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

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Abstract: Agent-based simulation (ABS) is being increasingly used in environmental management. However, the efficient and effective use of ABS for environmental modelling is hindered by the fact that there is no fixed and clear definition of what an ABS is or even what an agent should be. Terminology has proliferated and definitions of agency have been drawn from an application area, Distributed Artificial Intelligence, which is not wholly relevant to the task of environmental simulation. This situation leaves modellers with little practical support for clearly identifying ABS techniques and how to implement them. This paper is intended to provide an overview of ABS in environmental modelling so that modellers can link their requirements to the current state of the art in the techniques that are currently used to satisfy them. Terminology is clarified and then simplified to two key existing terms, *agent-based modelling* and *multi-agent simulation*, which represent subtly different approaches to ABS, reflected in their respective Artificial Life and Distributed Artificial Intelligence roots. A selected set of case studies are reviewed, from which a classification scheme is developed as a stepping-stone to developing a taxonomy. The taxonomy can then be used by modellers to match ABS techniques to their requirements.

Keywords: Agent-based simulation; Multi-agent systems; Taxonomy; Environmental management

1. INTRODUCTION.

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

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

Thus, this paper is intended to provide an overview of agent-based simulation in environmental modelling and offers a simple, preliminary, taxonomic structure that classifies models so that modellers can link their requirements to the current state of the art in the techniques that are currently used to satisfy them. Sections 2 and 3 begin the process by clarifying terminology and explaining why current definitions of agency are unhelpful. Section 4 proposes a set of seven case studies that are used to link five modelling requirements (environmental model coupling; micro-level decision-making; social interaction; adaptive decision making; and multiple scale level decision-making) to specific techniques implemented in these studies. Section 5 proposes a first step towards a taxonomy. As further studies emerge in the literature, they will be reviewed, assessed, and incorporated into this classification scheme.

2. DISENTANGLING TERMINOLOGY

A review of the literature reveals many different terms being used to describe what, for want of a neutral term, we have in this paper so far called agent-based simulation. These terms include *agent-based modelling* [Epstein and Axtell, 1996]; *multi-agent simulation* [Ferber, 1999; Gilbert and Troitzsch, 2000]; *multi-agent-based simulation* [Edmonds, 2001]; *agent-based social simulation* [Doran, 2001; Downing et al., 2001]; *individual based configuration modelling* [Judson, 1994]).

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

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

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

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

"Agent-based modelling [is used to] discover fundamental local micro mechanisms that generate macro structures." [Epstein and Axtell, 1996].

"Agent-based modelling [is] the set of techniques [in which] relations and descriptions of global variables are replaced by an explicit representation of the microscopic features of the system, typically in the form of microscopic entities ("agents") that interact with each other and their environment according to (often very simple) rules in a discrete space-time." [Gross and Strand, 2000:p27]

Of the other terms used, *multi-agent-based simulation* (MABS) is defined as the simulation of a multi-agent system, which mirrors Gilbert & Troitzsch's definition given above. *Individual-based configuration models* are defined in terms of simpler interacting agents and thus fall into the category of ABM. Doran's [2001] definition of *agent-based social simulation* (ABSS) is essentially the same as Gilbert & Troitzsch's and therefore is simply another term for a multi-agent simulation. Downing et al.'s definition of ABSS appears to be an umbrella term stretching across both ABM and MABS, for models which use heterogeneous agents with boundedly rationality that map to human actors in the real world. From herein, the umbrella term agent-based simulation (also used by Doran [1996]) will still be used.

3. UNHELPFUL CRITERIA FOR AGENCY

Having a clearer set of terms still does not help us to know how to best design an ABS. Looking up definitions of what an agent should be is also not very helpful. Most definitions [e.g. Davidsson, 2001; Doran, 2001; Gilbert and Troitzsch, 2000]) look to the field of DAI and use versions of the definition of agency supplied by [Wooldridge and

Jennings, 1995]. The problem here is that this definition is used for a particular application, DAI, in which software agents operate in a real world, be they robots moving around a room or software agents moving in different parts of the internet. In this case, whether or not a prospective agent meets these criteria is a functional fact. If the agent cannot communicate explicitly using a language, then it is dumb and no amount of interpretation of its actions will prove the contrary.

