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The Potential of Agent-Based Modelling for Performing Economic Analysis of Adaptive Natural Resource Management

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ABSTRACT *This paper explores how individual agent-based modelling can be used by economists and others to evaluate the economic aspects of adaptive management of natural resources. To date, economists have had few tools to perform economic analysis on adaptive natural resource management strategies and there has been limited economic analysis of adaptive management. Part of the reason for this situation may be the inherent nature of adaptive management which involves a series of 'if-then'* in situ *experiments in which expected outputs are not known with certainty, and future management actions depend on the outcome of the experiments. Individual agent-based modelling allows simulation of system wide emergent ecosystem properties that can reflect adaptation of individual agents with bounded rationality to their environment and to the interaction with other agents. These simulations can be used to mimic adaptive management experiments when insufficient information is available for more structured equation-based simulation models. The distribution of simulated outputs from individual agent-based models along with costs of the management actions may give economists the ability to better apply economic analysis to evaluate alternative adaptive management strategies.*

Application of Traditional Benefit–Cost Analysis to Adaptive Management

The standard neo-classical, microeconomic-based benefit–cost policy evaluation model typically applied by environmental and resource economists requires information (usually supplied by physical and/or biological scientists) to predict the future consequences (or states) of distinct management actions over one or more decades. Economists then estimate the benefits and costs of these consequences, resulting in a description of tradeoffs between, say, alternative levels of environmental quality. This information is then used in a public policy context to perform regulatory impact analyses or set regulations. If the outcomes are not known with certainty, the likelihood of different outcomes is commonly addressed through estimating high and low ranges or a probability distribution over the expected resultant states. This approach has served the economics profession and society well, especially when the policies evaluated were either (1) 'concrete' in that the projects (e.g. dams, highways, wastewater treatment plants, installation of scrubbers or specific

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regulatory policies) were well-defined with fairly predictable outcomes; and/or (2) attention was restricted to the subset of known or predictable outcomes to the exclusion of the more unknown or complicated outcomes (e.g. impacts on ecosystem services).

However, in the last decade, important environmental management challenges have emerged which cannot be readily analysed by this standard evaluation approach. For example, the restoration of natural environments of the Everglades (CISRERP, 2006) and the Grand Canyon (Gloss *et al*., 2005), and the respective population response of endangered species involve great uncertainty (i.e. a probability distribution of outcomes is not known). In this case, it is both the optimal management action (defined as maximizing the net benefits of restoration) and the physical and biological outcomes that are unknown. These restoration projects involve billions of dollars in direct management costs and opportunity costs, yet the net economic benefits of these restoration projects have not been comprehensively quantified (Milon *et al*., 1998; Loomis *et al*., 2005).

To address uncertainty in large-scale environmental management, ecologists have proposed the paradigm of 'Adaptive Management' (AM). AM is motivated by ecological data that indicates '[e]cosystems are moving targets with multiple potential futures that are uncertain and unpredictable. Therefore management has to be flexible, adaptive and experimental . . .' (Holling & Meffe, 1996, p. 332). The approach embodied in AM, however, prescribes future management actions that depend on the (partial) resolution of uncertainties, often in the form of rejection or non-rejection of hypotheses about system response that the experiments are designed to test. The inherent nature of AM, then, is of state-dependent management paths coupled with severe outcome uncertainty. Traditional benefit–cost methods are not well-suited to address problems of this type.

This paper explores the potential use of individual agent-based modelling (ABM) as a tool to help economists and other policy professionals evaluate the economic aspects of adaptive management of natural resources. While we do not discuss the admittedly demanding task of developing, parameterizing and testing these models, our discussion identifies several major contributions that ABM can make to the evaluation of AM programmes, as well some of the advantages and disadvantages of ABM over alternative modelling approaches. We begin by briefly describing the AM approach and then detail the challenges and opportunities that AM provides to natural resource economists. We next discuss ABM and its potential role in helping to evaluate AM practices. A brief comparison of ABM with substitute modelling approaches is then provided, followed by a discussion of the limitations of ABM. A final section concludes.

