Selecting Among Six Modelling Approaches for Integrated Environmental Assessment and Management

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Abstract
The design and implementation of effective environmental policies need to be informed by a holistic understanding of the systems processes (biophysical, social, and economic), their complex interactions, and how they respond to various changes. Models, integrating different system processes into a unified framework, are seen as useful tools to help analyse alternatives with stakeholders, quantitatively assess their outcomes, and communicate results. This paper reviews six approaches or model types that have the capacity to integrate knowledge (sources and types) to develop models that can accommodate multiple issues, values, scales and uncertainty considerations, as well as facilitate stakeholder engagement. The approaches are: systems dynamics, Bayesian networks, coupling of component models, meta-modelling, agent-based models and knowledge-based models. We start by discussing several considerations in model development, such as the purpose of model building, the availability of qualitative versus quantitative data for model specification, the level of spatio-temporal detail required, and treatment of uncertainty. These considerations and a review of applications are then used to develop a framework to assist modellers and model users in the choice of an appropriate modelling approach for their integrated assessment applications.

Keywords: Integrated Assessment; system dynamics; Bayesian network; coupled component model; metamodel; agent-based model; knowledge-based model.

1 INTRODUCTION
Effective environmental management requires an understanding of the interactions between policy choice and complex social, economic, technical and environmental processes. The predicted outcomes then need to be assessed with regard to feedbacks, side effects and, where possible, trade-offs among various, often conflicting, objectives or as distributional impacts within one objective, for example spatial trade-offs. Both positive and negative impacts may also occur over very different time scales, with environmental benefits not being seen for years and in some cases decades, while economic and social costs may be more immediate (e.g. lost income). There is an increasing awareness of the complexity of evaluating these types of interdependences to inform decision-making. Models, systematically integrating knowledge developed across a broad range of fields...
(such as economics, ecology, psychology and sociology, hydrology and agronomy), are essential to evaluate, or even understand the nature of, these types of trade-offs. The need for such models (known as integrated assessment models/tools) to enhance the effectiveness of decision-making and management has been widely acknowledged (see for example Jakeman and Letcher, 2003; Bland, 1999; Gough, 1998; Schneider, 1997; Pahl-Wostl, 2007; Bousquet and Voinov, 2010).

This paper reviews six broad approaches that have the capacity to integrate knowledge (sources and types) to develop models, which can be used to understand these complex trade-offs. The paper starts by considering the use of the term ‘integration’ for modelling studies. Various purposes for developing models are then explored and several considerations including temporal and spatial scales, uncertainty and data availability are discussed. These sections then inform a review of approaches to developing integrated assessment model types that have been applied in the literature. The paper concludes with a framework for choosing the appropriate method given the nature of the integrated assessment application.

1.1 What is meant by ‘integration’?

The term ‘integration’ is used by different people in different ways. At least five different uses of the term ‘integration’ in the context of integrated assessment can be identified in the literature with various loci in the modelling process. Integration, according to Jakeman and Letcher (2003), is a process not just an outcome, and may refer to:

1. **Integrated treatment of issues** - arises because management options for many natural resource problems have impacts on other social, resource and environmental issues. Concurrently considering the combined or integrated effects of management options may improve management decisions and reduce the occurrence of negative externalities. In this case integration is a systems approach, where one tries to look at various parts of the system as a whole. Here, the target system can be subdivided into subsystems according to more focused stakes. This is an initial step in integration, which may involve stakeholders.

2. **Integration with stakeholders.** The level and success at which research outcomes are applied and adopted will often depend on how connected stakeholders are to the research output and how relevant research outcomes are to policy and extension activities. Integration with and among stakeholders may vary from simple updates of research to community groups to large-scale inclusion of stakeholder views and knowledge at all stages in a project. Various classifications of the types of integration between stakeholders and researchers have been given in the literature (e.g., Biggs 1987, Martin and Sherington, 1997, Pretty 1995). Here integration of knowledge –usually known as participation or engagement - is a side activity in the modelling process and may occur at any stage from elaboration of knowledge to use of models (Barreteau et al 2012).

3. **Integration of disciplines** - involves the integrated consideration of two or more disciplinary views of a management problem and its associated system boundaries. An integrated knowledge of the target system comes after these disciplinary analyses, negotiating with interest groups, with the challenge of transforming this integrated (most often complex) knowledge into a model.

4. **Integration of processes** and models - requires combining two or more models of different systems or processes in a system. These processes may be biological, chemical, physical, economic or social. However, such integration may necessitate combining modelling techniques from disparate disciplines. This type of integration may involve not just the integration of models and disciplines, but also the integration of different issues and scales. Here again the target system is analysed with various lenses that all lead to a specific model.
5. Integration of scales of consideration - resource and environmental issues may often be considered at a variety of temporal and spatial scales. Components of a system may operate on different scales. While catchment boundaries may be most appropriate for considering hydrology-related issues, social and economic boundaries are likely to differ, (e.g., households, farms, or political entities). Even within the physical component of a system under study, linked subsystems may operate at different scales. In hydrological systems for instance, the groundwater and surface water components tend to operate at very different spatial and temporal scales. Treatment of issues at different scales may occasionally be achieved by nesting scales, but knowledge and computational constraints typically necessitate some compromise between the scales of component processes.

Of course, these five types of integration are not mutually exclusive. For example, an integrated treatment of environmental, social or economic issues may require an integration of modelling techniques at a variety of scales. Some level of stakeholder integration is likely to be a feature of any integrated modelling exercise.

Several modelling approaches are used for integrated assessment. There are different ways to cope with the specific requirements of the various types of integration above - starting with coupling models from different disciplines, up to approaches that suit putting integrated knowledge and representations into models. Below we review some of the most relevant modelling approaches to provide some guidance in choosing the most appropriate one(s).

2 CONSIDERATIONS FOR MODEL CHOICE

When choosing the type of modelling approach to be used it is important to consider three main issues: what is the purpose of the model; what types of data are available to develop and specify the model; and, who are the model users and what requirements are there on the scales and formats of model outputs?

2.1 Model Purpose

In the field of integrated assessment, models are generally built to satisfy one or more of five main purposes:

Prediction involves estimating the value (quantitative or qualitative) of a system variable in a specified time period given knowledge of other system variables in the same time period. Models are often developed to predict the effect of a change in system drivers or inputs on system outputs. For example, a model may predict a change in the probability of an algal bloom occurring in a water body given that there is going to be an increase in the level of nutrients delivered to the water body. Predictive models may be very simple (often empirical) or may be more complex. In many cases increased complexity of a model does not lead to improved predictive performance, so many successful predictive models have relatively simple structures that are well grounded in observations. Predictive models are generally required to have some level of accuracy in reproducing historic observations. For models aiming at implementing an integrated representation, whatever the path to get it, ‘validating’ the predictive accuracy of these models is not straightforward due to a lack of appropriate data for ‘validation’.

Forecasting refers to predicting the value of a system variable in future time periods, without knowledge of the values of other system variables in those periods. For example, a model may use observed rainfall today to forecast the chance of rainfall tomorrow. Time series methods are very commonly used for forecasting problems (e.g. Box and Jenkins, 1976). The accuracy of forecasting models is commonly tested by considering the difference between ‘forecast’ values
and historic observations. With less information available for use in prediction, forecasting is typically more uncertain than contemporaneous prediction, unless coupled with real-time observational correction, and uncertainty typically grows with the length of the time horizon.