When these criteria are applied to simulations of agents, however, whether a criteria is met can depend on the use of metaphor, not on functionality. For example, in two functionally identical implementations of social imitation, [Lansing and Kremer, 1994] describe the imitation process as one of "communication" between neighbours in group meetings, whilst [Moss et al., 2000] describe it not only as communication but also as agents "observing" their "visible" neighbours' actions. Such use of metaphor to describe behaviour weakens the value of the criteria. Additionally, it is unclear whether Lansing & Kremer's version of communication is as worthy of passing the criteria of communication as a simulation that actually uses a language for communication between agents [e.g. Legeard, 1999]. A final problem is that it is unclear how many of the criteria need to be met for a prospective agent to be deemed an actual agent. A different approach to helping modellers design the right ABS for their needs is required.

4. THE CASE STUDIES

The approach taken in this paper is, therefore, to start from problem requirements, not terminology, in providing a key to choosing a suitable agent-based simulation design. In the rest of this paper, different requirements for environmental management models identified in Section 1 are matched to different techniques used in a representative set of cases of ABS found in a variety of different literature. With this key, prospective environmental modellers will be able to match requirements to techniques.

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

- the evolution of Balinese water networks [Lansing and Kremer, 1994] - from hereon referred to as the "Bali" model - this model investigates whether a specific Balinese system of water temple networks, managing irrigation practices, could have self-organised. Simulation is used to test this theory.
- the co-evolution of sustainable rangeland management [Janssen et al., 2000] - the "Rangeland" model - this model explores the range of possible collective responses of hypothetical pastoralists to regulators' policies for sustainability.
- lake management assessment [Janssen, 2001] - the "Lake" model - this model assesses farmers' collective responses to regulators' taxation measures for reducing phosphorus levels in a hypothetical lake.
- flood mitigation decision support [Legeard, 1999] - "MAGIC" - this is a tool in which various "expert agents" cooperate with each other in order to come up with decision support advice for human flood catastrophe response teams.
- urban water demand management [Moss et al., 2000; Downing et al., 2001] - the "Thames" model - this model investigates how social structure and learning affects the efficacy of a regulator's exhortations for consumers to save water as part of a drought management policy. The model has a specific region to model.
- animal waste management negotiation [Guerrin et al., 1999] - "Biomas" - this model explores possible negotiating strategies and outcomes used by simulated actors involved in managing the removal, transportation and processing of animal wastes.
- land use change [Polhill et al., 2001] - "FEARLUS" - this conceptual model investigates how well different social learning strategies employed by decision makers compete against each other in the face of a changing, heterogeneous environment.

4.1 Requirement One: Coupling Social and Environmental Models.

In environmental modelling, having an environment in which to embed agents is the first priority. Space can be represented either explicitly or non-explicitly. Typically, if spatial patterns or processes are not an important aspect of the modelling application, then a spatially non-explicit representation of space should be adopted. For example, a spatially non-explicit representation of space can be a database representation. However, in certain applications, e.g. modelling land use patterns, if the landscape spatial pattern is of interest, then a spatially explicit representation of the environment is required. Such a representation could be a GIS or a simple grid. Neighbourhood rules do not necessarily dictate the need for a spatially explicit environment as neighbourhood associations can be modelling aspatially in a database. Care should be given to this topic as each representation can affect the computational performance of a simulation model.

A spatially **non-explicit** representation is used in the Lake model, the Rangeland model and in the Thames model. In these cases the environment is simply a spatially abstract mathematical model linked to the agents. Making the link requires recognition that the environmental model and agents may be at different scales. The output from the environmental model may have to be distributed to individual agents. Conversely, individual agents' decisions affecting the environmental model may have to be aggregated in some way. In the Lake model, all agents interact with the whole lake. Each agent's decision about phosphorous use is therefore aggregated and an aggregate figure for phosphorous inputs is applied to the lake. Each agent therefore perceives the same overall figure for lake water quality calculated by the environmental model. In contrast, such issues are not problematic when, as in the Rangeland model, each agent has its own model representing their own area of the environment.

