspect of agent-behaviour an important one when multi-agent models are used for simulation purposes, the agents may very well be mobile, but often this is not a crucial characteristic. In such simulations, declarative agents may have a wide range of attributes representing various mentalistic characteristics, which will be briefly discussed.

1. Inference, Belief or Knowledge

Agents base their actions on what they know about their environment (including other agents). Some of the information they have may be incorrect because of wrong perception, wrong inference, or incomplete knowledge. An agent’s (possibly erroneous) information is called the agent’s beliefs in order to distinguish them from ‘true’ knowledge. Beliefs can be viewed as the ‘informative’ component of the agent’s state.

Closely related to the intra-agent models, an agent may infer, draw conclusions, from the beliefs it has. Inference is a method for perceiving explicitly relationships that lie implicitly in the agent’s incomplete beliefs (Doyle 1992). For example, two agents (X and Y) meet in time step t and exchange ‘relevant’ history. Agent X receives the knowledge (the fact) that agent Y has recently consumed some ‘food’. Unfortunately for agent X, the knowledge transfer does not include the answers to questions like: how many time steps ago did agent Y eat and is there still food left? Still, agent X might infer that a possible food source location is in the opposite direction of agent Y movement. Inferences do not necessarily lead to ‘true’ conclusions. Inferences create beliefs, which in turn may be wrong. In this example, it could be that agent Y already consumed all the food or that the food source is to be found in a different direction.

2. Desires or Goals

Since agents are built to be autonomous and purposeful, if they are to engage in action they need to be driven by some internal goal (e.g. survival). This main, global desire or goal may in turn require the satisfaction of subsidiary goals or desires. Thus, it is necessary that an agent has information about how it accomplishes its goals. These goals or desires are representing the motivational state of the agent. Closely related to these attributes of an agent are the planning and strategy capabilities of an agent.

3. Intentions, Strategies

The intentions of an agent describe the currently chosen course of action1. Following Bratman (Bratman 1987), Cohen and Levesque (1990; in Wooldridge and Jennings 1995) identify seven properties that must be satisfied by a reasonable theory of intention:

- Intentions pose problems for agents, who need to determine ways of achieving them.
- Intentions provide a ‘filter’ for adopting other intentions, which must not conflict.
- Agents track the success of their intentions, and are inclined to try again if their attempts fail.
- Agents believe their intentions are possible.
- Agents do not believe that it is impossible to bring about their intentions.
- Under certain circumstances agents believe they will bring about their intentions.
- Agents need not intend all the expected side effects of their intentions.

There is a subtle difference between strategy rules and planning rules. Strategies do not imply that an agent has reasoned about the outcome of its actions, while planning involves ‘reasoning’ backwards from a desired goal state, deducting which actions might lead to that goal, until one gets back to the current situation of the agent. Objections to elaborate planning actions, for example, the argument that most human action is driven by routine reaction (e.g. see psychologically based multi-agent models) need also consideration.

A good example, of an implementation of different agent strategies, is the work of Bonatti et al (2001). Their research objective was to come to an evaluation of several interrelated strategies (pricing strategies, development strategies, and purchasing strategies) of enterprises in the information economy.

[1] This description is derived from Wooldridge and Jennings (1995).

4. Intra-agent Models, Learning, Memory

Some agents may be capable of learning about the interrelationships between other agents in their world, for example, that agent A has recently interacted with agent B. On the basis of such data exchange, an agent may be able to put together an idea or picture of social relationships in this world. This picture that an agent derives is called a 'social model'. Such intra-agent models do not necessarily need to be of social origin, hence agents may also have models of other aspects of their world. For example, they may develop a model of the 'geography' of their world. Note that these intra-agent models are quite different from conventional simulation models. Here the agents themselves build agent models while the simulation runs.

In order to construct these intra-agent models, agents need some way to represent their beliefs and knowledge. Research concerning the 'logic' representation of intra-agent models is done under the title of 'knowledge representation'. Some of the approaches relate objects and their attributes together, within a hierarchy. For example, an agent may know that all sources of food yield energy, and also know about several specific kinds of food, each with different energy levels and different means of extracting that energy. These facts would be related in a tree-like structure with the most general facts about food at its root and more specific facts about different types of food at its branches.

Limited information

In particular, interest goes to agents, which only have limited information about their environment. In general, an agent will only acquire information through interaction with its environment or with other agents. The environment, but also other agents change dynamically, and thus agents cannot have a perfect model of their environment or society (intra-agent model). Another aspect that relates closely to bounded rationality is the idea that agents have limited logical power and may not think logical in all decisions; other resources, like memory can be limited (agents may forget things in time, or have limited intra-agent capacity).

Social norms

This brief survey of the characteristics of autonomous agents implies that, underlying all these concepts and attributes (of agents) there remain many significant problematic issues. It would be unrealistic to expect multi-agent models to be able to simulate the great majority of human psychological and social phenomena to any level of detail. An example is given in the work of Boman (1997) in which he sketches the trade-off between, on the one hand, complete obedience of agents to social norms and on the other hand the autonomy of the agent. In order to solve this conflict, Boman proposes to implement social norms as constraints on autonomous agent actions.

Social norms are not only constraining actors' actions. Actors may deliberately choose to conform to a certain social norms, because it is the right thing to do. In such considerations, actors do not even have to rationalise an output. Actors act according to social norms, because they must, according to their belief system. As such, social norms are part of the moral system of an actor. In such an implementation the social norms need to be part of the courses of action.

Group behaviour

Another interesting issue that comes to mind when simulating human behaviour is the behaviour of individuals in a group, and the group-behaviour of a society. The question as to how autonomous agents reorganise their society as result of environmental changes (or social changes) is a relevant example. In the work of Glaser and Morignot (1997) parts of such a meta-question are answered and implemented; they embed co-operation skills (social competencies) in the behaviour of autonomous agents, because agents cannot always achieve global goals individually, or can achieve individual goals at lower costs when working together with others. The simulation of these effects of the individual behaviour on the group outcome is one of the interesting possibilities to be explored with agent based modelling.

2.3 The World

An agent is 'alive' in its environment. An agent has direct interactions with its world. The agent may act on the environment, which in turn provides perceptions to the agent. The complexity of these interactions is primarily constructed in the agent, and not in the environment. An agent observes and interprets the world. The environment may change, but the agent will have to observe these changes.

However, some agent models have built in agent facilitating functions (for example an options-pool, stored in the environment, in which all messages for all the agents are kept, until the agents have to decide the action for the next time step). How the environment is conceptualised and what attributes it has, depends on what is being modelled. In general, one of the main functions of the world is, to provide a 'spatial context'. In many agent based models, the agents will be able to move around the environment (mobility). Although such a spatial world is the most common environment, others are possible. For instance, the agents may move through a network of nodes and links.

