Integrating Agent-Based Social Models And Biophysical Models

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EXTENDED ABSTRACT

Spatially and temporally explicit simulation modelling of natural resource management systems provides a framework to draw together in a mathematically unambiguous manner a wealth of information, and, as such, allows rigorous testing of hypotheses of how such systems can be changed, without the time, expense and moral implications of altering a real system. In recent years, a large number of integrated assessment models linking the human and biophysical components of particular systems have been developed to address this need, but in many of these models the human dimension is based on economic cost-benefit principles that attempt to optimise use of resources such as capital or labour to maximise a particular output. Limitations to these approaches are that they are structured to represent an equilibrium when production has stabilised, they presuppose a 'goal' of the system, and do not adequately consider the micro-decisions being made by the various actors within it.

Agent-based modelling (ABM) is an approach that has been receiving attention in recent years as a way of linking the biophysical and socio-economic characteristics of a system, and which provides a way of addressing these limitations. ABM has aroused the interest of environmental modellers, mainly because it offers a way of incorporating the influence of human decision-making on the environment in a mechanistic and spatially explicit way, taking into account social interaction, adaptation, and multiple scales of decision-making. Several such models are now beginning to appear, many of which involve the grafting of an ABM representing a number of households onto a cellular automata 'landscape', with each agent being linked in some way to the cells over which it has influence. Apart from changes in actual land cover, however, these models generally treat the landscape as a relatively static entity, and do not simulate processes such as soil water and nutrient dynamics. The ones that do include such processes, do so somewhat simplistically.

There is a need, therefore, to integrate dynamic biophysical simulation models with these emerging agent-based social simulation models. Different approaches to integrating such models are recognised – one such scheme refers to 'loosely-coupled', 'closely-coupled', and 'fully integrated' levels of integration. Loose- and closely-coupled models exchange driving variables between them, with closely-coupled models sharing common sub-processes, meaning that temporal and spatial scales may be determined by the original (sub-)models being coupled together. By contrast, in fully integrated models, these scales are dictated by the processes being simulated. It is our view that it is necessary to focus on the fully integrated level in developing models to adequately understand the behaviour of managed ecosystems.

We discuss an agent architecture that allows agents to communicate regardless of the programming language used – each agent should have a translation module that translates incoming messages and triggers the appropriate internal response, and a conversation module which checks ingoing and outgoing messages, and manages communications between multiple agents. The overall system should be coordinated by manager and router agents to ensure the provision of global information and correct delivery of communications between agents, respectively. To link this to different sub-models of biophysical processes, a limited number of common properties of the sub-models are required: (a) each sub-model must have the ability to advance one time-step on request, (b) it should be able to save the states of all its variables at the end of each time-step on request, and be able to reload these later, also on request, (c) it must be able to respond to predefined message requests for information, and (d) the calculation of rates of change of its state variables must be separate from the updating of those state variables, with both operations being carried out on request.

There is a danger that such models become too complex – it is suggested that the best way forward may be to take a simple framework as the starting point, and incorporate additional detail as necessary to describe the processes of interest.

1. INTRODUCTION

There is a growing awareness that single factor-based research has been inadequate in addressing many environmental problems, and that more interdisciplinary approaches are required, in which account is taken of human and biophysical processes interacting together. Some authors have conceptualised this as a need to integrate the *geosphere* (the inanimate world), the *biosphere* (the animate world), and the *noosphere* (the conscious world) (e.g. Naveh, 2001); others have seen it as a combination of the social, economic and natural sciences (e.g. Gunderson & Holling, 2001). Either way, the essential idea is that humans are seen as an integral part of the systems being considered, rather than as impartial observers or external drivers influencing ecosystems but not being influenced by them, as has often been the case in ecological studies, or, conversely, being influenced by the environment but not influencing it, as has been the case in neoclassical microeconomics.