Spatially explicit environmental space can be represented either as a GIS or a simpler abstraction, e.g. a grid. The desire to accurately model a specific location is normally the driving factor in choosing the high-cost approach of embedding agents in a GIS. MAGIC is a good example of this in that it focuses on providing decision support for a particular region. A simpler approach is taken in the conceptual model of FEARLUS. In this model the environment is a grid-based representation of land parcels. Each grid cell contains the relevant attribute information pertaining to a land parcel. Their choice was appropriate to their exploratory goals of investigating how spatial factors, such as proximity to like-minded farmers, affects farmer decision-making. The same problems of scale have to be considered when linking agents to explicit environmental models.

4.2 Requirement Two: Micro-Level Decision- Making

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

The range of decision-making models used in the exemplars in this paper represents a continuum from sophisticated knowledge-based rule inferencing (e.g. MAGIC) to simple single behaviour agents (the Bali model). Decisions about complexity usually stem from the number of agents being modelled and the goal of the model. MAGIC uses distributed agents to come up with decision support for mitigating flood catastrophes. There are only three agents, each of which is responsible for generating recommendations for a particular flood situation. The issue is complicated, the numbers of agents are low, and each agent has to flexibly support the other with appropriate information, thus the agent design is complex. The agents have explicit perception and communication modules that are used to update a knowledge base. An inference engine is used to generate recommendations.

Further down the continuum are decision-making agents whose behaviours are decided by simple sets of rules. In Biomas, agents are closer in style to those in MAGIC, but not so sophisticated. They are greater in number and their rules are designed to control their negotiations over waste carriage and processing. The agents in the Thames model use rules to determine consumers' water use in response to climate and exhortations from a water regulator. This model represents a move towards simulations representing many agents (70+).

Other simulation models with large number of agents reduce the complexity of their agent decision-making by using objective functions. For example, in the Rangeland model, 100 pastoralist agents are simulated and the goal of the simulation exercise is to assess their aggregate response to management policies. Each agent is designed to decide on a stocking level by finding the level that results in a desired level of utility as calculated by an objective function. The FEARLUS model uses agents that calculate the financial returns from the adoption of each possible particular land use and then choose the use that maximises returns.

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

4.3 Requirement Three: Social Interaction

Of increasing importance in environmental modelling is to be able to explicitly represent social interactions [Downing et al., 2001]; interactions that may make a difference to environmental policy effectiveness. In the exemplars in this paper, social interaction is treated in a number of different ways, however it is important to note that not all agent-based simulations use social agents. As already mentioned, the Rangeland model represents none. The assumption has been made that pastoralist behaviour is not socially mediated.

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

Task based interactions. With the decision support agents in MAGIC, and the negotiation agents in Biomas, there is need for explicit message communication protocols to share knowledge, deliberations and in the latter case, offers. Both models represent distributed tasks, hence social interaction is task-centred whereby each agent interacts with only the agents it needs to perform the task.

Local social learning. In the Thames model, the psychological principle of consistency is used as a mechanism by which agents learn new behaviours. Agents thus only imitate agents that they know and that are similar to themselves. The social network is represented by a grid and knowledge of another agent depends on them being near that agent on this social network. Both the Bali and FEARLUS models have concentrated on the importance of the effect of spatial proximity on the spread of behaviours. The agents in their models imitate neighbours who are spatially close in the environment. In FEARLUS, this means that land managers must have land parcels that border each other on the environmental grid. Note that, although, the metaphor is different, both social networks and physical proximity can be modelled in the same way - by grids.

Global social learning. The Lake model refers to imitation and the psychological principle of social comparability to determine how the agents learn each other's behaviours. No network or space is represented. Rather, the agents can copy any other agent's behaviour.

4.4 Requirement Four: Adaptive decision making and behaviour

A further interest to environmental modellers is how to explore the change in or emergence of agent behaviour over time in response to management policies and / or environmental change. There are multiple strategy, fine tuning and evolutionary approaches.

Multiple Strategies - This refers to the modelling of agents as having more than one means of making decisions. Which one they choose will depend on environmental and personal circumstances that will change during the simulation. One possible approach to this is the use of the "consumat" model method [Jager et al., cited by Janssen, 2001] as used in the Lake model. In this model, the agent has a variety of decision-making methods (imitation, social comparability, repetition, and deliberation) and switches between them depending upon the agent's uncertainty and financial returns (satisfaction). An alternative method is provided by endorsements [Cohen, cited by Downing et al, 2001]. In the Thames model endorsement values are attached to particular rules which control whether or not the agent imitates, deliberates, or obeys authority. The endorsements function as a conflict resolution device. The rule with the currently highest endorsement is used.

