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Hybrid modelling of complex ecological systems for decision support: Recent successes and future perspectives

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A B S T R A C T

Hybrid models combine multiple modelling approaches to represent complex, integrated systems of human and biophysical components. These models are highly data driven, and serve to aid in pattern extraction and knowledge synthesis, providing an important link between data sources and decision support. By allowing the simulation of the many emergent plausible futures for complex systems, hybrid models will become increasingly important decision-support tools.

Contents

1. Introduction

Over the last ten years, the field of ecological informatics has seen rapid growth in the area of *hybrid modelling* – the integration of multiple modelling approaches and technologies borrowed across the disciplines – to represent the structures and dynamics of ecosystems. Such hybrid models may combine approaches from artificial life and evolutionary computing with systems models, ecological process-based models or spatial models from geographic information systems, for example. This hybridization of approaches has been driven by the increasing need to deal with and adequately represent the true complexity of ecological systems, as well as the growing interest in modelling integrated systems of human and biophysical components. Ecological modelling is thus becoming progressively more multidisciplinary, as modellers seek to expand and diversify their repertoire of tools.

Modelling is an important step in data integration and knowledge synthesis. Models serve to represent the patterns extracted from data

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and to test hypotheses about the processes and mechanisms that generate these patterns. Modelling is thus an integral part of the field of ecological informatics, as it forms the bridge between data sources and decision support (Recknagel, this issue). As decision support tools, hybrid models provide natural resource managers with the ability to better understand the current dynamics of their system, as well as to explore plausible futures given different management scenarios. In this overview, I will present some of the recent conceptual and technical advances in hybrid modelling for decision support and will then discuss future challenges and perspectives for the discipline.

2. Recent advances in hybrid modelling

2.1. Conceptual advances

It is becoming increasingly clear that ecosystems are complex systems and thus should be studied within the conceptual framework of complex systems studies (Harris, 2007; Levin, 1998; Levin, 1999). A complex system can be defined as any system composed of multiple interacting components, whose combined behaviour gives rise to aggregate structures and functions, the presence of which typically feeds back upon and affects the behaviour of the underlying components (Parrott, 2002). The concept of hierarchy is thus important, since a complex system cannot be studied at a single resolution. The entities (patterns, processes) observed at one scale or resolution are understood as being the emergent result of interactions at a lower level. The study of complex systems thus requires a multi-scale approach, in which interactions occurring across many scales of space, time and organization, are taken into account (Fig. 1). It is the presence of such cross-scale interactions that gives rise to a non-linear dynamics in space and time that makes pattern recognition, prediction and forecasting extremely difficult for all complex systems.

Within this framework, ecological dynamics is perceived as being the aggregate result of: 1) interactions between individuals, 2) interactions between individuals and the biophysical environment, and 3) the feedback between group or community-level processes and individual behaviour. Given that ecosystems are open systems in constant interaction with the external environment, these interactions and feedbacks are not occurring in isolation and are continually mediated by environmental variability (Anand et al., 2010). Memory effects due to the historical legacy of past events are also extremely important in determining the future trajectory of a system (Foster et al., 2003). Lastly, the human domination of land use and of most hydrological and chemical cycles on Earth has tightly coupled the human-environment interface over the past century, making it increasingly difficult (and perhaps even irrelevant) to study ecosystems separately from human systems (Foley et al., 2005; Wackernagel et al., 2002). Ecological dynamics is thus closely intertwined with the dynamics of human systems, adding an additional dimension of complexity to conceptual models (Liu et al., 2007a; Liu et al., 2007b; Ostrom, 2009).

2.2. New approaches

Over the past 20 years, much of the development in ecological modelling has been focused on reproducing the multi-scale structure of ecosystems and the emergent dynamics that result from interactions between components within and across scales as well as across coupled sub-systems. The field has thus evolved from the simple population models widely studied in the 1970's (May, 1973), to more integrated representations of the multiple facets of a functioning ecosystem. Systems approaches present ecosystems as complete systems of interlinked stocks of materials with flows between them, and in some examples present the human system in terms of its pressure on flows (Boumans et al., 2002; Guo et al., 2001; Odum, 1968). Through its emphasis on inclusivity of all components of a system, and the importance of flows, interactions and feedback between components, the systems perspective is complementary to modern conceptual models of complex systems. The conceptual approach of complex systems studies adds, however, several additional dimensions – notably, hierarchy, aggregation and emergence – to a systemic representation of the ecosystem.