Paradigm of Adaptive Management (AM)

To address the uncertainty and unpredictability of ecosystems, AM is a necessarily dynamic process whose key features involve the resolution of uncertainties through experimental learning. It 'champions an experimental approach that allows policy makers to learn from their mistakes and apply those lessons to future projects' (Thrower & Martinez, 2000, p. 88). While the term 'mistakes' may be too harsh, the core principle of AM is that initial projects, policies or regulatory changes (management actions) are viewed as experiments to test 'hypotheses' *in situ*, with results helping to resolve the uncertainty about the cause-and-effect relationship of the action and the system. After implementation of the management action, the effects are monitored, and then the action continued only if the hypothesis of how the ecosystem responds to a particular management action is supported. However, subsequent management actions are subject to drastic change if the hypothesis is rejected. Thus, future management actions are dependent on what is learned during the initial experiments, leading to a sequential, path-dependent management process designed to provide not only desired environmental outcomes, but also new information that reduces uncertainty about the behaviour of the system (Walters, 1986). An AM strategy, then, is defined as a set of linked (if-then) management actions.

It should be noted that a distinction between active and passive adaptive management has been made in previous literature (Prato, 2005; Wilhere, 2002; Walters & Hilborn, 1978; Hilborn, 1992). Passive adaptive management starts with a simulation or predictive model of the ecosystem responses to the initial management actions, and the actual management actions are guided by this model (Prato, 2005). Model parameters are then updated based on monitoring results of these actions (Prato, 2005). This approach has been criticized, however, for lack of scientific rigour and the potential to generate incorrect information about ecosystem response (Prato, 2005). Active adaptive management, on the other hand, implements formal on-the-ground experiments (e.g. new management action (treatment), control, replications) that are designed to test hypotheses about whether the ecosystem responds in the desired way to achieve the managers' target (Prato, 2005). Although this latter approach provides the missing rigour, it is likely to be more expensive and more complicated (Prato, 2005).

While the categories of active and passive adaptive management are useful distinctions, it should be noted that an optimal AM programme need not fall exclusively into either category. It may be the case that simulation modelling of some sort might be used to inform the choice of formal experiments, the results of which are used to update the simulation model. Or, perhaps after a decade of implementing experiments, enough has been learned about the functioning of the ecosystem to estimate a more traditional structural equation-based mathematical model to guide passive AM over the next decade. In other words, modelling and on-the-ground experiments need not be substitutes, but instead may be complementary tools for ecosystem management using AM.

Challenges and Opportunities for Natural Resource Economists

The nature of the uncertainty being addressed in AM regimes is different than that typically assumed in traditional cost–benefit analysis where at least the outputs and costs of a worse-case and best-case scenario can be quantified. The complexity and multi-dimensional nature of large-scale environmental systems is such that nearly all management strategies are likely to create a host of unknown (and possibly, inestimable in a statistical sense) effects in addition to those expected *ex ante*. In other words, the probability distribution of the output vector is not known or cannot be derived with commonly used methods and/or the dataset available. With uncertainty about system response and the sequence of management actions, there may be a multitude of possible combinations of management actions and time paths of implementation. In this case, economists would find it very difficult to calculate the present value of costs and benefits given the uncertainty about which management actions will be taken and when, if at all, they would be taken. To date much of the economic analysis of adaptive management has been limited to providing the direct cost estimates of the *initial* management action and opportunity cost estimates of this initial management action (Harpman, 1999a,b).

In some instances, it may be possible to reduce the complexity of the problem by implementing one of the management actions in one area and a competing management action in another area not connected to the first. This may be possible in, say, separate tributary rivers or canals of the Everglades due to the system's immense size. However, in a small area or one where all the parts are ecologically connected (e.g. the Grand Canyon), or facing binding budget constraints, the policy decision facing public officials may be to determine which possible AM action to start with, which may imply a tree-diagram like set of future management actions (e.g. if A does not work well, then try B).

For example, one initial AM strategy (A) for recovering, say, humpback chub populations in the Colorado River might involve individual management actions such as increased river flows and physical habitat improvements (e.g. developing backwaters). Another initial strategy (B) might involve a management action such as directly changing incoming river water temperature (e.g. by changing the elevation in the reservoir from which the water is withdrawn and subsequently discharged downstream). While there may be some qualitative information about the likely effects of strategies (A) and (B) on humpback chub populations, specific quantitative information may not be available or known with very little certainty (i.e. very uniformed priors about the likely effects of the actions). Furthermore, depending on the information available about the ecological system as a whole, implementation of (A) or (B) might be expected to impact other natural populations, but there is little information regarding these unintended impacts.