Management and decision-making can often benefit from models, which are used in problem formulations and may be operated by decision support systems and integrated assessment tools in this context. These models may be simulation-based (i.e. developed to answer ‘what if’ type questions) or optimisation-based (developed to provide the ‘best’ option under a given objective subject to constraints). Tools such as multi-criteria analysis are essentially optimisation-based models developed to provide the optimal trade-off of multiple objectives. Management and decision-making models are usually needed to be able to differentiate between decision alternatives or management options. This usually requires the model to give sufficiently accurate estimates of the magnitude and direction of changes in the achievement of objectives in response to changes in management actions and other system drivers (Reichert and Borsuk, 2005).

Social learning is an increasingly common purpose for building models. Social learning refers to the capacity of a social network to communicate, learn from past behaviour, and perform collective action. Complex issues such as river basin management might be well served by taking into account the diversity of interests and mental models, and representing the processes of information and knowledge dissemination (Maurel et al., in press). Of particular interest is the use of system dynamics, agent-based approaches and Bayesian networks (see for example Brown et al., 2004; Pahl-Wostl, 2005; Monticino et al., 2007). In this case, models are developed to allow individuals (not the model builder) to learn and experiment so as to inform their understanding of the way in which the system may work and the way their actions may interact with the actions of others to create system outcomes. Models developed for social learning generally have a large emphasis on the interactions between individuals or groups and may include representations of less well-understood processes. The emphasis in models developed for social learning tends to fall more on the plausibility of interactions and outcomes than the predictive accuracy of the model.

Developing system understanding/experimentation is the purpose of many models developed to summarise and integrate available knowledge on system components in order to improve understanding of the entire system and the way it may react to changes in system drivers. Such models may include components that are less certain (to test the potential effect of the various assumptions) than those used for prediction, forecasting or decision-making. These models tend to be ‘research’ models, accessible to the model builder and other researchers, as opposed to stakeholder models that are generally developed with a large non-technical audience in mind. As with social learning models, model veracity tends to be considered in terms of plausibility and possible implications for the system rather than historical accuracy.

2.2 Types of data available

There are two main types of data available to construct a model: quantitative data and qualitative data. Quantitative data refers to the measurable characteristics or fluxes in a system and may include time series, spatial, or survey data. Qualitative data or information includes expert opinion, stakeholder beliefs or some types of information derived from surveys and interviews. It may be categorical in nature, e.g. yes/no; high/medium/low. Almost all model development relies on both quantitative and qualitative information. For example, even purely quantitative models rely on theory or knowledge about systems interactions in the development of their underlying conceptual frameworks. However, some modelling approaches
allow qualitative information to be explicitly incorporated not just in the system conceptualisation but also in the calibration and parameterisation of the model. In this paper, the distinction between an approach’s ability to use quantitative or qualitative data refers specifically to explicit incorporation of such information in model specification, rather than conceptualisation.

2.3 Output requirements

2.3.1 Treatment of space:

There are essentially four different approaches to treating space in a model:

1. **Non-spatial models** do not make reference to space. For example a predator-prey model may not refer to any particular spatial scale (Ramos-Jiliberto, 2005).

2. **Lumped spatial models** provide a single set of outputs (and calculate internal states) for the entire area modelled. For example, the impact of a change in nutrient delivery to a lake may be modelled using a simple function as a total change in biomass for the entire lake system. In this case the lake system is not disaggregated into smaller units and the interactions between parts of the lake system are not considered explicitly.

3. **“Region”-based, compartmental spatial models** provide outputs (and calculate internal states) for homogenous sub-areas of the total area modelled. These sub-areas are defined as homogenous in a key characteristic(s) relevant to the model, e.g. homogenous soil types or similar production systems. For example a lake system may be disaggregated into areas within 1-2m of the shoreline, the creek leading into the lake and the deeper lake systems. Interactions between these three ‘regions’ are then considered by the model. The model is also able to output impacts for each of these regions.

4. **Grid, cell or element-based spatial models** provide outputs (and calculate internal states) on a uniform or non-uniform grid basis (see for example Schaldach and Alcamo, 2006; Pausas and Ramos, 2006; Brown Gaddis et al., 2010; Laughlin et al., in press). Neighbouring grid elements or cells may have some of the same characteristics but will still be modelled separately, as opposed to homogenous region-based spatial models where these areas would be lumped together. For example when considering the impact of land use changes on terrestrial ecosystems, the landscape may be divided into a uniform grid, where the descriptors of each grid cell are based on either a single measurement or an average of measurements in that cell (e.g. land cover, species distribution, soils). These cells may then be modelled either independently or as a connected series depending on the conceptualization of the model.

5. **Continuous space models** like partial differential equations are typically discretised in environmental modelling into one of the above.

2.3.2 Treatment of time

Similar to treatment of space, are a few common approaches to dealing with time in models:

1. **Non-temporal, static models** do not make reference to time. For example, key ecological attributes of a landscape may be considered to be patch size and connectivity. These may be modelled for different scenarios from a static land use or management decision using appropriate ecological indicators. This is essentially a simple model of ecological impact of land use change that has no reference to time.

2. **Lumped, discrete temporal models** generally provide outputs over a single time period, such as average annual outputs. For example many nutrient and sediment export models output an average annual load, rather than an annual or daily time series (e.g. Lu et al., 2006; Shrestha et al., 2006).

3. **Dynamic, quasi-continuous models** provide outputs for each time-step over a specified period. The time step can be made as small as needed. For
example, a model may calculate the change in system variables each day, month or year. This approach is usually taken when the response of the system to a time varying input is required.

For integrated models, the entire model may not employ a single spatial or temporal scale, which creates additional problems in integration. For example, a dynamic, grid-based lake model may be linked to a spatially and temporally averaged economic or ecological model. In general, the choice of aggregation or disaggregation level is subjective and is likely to affect model outputs. Sensitivity to such a choice should be considered when interpreting model results, and if the influence is too great the model may need to be modified (for example component models may need to be redesigned to work at a different scale).

2.3.2 Treatment of individuals

Some models are designed to estimate average or distributional characteristics of a population or phenomena, while others, referred to as agent-based models, simulate the individual ‘agents’ and their interactions with each other and their environment (see for example Hood, 1999; van der Veen and Otter, 2001; Filatova et al., 2011). Also referred to as multi-agent systems or individual-based models, these representations are based on the idea that detailed knowledge and information are available on the properties of individuals and that system properties are a potentially non-linear consequence of agent actions (Hood, 1999). Thus the concept of ‘emergent behaviour’ of the system as a result of individual interactions is a key concern of agent-based modelling. These types of models are most commonly developed for ecological or socio-economic applications in which agents represent humans or non-human animals.

2.3.3 Treatment of uncertainty

Uncertainty is an important consideration in developing any model, but is particularly important and usually difficult to deal with in the case of models of complex systems. Uncertainty in models may be derived from uncertainties in system understanding (i.e. what processes should be included, how do different processes interact), from uncertainties in data and measurements used to parameterise the model or from uncertainty in the inputs or conditions used for model runs.

Some modelling approaches are able to explicitly deal with uncertainty in data, measurements or conditions. Other approaches require comprehensive testing of the model to allow this understanding to be developed. The level of testing required to develop this understanding is rarely carried out however, largely due to time and other resource constraints. Such a task can be complex for even relatively simple integrated models (see for example Refsgaard et al., in press; Norton and Andrews, 2006; Norton et al., 2005; Norton et al., 2003; Norton et al., in press).

For example, the sensitivity of a model to changes in one or two parameters at a time might be tested but analysis rarely involves more complex combinations of parameter changes. The results from such a testing regime can also be quite difficult to interpret. Very few approaches explicitly consider uncertainty introduced by the system conceptualisation or model framework.