Thus, today's models must be able to adequately represent many of the complex features of ecological structures and dynamics, namely: hierarchy and cross-scale interactions, self-organization and emergence, evolution and adaptation of components, non-linearity and uncertainty. For this reason, an "object-based" approach (*sensu* Parrott and Kok, 2000), in which entities such as individual organisms, human stakeholders or parcels of land are represented as distinct objects is typically privileged. Object-based models include cellular automata (Hogeweg, this issue), agent- and individual-based approaches (Bonabeau, 2002; Grimm and Railsback, 2005; Parrott, 2008)(Fig. 2). Object-based modelling is generative, or "bottom-up", in that, by modelling entities and their interactions at a low level in the organizational hierarchy, higher-level entities are allowed to emerge via simulation (Fig. 3a). Thus, the approach very closely follows the hierarchical conceptual model of complex systems (Parrott and Kok, 2000).

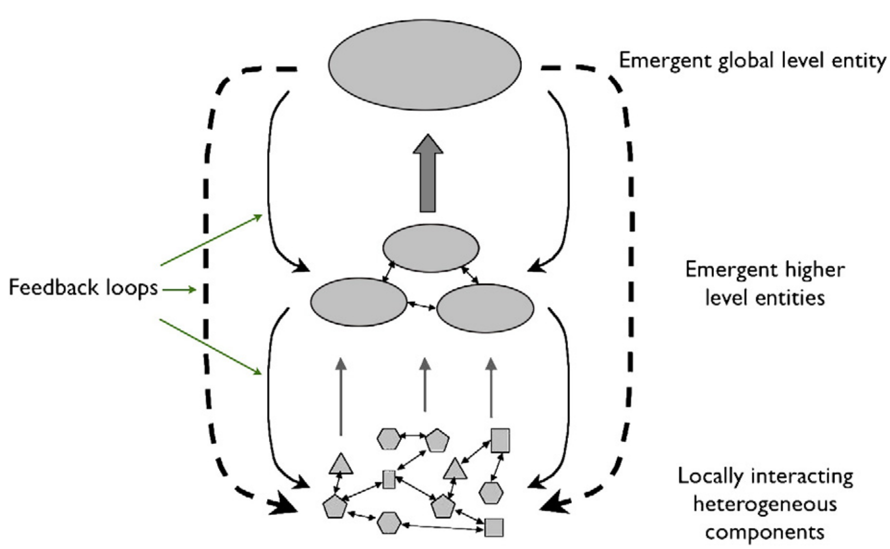

Fig. 1. A conceptual model of a complex system (adapted from (Parrott, 2002)).

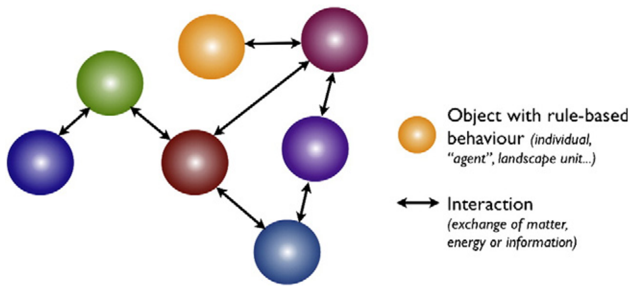

Fig. 2. Many hybrid models of ecological systems use an object-based approach. In this approach, the individual entities in the system (such as individuals, stakeholders, land units) are represented as distinct objects that interact according to rule-based functions or heuristics.

Object-based models have been used in ecology since the 1990's (see (Judson, 1994; Kawata and Toquenaga, 1994) for early reviews). Many ecological models have successfully reproduced spatial vegetation and animal foraging or movement patterns using object-based approaches. For example, Wootton (2001) developed a cellular automata model of an inter-tidal ecosystem in which 15 species competed for space on the rocks. Through simple, local transition rules, the model successfully reproduced the species abundance curves for the real system and demonstrated the importance of wave action (disturbance) in determining the system's spatial structure. Cellular automata models of vegetation in arid zones have also successfully reproduced empirically observed banding and clumping patterns based on local interaction rules (Thiery, 1995). For non-sessile organisms, individual-based models have been widely used in ecology to reproduce patterns of movement or social foraging, demonstrating again how locally applied rules can lead to the emergence of population or group level behaviours from the bottom-up. Examples include the BOIDs model (Reynolds, 1987) of flocking birds, the success of which has inspired many other models of mass movement (Couzin et al., 2002). Individual-based models have also been developed for social insects, showing how collective foraging patterns can emerge from simple rules defining individual behaviour and feedback from environmental cues (Camazine et al., 2003).