Fine Tuning - These techniques are used to improve the decision making, rather than the behaviour. Agents can update their mental models of parameter values when a particular satisfaction criterion is not met (e.g. the Lake and Rangeland models). Or else they can update their rule-base with respect to new information gathered from the environment or other agents (e.g. MAGIC).

Evolutionary - In these approaches, behaviours rather than decision-making strategies of agents adapt to match the successful behaviours of others'. In this way, so the analogy goes, successful behaviours are selected for replication in the general population of agents. This can occur in two ways, through replacement or social learning (see Section 4.3). Replacement involves the removal of unfit agents and their replacement with agents which copy the currently most successful behaviour (e.g. in the Rangeland model). In evolutionary approaches the best strategies spread through a population over time until the time that policy or environment changes, when other strategies may take over.

When, using these approaches it is important to bear in mind the relevance of the evolutionary metaphor to the application problem. Do unfit pastoralists necessarily get replaced by the fittest ones, even ones that are not locally positioned? When replacement or imitation is carried out non-locally, the process approximates to a global search for the fittest behaviours. It is important to consider whether or not humans collectively decide on management policy through such a process of searching. Search might be useful for finding the hypothetically optimal set of management decisions for a particular environment, but not necessarily for modelling reality.

4.5 Requirement Five: Multiple Scale Level Decision-Making

The use of agents to represent different scales of decision-making is claimed to be an important benefit to understanding systems [Downing et al., 2001]. However, sophisticated modelling of multiple scales of agents is not being dealt with yet. Guerrin et al. [1999] refer to a future version of the Biomas model in which groups of individual agents will be able to self-organise in order to generate constraints regarding individuals' decisions. In other models (the Thames and Rangeland models) a single regulator agent is represented to oversee the activities of the individual agents. These agents are currently very simple reactive agents with no capacity for devising new strategies of intervention. More work needs to be done in this area.

In addition to the lack of multiple-scale level decision making, the case studies show that there are also many differences in the choice of scale level at which the decision makers are modelled. Despite the emphasis on modelling individuals in ABS, in these examples, only the MAGIC, Thames and Lake models explicitly model individuals. Of the others, FEARLUS represents families of land managers and the Bali model represents subaks - groups of irrigators.

Of particular interest is that Biomas not only represents human agents, it also represents physical objects as agents ("agents physiques"), such as "vehicles", and "breeding farms[1]". The physical agents are allowed to take an active part in the negotiation process involving the human agents. This process of representing non-individuals as agents has been referred to as *agentification* [Gaumé et al., 1999]. It is in the case of agentification that strict criteria for defining agency break down. In one sense, Wooldridge & Jennings' professed goal of providing criteria (see Sections 2-3), in order to prevent the term "agent" becoming a meaningless "noise" term, has failed. In another, the loss of the criteria brings some reality into the discussion of agents in simulation - agents should be designed to fit the modelling requirements, not to meet criteria developed for another field such as DAI.

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

5. TOWARDS A TAXONOMY: CLASSIFICATION OF CASE STUDIES

Organizing these requirements into an efficient taxonomic structure that makes sense to both experienced modellers and newcomers is a non-trivial task that will required continued debate. Creating such a taxonomy requires the development of a classification scheme for models that utilizes hierarchically arranged sets of characteristics. The more characteristics that are shared by two models, the closer they will be on the branches of a taxonomic tree. The development of such a taxonomy requires that these characteristics be first defined and then hierarchically arranged to form the taxonomic tree. Even this exercise is fraught with potential pitfalls that will require continued debate to resolve. Simple questions related to the characteristics that should be chosen and their hierarchical relationship will raise numerous questions. Franklin and Graesser [1996] point out that agents could be classified according to a subset of properties that they possess, the tasks they perform, their control architecture, or the programming language.

In Figure 1, we offer a simple, preliminary, taxonomic structure that classifies models by the requirements of those models. We believe this is an approach that is well suited to environmental modelling because it allows the classification of a wide range of models into general categories in a way that is informative to those who are new to the field or may be in the early stages of model development.