In order to find an adequate design of the environment certain aspects should be considered. Based on the work by Russell and Norvig (1995), these aspects or characteristics of an environment can be distinguished as follows:

Accessible versus Inaccessible

If an agent perceives the complete state of its world, then the environment is accessible. An environment is effectively accessible, when all the information is available to an agent.

Deterministic versus Non-deterministic

If the state of the environment in the next time-step(time = t + 1) is completely determined by the current state of the environment (time = t) plus the actions of the agents in the current state (time = t), then the environment is considered deterministic. The concept of a deterministic environment, from an agent's point of view, is closely related to uncertainty. If an agent 'lives' in a non-deterministic world, decision will depend on the nature and perception of uncertainties.

Static versus Dynamic

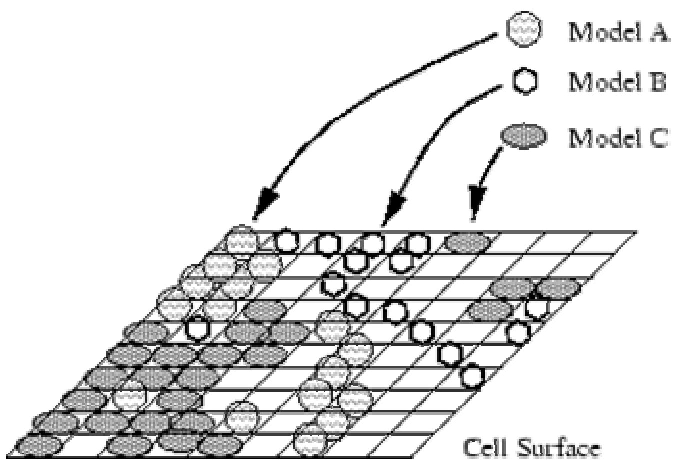
If an environment can change while the agent lives in it, for example when soil-erosion is an attribute of a grid-cell (that is part of the world-lattice), then the world is considered dynamic. If the world stays the same (in the viewpoint of the agent), then the environment is considered static. When the viewpoint of an agent on the environment changes, but the actual environment does not change, then the environment is considered semi-dynamic. A static environment consists of unchanging surroundings in which an agent navigates, manipulates, or simply solves problems. The agent does not need to adapt to new situations, nor do the model designers need to be concerned with the issue of emerging inconsistencies of the world model within the agent itself (e.g. knowledge representation, 'world' memory).

Discrete versus Continuous

In a discrete world, the number of the defined percepts and the number of actions are limited. Chess is discrete; there is a fixed number of possible moves on each turn. If the attributes of an agent are variable in each time step in relation to the environment, then the world is considered continuous.

Especially interesting for the use of agent based modelling in LUCC is the construction of the environment with GIS (-data). One way of encapsulating GIS-data into the environment is to consider the environment as a rectangular grid where each cell is an agent. Thus, the world is structured in a lattice, where each grid cell is an agent. The same advantages that object-orientation provides to agent-based design can be extended to this structure if the cells are represented as discrete objects (or agents). Each cell-object can contain a variety of internal state variables, which correspond to the layers of a GIS within that cell. In this construct, the cell represents a particular geographic location (or entity), and its internal state variables represent qualities of that location. One cell or plot may have completely different features in comparison to its neighbour. The attributes (e.g. soil quality, topography) of cells may differ, but also its internal model (the methods) of decision rules. One cell may have the possibility to regenerate its forest, while another cannot, due to its dependencies. In the final chapter a deeper exploration of this spatial explicitness is included. In the figure below, such an agent-cells world implementation is given. (Box (1999)).

Figure 3: A World, Cell surface object with 'models' in cells



2.4 Constructing an agent based model

Agent Architecture

In order to construct an agent one has to define its architecture. To get an idea about what agent architecture is, two definitions of an agent-architecture are included. Maes (1991 in Wooldridge and Jennings 1995) defines an agent-architecture as: “[A] Particular methodology for building [agents]. It specifies how (...) the agent can be decomposed into the construction of a set of component modules and how these modules should be made to interact. The total set of modules and their interactions has to provide an answer to the question of how the sensor data and the current internal state of the agent determine the actions (...) and future internal state of the agent. An architecture encompasses techniques and algorithms that support this methodology.” Kaelbling (1991 in Wooldridge and Jennings 1995) considers agent architecture to be the following: “[A] Specific collection of software (or hardware) modules, typically designated by boxes with arrows indicating the data and control flow among the modules. A more abstract view of an architecture is as a general methodology for designing particular modular decompositions for particular tasks.”

Although these definitions are useful for setting the domain boundaries of the agent architecture, they do not and cannot give insight in the actually implemented architecture of agents. The actual agent architecture is heavily dependent on several aspects and therefore, before modelling an agent, various questions need to be answered. Some are listed:

1. From which scientific theories is the agent based model derived?
2. What is the purpose of the developed model?
3. What is/are the goals/objectives of the agent(s)?
4. How to construct computer systems that satisfy the properties specified?
5. How complex are the agents in their communication with the environment and other agents?
6. What type of communication (e.g. negotiation, collaboration etc.) is simulated?
7. What are the cognitive abilities of an agent?

Due to the close fit between object-orientation and agent based modelling, nearly all simulations are written using an object oriented programming language. Examples of such languages are C++, Objective C, Smalltalk and Java.

Object Orientation; An agent is an object with beliefs, goals and rationality

A natural way of programming agents is to use an `object-oriented' programming language. Object-orientation (OO) offers a paradigm, a pattern of practice through which the traditions of modelling are applied. It gives means through which we can view the world. Object oriented program design and implementation has two main features: (i) independent model components or modularity and (ii) nonprocedural processing within the model. These characteristics allow for a higher degree of similarity between the real system and its model. An object-oriented specification should meet two requirements:

1. Each component should result in a self-contained software process. These models can be interfaced with each other thus becoming a larger, more comprehensive model on the next higher hierarchical level.
2. The ordering of component specifications should have no influence on their runtime behaviour, thus the resulting software system should be nonprocedural.

There are many definitions of an object, but a comparison with the more concrete definitions of an agent results in a nearly perfect fit: "An object has state, behaviour, and identity; the structure and behaviour of similar objects are defined in their common class". Other definitions (Smith and Tockey in Booch 1991) hold also a close reference to an agent: "An object represents an individual, identifiable item, unit, or entity, either real or abstract, with a well-defined role in the problem domain." Thus, objects are program structures that hold both data and procedures for operating those data.