In the face of this uncertainty, an immediate question in adaptive management is whether to do (A) first, and if it performs poorly, try (B), or vice versa, recognizing that future management decisions will incorporate the information gleaned through the chosen experiment. A second question might be the optimal extent or intensity of (A) or (B), given the opportunity costs and uncertainty associated with the experiment. A third question deals with the tradeoff between the expected value of information gained from experimental outcomes versus the value of the action on the primary management objective (in our example, restoration of humpback chub populations).

Despite these questions, there has been little response by natural resource economists to develop quantitative models capable of valuing different possible AM programmes. To address this gap some public policy analysts have responded with suggestions for incorporating non-monetary values within the AM framework (Norton & Steinemann, 2001). As noted by Milon *et al*. (1998), neither social scientists nor the responsible management agency (the Corps of Engineers) have defined a protocol to evaluate the effectiveness of their AM evaluation process in the Everglades. Yet, AM has become the dominant environmental management paradigm for endangered species recovery and environmental restoration of major natural environments.

AM programmes that impact unique natural environments are potentially multi-billion dollar programmes. The aforementioned Grand Canyon project is using AM to help restore several endangered fish, such as the humpback chub, that may require major modifications to the operation of Glen Canyon dam, where hundreds of millions of dollars in foregone hydropower is at stake (Bureau of Reclamation, 1995). Other large-scale management projects using AM include the Missouri River project (Prato, 2003) and the Klamath River Basin (USDA Natural Resources Conservation Service, 2004) to name a few. The US Council on Environmental Quality (CEQ) is also addressing AM in its effort to modernize the implementation of the National Environmental Policy Act (NEPA–CEQ 2007). Most noteworthy of these AM efforts is the first real policy application of agent-based modelling ATLSS (atlss.org) to AM in the Everglades restoration (Biological Resources Division, 1997; DeAngelis *et al*., 2000).

It is likely that economic principles could contribute to guiding adaptive management. That is, an adaptive management strategy should not be judged solely on the basis of whether it attained some target, but whether it did so in a cost-effective manner as well. If economists had improved tools to conduct *ex ante* analysis it may help managers select among competing effective strategies when more than one management strategy appears to work. Economists failure to develop such tools limits the contribution that natural resource economists could make to multi-billion dollar AM programs. With more and more federal and state agencies using AM as their primary paradigm, economists need to provide an evaluation protocol that can guide natural resource managers and policy makers at each decision point in their grand resource management experiments.

One small interim step for economic analysis of adaptive management may be to move from the ideal *ex ante* analysis of net present value to an *ex post* analysis of the successful AM strategies. Specifically, for management actions that had a positive effect on achieving the target (e.g. increasing humpback chub populations), economists could calculate either *ex post* net benefits or at least perform an *ex post* cost effectiveness analysis. As each successful management action was implemented, information about net benefits or costs per unit of output would accumulate, perhaps to guide prioritization among the successful management actions. Unsuccessful management actions may still have value however, if they provide information to design new management actions or reduce the dimensions of uncertainty. This incremental approach may eventually reduce uncertainty and allow an *ex ante* analysis to answer larger policy questions faced by agencies, such as which AM programmes are more valuable to undertake in the face of government budget constraints.

Potential Role for Agent-Based Modelling (ABM) of Complex Adaptive Systems

While AM conducts *in situ* real world experiments in natural resource management to learn about how to improve management, the number of possible experiments that can be run in any one area, at any one time is necessarily limited. Time, expense, uniqueness (there is only one Grand Canyon) and the potential for irreversible consequences typically limit the number of experiments, and thus the complete (or even 'reasonable') resolution of uncertainties. We suggest that using agent-based simulation models, or agent-based modelling (ABM) may allow analysts to conduct a wide range of virtual experiments to gain greater understanding of complex, non-linear systems and possible consequences of such real world experiments prior to selecting the actual AM experiments. As such, we conceptualize an AM programme that is essentially a mix of passive and active adaptive management, though initially it is more consistent with a pure passive AM strategy.