Requirements regarding model uncertainty are often associated with the purposes of the model. For example, the variation of a system output from the observed value may be very important for forecasting models, but may be much less critical for decision-making or management models. In this case, the user may be more concerned with being able to accurately distinguish between the approximate magnitude, or merely the direction, of impacts from two alternative management options (or scenarios) (Reichert and Borsuk, 2006).
2.4 Optimisation versus scenario-based approaches

There are two main approaches for generating output from models. The first of these is **scenario-based**, where the model is developed to consider the impacts of implementing management interventions or decision options (often referred to as ‘what if?’ analysis). This type of approach is intended to allow the user to explore the results of various actions and the effects and associated trade-offs. The second approach is **optimisation**, in which the model explicitly determines the best intervention or decision according to a specified objective (maximise net returns, minimise environmental costs) subject to various constraints. In this case, the model user is generally presented with a single ‘best’ option or intervention. The objective function may be defined as a weighted combination of multiple objectives.

A third intermediate approach considers conditions to respect sets of constraints instead of a single objective, with an aim of determining explicitly the sets of parameters and actions allowing to meet these requirements (Martin 2004). The choice of one approach over the other ones is often imposed by both computational and theoretical considerations. Optimisation often requires an exhaustive search of the space of alternatives, which for complex and large integrated models, can be prohibitively expensive. A possible solution is to simplify the model by use of a metamodel (see Section 3.3), but even if this is possible, another requirement is to be able to formally define an objective function to be optimised. In case of multi-objective, multi-stakeholder problems, such a formalisation is not an easy process.

3 APPROACHES TO MODELLING COMPLEX SYSTEMS

Given the different definitions of what constitutes integration and the varied purposes of modelling, many approaches to developing models of complex systems have been pursued. This section provides a classification of six model types for integrated assessment before providing an overview of applications of each approach. It concludes with a framework for choosing the appropriate approach, given requirements placed on the model. Of course, classification using a concise framework can be somewhat arbitrary, and particular models may belong to more than one class, or be a mixture of more than one class. For example, a Bayesian network that consists of interactions between individuals may also be viewed as an agent-based method or even an expert system if the structure of the network and the information that populates it are derived from expert opinion. A summary of each of the approaches, the types of model applications for which they are appropriate and the way in which they deal with the considerations described in Section 3 is given in Table 1. Table 2 provides a summary of several integrated assessment studies classified by the approach used.

3.1 System Dynamics

3.1.1 What is the system dynamics approach?

System dynamics modelling represents a set of conceptual and numerical methods that are used to understand the structure and behaviour of complex systems. According to Jay Forrester (1961), the founder of system dynamics, the methodology has three key principles: feedback control theory, understanding the decision making process, and the use of computer-based technologies to develop simulation models. There has been debate about how to view system dynamics (as philosophy, or paradigm, or methodology), and its epistemological and ontological stance (positivist or interpretivist) (Lane, 2001; Lane and Oliva, 1998).
In system dynamics, the fundamental premise is that the dynamic behaviour over time (BoT) is endogenously generated from the “systemic structure” or the network of interactions that bind system components together. Therefore, understanding this causal structure is prerequisite for understanding and managing the system. A system dynamics model represents the cause-effect relationships, feedback loops, delays, physical/information links, and decision rules that are thought to generate the system behaviour (Wolstenholme, 1999). This representation is known as “dynamic hypothesis”, and is treated as a working theory until it is proven or refuted based on how well the simulation model produces the historic behaviour (i.e. reference mode) (Randers, 1980 p.131 and 134).

To develop a numerical model, the modeller converts the dynamic hypothesis into a “stocks and flows” representation. Stocks (also known as accumulators or levels) represent the system state (Sterman, 2000a, p.199). Flows (also known as rates) are the processes that influence change in the stock levels. Next, differential equations are used to numerically show the rate of change in stocks. A simulation engine is used to run the numerical model, and simulate the change in the values of stocks and flows over time.

Even without developing a quantitative model, there are still many management implications that can be learned from mapping and analysing the dynamic hypothesis. Meadows (1999) presented a list of “leverage points” for management interventions that can be identified from the dynamic hypothesis. They vary in their effectiveness to change the system behaviour from parameters (least effective), to decision rules (moderately effective), and goal/power structure (highly effective). In system dynamics applications, there has been special emphasis on two important aspects of the modelling process. First, eliciting the causal assumptions that end users have about the system (known as mental models), and developing models that test the veracity of these assumptions. Second, engaging end users and stakeholders in a modelling process which fosters the values of openness, diversity, and self-reflection (i.e. social learning purpose) (Wolstenholme, 1997) (Costanza, R., & Ruth, M.) Based on these ideas, a number of system dynamics-based modelling approaches have emerged, such as: mediated modelling (van den Belt, 2004) and Group model building (Vennix, 1996).

Given the learning-oriented nature of system dynamics, it has been closely linked to fields of similar interests, such as: systems thinking, cognitive psychology, and organizational learning. Also, from its early beginning, system dynamics literature has much contributed to policy sciences, especially in environment and natural resource management (e.g. Meadows et al., 1972).

3.1.2 How do system dynamics approaches deal with model considerations?

System dynamics models may treat space and time in any of the ways outlined in Section 3, depending on the nature of the problem (Saeed, 1992). Uncertainty in data and inputs values must be considered by comprehensive testing of the model; that is, data uncertainty is not explicitly considered in the model structure. Each parameter needs to have a real world counterpart (Sterman, 2000), and should be tested for the values for which the model remains valid (Coyle, 2000).

Like other causal-descriptive models, it is not sufficient to generate accurate output behaviour but, more importantly, the model structure should be a sufficient representation of the real system under study (i.e. as often said the model should produce the “right output behaviour for the right reasons.”). The philosophical and technical aspects of model validation have been early addressed in system dynamics literature (e.g.: (Barlas, 1989, 1996)). These models are usually simulation-based, being developed to consider ‘what if’ type questions. Whereas qualitative data is often used throughout the modelling process (Luna-Reyes and Andersen, 2003), incorporating qualitative data into system dynamics models and assessing the impacts of soft is challenging. A number of methods have been
developed to address this requirement (e.g. Ford and Sterman, 1998; Mclucas 2003).
System dynamics models are most useful for social learning and enhancing system understanding or for experimentation applications (e.g. Seppelt and Richter, 2005; Yeh et al., 2006).

3.1.3 Advantages and disadvantages of system dynamics models

Aside from the capacity to model feedback, delays, and non-linear effects, using system dynamics provides several advantages to the modelling process and end users. First, system dynamics models (even just conceptual models) are useful learning tools that help improve system understanding and foster system thinking skills and knowledge integration for modellers and end users. For example, the distinction between stocks and flows sharpens thinking about the processes that drive the behaviour of the system. The focus on identifying and modelling feedback loops encourages closed-loop thinking (i.e. thinking in terms of interdependent variables rather than linear and uni-directional links) (Richmond, 1993). Moreover, a system dynamic model makes a useful distinction between the true and perceived system conditions. This distinction is essential for modelling decision making and social responses.

Secondly, thanks to advances in the development of high level dynamic modelling software applications (such as ithink, Vensim and Powersim), computational system dynamics modelling has become widely accessible to people (even with minimal technical background). These applications are often designed as communication layers: user-interface, stock-flow, mathematical equations, and programming code. This design separates a non-modeller user from the mathematical details of the model.

Thirdly, the system dynamics literature has made rich contribution to approaches that inform the modelling process, including: data collection methods (e.g. Luna-Reyes and Andersen, 2003), knowledge elicitation/mapping techniques, and policy analysis (e.g. Andersen et al., 2003).