On the other hand, objects (as looked upon in the OO) do not have beliefs or goals. Objects have no rational decision making systems. At most, one might consider objects to be very useful abstractions when developing agents. Thus, having control over their own behaviour is one characteristic that distinguishes agents from objects. Objects do not contain behaviour activation or action choice. In object-oriented terminology, an object may invoke any (publicly accessible) method on any other object at any time. Once the method is invoked, the corresponding actions are performed. In this sense, objects are totally obedient to one another, and do not have autonomy over their choice of action. Thus, the simulation of agents with sophisticated deliberative capabilities exceeds the frame of object oriented simulation systems. Agents require specific mechanisms to structure and expand the knowledge of common objects by internal models about the world they are interacting with (cf. Uhrmacher 1996).

In most object-oriented languages, objects are created from templates called 'classes' that specify the composition of the object, the data format it can hold and the methods it uses. Within the OO context, a class is a specification of structure (instance variables), behaviour (methods), and inheritance (parents, or recursive structure and behaviour) for objects. Furthermore, a class is a descriptor or constructor of objects. Martin (1992 in Booch 1991) defines a class as: "(…) a set of objects that share a common structure and a common behaviour". A single object is simply an instance of a class.

Class Inheritance ("In C we had to code our own bugs. In C++ we can inherit them")

Classes are arranged in a hierarchy. Subordinate classes (child) inherit the methods and slots of superior classes (parent or base or superclass or ancestor), and may add additional ones or replace the parent's slots and methods. Inheritance provides a natural classification for kinds of objects. Natural means the use concepts, classification, and generalisation to understand and deal with the complexities of the real world. Hence, inheritance is used as an is-a-kind-of (or is-a) relationship. For example, consider a simulation of farmers' decisions in a watershed area. There may be a class representing the structure and procedures of a simulated farmer. The class would define slots in which to store, for instance, the location of the farmer agent and its current direction, and a method that specifies how to walk, as well as several others. This basic agent class might have two sub-classes, one for educated farmers, and one for non-educated farmers. Both would inherit the slots concerning their location and direction from the basic farmer class, but the first would add a further slot to the structure to store the education level.

Other strengths of OO; Encapsulation and Segregation

Once a set of classes has been defined, individual agents are generated by creating instances from them (this is called `instantiation'). The advantage of the object- oriented approach is that the slots can represent the internal states of the agent (including its working memory and the rules), while the methods can implement the rule interpreter. Thus, by specifying the rules at the class level, all agents instantiated from that class can share the same rules, while the contents of their memories can differ between agents. In addition, the object-oriented approach leads naturally to a useful encapsulation, with each agent clearly distinguishable within the program.

Encapsulation is the process of hiding all of the details of an object that do not contribute to its essential characteristics. Thus, it is a principle, used when developing an overall program structure, that each component of a program should encapsulate or hide a single design decision. Hence, the interface to each module is defined in such a way as to reveal as little as possible about its inner workings (Oxford 1986 in Booch 1991, Booch 1991, Coad 1991).

Object-oriented programming allows modellers to segregate functions and state variables that are germane only to the internal workings of certain components (e.g. an agent). In other words, agents may have different levels of internal complexity; furthermore, the notion of other agents is limited strictly to a message interface. This allows them to be a unique creation, thus different agents can have any variety of internal individual details, but are able to interact in the simulation as long as the messaging interface is consistent.

In general, models designed with OO have the following strengths (Booch 1991):

1. Faster development
2. Strong equivalence with the real world
3. Increased software quality
4. Easier maintenance
5. Enhanced modifiability
6. Reuse of software and designs, frameworks
7. Systems more change resilient, evolvable
8. Reduced development risks for complex systems, integration spread out
9. Appeals to human cognition or naturalness.

The ease of modelling an environment in OO

Object Orientation in agent based modelling is particularly adept at dealing with spatial phenomena. Agent based modelling makes implicit use of that spatial complexity (cf. White, Engelen and Uljee 1997). A big advantage of OO and agent based modelling is that cells do not have to contain the same list of state variables (or even have the same internal structure). Each cell needs only contain those qualities (variables) that are relevant to that location. Thus, in an object-oriented design, as long as the messaging interface between objects is capable of handling the same messages, the objects themselves may have significant heterogeneity. This can be very advantageous if one is constructing a landscape where some areas have great internal complexity and others are relatively featureless (see e.g. Figure 3). Besides the internal content of a cell, also the shape of a cell is variable. A cell is just one of many possible abstractions of spatial units or entities. If the methods of a cell are encapsulated and the topological relationships are specified, then a cell does not have to be aware of its geometry (Torrens 2000).

2.5 Agent based modelling frameworks for simulation

Several computing frameworks for the implementation of agent-based models for simulation purposes exist. One of the most prominent infrastructures is Swarm. Chris Langton initiated the Swarm project in 1994 at the Santa Fe Institute. The first version was available by 1996, and since then it has evolved to serve not only researchers in biology, but also anthropology, computer science, ecology, economics, geography, industry, and political science. The primary feature of Swarm is the virtual machine. The virtual machine allows the researcher to describe agent behaviours while keeping an exact notion of time and concurrency in the world. Swarm also makes it possible to compose or decompose hierarchies of agents. This attribute is called composability. Furthermore, Swarm provides functionality like task schedule management, memory management, GUI widgets, random number generators, and a collections library. The generic qualities of Swarm are shown by the fact that other 'frameworks' evolved based upon the Swarm architecture (Langton et al. 1995).

The Brookings Institution has produced another important contribution to the agent-based simulation framework development by creating Agent Landscape (Ascape). Ascape is a research tool developed to support agent-based research. It is designed to be flexible and powerful, but also approachable, easy to use and expressive. A high-level framework supports complex model design, while end-user tools make it possible for non-programmers to explore many aspects of model dynamics. Ascape is written entirely in Java, and should run on any Java-enabled platform.

Another example of generic qualities of Swarm and Ascape is the Repast (REcursive Porous Agent Simulation Toolkit) by the University of Chicago's Social Science Research Computing. It provides a library of classes for creating, running, displaying and collecting data from an agent based simulation. Repast includes such features as run-time model manipulation via GUI widgets first found in the Ascape simulation toolkit (Collier 1999).

The goal of the Repast group is relevant and valuable in the perspective of possible qualitative verification techniques. Their goal is to move beyond the representation of agents as discrete, self-contained entities in favour of a view of social actors as permeable, interleaved and mutually defining, with cascading and recombinant motives and to allow situated histories to be replayed with altered assumptions.

Smalltalk2, another object oriented programming language, is used to create the Common-pool Resources and Multi-Agent Systems (CORMAS3). CORMAS provides

[2] In comparison to JAVA, Smalltalk has a 'pure' object model. This means that it follows a very simple ontology: 1) everything is an object, and 2) every object has a class. In Java, the low level types are not

the framework for building models of the interactions between individuals and groups using the resources. Interactions can be expressed by direct communication (exchanges of messages), and/or by sharing the same spatial support (less direct).