The past 10 years has led to the increasing hybridization of object-based models in ecology with the fields of machine learning and evolutionary programming to simulate awareness, decision-making, learning and goal-orientation within individuals and agents. Evolutionary programming has been used to evolve behavioural rule sets

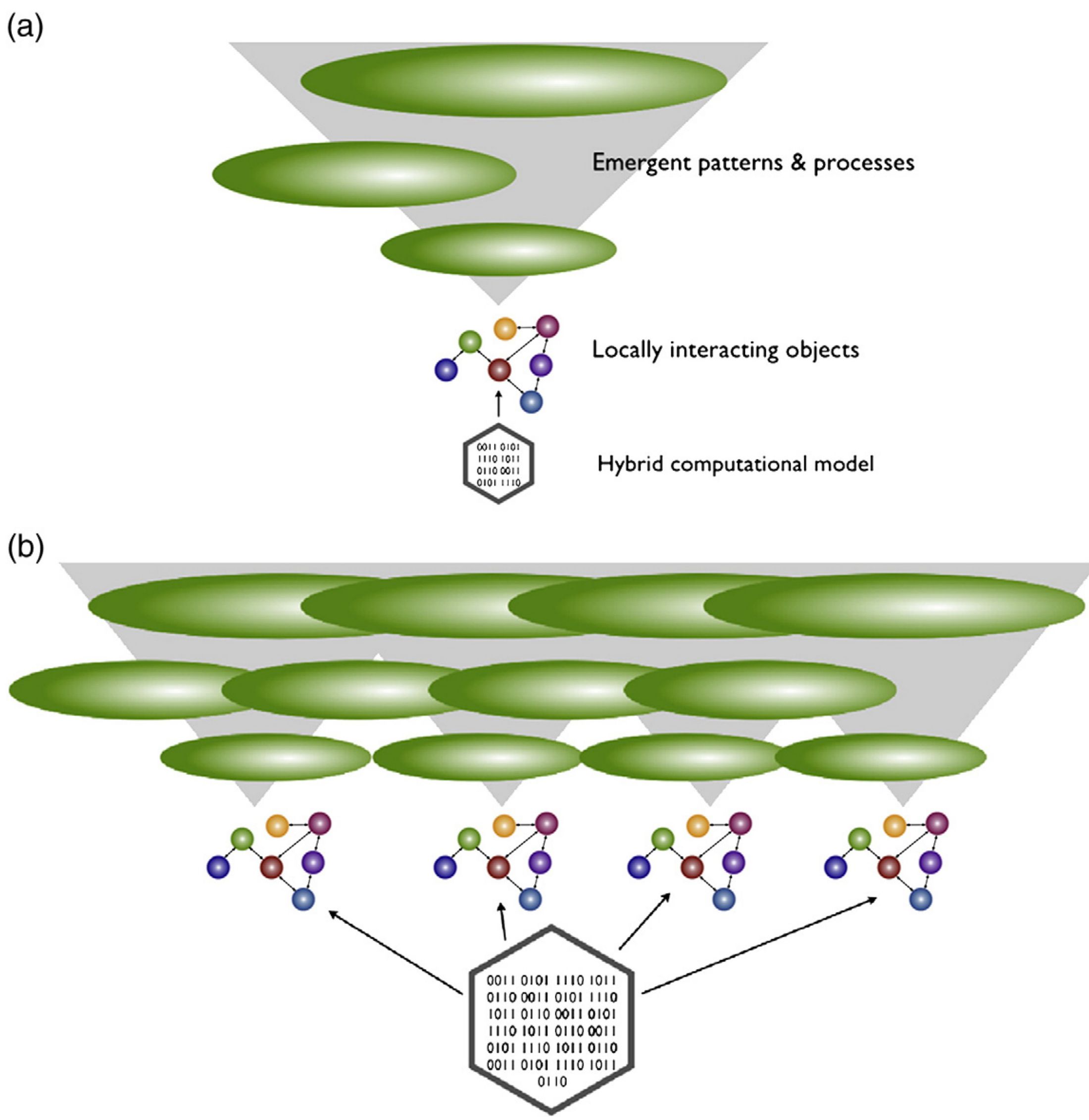

Fig. 3. (a): Following the conceptual model of an ecosystem as a complex system, an object-based approach allows the simulation of emergent structures at higher levels of organization. (b): An object-based model can be used to simulate the emergence of multiple future states for a system.

(Manson, 2005), neural networks and genetic algorithms have been used to represent an individual's memory and behavioural response to environmental stimuli (Morales et al., 2005) and modern techniques in cognitive engineering and heuristics are applied to represent agent decision-making (Manson, 2006; Valbuena et al., 2010). The representation of cognitive individuals and agents that are truly capable of learning and adapting their behaviour and re-assessing their goals is one of the current challenges for ecological modelling. Accomplishing this feat may permit the simulation of non-trivial emergence in complex ecological systems, enabling the exploration of a wider range of possible future states for systems subject to accelerating rates of environmental change and increasing dominance by human activities.