Because ABM is a relatively new methodology for social scientists and policy analysts, we first define ABM. We then describe how ABM might aid in the economic evaluation of AM strategies. Those readers familiar with ABM methods may skim over this first subsection.

What is Agent-Based Modelling (ABM)?

Agent-based modelling (ABM) has also been called 'agent-based computational economics' in the economics discipline (Tesfatsion, 2006) or 'individual-based modelling' (IBM) in ecology (Grimm & Railsback, 2006). ABM is a computationally intensive dynamic simulation model of how individual agents (typically using simple behavioural rules) interact with their environment and each other, giving rise to system-wide macro patterns or emergent properties which cannot be deduced from the individual agent's rules (Billari *et al*., 2006; Tefatsion, 2006; Garifullin *et al*., 2007). Agents can be individual persons (e.g. managers, agency decision-makers, households), institutions (e.g. government, firms) and/or biological entities such as animals or plants. These agents are assumed to follow relatively simple rules that govern their behaviour (e.g. adopt a technology if neighbours have in the previous period or do not visit a beach if during the last period's visit there were more than 60 people present). Agents are endowed with initial information and can be allowed to learn from their choices in the previous period giving rise to adaptive behaviour, a feature useful for modelling AM.

Rather than assuming a homogenous agent or 'representative individual', ABM can model heterogeneity among agents (Miller & Page, 2007, pp. 84, 101). This may be more realistic as one would suspect that not all agents are alike in all respects. To account for this, one can program a distribution of agent characteristics or agent knowledge to allow for different behavioural responses among the same class of agents, including natural resource managers.

Gebetsroither *et al*. (2006) characterizes the necessary information to specify in the creation of an ABM model with respect to the interacting agents. Specifically, each agent is endowed with certain values, targets and objectives (or generally, preferences that in part govern behaviour), as well as an initial endowment of resources. Agents use these endowments to observe their aggregate environment (including other agents), form expectations, and provide updates to their preferences (learning). The rules, search routines, and potential actions or decisions of each agent are specified, and the system is simulated in a 'cycle of action, evaluation, and updat[ing]' (Billari *et al*., 2006). While the model is defined solely at the micro (agent) scale, agent interactions produce distributions of outcomes that may have macro-level regularities, equilibria, and the dynamics of the system as a whole (Billari *et al*., 2006). Manson and Evans (2007) illustrate how ABM can serve as an integrating model for what they term 'sustainability science'.

How Might Agent-Based Modelling Be Applied to Evaluate Adaptive Management?

One of the primary conundrums of AM for public officials wishing for both certainty and useful information regarding tradeoffs, and for economists trying to evaluate AM policies is that the specific effects of a single real world management action (or even the probability distribution of the outcome(s)) are not known ahead of time. As such, a management action has two components: (1) the (uncertain) effects of that action on the state of the overall system, and (2) it's information value from which to learn about system response. This new information can then be used to refine the management action if necessary, or switch to an entirely new management action, especially if specific hypotheses underlying the management action are rejected. Thus, we identify three major contributions that ABM can make to the process of AM:

(1) identification of potential outcomes from any given management decision;
(2) identification of key parameters and other system properties about which more information is needed to reduce uncertainty about the outcomes;
(3) the ability to represent potential paths of AM by utilizing the ability of ABM to model adaptive behaviour and learning.

We discuss each in turn.

Identification of potential management outcomes. One of the strengths of ABM is that *emergent properties*, or aggregate patterns of ecosystem response that might not have been deduced from the reductionist approach of analysing each element separately, might become apparent ahead of time (Miller & Page, 2007, p. 66). *Emergent properties* are defined as well-organized or self-organized patterns of aggregate behaviour or outcomes arising from individual behaviour or collections of small group behaviour. In many cases, the resulting pattern of aggregate behaviour may not have been predictable from studying the behaviour of the individual agents themselves because it is specifically the *interaction* among multiple agents of the same class (e.g. anglers) and of different classes (e.g. anglers and salmon) that gives rise to the emergent macro-level properties. For example, with agent-based modelling, a typical predator–prey cycle can arise from a far simpler system than a traditional mathematical model. The reliance on modelling interacting agents, each of which uses simple behavioural rules, may also help avoid reliance on the 'as if' story, in which individuals are assumed to behave as if they were maximizing a complex mathematical function or operator (Miller & Page, 2007).