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objects, and thus do not have defining classes. In combination with Java's strong typing, it is impossible to use any low level types in heterogeneous collections and thus leads to a breakdown in polymorphic design. Smalltalk's object model is very reflective. In Smalltalk object can introspect its structure and capabilities. An instance can query its class and figure out what methods are defined directly and in super classes. An advantage is, for example, that it can execute a method without knowing that method at the time that the programmer wrote the code. In relationship to this, applications have possibility to define the object model itself (in Meta object programming), which is interesting when considering the learning capabilities of an agent. In Java, an instance does have the ability to query its class for various pieces of information (like available methods), but unlike in Smalltalk one does not get an instance that is the definition of that method.

[3] CORMAS is a software package designed by CIRAD (Centre de coopération internationale en recherche agronomique pour le développement) for renewable resource management (website).

3 Strengths and Limitations of Agent based modelling in LUCC

3.1 Introduction; complexity and flexibility

Agent based modelling is particularly strong in complexity research. Complexity[4] theory studies non-linear processes. In complex models, simple linear causality is not applied; causality is not only one-way directed. Everything relates to everything else in a tangled dynamic web of interdependent relationships. The modelling approach in complexity theories is holistic. The premise is that an effective description of a system cannot be reduced to the descriptions of its separately analysable parts, because separately analysed components can never create an adequate description of the whole. Positive and negative feedback loops are permanently driving the overall behaviour out of equilibrium (towards a dynamics - or system transition[5]) (Langton et al., 1992). The agents' rules are not derived from or dependent on an equilibrium. Interacting agents might have a goal to reach equilibrium among each other, the agents' behaviour is not derived from the equilibrium that happens to be present, but rather from the agents' perception on how such an equilibrium should be. Oppositely, a system in equilibrium may be a result of interacting agents that do not have such a common goal.

Agent based modelling in LUCC is trying to understand the complexity of heterogeneous human behaviours in an ever-changing environment, that is characterized by interdependencies, heterogeneity, and nested hierarchies among both agents and their environment (Arthur, Durlaf and Lane 1997; Holland 1998; Epstein 1999; Kohler 2000; LeBaron 2001; Manson 2001 in Parker et al. 2001). On the question why agent based modelling techniques are beneficial in LUCC studies, some answers are easily available. First of all, LUCC is a field that is formed out of the interfaces of several sciences. These interfaces demand for interdisciplinary and multi-disciplinary approaches in which conceptual modelling flexibility is a prerequisite. Agent based modelling allows combining theoretical approaches from different disciplines within one model. Not only is the agent rationality chosen flexibly, as shown in the previous chapter, but also bio-physical and environmental modules can be easily incorporated or left out, due to the highly modular structure of agent based modelling. With OO applied effectively, classes are easily taken out or brought into a model, and even exchanged over models (e.g., we could see how a Dutch farmer would behave in a Philippine environment). Another practical advantage of agent based modelling, of a parallel processing approach in particular, is that they are highly decentralized. Multi-threading (events take place at the same time) and the decentralized character of the modules (or agents) enhance and enrich complexity of an agent based model in comparison to serially timed modelling.

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[4] Chaos explores how complex interwoven patterns of behaviour can emerge out of relatively simple nonlinear dynamics, while Complexity tries to understand how relatively simply patterns can emerge out of complexly interwoven dynamics.
[5] Langton et al. (1992) call this the *Edge of Chaos* - a critical zone between disorder and order, where emergence of new qualitative states takes place, and transformation of the system as a whole occurs.

This flexibility also has its downside; because a researcher may easily be trapped in modelling causal and non-causal factors, drivers and processes, important and irrelevant. Hence, complexity studies have been criticized for harbouring a 'reminiscence syndrome', which says that: "just because the dynamic activity displayed in a computer model resembles a real-life process, does not necessarily mean that it is a good model for that phenomenon" (Horgan 1995 in Torrens 2000). Similarly, just because the patterns that an agent-based model generates may look like the real world phenomenon, that does not mean that an agent-based model is always appropriate for representing specific real world phenomena. Researchers may assume that such an outward representation of reality alone is justification for a modelling paradigm, even though this look-alike may be accidental, coincidental, or may be a construct of the researcher's own ideas. Obviously, the issues of reminiscence and relevancy closely relate to the difficulties of output interpretation and the validation and verification steps of an agent based model.

A sub-field of Artificial Intelligence called distributed artificial intelligence (DAI) has influenced multi-agent system methodologies enormously. DAI is concerned with the properties and the design of networks of interacting agents, for example, how one might design a group of agents, where each has a different expertise of co-operation or to solve a problem. Castelfranchi (2001) points out that Artificial Intelligence (AI) will have a significant contribution to the clarification-processes of the possibility of unconscious, unplanned forms of co-operation and intelligence among intentional agents (e.g. the issue of the 'invisible hand', of the 'spontaneous social order' but also of 'social functions'). In addition, besides AI supporting the social sciences, Castelfranchi (2001) mentions a significant interdisciplinary fertilisation; social sciences have an important role in the modelling of the cognitive agents' mental representation. Relevant in these fertilisation processes are the studies on emerging social functions. Gilbert and Conte (1995) and Epstein and Axtell (1996) make similar statements about this cross-fertilisation. They stated that: "In recent years, agent based artificial societies have been recognised as a powerful means to the development of social theory".

3.2 Agent based modelling in LUCC components; heterogeneity and hierarchies

In order to get a clear overview on the LUCC dynamics, especially when approached with an agent based modelling technique, four to play key roles.

These are:

1. The world or environment; spatial scales and their representation
2. Agents and their behaviour
3. Organisational levels, agent group behaviour
4. Time

In the previous chapter, the components 'agent' and 'world' have been discussed. In social theory the agents are known as actors. Agents can be individual actors as well as collective actors. Actors decide on actions and act in their world. This simulation world is a one-, two-or three- dimensional representation of the real actors' environment. The simulated world allows us to define questions that are spatially explicit. Actors decide upon their actions within a time frame. This allows for a temporally explicit approach.

In a next section, the temporal and spatial aspects are discussed in detail. Agent group behaviour has not yet had much emphasis in the agent based modelling in LUCC approaches. Possibly, LUCC researchers are as yet so focussed on the interaction between actors and world that the interactions among actors has not got much attention.

Time, often called the fourth dimension, influences agent based modelling in LUCC in two ways. First it may define attributes of the actors (e.g. age) and secondly, it affects the modelling on the system level (e.g. in 1920 agricultural machines where rare, which obviously affects LUCC). Time makes the modelling dynamic. Agents interact with each other and with their environment over time. Time plays a very important role in complex agent based modelling for LUCC. In order to deal effectively with time as a modelling dimension, we may make a distinction between static input/output and dynamic input/output. In *Figure 4* an overview is given of the various components.