However, as it is not usually possible to manipulate such 'socio-ecological' systems experimentally, there is a clear need for modelling studies to explore how such systems work. In recent years, a large number of integrated assessment models linking the human and biophysical components of particular systems have been developed to address this need, but in many of these models the human dimension is based on economic cost-benefit principles that attempt to optimise use of resources such as capital or labour to maximise a particular output. Limitations to these modelling approaches are that they are structured to represent an equilibrium when production has stabilised, they presuppose a 'goal' of the system, and they do not adequately consider the micro-decisions being made by the various actors within it. Indeed, it has even been argued that the assumptions used in these models are flawed and that their predictions are untrustworthy (e.g. Moss *et al.*, 2001). For example, Becu *et al.* (2003) showed that the common practice of planting rice in the wet season in Thailand could not be justified on the basis of an economic analysis alone, noting that it is mostly motivated by socio-cultural preferences and household food security strategies.

Agent-based modelling (ABM) has aroused the interest of environmental researchers recently, mainly because it offers a way of replacing differential equations at an aggregate level with decision rules of entities at a lower level (i.e. individuals or groups of individuals) along with the appropriate environmental feedbacks. Originating from the fields of distributed artificial intelligence and artificial life (depending on the level of detail with which cognition is represented (Hare & Deadman, 2004)), and with parallels with Individual Based Modelling (IBM) in ecology (Huston *et al.*, 1988), agent-based models consist of a number of 'agents' which interact both with each other and with their environment, and can make decisions and change their actions as a result of this interaction (Ferber, 1999). Agents may contain their own 'mental model' of their environment (which may not necessarily be complete or even true) built up from its interactions with it. The behaviour of the whole system depends on the aggregated individual behaviour of each agent. This allows the influence of human decision-making on the environment to be incorporated in a mechanistic and spatially explicit way, also taking into account social interaction, adaptation, and multiple scales of decision-making. Agents can interact either through a shared environment and/or directly with each other through markets, social networks, and institutions. Higher-order variables (e.g. commodity prices, population dynamics, etc.) are not specified as they are in conventional mathematical programming techniques or econometrics, but, instead, may be emergent outcomes. A number of such agent-based models are now beginning to appear (see recent reviews by Parker *et al.*, 2002; Bousquet & Le Page, 2004), many of which involve the grafting of a multi-agent system representing a number of households onto a cellular automata 'landscape', with each agent being linked in some way to the cells over which it has influence. Apart from changes in actual land cover, however, these models generally treat the landscape as a relatively static entity, and do not simulate processes such as soil water and nutrient dynamics (e.g. Balmann *et al.*, 2002; Deffuant *et al.*, 2002). Some do include such processes, but somewhat simplistically –Lim *et al.* (2002), for example, use multiple regression equations for changes in soil characteristics and estimations of crop yields.

However, as the interactions between humans and their environment are two-way, in that actions occurring as a result of human decisions affect aspects of the environment, which in turn may influence further decisions made, it would seem important, if we are to deepen our understanding of the way socio-ecological systems function, to represent environmental processes in an acceptably realistic way. Thus, there would appear to be a need to integrate existing dynamic biophysical simulation models with these emerging ABMs. However, due to different disciplinary paradigms and model architectures, this is not a straightforward exercise. In this paper, we examine when it is appropriate to combine social and biophysical models, and discuss approaches to linking them.

2. WHEN SHOULD WE COMBINE SOCIAL AND BIOPHYSICAL MODELS?

Although not all problems lend themselves to coupling social and environmental processes, there are many cases where human-environmental interactions are non-linear, with the environment being affected by human decisions which in turn impact on the environment, potentially leading to complex systems behaviour, and when there is path dependence (in which the state of a system depends on its starting position and the route it followed to get there). For example, gradual changes in slow variables can result in thresholds suddenly being reached when unexpected behaviour may be triggered (Scheffer & Carpenter, 2003; Walker & Meyers, 2004). In such cases, it is important to know under what conditions the dynamics of a socio-ecological system become unpredictable or radically change its mode of functioning, and what the impacts of different human responses are likely to be. Such ‘catastrophic’ behaviour can often be accompanied by hysteresis, when the forward trajectory of a process is not the same as its return trajectory. Carpenter & Cottingham (2002) give an example of the build-up of phosphorus in lakes causing a sudden change in the eutrophication level to a new stable state which is difficult to reverse even if the phosphorous level is lowered.