These emergent properties can be used to generate estimates of the potential space of possible outcomes that result from a management decision as well as the probability density of each output. In particular, output from running ABM programs can provide a graph of the distribution and range of outputs regarding the state of the system and/or the behaviour of each type of agent over time. These graphs can also provide the concurrent distributions of all types of agents at the same point in time (i.e. how each agent's population at a given time temporally relate to the population other agents). For example, in a three agent model of sheep, wolves and grass, one can observe how the populations of sheep, wolves and grass change over time, and repeat the simulation using different assumptions about sheep and wolf reproduction rates and grass growth rates. Then probability distributions of the outputs can be calculated from these simulated outputs.

The model's distributions of outcomes generated by a series of agent-based simulations allow economists to value the range of possible outcomes (or their expected values) associated with various management strategies prior to an agency implementing one. Thus, one contribution of ABM for *ex ante* evaluation of competing AM strategies is the ability of this simulation modelling approach to produce a range of outcomes under a range of different assumptions. In fact, ABM can be considered a 'virtual laboratory' for simulating interactions among large numbers of human and non-human actors (Billari *et al*., 2006). While this feature is true of most simulation models, including the one currently in use as one tool to inform AM decisions in the Grand Canyon (Walters *et al*., 2000), agent-based models can have advantages over traditional simulation models (Miller & Page, 2007, pp. 67–68). We further discuss these advantages in ABM Versus General Integrated Modelling Approaches and Experimentation, and detail some limitations in the next section (Limitations of ABM Models).

Identification of information needed for key parameters and system properties. Another advantage of agent-based modelling is what Tesfatsion (2006, p. 855) calls 'informational exploration'. Here there is a direct parallel between ABM and AM. Specifically, in AM, managers may purposely allocate some of their limited resources (labour, budget) to management actions that may not necessarily be optimal in the short run, in order to learn more about the system response so as to refine future management actions in the long run. In essence, resource managers face a multi-dimensional production possibilities frontier characterized by tradeoffs in attaining short run management objectives (e.g. short run population increases of endangered species) and learning about the sum total of effects of a particular management practice on the ecosystem. This learning or information exploration will help in designing better future management strategies that attain a higher level of the objective than would have been possible without learning. In the presence of uncertainty about the ecosystem, it may be advantageous in the long run to forego sole reliance upon management actions that quickly contribute a small amount to the specific management objectives in order to resolve some of the uncertainty for use in future decisions (see, e.g. Bar-Shalom & Tse, 1976). The information gained about ecosystem response or species behaviour has a specific estimable value that must be taken into account in order to properly plan an AM decision sequence.

In an ABM context, this uncertainty often takes the form of uncertainty in the parameterization of models, as many system parameters are uncertain or unknown, even at the individual level (Grimm & Railsback, 2006). This problem has been addressed in the ecology literature by using 'pattern-oriented' modelling in which model validation is done, in part, by comparing the emergent properties of the estimated system to observed patterns of the real system. Wiegand *et al*. (2004) demonstrate the process of parameter identification in an ABM model of brown bear populations in the Alps. Initially a broad parameter set was identified based on previous literature and other prior information. Next, ABM model simulations were run and results were compared to observed patterns in the brown bear population. Parameter sets that did not replicate observed patterns were eliminated and the resulting smaller set of parameters essentially created confidence intervals around each parameter.

This process, known in other disciplines as inverse modelling (Grimm & Railsback, 2006), can serve several purposes in an AM framework. First, the exercise can point out limitations in the ABM model; namely, the inability to replicate observed patterns and thus the inadequacy of the assumed agent rules underlying the model. This failure provides information to the modeler. One or several hypotheses can be formed about the cause of the limitations. In this sense, ABM provides an opportunity for more informed sensitivity analysis than is often the case in standard benefit–cost analysis. As with the results of any sensitivity analysis, an AM experiment can be planned to help resolve the uncertainty about key parameters identified in the ABM, and subsequently update the ABM results. Second, if observed patterns can be replicated by the model structure under some subset of parameter values, then varying these values provides information about ecosystem response to these variations, and thus guidance as to the key driving parameters. If several key parameter values are not known with certainty, then this exercise helps decision-makers to prioritize AM experiments designed to obtain information about these unknown values.