Some disadvantages of this approach relate to the relative simplicity of linking variables, meaning that models can quickly grow in size and complexity. This may result in developing “super-elegant” but less useful models, which obscure the key structures that generate the dynamic behaviour and draw attention away from the most influential leverage points. The existence of user-friendly graphic interfaces has in some cases been a disservice by offering that false impression that modelling is always easy and additional variables and processes can be included with a few clicks of the mouse. As a result models that are overly complex and lack balance between data availability and accuracy can easily come out of the process.

Additionally, inclusion of uncertain or postulated feedback loops may create complex model behaviour that does not correspond to real world behaviour and that is often very difficult to verify or validate. Treatment of space is actually also very limited. Probably only Simile provides some functionality for that, but not the others. This has been partially compensated by add-on software packages, such as SME (ref.) or StellaR that link system dynamics software to more powerful spatial engines.

Moreover, despite all the claims about the potential learning outcomes of system dynamics modelling, the empirical evidence on its effectiveness is still inconclusive (Karakul and Qudrat-Ullah, 2008, p.3)

3.1.4 Brief overview of applications

Table 2 summarises some examples of how the system dynamics approach has been utilised to investigate complex interactions between humans and ecosystems. These examples show the use of system dynamics for a broad range of
applications, from an exploratory model not tied to a specific application site, to studies, which integrate social, institutional, agricultural, physical and ecological factors for specific case study areas. None of these case studies investigate uncertainty in a comprehensive way. All of the case studies focus on scenario-based analysis rather than optimisation. All focus on the development of system understanding rather than any of the other purposes. The type of problem and location of case study differs widely though, showing the capacity of the approach to address a broad range of problems and settings where the focus is on improved systems understanding.

3.2 Bayesian Networks

3.2.1 What are Bayesian Networks?

Bayesian networks (BN) are most commonly used in modelling for decision-making and management applications in which uncertainty is a key consideration (see for example Pearl, 1990; Ames, 2002; Jenson, 1996; Varis and Kuikka, 1999; Varis, 2002; Bromley et al., 2005). This is because, unlike other modelling approaches, BNs use probabilistic rather than deterministic relationships to describe the connections among system variables (Borsuk et al., 2004). In a BN, variables are represented by nodes connected by arrows which represent causal dependences or an aggregate summary of complex associations (Reckhow, 2003). Each dependence is then characterized by a conditional probability distribution (Borsuk et al., 2004) for the variable at the head of an arrow, given all possible values of its ‘parents’ at the tails of arrows. Variables without parents are represented by unconditional (i.e., marginal) distributions. Bayesian decision networks (BDN) are BNs that include decision (i.e. management) variables and utility (i.e. monetary and non-monetary cost-benefit) variables (Ames, 2002). Feedback loops cannot be conveniently represented in BNs.

3.2.2 How do Bayesian Networks deal with model considerations?

BNs are able to explicitly incorporate both quantitative and qualitative information to specify the model. Thus, BNs are particularly useful when historical data are lacking, but other types of knowledge are available (e.g. Sadoddin et al., 2005). Most applications of BNs are not explicitly spatial or temporal. Where space or time is incorporated into a BN model it is often lumped (so that variables representing different locations or times are represented by different nodes). BNs are capable of incorporating qualitative state variables, for example ‘river health is better’ or ‘river health is worse’, strengthening the relevance for management and decision making. Because all relations in a BN are probabilistic, modelled outcomes inherently include information about predictive uncertainty.

3.2.3 What types of applications are Bayesian Networks used for?

Because of their historical roots in decision theory, BNs are especially useful for management and decision-making applications. Results are presented in terms of the probability of occurrence for different event or output states. These states may be qualitative or quantitative and, because BNs can incorporate a wide range of information types, predictions can usually be associated directly to management targets. This makes BNs very accessible to decision-makers.
3.2.4 Advantages and disadvantages

BNs break down complex causal chains into components that can be addressed separately (Borsuk et al. 2006). BNs also have the capacity to use and integrate different sources of information in order to derive the conditional probability distribution between variables, reducing constraints imposed by lack of data (Sadoddin et al. 2003; Wintle et al. 2003). For example, the conditional probabilities connecting variables can be specified using everything from detailed models to qualitative experiential understanding, overcoming the problems of ‘simple links’ found in system dynamics approaches. This also implies that very complex systems with many state variables can be considered. Another important advantage of the BN approach is in communicating model results, given that the definitions and appropriate states of outputs have often been constructed in collaboration with model users. BNs have some important limitations. Probabilistic relations within BNs reflect uncertainty in model parameterization, not model structure. Because structures of BNs are relatively simple, they may be more prone to structural errors than more mechanistic models. Practical implementation of BNs often requires discretization of continuous variables. This may add substantial imprecision to variable relationships and model predictions, which is not always considered. Finally, as mentioned above, BNs are not capable of adequately considering feedback loops.

3.2.5 Brief overview of applications

Bayesian Networks have been used for a very broad range of problem applications (see Table 2 for examples). BN models are rarely explicitly spatial nor temporal, although lumped representations of space and time are occasionally used. This is not necessarily due to a limitation in the method; it has more to the nature of applications for which BNs have been applied in the past. Similarly, BNs have often been used for problems in which there is only a simple decision criterion and a limited number of options to be considered. However, applications such as Ticehurst et al. (in press) demonstrate that this is not a true limitation of the technique. The use BNs to consider systems with greater than 50 criteria or variables of interest to the decision maker and on the order of a million different decision options or scenarios.

The majority of BN applications use a discrete rather than continuous representation of variables in the network, although the approach does allow for continuous variables under certain constraints. Most BN applications have been developed for decision-making and management purposes, and there is a strong focus on stakeholder participation in model development.

3.3 Metamodels

3.3.1 What are metamodels?

Metamodel application as a method of integrated modelling is relatively new. Metamodelling derives simple concepts from complex models and integrates these concepts into a new model; in other words they are models of models. Regression and other data mining techniques are commonly used to create metamodels (see for example Piñeros Garcet et al., 2006), but this approach hides the model mechanics. Another approach to metamodelling is model reduction (Ratto et al. 2012)) which preserves the dynamic structure of the model, by reducing the state space.

Metamodels are usually created with a specific goal in mind. Bouzaher et al. (1993) suggests that the metamodel attempts to approximate and aid in the interpretation of the simulation model. Simulation outputs can result in large tables
of information which can be complicated and time consuming to interpret. Metamodels may provide look up tables, or simpler functions that represent the information in these more detailed models. Metamodelling can be used in two ways in integration: a metamodel of a detailed integrated model can be developed as a summary of this model, or a metamodel can be created for detailed system components which are then coupled to create the integrated system model.

3.3.2 How do metamodels deal with model considerations?

Metamodels may retain many of the features (such as spatial or temporal scales) of the models from which they are built. It is likely that both spatial and temporal scales in the metamodel will be coarser than those of the underlying model. Metamodels may treat time and space in any of the ways outlined in Section 3. Metamodels do not explicitly allow for the uncertainty in model parameters or structure. Most data mining approaches provide estimates of uncertainty when fitting a model to data, but in the case of metamodels this uncertainty refers to the level of agreement between the original model and the metamodel, not between the metamodel and the real world. Thus a metamodel may have a good fit to the underlying model but may or may not adequately represent the real world process. Where the original model is well-fit by a much simpler model it is likely that the original model was overspecified – that is, it had many more degrees of freedom than could be justified by the information in any observed data. This may indicate that the simpler metamodel structure is a better representation of the underlying data, but would be more accurate if fitted to the observed data than the overspecified model. This may not be a problem if the process representation of the metamodel is required to be substantially aggregated compared to the original model (i.e. the information required from the metamodel is less). Thus careful testing and consideration of the metamodel is necessary before it is integrated.