3. APPROACHES TO COMBINING SOCIAL AND BIOPHYSICAL MODELS

There are various approaches to classifying and understanding work that couples models together, with several authors having identified three levels of model integration. Hartkamp *et al*. (1999), for example, used the terms ‘linking’, ‘combining’, and ‘integration’ when discussing the coupling of GIS with environmental process models, with ‘linking’ referring to exchanging data as input and output between the GIS and the model, ‘combining’ to exchanging data and functionality, and ‘integration’ to a complete embedding of a model within a GIS or *vice versa*. A comparable scheme was proposed by Antle *et al*. (2001) who referred to ‘loosely-coupled’, ‘closely-coupled’, and ‘fully integrated’ levels of integration. Loose- and closely-coupled models exchange driving variables between them, with closely-coupled models sharing common sub-processes, meaning that temporal and spatial scales may be determined by the original (sub-)models being coupled together. By contrast, in fully integrated models, these scales are dictated by the processes being simulated. Similarly, Westervelt (2002) used the terms ‘loose’ for when the programs run independently and exchange data using ordinary text files, ‘moderate’ for when they run independently but exchange information using specialised files, and ‘tight’, for when the agent-based model and GIS are compiled into a single program. Antle *et al*. (2001) argue that it is necessary to focus on the fully integrated level in each case in developing models that adequately capture the behaviour of managed ecosystems.

Clarke & Dietzel (2004) noted that when they coupled a biophysical model to a social model the result was something that only the developers could understand. Frysinger (2002) also expresses concern about what he calls tightly coupled models (which corresponds to the closely coupled classification of Antle *et al*. (2001)), arguing that modifying the code of one model to couple it with another could interfere with its functionality, raising questions over the quality of the result. He suggested modular designs as an approach to addressing this issue. Modularity is one of the key benefits of object-oriented (OO) programming, and many commonly used programming languages (Java, C++, Objective-C and Delphi) offer OO functionality. However, classes in object-oriented programming languages are still open to misuse, especially, as is often the case, if appropriate documentation for the source code is not available. Agent-oriented (AO) design approaches (Deloach et al., 2001; Bauer et al., 2001; Wooldridge et al., 2000), which entail a much stronger concept of encapsulation (Wooldridge et al., 2000, p. 307), may offer a more rigorous alternative, particularly if the software agents[1] are self-describing.

Kuhlman (2004) outlined four key challenges when coupling models, based on his experience involving linkages among no less than seven models. Firstly, there may be differences in the understanding of the scenario among members of the interdisciplinary team. Next, there may also be variations in the underlying assumptions among team members, and hence in the sub-models. Thirdly, there can be multiple sources for what are essentially the same data, with the various sub-models not necessarily all using the same source. Finally, there can be overlap in functionality between sub-models. This last point is worth emphasising, as it presents a critical technical issue with integrative efforts that fall under the loosely- and closely-coupled, rather than fully integrated, classes of Antle *et al*. (2001). Two (or more) sub-

[1] Software agents should not be confused with the concept of an agent in an agent-based model.

models that, for one reason or another, happen to contain subcomponents representing the same real world phenomenon, are at risk of telling a different story about the fate of that phenomenon in the coupled whole, with potentially disastrous knock-on effects on other sub-components and sub-models that take input from them through feedback loops. This is a particular vulnerability in coupled systems with models that simulate the shared subcomponent at different spatial or temporal scales, or use dissimilar data structures and algorithms to represent its state and processes. Clearly, any coupled model where, for example, a bumper harvest and a severe crop failure could feasibly occur in the same place at the same time is not one to be trusted. An approach that begins with a shared ontology, as stipulated by full integration, should avoid such undesirable consequences.