1. *Static input* data refers to data commonly used in simulation models, like soil type, yield per hectare, wage rate, etc. In agent based modelling we may make a distinction between:
   a. Land use/cover data at the beginning of the simulation
   b. Agent and agent group attributes at the beginning of the simulation
2. *Static output* or results are single-moment data, e.g., a population map of a region after 10 time steps. The 'static results' do not reveal anything about the processes among objects determining the results. They do not reveal causality.
3. *Land use/cover and other physical data at the end of the simulation*
4. *Agent and agent group attributes at the end of a simulation*

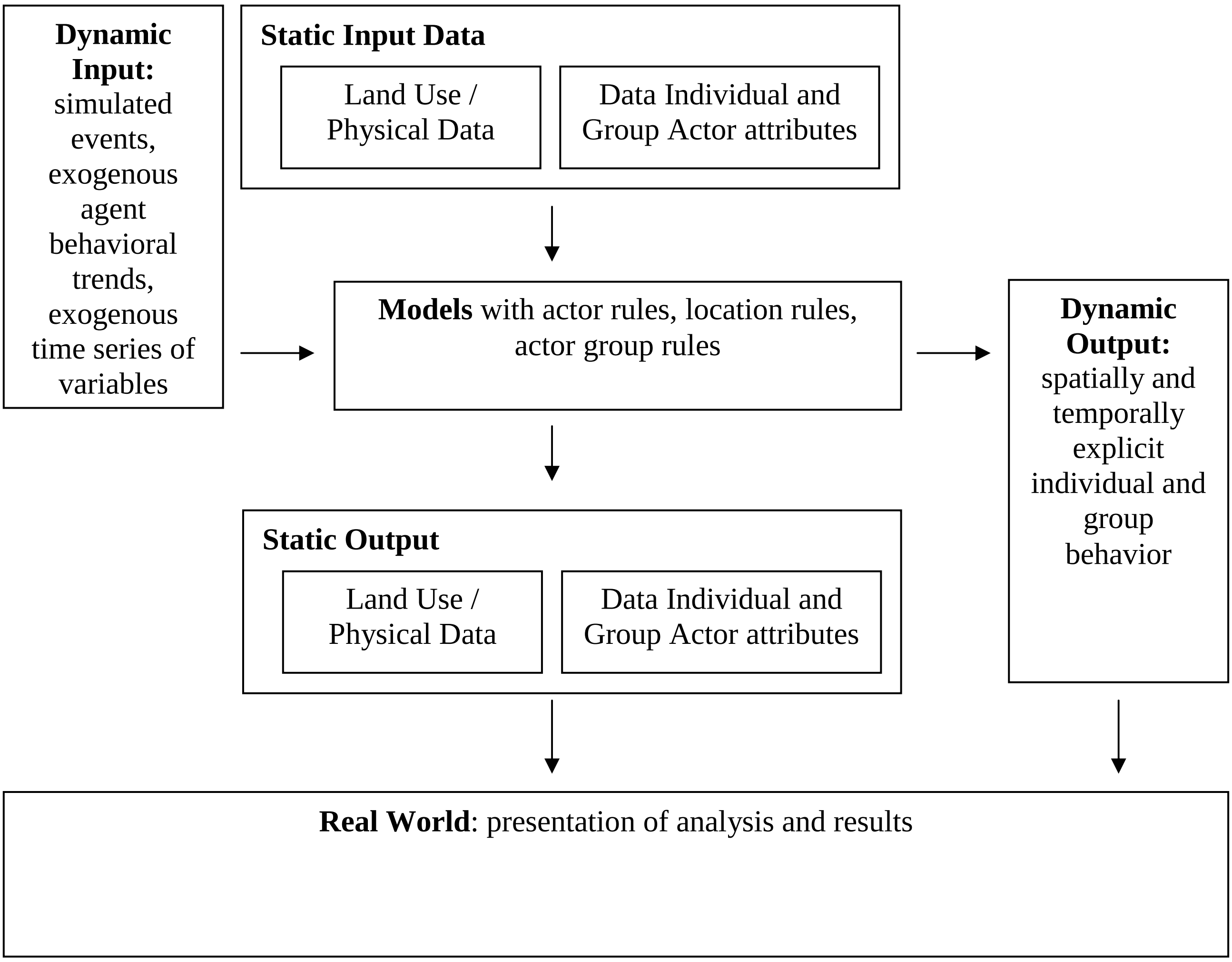
Dynamic input denotes data that describe the ongoing contextual trends, processes and the events that are modelled during a simulation. For example, the MameLuke settlement model (Huigen 2003) includes a time-series of the variable "number of migrants". Every time-step, which represents a year, the simulation retrieves the number of migrants that want to settle in the simulated world.

D*ynamic output* denotes output that illustrates (parts of) the process under observation. It may have various forms, such as a graph displaying a variable over time, a series of maps describing the change of spatial variables or proxies over time. We can classify the dynamic output in the following:

a. Agent behavioural changes
b. Group behavioural changes
c. Spatial patterns
d. Temporal patterns

The dynamic results are reciprocal and need to be analysed as such. Spatially and temporally explicit reciprocal dependencies exist between agents, between agents and groups, among environmental units and between agents and their biophysical environment. For example, farmers and groups of farmers have dynamic impacts on the land use and land cover such as soil quality, biodiversity, and the type and succession of vegetation cover. Vice versa, many spatial, environmental factors impact agent/group behaviour. These include spatial influences among agents, such as flows of information, diffusion of technology, local coordination, social networks, and positive and negative externalities among neighbours (see Kanemoto 1987; Case 1991; Case 1992; Brander and Taylor 1998; Sanchirico and Wilen 1999; Parker 1999; Ray and Williams 1999; Parker 2000; Irwin and Bockstael 2001 in Parker 2001).

Figure 4: Components in an agent based LUCC model.