3.3.3 What types of applications are metamodels used for?

Metamodels are useful for all types of applications, but their advantage is seen in decision-making and management applications where a simpler model structure and a faster running model are often required. They are also useful in social learning applications.

3.3.4 Advantages and disadvantages

Metamodels relieve the interpretation of simulation models by providing a set of rules for the simulation model. This knowledge can then be utilised in decision-making or introduced into a knowledge-based system (Pierreval, 2003). Another advantage of metamodelling is that it allows the evaluation of consequences of alternative policies without additional simulations (Bouzaher et al., 1993). Other advantages include: reduced data requirements, simplified form, less demanding modelling effort, and a high integrative potential (Graham et al., 2003). However, metamodelling can result in the loss of some accuracy and detail (Graham et al., 2003), although the need for high accuracy is more important in simulation models. Metamodels can be used to interpret complex models.

3.3.5 Brief overview of applications

There are relatively few applications of metamodelling as the sole approach to developing an integrated model. Most applications couple metamodels with more complex models to create an integrated systems model. However there are a few
applications in which the majority of the integrated model can be considered to consist of metamodelled components. The use of these types of approaches as a component of an integrated model is also increasing as the difficulties of ‘bolting-on’ complex components to an increasingly complex integrated model becomes more apparent. Metamodels are frequently used to represent a component of the system for which a fairly simple output is required, derived from only one or a few inputs from a very detailed and complex model which may itself consider a much broader range of system drivers than needs to be considered in the model.

3.4 Coupling Component Models

3.4.1 What are coupled component models?

The approach of coupling component models involves combining complex models from different disciplines to come up with an integrated outcome (see for example Matthies et al., 2006; Prato, 2005; Rivington et al., in press; Letcher et al., 2004; Grant et al., 2002; Fennessy and Shukla, 2000; Schneider et al., 1999; Laniak et al., 2012). Coupling may be loose, where outputs from models are linked together ‘manually’ (i.e., externally to the original models), or tight where the component models are engineered to work together to share inputs and outputs. At the extreme, components may be designed specifically to work together to the extent that they have limited use on their own without extensive recoding. The conceptual framework for a coupled component model generally represents links between system components, so that nodes often represent detailed component models, while links correspond to data passing between models. These models are able to incorporate feedback.

3.4.2 How do coupled component models deal with model considerations?

Coupled component models inherit the features of the component models that comprise them. This means that space and time may be treated in any of the ways outlined in Section 3. Importantly the integrated model does not necessarily work on the same space and time scales as the component models (it may be more aggregated) and individual components often operate over disparate time and space scales. In these cases, disaggregation and aggregation procedures must often be applied to link models. For example, an ecological model may operate on a grid, while the linked economic model may be lumped spatially for the entire area, or may be region-based.

Coupled component models generally only incorporate quantitative data in model parameterisation. The effects of uncertainty are not explicitly incorporated in model outputs, but must be determined through detailed testing and analysis. The level of testing required is generally large given the complexity of the underlying models and their links, such that the true uncertainty in these models is rarely well understood and is difficult to represent. These models may be optimisation or scenario-based.

3.4.3 What types of applications are coupled component models used for?

These models are useful for prediction, forecasting, management and decision-making, social learning and developing system understanding/experimentation. However, the added model complexity can make these models inappropriate or difficult to successfully use in forecasting or prediction applications for which uncertainty assessments are required (Voinov and Cerco, 2010).
3.4.4 Advantages and disadvantages

A coupled component model can explore dynamic feedbacks between socioeconomic change and ecological perturbations (Voinov et al., 1999) and can incorporate very detailed representations of system components and their links. When compared to other simpler approaches, coupled component models allow for more depth in the representation of individual components, but tend to compromise the breadth of the system able to be represented. This is because the complexity of underlying components imposes limitations in terms of time and other resources required to develop and run the models, as well as estimate uncertainty (Voinov and Shugart, 2012). There is also a concern for social learning. This approach does not benefit from the interfaces available for SD, BN or ABM, because they feature an ad hoc integration while the others provide a shell to implement an integrated representation.

3.4.5 Brief overview of applications

Coupled component modeling is the most commonly used approach to integrated modeling. Applications vary greatly in terms of spatial and temporal scales, the system components considered, the types of problems being addressed and the approach required. This can be seen clearly from the breadth of examples provided in Table 2. As was stated in Section 5.3, coupled component models commonly contain metamodelled elements, or even components, which mix the other integrated modelling approaches. The examples provided also demonstrate another common feature of coupled component models: a focus on depth of description for a few system components rather than on breadth of description of the entire system. The examples shown tend to focus on a few components of the system, rather than providing descriptions of numerous social, economic, ecological and physical processes and their interactions. This type of model approach can also be used for scenario-based or optimisation-based styles of modelling, while the majority of other approaches tend to primarily use a scenario-based approach.

3.5 Agent-based models

3.5.1 What are agent-based models?

Agent-based models focus on representation of the interactions between individuals or agents in a system (see for example Lansing & Kremer 1994; Sichman et al. 1998; Janssen 2002; Pahl-Wostl, 2002; Moss et al., 2001; Monticino et al., in press; Znidarsic et al., 2006; Fialtova et al., 2012). They are based on the Multi-agent system paradigm that features autonomous entities in a common environment able to act on it and communicate with an internal objective (Ferber 1999). ABMs are then made up of two or more agents that exist at the same time, share common resources and communicate with each other (Bousquet et al. 1999). Agents typically are able to adapt when the environment changes. A key focus of agent-based modelling is the discovery of emergent behaviour – that is, large scale outcomes that result from simple interactions and learning among individuals. For this reason they are particularly useful for social learning applications. Agent-based models are frequently theoretical and are usually applied to social and ecological applications. The conceptual framework for an agent-based model usually describes the autonomous entities interacting, their links and their behavioural patterns.
3.5.2 How do agent-based models deal with model considerations?

Agent-based models handle spatial features well and are tailored to represent individuals. Event-based frameworks exist, but time-based ones are easier to handle. The ABM approach benefits from the existence of dedicated platforms with easy to re-use component and nice visualisation features such as Cormas, NetLogo, Repast, etc. These platforms lead to the use of ABM for scenario exploration rather than to optimisation.

3.5.3 What types of applications are agent-based models used for?

Agent-based models are primarily used for social learning and are also used to improve system understanding or for experimentation. Bousquet and Le Page (2004) provide a review in the context of ecosystem management, and Berger (2001) discusses agent-based models in agriculture. Several books have been edited with collection of applications with target systems emanating from current (Gilbert DATE and REF needed) or ancient social issues (Kohler DATE and REF) as well as environmental ones (Janssen DATE and REF).

3.5.4 Advantages and disadvantages

Agent-based simulation provides a framework in which techniques can be applied which match various requirements of environmental management modelling (Hare and Deadman, 2004). They are very useful for developing a shared system understanding when working with stakeholder groups. The complexity of interactions between individuals means that detailed information is often required to parameterise the model, and the spatial scales of applications may be limited. The inclusion of less well-known or understood processes can limit their accuracy for prediction or forecasting applications. One of the most important features of ABMs is their ability to represent behaviour with a rule-based approach.

ABM is a quite good candidate for several dimensions of integration: with stakeholders with translation in role playing games (Bousquet et al 2002; Le Page et al. 2011), but also integration of stakes or integration of disciplines. They are not meant to integrate sub-models.