Full integration of models poses the greatest challenge in terms of required effort, but it is also the most rigorous as it ensures common understanding of underlying assumptions and theories. Any associated modelling software will be designed to meet the needs of the integrated work, instead of the work having to be fitted around constraints and assumptions of existing software. Examples of such integrated approaches include the integrated catchment assessment model of Scoccimarro et al. (1999) in northern Thailand, and the integrated urban development and ecological simulation model of Alberti & Waddell (2000).

4. HOW DO WE COMBINE SOCIAL AND BIOPHYSICAL MODELS?

There is a temptation to exploit the reusability of object-oriented software, and develop modular frameworks that can be used in a number of studies relating to coupled biophysical and socio-economic systems. There are ways in which this enhances rigour, as standardised free programming libraries create a shared resource that avoids remaking common errors in development of such software, whilst allowing corrections, enhancements and bug-fixes to be made quickly. Though not common practice, appropriate annotation of the modular components using semantic grid concepts (de Roure *et al.*, 2001) would facilitate the development of an ontology from the bottom-up (based on the modules used), allow potential conflicts in domain assumptions to be automatically detected, and create a searchable resource that is reusable by a wider community. However these benefits of standardised platforms should be weighed against the risk they create of a single point of failure: any mistakes or errors in the code will appear in the work of all scientists using it as the basis of their work. These issues can apply to seemingly trivial aspects such as use of random number generators (van Niel & Laffan, 2003) and floating point arithmetic (Polhill *et al.*, 2005a; Polhill *et al.*, 2005b), as well as more substantive issues such as representation of spatial data (McNoleg, 1998; Hauert & Doebeli, 2004) and scheduling (Kirchkamp, 2000).

Standardised libraries to facilitate development of simulation models are by their very nature tied to particular programming languages, preventing developers from choosing programming languages that best suit the task, meaning that they become the servants of the technology rather than the converse, as should be the case. Worse, libraries are not always available on all platforms, meaning that the choice of operating system and underlying hardware may also be undesirably constrained. Finally, the licensing of such libraries that is required to ensure standards of scientific rigour may contravene policies of less enlightened research institutions relating to intellectual property rights. The worst possible scenario from a scientific point of view is that an international standard relies on proprietary software that cannot be inspected, modified, and bug-fixed by the community using it to conduct their studies. Since issues can potentially derive from any software involved in the development and use of the framework, this point applies to the operating system and compiler (or interpreter) as well as the programming libraries themselves. A framework built around the semantic grid, however, need not be so vulnerable to these issues. A suite of resources, some of which implement the same utility, can be built using a variety of programming languages, avoiding reliance on any one library, operating system, or hardware platform. With appropriate modularity in the design of such a framework, and compositional modelling tools to facilitate model development, researchers would be able to check the ‘algorithmic sensitivity’ (Edwards et al., 2005) of their work.

Mentges (1999), recognising that a unified modelling and simulation language for agent-based simulation is unrealistic, proposed instead a modelling framework consisting of a number of layers with increasing abstraction levels. Models can be developed within any layer without knowledge of the specifics of models in other layers. On the lowest layer, agents communicate by exchanging messages using the quasi-standard agent communication language KQML (Mayfield *et al.*, 1996). On the next level up, common message sequences can be defined as basic building blocks of communication between agents. In the third layer, agents are given generic role properties determining goals, responsibilities, task and expertise, which can be used as the building blocks of more specialised heterogeneous agents. Mentges (1999) then proposes an agent architecture that allows agents to communicate regardless of the programming language used – each agent has a translation module that translates incoming KQML messages and triggers the appropriate internal response, and a conversation module which checks ingoing and outgoing messages, and managing communications between multiple agents. The whole multi-agent system is coordinated by manager and router agents to ensure the provision of global information and correct delivery of communications between agents, respectively. Such an approach allows the distributed design and distribution of models, with sub-models even in different geographical locations.