Using learning and adaptive behaviour to model adaptive management paths. ABM also provides the ability to model the evolution of a system over time by allowing agents to adapt to their environment or learn from their prior choices. ABM can be set up to allow agents (e.g. fish) to either survive from period to period or to perish if there is a mismatch between agent life requirements and the environment. Thus, ABM is not only dynamic, but allows the analyst to observe 'internal' adaptation of the agents as the environment changes due to the implementation of the management actions (Manson & Evans, 2007). For example, using evolving cellular automata within an agent-based model creates dynamic models of spatial interactions between cells or agents (Hand, 2005). Rules can be written that allow the individual agents to react to decisions of their adjacent neighbours (e.g. anglers or predator fish) or for the agents to update their prior beliefs based on outcomes (payoffs) arising from previous periods decisions (Miller & Page, 2007). Genetic algorithms exist which allow agents whose actions result in higher fitness (rating on a performance criteria) to have a higher probability of persisting and reproducing in the next period (Miller & Page, 2007). The performance criteria can be an exogenous fixed standard, or it can be co-evolutionary when relative performance depends on the action of other agents (Miller & Page, 2007). Thus, there is a potential to move from static agents that simply repeat the same behaviour over and over again, to adaptive agents. Adaptive agents may modify their behavioural decisions in order to increase attainment of their ultimate objective such as profit or survival (Miller & Page, 2007, p. 149).

A special (and higher order) case of adaptation includes an agent's ability to learn from their own past behaviour and that of other agents surrounding them. Agents endowed with these characteristics can carry forward the more successful rules of their parents due to the evolutionary pressure of the system (Manson & Evans, 2007). The combined effect of adaptation and learning rules may allow for the unintended consequences of a management action to be 'discovered' as an emergent property of the system prior to real world implementation. Even though each individual agent has bounded rationality and uses very simplistic individual rules, the interaction of agents can move the system to an efficient outcome.

Ex ante *evaluation of AM strategies using ABM.* Just as individual agents can adapt and learn in an ABM framework, management entities and their actions can be similarly modelled. Based again on relatively simple rules and incorporating the ability to monitor and learn about the environmental system, it is quite possible that sets of AM paths based on different rules can be simulated through the use of ABM. Thus, one of the primary contributions of using ABM to guide AM is the ability to model adaptive behaviour for both the managing agent (at the policy level) and the other individual agents in the model.

Although it is likely to be quite computationally intensive, this exercise can help decision-makers to estimate the potential AM action space (as opposed to just the state space), which presumably could then be analysed in a typical benefit–cost economic framework. This information could save agency managers millions of dollars, years of wasted time on failed experiments, and possibly avoid the ultimate extinction of some species. In high profile natural resources, such as the Grand Canyon and the Everglades, the delicately balanced support for AM rests on making progress toward species recovery or restoration, and avoiding harm to the resource. Initially using ABM to guide AM may reduce the chances of disastrous unintended outcomes that can be politically embarrassing and undercut funding requests for continued AM experiments. Thus, agent-based models may provide another useful tool to those managers and scientists under public scrutiny to reduce the likelihood of failed experiments that might not be detected with traditional simulation models. A description of such a model in the context of forest management is provided by Gebetsroither *et al*. (2006) and for the Everglades by DeAngelis *et al*. (2000) and ATLSS.org.