In the previous chapter it was illustrated that agents may have a large variety of mentalistic characteristics. This heterogeneity may change over time and/or space due to agent learning and spatial changes. Another core component, the group or organisational levels, holds an interesting aspect of agent based modelling. Much research LUCC is challenged by a dichotomy between the individual (e.g. the household) and the aggregate (e.g. populations). Agent based modelling enables us to narrow this gap between the micro- and macro levels and scales. In this paper, a level refers to level of organisation in a hierarchically organised system and is characterised by its rank ordering in the hierarchical system. Many interactions and feedback between processes at different levels of organisations occur (Verburg et al., 2003). If an interaction occurs within one level, for example two farmers competing for a location, then we speak of a horizontal power line. An interaction between actors of two levels, such as a politician and a farmer, where the politician is defined on a higher social level of the system, is considered a vertical power line. One of the characteristics of a vertical interaction/relationship is that the actor of the lower level has less power than the actor of the higher level. The lower level actor cannot easily approach the higher level actor. Vice versa, the higher level actor can impose its immediate powers on the lower level actor. The actors that are engaged in a horizontal relationship are of the same level, and have little or no social differences. If actors of one level interact and co-operate within their social network we speak of collective action (cf. Ostrom 1992). If such a collective action is continuous, it may result in a collective actor group. Such a collective actor is often residing on a higher level than the individual members of the group. A good example is a co-operation of farmers. Alone, a farmer cannot approach the mayor of the city by himself, but the farmers' co-operation president has worked himself up, and may be considered of the same level as the mayor. Much of the contemporary agent based LUCC studies apply and focus on such horizontal social power lines. The actors are often of one social level. Perhaps more emphasis could go to the vertical power lines by using a more socially diverse conceptual model. The Action-in-Context (De Groot 1992) framework for example, has a relevant focus on vertical interfaces between agents/actors.

As seen in the previous chapter, the object orientated programming techniques use hierarchical classes, which allow to easily program heterogeneous hierarchical relations. To get to a more heterogeneous picture of a multi-levelled society, group-clusters and group-theoretical elements can be considered in a model. Agents being part of a group will have different rationalities in comparison to agents without group influences. For example, it sounds reasonable that farmers, who are members of a farmer-co-operation, tend to invest more and plan for a longer time span, due to the financial loans and security by the co-operation. When dealing with complexity of an individual or an organisation or a society as a whole, understanding is needed about the attractors that propel the complex dynamics of this individual, organisation or society. Closely related to the possibilities of group theoretical aspects in the model is the 'emergence' or the emergent properties of a system.

Emergence is the description of a macro-scale phenomenon that arises from micro-interactions. The concept of emergence is directly related to the agent based modelling characteristic of hierarchies that characterise complex systems. Agent based modelling has the possibility to witness some types of emergence. However, an agent based model needs agents that adjust their behaviour and strategies via 'reasoning' in order to produce emergence. In so-called emergent systems, a small number of rules or laws, applied at a local level and among many objects or agents, are capable of generating surprising complexity in aggregate form. These patterns manifest themselves in such a way that the actions of the parts do not simply sum to the activity of the whole. Essentially, emergence means that there is more going on in the dynamics of the system than simply aggregating individual elements into larger units. It means that new system behaviour evolves within an existing system caused by the many interactions of the system elements. Hence, the systems are dynamic and change over time and the dynamics operate without the direction of a centralised executive (cf. Holland 1998; Torrens 2000).

The main objective of complexity studies is to extract simple features of complex behaviour that are common across a wide-range of systems, and eventually to devise universal laws of complex systems derived from such common principles. One aspect of complex systems worth mentioning is the dependence of outcomes on initial conditions.

A slight change in parameterisation or starting values of a model may generate significantly different behaviour. Lorenz labelled this phenomenon as the well known "butterfly effect"[6]. Related to this, agent based modelling systems may exhibit path dependency and lock-in effects.

3.3 Time, Scales and Levels in agent based models of LUCC

Besides a distinction between various organisational levels, LUCC processes operate on various characteristic scales in space and time. In this paper, the term scale refers to the spatial, temporal, or analytic dimensions used by scientists to measure and study objects and processes. For each process important to land use and land cover change, a range of scales may be defined over which it has a significant influence on the land use pattern (Meentemeyer 1989, Dovers 1995 in Verburg et al., 2001). In most of the contemporary agent based LUCC modelling, the dimension time is discrete. Time proceeds in iterative steps of whatever length the model designer cares to conjure. Furthermore, in these simulations the environment of the model and the behaviour of agents are episodic. In an episodic environment, the agent's experience is divided into 'episodes' (or timeframes). Each timeframe consists of the agent perceiving and then acting. The quality of its action depends just on the timeframe, because subsequent timeframes do not depend on what actions occur in previous timeframes.
Thus, when the agent-environment interaction is broken down into a sequence of separate episodes, it is called an episodic approach. However, one may use events instead of episodic time-steps, which makes the behaviour more continuous. Discrete Event modelling (or queuing models) can be used to explicitly order events. In a queuing model, time is neither continuous nor does it pass in equidistant discrete steps, but it proceeds from event to event. Events are scheduled in a so-called agenda, i.e. a list of all those future events that can be predetermined at a given time. Past events are removed from this list, and events may generate new events and insert themselves into the agenda. The queuing model approach is event-driven, and that makes it often harder to implement for LUCC simulation purposes, because LUCC processes often demand temporal explicitness that is difficult to simulate with event-driven models.

In both types of modelling, the modeller needs to decide the order in which the agents in the simulation are given computing time. The decision making order among agents can have an important effect on the course of the simulation, unless precautions are taken. For example, if agent A sends a message to agent B, but B is considered before A, agent B will not get the message from A until the next round, by which time the message may be no longer relevant. In agent based LUCC simulations, it seems more appropriate to use the episodic world because one wants to have time as a variable, parameter, or constraint. In a continuous world, only the computational processes use the dimension time (cf. Sutton and Barto 1998).

When modelling LUCC processes, the modelling needs to be done over the dimensions time and space. Furthermore, the temporal scales must be theoretically congruent with

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[6] The variables used to describe real-life complexity have threshold values; pushing a complex system beyond these values, even slightly, huge changes may occur with the system as a whole leading to unpredictable behaviour.

the spatial scales. In practice, the measurement of relevant social variables is often problematic. Migration, for instance, may be partly explained by the spatial distribution of economic opportunities. The more decisive variable, however, is the perception of these opportunities by potential migrants, mixed with the degree of perceived risk at the potential place of destination, which, in turn, may partly depend on the degree to which family or ethnic group members are already settled at that place. Such data usually is outside the reach of empirical studies. However, theoretically, it has been already shown that it is perfectly possible to connect the macro-scale maps of opportunities with an individual-level (micro-level) model of migration decision-making, in which such factors are incorporated (e.g. de Groot 1992; Verburg et al. 2003).

Using agent based techniques, the information about behaviour obtained by extensive field studies of sociologists can be put in the relevant context. The importance of different processes influencing land-use change can be tested by sensitivity analysis and a link to higher levels of aggregation can be made: the simulated local-level processes and interactions result in the land-use dynamics at more aggregate levels. In practice, this linking of scales and levels is perfectly possible in agent based modelling (cf. Berger 2001, Verburg 2003). A model may have several scales and levels that are linked and interact with each other. (Aggregated) macro-scale regional (e.g. population-pressure) as well as individual variables (e.g. consumer preferences) can be combined in one model. Because of the flexible definition of an environment and the richness of included detail, agent based modelling is very powerful in its spatial explicitness over various scales.