3.5.5 Brief overview of applications

In general, agent-based models have been used for two purposes: as part of a social learning experience with relatively smaller numbers of stakeholders considering resource competition problems at local scales; and, as part of a more theoretical or academic study aimed at developing understanding of social and biophysical systems. Problems considered are generally explicitly spatial (often represented with a grid) and temporal. These models are increasingly being called upon to consider larger spatial and social scales, including issues with more policy relevance (eg Smajgl et al. 2011).

3.6 Knowledge-based models

3.6.1 What are knowledge-based models?

Knowledge-based models can be seen as a type of qualitative model; knowledge is encoded into a knowledge base and then an inference engine uses logic to infer conclusions (Davis, 1995; Davis et al., 1992). Knowledge-based models can be
divided into rule-based models, where the model is formalised by a set of “if-then-else” rules, logic-based models where the models is expressed as a series of logic statements, called facts, formalised according to a logic system. Strictly related to logic-based models are declarative models (Muetzelfeldt et al., 1989) the aim of which is to separate the mechanics of numerical integration, required to simulate the model on a computer, from the logic describing the mathematical relationships among the model’s variables. Knowledge-based models can also be ‘learned’ based on the experience of the user and the knowledge inputs to the system, through a process called ‘knowledge elicitation’. Knowledge-based models are typically used by Expert Systems which, according to Haan (1994), are ‘computer software that offers advice to the software user based on its own store of knowledge and the user’s response to a number of if-then rules or questions.’ In this case, the knowledge base will contain a number of models, and their quality is fundamental as the knowledge base determines the success of the system (Forsyth, 1984).

3.6.2 How do knowledge-based models deal with model considerations?

Knowledge-based models are able to incorporate both quantitative and qualitative data and information. When embedded in Expert Systems they commonly incorporate high-level expertise obtained from top experts in the field to aid in problem-solving (Waterman, 1985). Simple models do not incorporate the uncertainty associated with rules and information. More sophisticated models, however, do allow for these sources of uncertainty to be accounted for explicitly and the effects of these of the certainty of the recommendation to be considered. Most knowledge-based models are non-temporal, but rules can be created that incorporate either lumped temporal outputs or outcomes in specific time periods (e.g. if it rains today it will probably rain tomorrow). Spatial rule-based models have been prototyped, but are less commonly applied than nonspatial systems, even if we can remark that Cellular Automata are based on simple spatial rule-based models. Rule-based models provide scenario-based outcomes using ‘what if’ rules, so are not appropriate for optimisation-based applications.

3.6.3 What types of applications are rule-based models used for?

The operation of rule-based models by expert systems is useful for all purposes but they are most useful for management and decision-making applications. Most rule-based systems are non-temporal and are used for design purposes, but it is possible to design rules that aid in prediction or forecasting, for example by having rules that relate an outcome to previous outcomes.

3.6.4 Advantages and disadvantages

There are many advantages in using knowledge-based models. Human experts have to be trained in a specific area in order to gain expertise in that area. However, if we input expert knowledge into a knowledge base then others are able to use that knowledge. Combining expert systems, which contain various knowledge-based models, provides a comprehensive knowledge base (Hart, 1986). Since an expert system is essentially a program, it is consistent. Mistakes can occur, but it is rare. Knowledge-based models have several disadvantages. The knowledge must be kept up to date in order to incorporate new findings which might overturn or improve the previous knowledge. Moreover, all knowledge must be acquired before it can be represented (Hart, 1986). Some problems can be too complex for being formalised using a knowledge-based model, containing too many rules or facts that can be time consuming for the inference engine to
3.6.5 Brief overview of applications

Knowledge-based models are an unorthodox approach to integration. They do not provide any explicit construct to build an integrated model, but the simple fact that they are based on our pre-processed knowledge of how we see a problem, means that they are integrated models “per-se”. They are clearly instrumental in integration of knowledge. In particular, they have proven useful for problem diagnosis for waste-water treatment plants, as recently shown by Aulinas et al. (2011). In the case of waste-water treatment plants there are many complex issues pertaining non-linearities in biochemical processes which cannot be simply formalised by a traditional modelling approach. The knowledge-based model can be used to elicit the experience of the plant operator and therefore be able to incorporate also qualitative information. In other contexts, the knowledge based approach has been primarily used to consider fairly simple decision or management problems, such as the management of total maximum daily loads (Dai et al., 2004) or algal blooms (Marsili-Libelli, 2004). They use a scenario-based approach to the problem and tend to consider outcomes for one or a few decision criteria. They are not explicitly spatial but may be temporal or used for forecasting, for instance forecasting the incidence of algal blooms given antecedent conditions. Knowledge-based models are often used as a component with other types of approaches (e.g. Sojda, in press; Roetter et al., 2005).

4 SELECTING THE APPROPRIATE MODELLING APPROACH

The attributes of each of the different modelling approaches described in Section 5 have been used to develop a framework for selecting an appropriate approach for new applications (see Table 3). This table allows modellers and model users to consider their aims in model development, the types of data available to them, the preferred compromise between breadth and depth of system description, their preferred treatment of uncertainty, and whether they are interested in considering interactions among agents explicitly in choosing an appropriate model type for their application.

5 DISCUSSION

There are some considerations in model-building that we have not addressed here, and some that require more attention, for example public participation (Voinov and Bousquet, 2010). According to Mostert (2006), there are several reasons for inviting public participation. These include the possibility of:

- more informed and creative decision-making
- more public acceptance and ownership of the decisions
- more open and integrated government
- enhanced democracy
- social learning to manage issues

Modelling can provide an important and useful mechanism for accomplishing the above goals. A model can capture a shared understanding of system processes and can help people to manage disagreements. With the aid of a model, for example, conflict over management options can often be reduced to more easily resolvable conflicts concerning underlying system assumptions. In this way, models provide a less threatening means for developing a shared system understanding than interactions focused on resolution of specific environmental problems. Involving communities in model development can also add to the validity of the final model developed, as well as create an opportunity for shared governance. Delivery of models through software or a decision-support system can...
permit the model to be used by others to make management decisions beyond the timeframe of a scientific research project.

6 CONCLUSIONS

This paper has reviewed six common approaches to developing models for natural resource management and integrated assessment. It demonstrates that there is a variety of approaches that may be called on to suit different application situations and an increasing body of literature that use these approaches to solve a wide variety of problems. As with all modelling problems, integrated model developers need to first have a good understanding of the needs of their model and of the types of data available to parameterise it before they select an approach. This paper has provided a framework for choosing an appropriate modelling approach considering spatial and temporal scales required, reliance on qualitative data, characterisation of uncertainty, and the purpose for which the model is being developed. Importantly the compromise between representing depth in individual system components and representing breadth of the overall system has been demonstrated. The challenge to integrated modellers is to capture the advantages of these approaches while overcoming some of their limitations, possibly through the development of more hybrid models, which use a variety of approaches to knowledge integration. Finally while improved rigour in modelling is required it is clear from this review that there are many approaches available for those interested in developing models as well as an ever improving literature of applications and lessons learnt. We are now in a position to reflect on the discipline of modelling complex systems and improve its rigour and methods according to the specific kind of integration at stake in the investigation / modelling of the target system.
REFERENCES


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SDS, 2004. Systems Dynamics Society


Seppelt, R., Richter, O., 2005. "It was an artefact not the result": A note on systems dynamic model development tools. *Environmental Modelling and Software* 20, 1543-1548.


Sojda, R.S., in press. Empirical evaluation of decision support systems: needs, definitions, potential methods, and an example pertaining to water fowl management. *Environmental Modelling and Software*.