The taxonomic structure has two basic levels that differentiate models on the basis of the three of the requirements listed in the previous section (micro-level decision-making; social interaction and adaptive-decision making). While not exhaustive, focussing on these three requirements allows us to present a preliminary taxonomy complex enough to foster a discussion. The arrangement we offer here places the most potentially complex undertakings towards the base of the taxonomic tree. The highest branch on the taxonomic tree differentiates between models in terms of levels of agent social interaction implemented, ranging from less complex models with no interaction through to the most complex models involving group decision making. The next branch on the tree differentiates between models which implement different levels of adaptive decision making: none, multiple

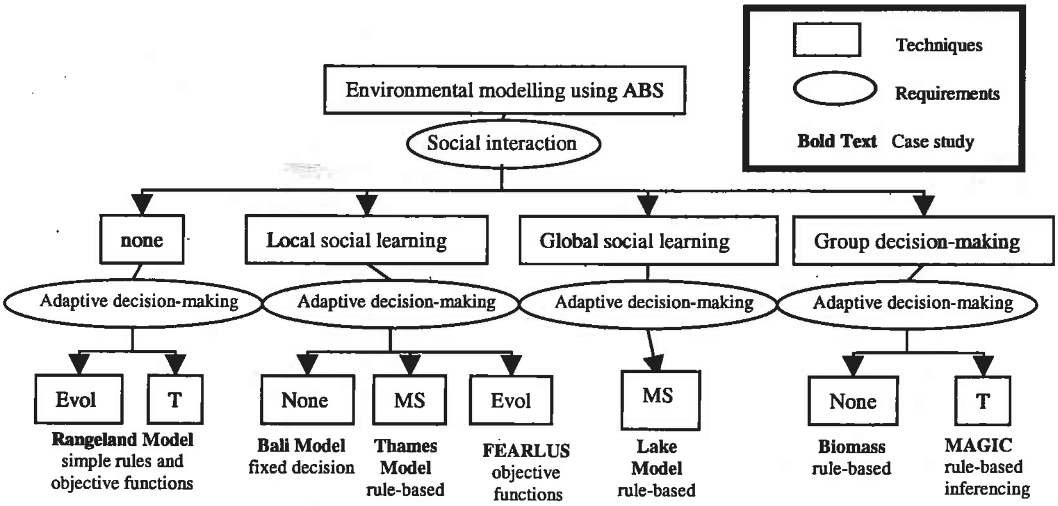

Figure 1. The taxonomic tree. Key to adaptive decision-making techniques: Evol - evolutionary; MS - multi-strategy; T - tuning. Description underneath case study name represents the basic decision making technique used.

strategy, fine tuning and evolutionary. In this case, the decision-making characteristics of the agents are viewed as being dependent upon the level of social interaction, as more complex social interaction in turn requires more complex decision-making abilities in agents.

6. CONCLUSIONS

This paper has begun disentangling the morass of terms used to describe agent-based simulation and as such recommends the use of only two existing terms for describing conceptually different sub-classes of this methodology: agent-based modelling and multi-agent simulation. The former describes simulations in which agent interactions rather than agent cognition are of topmost importance. The latter describes simulations in which social cognition plays an important role.

Clearer terminology alone does not help to know how to best design an ABS. A selected set of seven case studies have therefore also been examined and from them a classification scheme has been developed as a stepping-stone to the development of a full taxonomy. The taxonomy is intended to be used by modellers to match their modelling requirements to state-of-the-art ABS techniques. Clearly, the taxonomy presented here is a first step, designed to provoke discussion and feedback. A number of questions will require further development of the taxonomy before they can be addressed, e.g., additional model requirements, such as those related to scales of decision making, could have a place in a taxonomic tree.

Already, the taxonomy can provide salutary information. It shows, for example, how the Lake model is in a minority among social learning case studies since it uses a social learning technique based upon global, rather than local agent interactions. Its isolation is probably not a coincidence since, as already discussed, one reason why agent-based simulations are so useful is because they can generate emergent phenomena, the generation of which is important to study if more is to be understood about the development of collective environmental management practices. However, a precondition of emergence is that agents are able to interact locally [Cariana, 1991]. Thus, the Lake model does not exploit the facility of emergence that ABS offers and, arguably, this omission weakens its scope and conclusions.

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

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