Like the conceptual model (e.g. content, size, function) of organisational levels (formal, non-formal, abstract body, group of persons) also the conceptualisation of spatial scales is completely flexible. A scale may be constructed based upon the availability and type of data. The shape (grid, polygons, vectors), extent and resolution of a spatial unit in an agent based model for LUCC, may be determined after data is collected and analysed. Currently however, agent based LUCC models mainly focus on the micro-level (e.g. village), because of limited data availability (socio-economic, behavioural) and the types of activities modelled.

Nowadays, agent based LUCC modelling does not yet have the same level of database support, which GIS provide for environmental analysis, although there are strong links to raster-based GIS. More and more object-based modelling provides inputs to GIS and vice versa, in order to come to the full potential for simulating individual actions and decisions in space (Batty and Jiang 1999).

3.4 The use and benefits of agent based modelling in LUCC

The validation and verification aspects in agent based LUCC modelling are a topic of heated debates. Due to the huge parameter space, the model outcomes cannot be captured easily and thus cannot easily be analysed and validated by formal methods. Furthermore, alongside the increase of computational power and the increased ease of modelling, the complexity of models has increased manifold. The complexity of such models makes it practically impossible to validate model outputs in the strict sense, because too many (subjective) assumptions are required and far too little data is available. Jansen and de Vries (1999 in Van Dijkum et al. 1999) discuss validation problems in integrated assessment modelling7. Various scholars indicate also the lack of sufficient ‘real’ data which poses great problems for any holistic and integrated modelling approach. The complexity of such a model in combination with the time and data needed to empirically estimate parameters of all the equations are very large demands. Being in essence based on the possibility of conducting repeatedly controlled experiments, the currently used formal validation and verification techniques are not applicable. Complex modelling of ‘real world’ systems in general, and agent based simulation modelling in particular, requires innovative procedures for verification (and validation). Several quantitative techniques (e.g. statistical measures of similarity for linear and partly non-linear models) already exist that may be used. Additionally, validation techniques with a low-level quantification are at least as important in understanding the results of agent based modelling in combination with theoretical and qualitative knowledge. In such validation approaches the application of sensitivity analysis and error analysis of modular elements of the system may allow for accreditation. Besides the application of statistical validation methods, agent based modelling demands for validation and verification techniques that aim at accreditation of the systems’ internal dynamics via expert and stakeholder debates (cf. Barreteau 2001).

In addition to these issues, another new modelling element is the inclusion of 'qualitative' variables. That is, most of what we know about the world is descriptive, difficult to quantify, or has never been recorded. Nevertheless, such information is crucial for understanding and modelling complex systems. Validation and verification of such data is difficult, and the agent based LUCC community needs to address question such as:

- How can the accuracy of estimates about qualitative data be tested?
- How can statistical tests be performed without numerical data?

Actually, there should be no limitations on the inclusion of qualitative variables in models. After all, the point of simulation models is to portray decision making as closely and realistically as possible, and qualitative variables—including intangibles such as desires, reputation, expectations, and optimism/pessimism – are often of critical importance in decision making.

Besides applying ‘best practices’ in model building and using current validation and verification techniques, new methods need to be developed. In these new techniques the focus should not be restricted to the relationships between variables (equation-based thinking) but must be on the dynamics of the complexity itself (behavioural patterns, agent processes). Van Dijkum and Van Kuijk (1999 in Van Dijkum et al. 1999) state that science (and especially social sciences) requires new procedures for validation dealing with feedback and non-linear processes.

Agent based LUCC modelling provides the opportunity to work with and develop theories, testing simulations and to making predictions about likely behaviour given a set of environmental circumstances, that was unthinkable in earlier models. The downside of this enormous flexibility in theory application and combination is, of

[7] Integrated assessment modelling is a multi-disciplinary perspective and integrates different complexity levels (physical environment, human behaviour, information flows, human values, beliefs and ideas).

course, the fact that a model must accurately represent how the actors in the system behave. The model should respond to change in the same way the real actors would. It will do this only if the model's assumptions correctly describe the decision rules and relations that apply under different circumstances. The model therefore must reflect the actual strategies used by the people in the system being modeled, including the limitations and errors in their strategies. Discovering decision rules is often difficult. They cannot be determined from aggregate statistical data, but must be investigated at the level of decision-making, i.e., usually the household or individual. Some scholars pronounce this by calling agent based LUCC modelling a simulated social laboratory or computarium in which to test hypotheses that link land-use behaviours to landscape outcomes. Agent based LUCC research can design and execute experiments to explore alternative hypotheses with the mechanisms of the model programmed via empirically derived rules or simply stipulated to explore outcomes under alternative behaviour.

The idea of heterogeneous agents interacting individually or group-based is very appealing. Agents have different intra-agent models and thus may simulate different cultures, societies and/or worldviews. Obersteiner (2000) reasoned that agent based modelling does not need assumptions on perfect competition and perfect information, because agent behaviour may have variation. Another possibility for agent based modelling is that policy distortions, may be included. In policy-scenario analysis based on aggregate frameworks, depicting 'hidden' policy distortions (as a result of a limited number of agents) is often impossible. Agent based modelling gives understanding on how policy implementations affect agent societies and how agent societies affect policy.

A further example of the strength of agent based modelling is the possible ways of modelling "technology adoption". The benefits of a new technology are often uncertain. Therefore, an agent with greater access to resources to ensure a subsistence level of consumption (such as stored wealth or access to credit) may be more willing to accept the risk associated with the adoption of a new technology. The success or failure of the new technology will provide information about the payoffs from the technology to other agents, potentially reducing uncertainty. As a consequence, agents having a higher level of risk aversion may now adopt the technology. Berger (2001) uses an multi-agent simulation model to analyze diffusion of technology among heterogeneous farm households.

Besides testing new hypotheses, and generating new theories, agent based LUCC modelling also offers opportunities to communicate scientific theory to stakeholders. A good example of such fruitful communication is shown by the work of Barreteau et al (2001). They use reciprocal communication in order to explain theory and validate/verify their work. They propose to use role games as a way to present agent based models to the stakeholders. The purpose is to increase knowledge on the interactions, validate the agent based models and provide a discussion tool. Agent based modelling and role playing games have both been developed separately and offer promising potential for synergetic joint application in the field of renewable resource management, for research, training and negotiation support. While such systems may give more control over the processes involved in role playing games, role-playing games are good at explaining the content of multi-agent systems. Role-playing games first enabled to work on the validation of the agent based modelling. Subsequently, the combination of both tools has proved to be an effective discussion support tool. The use of agent based modelling for research purposes leads to the creation and validation of theories. The validation of these theories relies upon finding a match between observed and simulated results as well as between modelled and real processes. Verburg et al (2001) also point out the importance of good communication with stakeholders. Most stakeholders do not want to access scientific papers or bulky reports. For the presentation of spatially explicit assessments of land use change the researcher can make use of the visual capabilities of geographical information systems. The presentation of maps to decision-makers can communicate results and provoke discussions between policy makers and scientists on the importance of the foreseen changes (Goodchild, 2000 in Verburg et al. 2001). Spatially explicit representation of land-use changes has also proven to be an appropriate means to discuss with farmers their resource base, spatial connectedness between areas, and the consequences of local actions (Gonzalez, 2000 in Verburg et al. 2001).