ABM Versus General Integrated Modelling Approaches and Experimentation

A number of modelling approaches have been used by scientists and economists for decades. Parker *et al*. (2003) concisely summarize the alternative modelling approaches that can and have been used in the past by many disciplines whether independently or in an interdisciplinary fashion. Some of these modelling approaches share similarities to ABM. However, in contrast to ABM, *statistical models* generally require fairly large data sets (i.e. information) to test hypotheses about cause-and-effect relationships, and are often used to parameterize *equation based mathematical models* (or structural equation models). In general, this latter class is characterized by mathematical equations that describe the key variables of the system, often informed by theory, literature, or previous statistical analysis. *System models* are a subset of this class involving differential equations; in other words, they tend to be dynamic in nature. When the literature on a topic is sparse, *expert models* can be developed by using for example a Delphi technique that draws from the collective experience of experts, the results of which can sometimes be formalized into a set of rules. An *evolutionary model* mimics a selection process over several generations, sometimes using particular mathematical structures such as neural networks (Parker *et al*., 2003). Finally, *cellular models*, often in the form of *cellular automata***,** replicate a discrete dynamic system for modelling complex behaviour based on simple local rules animating cells on a lattice or grid (Tesfatsion, 2008; Hand, 2005; Miller & Page, 2007). As such, this structure is very close to an ABM approach.

Several of these model types have features that are attractive for use in answering key economic AM questions. For example, the rule-based predictive behaviour of agents in expert models or cellular models allow for relatively simple representations of heterogeneity, and as discussed above, evolution of the rules can help model dynamic AM paths. This endogenous learning is a feature shared by ABM, which while possible in structural equation-based mathematical modelling, is quite rare. Furthermore, incorporation of heterogeneous agents following simple rules with bounded rationality is in contrast with standard neoclassical models that assume complete information of homogenous agents that process this information to carry out complex optimizations. In ABM, the optimization is the result of agent interaction that leads to overall efficiency as an emergent property of the system, not individual behaviour.

As recently noted by Matthews *et al*. (2007, p. 1447) in their review of ABM in modelling land use: ‘Agent based modelling is an approach . . . that offers a way of incorporating the influence of human decision making . . ., taking into account social interaction, adaptation, and decision making at different levels. Specific advantages of agent based models include their ability to model individual decision making entities and their interactions, to incorporate social processes and non monetary influences on decision making and to dynamically link social and environmental processes’. As such, a key advantage of the ABM approach is the ability of agents following simple rules to simulate a complex, nonlinear, and dynamic system from the ‘bottom up’ (based on individual behaviour) rather than being imposed from the top down or using ‘representative agents’ that may not reflect the potential for agents self-organizing behaviour (Gebetsroither *et al*., 2006). In this way, ABM can be used to estimate a state-space resulting from management actions that is potentially more robust than the one generated using highly structured traditional methods, such as equation-based mathematical models, and more likely to identify unexpected outcomes. In general, less information is needed about parameters and functional relationships between variables in ABM than in a structural equation-based mathematical model. Thus, ABM may be particularly useful when too little is known about a system to construct an operating structural equation-based mathematical simulation model.

ABM also has features that make it useful for addressing ecosystem management (Bousquet & Page, 2004). While there are many definitions of ecosystem management most definitions emphasize attaining desired future conditions that sustain ecosystem structure and function (Loomis, 2002, p. 531). Ecosystem management also involves a great deal of uncertainty about how the various components of an ecosystem interact, the synergistic effects of those interactions and ecosystem responses to changes in biophysical conditions and human behaviour (Loomis, 2002, p. 534). ABM has the potential to mimic these synergistic effects of interactions that give rise to emergent properties of the system as a whole.

Of course, as recognized by active AM, modelling is not the only way humans generate knowledge. There is a long tradition in the 'hard sciences' of using laboratory experiments to test hypotheses. This approach was adapted to economics by Vernon Smith, who won the Nobel Prize in economics for his pioneering work of bringing lab experiments into economics (e.g. Smith, 1989, 1990). ABM and experimentation are similar in that both are bottom-up approaches to science in the sense that aggregate phenomenon arise from the action of individual agents (Hailu & Schilizzi, 2004). In addition, the two approaches can be complementary in the sense that lab experiments provide one shot or up to, say, ten rounds of transactions or trading periods in a single session, whereas ABM can generate results over a much larger number of trading periods that would be insufferable for real experimental subjects to endure (Hailu & Schilizzi, 2004). Initial lab experiments can further generate data to set initial behavioural rules of participants that can be utilized in the subsequent multiple-period ABM (Hailu & Schilizzi, 2004).