Figure 1. Example of conceptual framework for a lake system affected by changes in water quality
<table>
<thead>
<tr>
<th>Approach</th>
<th>Typical Applications</th>
<th>Types of Data</th>
<th>Treatment of Space</th>
<th>Treatment of Time</th>
<th>Treatment of Uncertainty in Inputs/Parameters</th>
<th>Treatment of Uncertainty in Model Structure</th>
<th>Optimisation or Scenario-Based</th>
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<td>System Dynamics</td>
<td>• System understanding/experimentation</td>
<td>Quantitative</td>
<td>Various</td>
<td>Various</td>
<td>None</td>
<td>None –easier to test than others</td>
<td>Scenario-based</td>
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<td>• Social learning</td>
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<tr>
<td></td>
<td>• Decision-making and management</td>
<td>Both</td>
<td>Various – lumped, non-spatial more common</td>
<td>Various – lumped temporal or nontemporal more common</td>
<td>Explicit</td>
<td>None</td>
<td>Scenario-based</td>
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<td>Bayesian Networks</td>
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<td>Coupling Complex Models</td>
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<tr>
<td>Agent-Based Models</td>
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<tr>
<td>Expert Systems</td>
<td>• All</td>
<td>Both</td>
<td>Various</td>
<td>Various - usually nontemporal but rules can be ‘forecast’ based</td>
<td>Explicit</td>
<td>None</td>
<td>Scenario-based</td>
</tr>
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</table>
Table 2.
A few applications of integration approaches

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<tr>
<td><strong>System Dynamics</strong></td>
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<td></td>
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<tr>
<td>Janssen (2001)</td>
<td>Lake eutrophication</td>
<td>Not implemented for a specific case – exploratory model</td>
<td>Lake ecosystem model (movement of phosphorus through the system – soil, water, mud) Human system model (behaviour of agents – farmers)</td>
<td>Lake specific</td>
<td>Various</td>
<td>Scenario-based</td>
<td>Agents degree of uncertainty is quantified as the difference between expected returns and the actual returns of the decisions made in the previous time step</td>
</tr>
<tr>
<td>Fernandez and Selma (2004)</td>
<td>Water resource management</td>
<td>Irrigated lands of Mazarrón and Aguilas, SE Spain</td>
<td>Agriculture Socio-economic Water resources Pollution</td>
<td>Various</td>
<td>Monthly (1960-present)</td>
<td>Scenario-based</td>
<td>N/A</td>
</tr>
<tr>
<td>Hilty et al. (2006)</td>
<td>Impact of Information and Communication Technologies on environmental sustainability</td>
<td>European Union</td>
<td>ICT industry ICT use Energy Transport Goods and Services Waste</td>
<td>Various</td>
<td>Various</td>
<td>Scenario-based</td>
<td>Model output generated for each scenario was compared with qualitative estimation and validation from experts</td>
</tr>
<tr>
<td>Study</td>
<td>Issue</td>
<td>Location</td>
<td>Sector</td>
<td>Various</td>
<td>Various</td>
<td>Scenario-based</td>
<td>Notes</td>
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<tr>
<td>Settle et al. (2002)</td>
<td>Exotic species invasion</td>
<td>Yellowstone Lake, WY, USA</td>
<td>Aquatic ecology</td>
<td>Various</td>
<td>Various</td>
<td>Scenario-based</td>
<td>N/A</td>
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<tr>
<td>Yeh et al. (2006)</td>
<td>Soil erosion and nutrient pollution</td>
<td>Keelung River, Taipei, Taiwan</td>
<td>Soil erosion</td>
<td>Various</td>
<td>Various</td>
<td>Scenario-based</td>
<td>N/A</td>
</tr>
<tr>
<td>Bacon et al. (2002)</td>
<td>Land use change</td>
<td>Wales</td>
<td>Land use change</td>
<td>Various</td>
<td>Various</td>
<td>Scenario-based</td>
<td>First stage of model acknowledges that findings are not absolute and estimates errors</td>
</tr>
<tr>
<td>Bromley et al. (2005)</td>
<td>Water resource planning</td>
<td>Lodden catchment, UK</td>
<td>Socio-economic</td>
<td>Various</td>
<td>Various</td>
<td>Scenario-based</td>
<td>N/A</td>
</tr>
<tr>
<td>De Santa Olalla et al. (in press)</td>
<td>Aquifer planning</td>
<td>Eastern Mancha, Spain</td>
<td>Water inputs Environment restrictions Urban consumption Agricultural consumption</td>
<td>Hydrogeological unit</td>
<td>Years</td>
<td>Scenario-based</td>
<td>Each node has a conditional probability table, which quantifies how much that node is related to its parent nodes in probabilistic terms</td>
</tr>
<tr>
<td>Dorner et al. (in press)</td>
<td>Non-point source pollution</td>
<td>Stratford Avon upper</td>
<td>Erosion and sediment transport</td>
<td>Field- and Catchmen</td>
<td>Various</td>
<td>Scenario-based</td>
<td>Monte Carlo simulation to compute probability</td>
</tr>
<tr>
<td>Study</td>
<td>Type</td>
<td>Location</td>
<td>Focus</td>
<td>Timeframe</td>
<td>Analysis</td>
<td>Uncertainty</td>
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<tr>
<td>Henriksen et al. (in press)</td>
<td>Groundwater contamination</td>
<td>Havelse Creek catchment, Denmark</td>
<td>Groundwater flow and transport Urban and rural pesticide sources Farm economics Ecological and sociological impacts</td>
<td>Catchment</td>
<td>Not specified</td>
<td>Scenario-based</td>
<td>Uncertainty in parameterization through expert elicited and data-based conditional probabilities. Sensitivity analysis helped identify errors in the network structure or CPTs.</td>
</tr>
<tr>
<td>Pollino et al. (in press)</td>
<td>Decline in native fish communities</td>
<td>Goulburn Catchment, Victoria, Australia</td>
<td>Water quality Hydraulic habitat Structural habitat Biological potential Species diversity</td>
<td>Various</td>
<td>Not specified</td>
<td>Scenario-based</td>
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<tr>
<td>Riemann et al. (2001)</td>
<td>Land management</td>
<td>Columbia River Basin, USA</td>
<td>Population dynamics (salmonids) Aquatic ecology</td>
<td>Catchment</td>
<td>Years</td>
<td>Scenario-based</td>
<td>N/A</td>
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<tr>
<td>Saddodin et al. (2005)</td>
<td>Salinity management</td>
<td>Little River catchment, Macquarie River Basin, Australia</td>
<td>Social acceptability Terrestrial ecology Economic impacts (agricultural returns) Hydrological Stream ecology</td>
<td>Catchment</td>
<td>Long to medium term</td>
<td>Scenario-based</td>
<td>Uncertainty in parameterization through conditional probabilities, no estimate of structural uncertainty</td>
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<tr>
<td>Ticehurst et al. (in press)</td>
<td>Management of coastal lakes and estuaries</td>
<td>Various, NSW Australia</td>
<td>Impacts on economic production Water quality Terrestrial habitat Social acceptability and cultural values Aquatic habitat, flora and fauna</td>
<td>Catchment</td>
<td>20-50 year time frame</td>
<td>Scenario-based</td>
<td>Uncertainty in parameterization through conditional probabilities, no estimate of structural uncertainty</td>
</tr>
</tbody>
</table>