A prototype of such an approach has, in fact, been implemented in the PALM model of farming systems in Nepal, in which not only households are agents with decision-making capability, but the landscape components and livestock are also reactive agents (Matthews, 2006). Each agent can send and receive messages from other agents, and indeed, can only interact with other components of the system via KQML messages (Figure 1). For example, if a household agent wants to know the state of one of its fields, it sends a message to the landscape agent requesting the information that it requires, to which the landscape agent will respond with another message containing the information, provided it has been able to interpret the requesting message. Messages can be requests for information, as in the example just given, or commands to carry out specified actions, for example to plant a crop on a certain date, which would result in a method within the landscape agent being called to plant the crop.

For different sub-models to interact in this way, a limited number of common properties are required: (a) each sub-model must have the ability to advance one time-step on request, (b) it should be able to save the states of all its variables at the end of each time-step on request, and be able to reload these later, also on request, (c) it must be able to respond to predefined message requests for information, and (d) the calculation of rates of change of its state variables must be separate from the updating of those state variables, with both operations being carried out on request. This last requirement allows all of the different sub-models to calculate their rates of change before any updating is carried out, approximating parallel running of each sub-model.

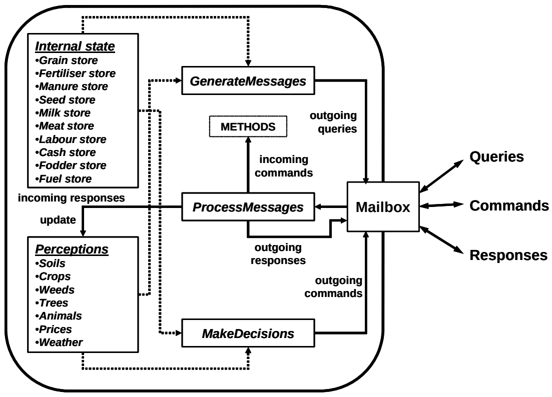

Figure 1: Internal structure and flows of information in a household agent in the PALM model (from Matthews, 2006).

5. MODEL COMPLEXITY

A key issue underlying all of these activities is that of complexity, which poses a dilemma for modellers. On one hand, there is the general preference of policy makers for simple explanations (Couclelis, 2002) so that they can justify their decisions to their constituencies, members of which may not be so appreciative of highly complex systems. On the other hand, there is no escaping the fact that socio-ecological systems are complicated systems in that a significant number of components interact with each other, and may also be complex adaptive systems in that they are path dependent with their current and future states depending on their history, and may exhibit nonlinear behaviour, self-organised criticality and clustered volatility (Bak, 1994). Certainly the complicatedness, and possibly the complex nature of such systems, require sufficiently detailed models to be developed in order to capture behaviours that would not be possible with simpler models. Thinking has moved on from the view that such systems can be modelled using a few elegant mathematical expressions to developing sophisticated software products with many tens, if not hundreds, of thousands of lines of computer code.

However, given that all models are simplifications of reality, the dilemma is what constitutes 'sufficient detail' for such models. One school of thought, referred to as 'greedy reductionism' by Pinker (2002:69), argues that increasingly detailed models are required that are capable of simulating processes at finer and finer levels. A contrasting point of view is that simpler frameworks, more readily aligned with end-users' modes of action, are required (e.g. Shorter *et al.*, 1991). The two approaches may not necessarily be mutually exclusive – the best way forward may be to take a simple framework as the starting point, and incorporate additional detail as necessary to describe the processes of interest. A danger of this approach, which needs to be guarded against, is that the resulting model may reflect the prejudices of the user, and only contain the components that he/she thinks are important.

6. CONCLUSIONS

Many of the environmental problems facing modern society can only be addressed by taking account of the social, economic and biophysical components of managed ecosystems. There is, therefore, a need to develop simulation models that link these components. Different approaches to linking existing models for each of these components are discussed, but it is suggested that the fully integrated models, with shared ontologies for each of the model components, is probably the best way forward, albeit the most challenging. A balance must be struck between incorporating enough sophistication in such models to capture all the relevant processes, and keeping them simple enough so that understanding of these processes and their interactions is not obscured.

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