3. Hybrid models for decision-support

Many of the hybrid models developed today are applied to guide decision-making in natural resource management. There are a number of excellent examples of models that combine bottom-up approaches such as those described above with sophisticated spatial models of the environment to represent a real system. The spatial environment is often represented by a static, multi-layer model coming from a geospatial database but may also include one or more dynamic components. For example, many agricultural land use change models couple a detailed spatial hydrological model with static descriptors of soil quality and topography to represent the landscape in which farm or household agents interact (Berger, 2001; Le et al., 2008). Models designed to support management of protected areas for diversity conservation often include detailed spatiotemporal representations of habitat dynamics coupled with agent-based models of human activities and individual-based models of flora and fauna of special concern. All of these models are highly data driven, requiring sufficient information about individual or agent behaviour under multiple circumstances, so as to develop and validate object rules, as well as requiring detailed spatial and temporal environmental data.

3.1. Models of socio-ecological systems

Hybrid models developed for decision-support typically represent a socio-ecological system in which the human dimension is an integral component and driver of system dynamics. This can be done explicitly, by including human agents in the model that make decisions and modify their environment, or via a user interface that allows real humans to pause a simulation at desired intervals, intervene and then allow the simulation to proceed. Land use change models incorporating farm or household agents that make cropping or other decisions that affect the local environment are examples of models that incorporate humans explicitly. Companion modelling techniques and interactive simulations allow human users to directly intervene in the virtual system (Bousquet et al., 1999; Hauhs and Lange, 2006). Alternatively, humans may be included implicitly in the model, by programming certain environmental variables to fluctuate according to known or predicted trends as a result of human activities. Examples include models in which habitat quality or availability is made to change automatically during the course of a simulation or models that use climate change scenarios as environmental inputs to a simulation (Matthews et al., 2007; Parker et al., 2003).

3.2. Scenario building

Current research in complex systems suggests that forecasting or predicting the future of a complex ecological or socio-ecological system cannot be done with precision. Models should not be used to predict the future of these systems, but should rather serve as platforms with which the potential response of the system, given in terms of envelopes of possible future states, can be explored (Lempert, 2002; Parrott and Meyer, 2010). Thus, rather than providing a user with a single response, models used in decision-support systems should provide a range of plausible futures for the system. Models should be designed to simulate the full variety of potential emergent system responses to a given management or intervention scenario (Fig. 3b). Users may then explore how a given intervention or disturbance may change the shape or volume of this envelope of possible future states, rendering some states unattainable or others more probable. Actions and interventions can then be discussed in terms of risk and probability of the system ending up in an undesired state. By simulating real systems from the bottom up, using the most recent techniques in evolutionary computing and other fields, hybrid models may achieve this goal.

3.3. Visualization

Visualization of real and simulated data is an important component of any decision-support system. Hybrid models often provide visual support, being linked with geographic information systems (GIS), virtual globes (using technology such as Google Earth or NASA's WorldWind) or sophisticated animation systems that allow the user to immerse him/herself in the virtual world (Hauhs and Lange, 2006). Such technology is extremely important for knowledge transfer and the communication of simulation results. Having tangible (albeit virtual) and highly visual model output makes research results much more accessible to the end user and the general public. Future work in hybrid modelling for decision support should further exploit the visualization possibilities that are available and make high quality visualization an integral component of model development.

4. Outlook

In reality, the drivers of change in a complex ecological system are both bottom-up and top-down. For example, individuals compete with one another locally for space and light, thus structuring their immediate environment from the bottom-up, but policy decisions from the human system with which the ecosystem is coupled may designate the area as a potential building site, creating a top-down pressure. The current challenge in ecosystem modelling is to adequately capture the balance between bottom-up and top-down drivers of change and to represent the links and feedbacks between the scales (Verburg, 2006). Seminal work in cellular automata modelling of land use change (Engelen et al., 1997; Engelen et al., 1995), in which multiple layers of spatial arrays at different resolutions are coupled together, provide examples of how cross-scale interactions can be included.