3.5 Conclusions and Recommendations

Agent based LUCC modelling holds the promise to provide new insight into the processes and patterns of the human and biophysical interactions. Advances in computer technology make it possible to run almost infinite numbers of simulations with multiple heterogeneously shaped actors that reciprocally interact via vertical and horizontal power lines on various levels. All these societal aspects and processes take place in an artificial, spatially explicit world that may be as simple as a 1D social network or as complicated as a dynamic 3D world, depending on the needs of analysis. The possibilities of shaping the agents, the interaction protocols and world cell agents are relatively wide. Different theories and their combinations can be explored. Scientific disciplines can easily be combined in a modelled world (computarium).

However, any model is only as valid as its assumptions, theories and data. In the case of agent based LUCC simulation models, the key issues and assumptions concern the realm of choosing the descriptions of the physical system and the actors' decision rules. Representing the physical system is usually not a problem and not controversial; scholars have been investigating the physical system for a relatively long time now, and relevant data collection methods and databases are well established. Another factor that makes it easier to deal with the physical system, lies in the characteristics of biophysical data, because these theories and data can often discard the dynamical element due to the intrinsic time scale being often much larger than the research scope. Hence, the physical environment can be portrayed with great detail and accuracy as needed for the model purpose.

Most difficulties and controversies occur in the description of the agents' decision rules, the quantification of the rules and qualitative variables, and the choice of the model boundary. Which factors should be exogenous, which should be endogenous? What feedbacks should be incorporated into the model? Model development requires the skills of the anthropologist and the ethnographer and thus the extensive knowledge of decision making that has been developed in many disciplines, including psychology, sociology, and behavioural science. Validating and verifying qualitative data is difficult, but the option to exclude such variables from a model because of scarcity or a lack of quantified numerical data is problematic as well and may be less appropriate than including them and making reasonable estimates of their values. All relationships and parameters in models, whether based on qualitative or quantified variables, are imprecise and uncertain to some degree. Modelers and users must therefore perform sensitivity analysis within the spaces of the computarium to assess how conclusions might change if other plausible assumptions were made. Sensitivity analysis should not be restricted to uncertainty in parameter values, but should also consider the robustness of conclusions with regard to alternative structural assumptions and choices of model boundary.

If agent based LUCC simulation is to take up a place among the methodologies in land use research, principles need to be established that guide its application. Difficulties in gaining acceptance for simulation-based approaches within established academic communities can be noted. Some of the criticism may be due to conservationism or unfamiliarity with a new field but some scepticism is well founded. Difficulties exist partly because of the young age of complex systems research. Scientific work will firstly focus on the development of models, and will care only later about the validity and verification issues. Studies with complex systems are relatively young, a mere decade, and one may notice that more and more issues and challenges are raised and tackled concerning the difficulties of such models. Another related cause for slow acceptance of agent based modelling is the fact that many accepted works base their validity on statistical analyses that are often not applicable in these models.

In the following scheme a list for future orientation issues is given. It lists some future challenges and obstacles for agent based LUCC modelling. The issues are grouped based on the structure given in Figure 4:

I. Data Input

Data available in LUCC research is often too static and disregarding the temporal scales and levels of social and economic processes. Too often maps are digitized and compared to maps of earlier periods without considering adequate anthropogenic temporal scales. Patterns and processes can only be identified after a certain period of time, but more relevant, their often context-dependent characteristics may be valid for only a certain period of time until they dissolve or transform into another process or pattern. In the future, these cultural, political, social, economic dynamics need to be included at the appropriate spatial and temporal scales. Effort needs to be put into development of data gathering techniques that focus on spatially and temporally explicit anthropogenic data, notably systematic use and integration of survey and census data.

Another important issue is the identification and collection of data that link the various spatial scales.

II. Models

Model verification is of major importance. Openness of the model, its coding and algorithms, is strongly suggested. The way theoretical concepts are applied needs to be laid out so others can judge their appropriateness. Also, openness and justification of practical considerations as well as on the constraints on variables, parameters, etc. need to be given.

The fact that model outcomes are multi-dimensional and difficult to assess as to their plausibility and validity, that data input and data relations are often complex, suggests to choose a mixed methodology, one where validation and experimentation can take place iteratively, with a methodology directed at seeking verification of modeled behaviour taking place concurrently with simulation model development.

In this light, it is proposed that various ways to get to a standardization of modelling of complex systems should be developed in order to ease possible model replication. The agent based LUCC research community is probably still some steps away from such standardization. In order to get there, several hindrances need to be tackled. Axelrod (1997) has identified the following problems and issues that complicate the task of replication for simulations:

- Ambiguity in both model description and input data and presentation of results
- Gaps in descriptions
- Erroneous published description.

These issues may very well serve as a starting point and may guide us to protocols that encompass the iterative model-verification and- calibration issues.

III. Results

It has been argued that agent based modelling marks the beginning of a new era of computer modelling concerning complex processes. In order to create a solid path of communication, it is pleaded that a large scientific body that focuses on standardized modelling processes governs these developments, structurally.

Related to the development of validation techniques, attention should be paid to the reusability of model components and their generalisability. Because of the heterogeneity and path dependence, simulation results may be hardly generalisable, at least in terms of specific outcomes. It may be possible, however, to identify patterns of behaviour, typical of a certain class of systems. Such classes need to be discovered and analysed.

This report has emphasised the explanatory and explorative strengths of agent based LUCC modelling and recommends that besides the empirical and explorative scientific use of the agent based LUCC modelling, also the communication value of the approach be investigated and its use and appeals to stakeholders be evaluated.

IV. Real world

The systems being modelled are frequently very complex (hence the choice of simulation in the first place) making complete comparisons between model and real world behaviour impossible. Therefore the verification and justification of model outcomes need to be analysed in the light of the substantive interpretations made. Finally, it can not be stressed enough, that minimum standards for conduct, documentation and publication of computational based studies need to be addressed if fundamentals of scientific rigor and acceptance among scientific methods is to be achieved.

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