Limitations of ABM Models

Any model is just an abstraction of reality, and agent-based models are no different than other models in this respect. While the ABM approach typically makes fewer assumptions about specific agent relationships than many economic models, it is necessary to use some initial assumptions about agent behaviour and how the agents interact. As pointed out by Parker *et al.* (2003), it can be more difficult to validate agent-based models against the data than some other types of models, since ABM are typically non-linear and the emergent behavioural outcomes need not follow a normal distribution, which underlies many statistical tests. Unlike statistical processes for which the central limit theorem suggests one will often get relatively well-behaved distributions, Tesfatsion (2008) indicates that ABM output distributions can be multiple peaked and may have strong path dependencies. Indeed, perhaps the biggest challenge with ABM is the difficulty in development, testing, parameterization and validation of the models. These challenges are non-trivial and potentially costly, though we suspect that as the techniques evolve and are adopted by researchers, the costs will likely fall. As with any new field in which software programs are still in a developmental phase, the specific pattern of ABM results may be somewhat dependent on which of the many agent-based software programs is used.

Another challenge faced by any new technique is the difficulty in convincing one's peers and managers that ABM provides more than just colourful simulations, and the results should be taken seriously (Parker *et al*., 2003). No doubt this may have also been the reaction of scientists and managers to early GIS analyses that appeared just to produce colourful computerized maps. It took several years for other disciplines and managers to learn to harness the full power of GIS in interdisciplinary analysis and decision-making.

Some researchers would go so far as to say that at this time ABM is more useful for generating 'simple rules of thumb', and not as 'operational decision support tools' (Matthews *et al*., 2007, p. 1447). Thus to some, ABM is not yet ready to become a full-fledged decision support tool at this time. Perhaps in another decade as modellers, other scientists and decision makers gain more experience with ABM, it will become a well accepted decision support tool, especially for AM applications.

Conclusions

Given the limited number of formal decision aids being used to guide passive adaptive management (AM), we feel that agent-based modelling (ABM) has a promising future as a decision aid for guiding selection of efficient AM strategies from the set of all possible strategies. ABM's flexibility in modelling interactions between social and biological agents, and their adaptation to one another's behaviour would appear to be a natural fit for evaluating AM scenarios or strategies. ABM's ability to simulate the distribution of potential outcomes under uncertainty when probability distributions are unknown has some major advantages over other simulation models. The advantages include identifying the distributions of outcomes that may reflect emergent properties or system patterns that are difficult to deduce from the behavioural rules of the individual agents, and providing results that are useful to economists interested in doing economic evaluations of competing AM strategies, the potential outputs of which are not predictable applying more commonly used and data hungry simulation models.

Specifically, we identify three key contributions that ABM can make to AM:

(1) identification of potential outcomes from any given management decision;
(2) identification of key parameters and other system properties about which more information is needed to reduce uncertainty about the outcomes;
(3) the ability to represent potential paths of AM by utilizing the ability of ABM to model adaptive behaviour and learning.

Agent-based modelling is particularly useful when very little information is available for constructing a structural equation-based mathematical model, although the two approaches can also be complementary in the sense that ABM (perhaps in conjunction with AM experiments) can be used as a first step to develop plausible parameters for a structural model when the literature provides little or no guidance.

Agencies such as the USGS's Grand Canyon Research and Monitoring Center, the US Army Corps of Engineers' Everglades restoration and the USDA Natural Resources Conservation Service's adaptive management efforts in the Klamath River Basin, as well as agencies considering using adaptive management as a management philosophy, should seriously consider whether using ABM might help them better achieve their environmental goals than their current approaches. Economists might also investigate whether ABM might aid them in working with other disciplines to perform benefit–cost analysis on major adaptive management programmes such the Grand Canyon and the Everglades.

Individual ABM is *not* a magic black box that can turn uninformed guesses about human and non-human behaviour into accurate predictions of the unknown. ABM still conforms to the original GIGO rule of 'garbage in-garbage out', and the parameterization, simulation, and validation of these models is still a significant challenge. Nonetheless, well-reasoned ABM has the potential to add value in terms of increasing insights about the evolution of complex systems and possible macro/aggregate outcomes based on the interaction of different classes of individuals with each other and their environment. As with many modelling approaches, active participation by different actors (e.g. scientists, economists and decision-makers) in developing rules in ABM can provide an opportunity to better understand each other and the ecosystem they are managing prior to selecting an initial AM strategy.

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