Finding solutions to the hierarchical challenge will also lead to the development of more creative models that permit *structural emergence*: the generation of new institutions or objects (as opposed to simple emergence of aggregate groups or patterns) within a system (White, 2009). Currently, most programming frameworks do not permit the spontaneous creation of new, unforeseen objects and, similar to the problem of simulating consciousness or intelligence, it is unclear how such true emergence may be modelled. It is clear, however, that if the hybrid models of the future are to simulate the entire envelope of possible future states for a system, and not just an easily reachable subset, then models will have to become more creative and flexible, with structural emergence becoming a real possibility. For example, current modelling approaches put human institutions outside the model (and implicitly include their actions as imposed management plans or external pressures on the system) or else these institutions are explicitly included, but the possibility that agents coordinate their actions to create new institutional entities that can then have regulatory and decision-making power is currently beyond the scope of today's modelling techniques. This limits the predictions of models to future states that are within the realm of what is currently foreseeable, leaving out states that can only be reached via structural evolution of either the social or ecological system. With current demands on modellers to explore the effects of climate change on biodiversity, habitats and human communities, models must do more than simply reproduce known patterns. The hybrid models of the future must enable the emergence of true novelty and creativity so as to explore how complexity may lead to a diversity of system responses and adaptations.

5. Science or science fiction?

Of course, caution needs to be exercised as hybrid models are increasingly adopted as decision support tools. While the computer is an excellent virtual laboratory with which we can explore future scenarios and surrogate “would-be worlds”, the inherent uncertainty of complex systems and the complexity of hybrid models developed to represent these systems makes it difficult to judge the plausibility of modelled outcomes. Complex systems cannot be simplified through aggregation or reduction, since this would result in a loss of important structure and a subsequent simplification of the system's dynamics (Batty and Torrens, 2005). Thus, the common rule of parsimony must be broken when modelling complex systems. This recognition has led to the creation of hybrid models that have more and more detailed representations of the modelled system, as a means of trying to capture (or generate, via emergence) all of the essential structures and processes. The models themselves are thus complex systems that are imperfect representations of real complex systems. The modelling community is grappling with ways to assess the validity of such complex models and of their predictions (Batty and Torrens, 2005; Bradbury, 2002).

A number of authors have proposed ways to validate hybrid models, to ensure that the model faithfully represents at least some aspects of the modelled system. Grimm et al. (2005) propose comparing patterns generated by models with those in the real system. If a model consistently generates both the primary patterns that it was developed to produce, as well as other secondary patterns that it was not intended to produce, then users can be confident that at least some aspects of the real system's structure and processes have been adequately modelled. These authors also call for the adoption of a standard protocol for describing and communicating the results of hybrid models (Grimm et al., 2006). The problem, however, is that when hybrid models are used for decision support, they are typically applied to scenarios for which no data exists. As in climate modelling, one of the best ways to validate predictions may be through the arduous task of creating many different models of the same system and then comparing predictions between models. Whichever approach is taken, clearly, the limitations of hybrid models need to be adequately explained to decision makers before the model's output is used to inform policy decisions.

6. Conclusion

The recognition that ecosystems are complex systems has changed the focus of ecological modelling towards more integrative, hybrid approaches that enable the simulation of emergence, cross-scale interactions and non-linear dynamics. These new models are increasingly being used in ecological informatics to create the bridge between data sources and decision-support. Such models may serve not only to synthesize and represent knowledge obtained from the data, but also to explore possible future system states, given different management, policy or environmental scenarios.

Decision-support systems serve to synthesize and integrate knowledge about a real system so as to assist decision-making for policy and management. A good decision-support system will provide insight and knowledge that is not immediately evident from data sources, providing added value to available data. With the reams of data that are, and will be, collected from automated environmental monitoring systems, it will be increasingly necessary to find and model patterns in these data, and to incorporate them into dynamic models that can be used for scenario-building. If this is not done, the current major investments in the construction of new automated networks for data collection will be squandered. The field of ecological informatics combines the collection of tools, methods and approaches necessary to go from the collection and archiving of raw data to pattern extraction to modelling, culminating in the development of hybrid models for decision support.

Increasingly, the modeller needs to be a geographer, an ecologist, a social scientist, a programmer and everything in-between. Modern hybrid models combine expertise in geographic information systems, cartography and spatial analysis with data management, non-linear mathematics, systems theory and engineering, to name just a few of the multiple aspects involved in building these models. Hybrid modelling is thus a very multi-disciplinary field, in which teams of researchers from the applied, natural and social sciences need to collaborate in model building. This can be both an advantage and a disadvantage. While multi-disciplinary work is widely touted by funding agencies and administrators as being the wave of the future, most academic institutions still operate with departmental structures that maintain traditional barriers between the disciplines. In addition, publication of inter-disciplinary work is often difficult due to the fact that it rarely meets the accepted protocols and standards of a single discipline. By providing a forum for the publication of outstanding, multi-disciplinary research in hybrid modelling, journals such as Ecological Informatics may lead the scientific community in this regard.

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