**Metamodelling**

<table>
<thead>
<tr>
<th>Study</th>
<th>Type</th>
<th>Location</th>
<th>Focus</th>
<th>Timeframe</th>
<th>Analysis</th>
<th>Uncertainty</th>
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</thead>
<tbody>
<tr>
<td>Bouman et al. (1999)</td>
<td>Regional rural development</td>
<td>North Atlantic Zone of Costa Rica (Caribbean lowlands)</td>
<td>Economic sustainability Agriculture</td>
<td>Field-region</td>
<td>Various</td>
<td>Optimisation</td>
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<td>Bouzaher et al.</td>
<td>Non point</td>
<td>Corn Belt</td>
<td>Groundwater and surface water</td>
<td>Various</td>
<td>Various</td>
<td>Scenario-</td>
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<tr>
<td>Year</td>
<td>Study Type</td>
<td>Region/Location</td>
<td>Methodology</td>
<td>Area</td>
<td>Approach</td>
<td>Results</td>
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<tr>
<td>------------</td>
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<td>---------------------------------------------------------------------------------</td>
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<td>----------</td>
<td>--------------</td>
<td>-------------------------------------------------------------------------</td>
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<tr>
<td>(1993)</td>
<td></td>
<td>pollution in agriculture and Lake States regions, USA</td>
<td>herbicide concentrations Ecological-economic model</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Graham et al. (2003)</td>
<td>Dryland salinity</td>
<td>Western Australia Wheatbelt – Date Creek (within Blackwood River Catchment)</td>
<td>Groundwater Economic</td>
<td>Various</td>
<td>Various</td>
<td>Optimisation</td>
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<tr>
<td>Kampas and White (2002)</td>
<td>Nitrate pollution</td>
<td>Kennet catchment South East England</td>
<td>Economic Water quality</td>
<td>Various</td>
<td>Various</td>
<td>Optimisation</td>
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<tr>
<td>Coupled component Models</td>
<td>Fischer and Sun (2001)</td>
<td>Analysing and projecting regional land use</td>
<td>Terrestrial ecology Economics</td>
<td>Regional</td>
<td>Various</td>
<td>Optimisation</td>
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<tr>
<td>Krol et al. (2001)</td>
<td>Semi-arid regions and vulnerability to climate change</td>
<td>North East Brazil</td>
<td>Water resources Agriculture Socioeconomic</td>
<td>Regional</td>
<td>Various</td>
<td>Scenario-based</td>
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<tr>
<td>Lehtonen et al. (in press)</td>
<td>Agricultural development</td>
<td>Ylaneenjoki and Taipaleenjoki regions, Finland</td>
<td>Nutrient leaching Economic</td>
<td>Regional</td>
<td>Various</td>
<td>Scenario-based</td>
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<tr>
<td>Letcher et al. (2004)</td>
<td>Water allocation, access and pricing</td>
<td>Namoi River Basin, NSW, Australia</td>
<td>Hydrology Farm returns and decision-making Policy and access arrangements Catchment (large &gt; 40,000km²) Daily hydrology Annual economics Full model multi-year</td>
<td>Limited analysis of parameter sensitivity conducted.</td>
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<tr>
<td>Study</td>
<td>Topic</td>
<td>Region</td>
<td>Focus Areas</td>
<td>Timeframe</td>
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<tr>
<td>Letcher et al. (2006 a,b)</td>
<td>Integrated Water Resources Management</td>
<td>Numerous small catchments, northern Thailand</td>
<td>Hydrology, Crop growth, Household returns and making Erosion</td>
<td>Small catchment, economic on household basis</td>
<td>Daily hydrology, Seasonal economics, Full model multi-year</td>
<td>Scenario-based</td>
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<tr>
<td>Matthies et al. (2006)</td>
<td>Water quality management</td>
<td>Elbe River basin, Germany</td>
<td>Precipitation-runoff, Nutrient loads, Hazardous substance loads</td>
<td>Various</td>
<td>Yearly</td>
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<td>Münier et al. (2004)</td>
<td>Agricultural land use change</td>
<td>Denmark</td>
<td>Economic, Terrestrial ecology</td>
<td>Project area 6082km²</td>
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<td>Scenario-based</td>
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<td>Prato (2005)</td>
<td>Landscape change</td>
<td>Rock Mountain West, USA</td>
<td>Economic, Land use change, Ecological assessment, Policy</td>
<td>Various</td>
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<tr>
<td>Rivington et al. (in press)</td>
<td>Climate change impact</td>
<td>‘Hartwood farm’, Scotland and ‘Agrichiana farm’, Italy</td>
<td>Biophysical systems model, Management systems model</td>
<td>Farm</td>
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<td>Schluter and Ruger (in press)</td>
<td>Water management</td>
<td>Amudarya river delta, Central Asia</td>
<td>Water allocation, Changes to major environmental variables, Habitat suitability</td>
<td>Various</td>
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<td>Turner et al. (2000)</td>
<td>Wetland management and policy</td>
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<td>Wetland ecology</td>
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<td>Van Delden et al. (in press)</td>
<td>Catchment management</td>
<td>Mediterranean catchments (non specific)</td>
<td>Climate and weather, Hydrology, Sedimentation, Salinisation, Water demands and usage, Water resources, Land use, Profit and crop choice</td>
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<td>Various</td>
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<td>Authors and References</td>
<td>Model Title</td>
<td>Model Description</td>
<td>Modeling Objectives</td>
<td>Spatial and Temporal Resolution</td>
<td>Model Type</td>
<td>Notes</td>
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<td>Van der Veeren and Lorenz (2002)</td>
<td>Catchment management</td>
<td>Nutrient generation and transport</td>
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<td>Rhine River Basin</td>
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<td>Voinov et al. (1999)</td>
<td>Catchment management</td>
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<td>Patuxent watershed, Maryland, USA</td>
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<td><strong>Agent-based models</strong></td>
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<td>Janssen et al. (2000)</td>
<td>Rangeland management</td>
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<td>Rangeland ecology</td>
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<td>Gross et al. (2006)</td>
<td>Rangeland management</td>
<td>Plant and livestock dynamics</td>
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<td>North-east Australia</td>
<td>Management actions and characteristics</td>
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<td>Kaufmann and Gebetsroither (2004)</td>
<td>Sustainable use of renewable resources</td>
<td>Socioeconomic</td>
<td>Various</td>
<td>Various</td>
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<td>Mathevet et al. (2003)</td>
<td>Conservation management</td>
<td>Socioeconomic</td>
<td>Regional</td>
<td>Seasons</td>
<td>Scenario-based</td>
<td>N/A</td>
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<td></td>
<td>Camargue, France</td>
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<td>Moreno et al. (in press)</td>
<td>Deforestation</td>
<td>Socioeconomic (settler, concessionaire and government agents)</td>
<td>4 ha cells</td>
<td>Half-yearly</td>
<td>Scenario-based</td>
<td>N/A</td>
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<tr>
<td></td>
<td>Caparo Forest Reserve, Venezuela</td>
<td>*Agent-based model combined with a Cellular Automata model on land use change</td>
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<tr>
<td>Van der Veen and Otter (2001)</td>
<td>Land use change</td>
<td>Socio-economic</td>
<td>Various</td>
<td>Various</td>
<td>Scenario-based</td>
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<td>Not specified</td>
<td>Spatial heterogeneity</td>
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<td><strong>Expert Systems</strong></td>
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<td>Dai et al. (2004)</td>
<td>Water quality</td>
<td>Water pollution</td>
<td>430km²</td>
<td>Various</td>
<td>Scenario-based</td>
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<td></td>
<td>Noyo River catchment, California</td>
<td>Water quality</td>
<td></td>
<td></td>
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<td></td>
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<td>Catchment management</td>
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Dynamic suitability
Plant growth
Natural vegetation
Land management
Van der Veeren and Lorenz (2002)
Catchment management, Natural vegetation
Land management
Various
Various
Scenario-based
N/A

Voinov et al. (1999)
Catchment management, Nutrient abatement
Various
Daily-yearly
Scenario-based
N/A

Agent-based models
Janssen et al. (2000)
Rangeland management, Socio-economic, Various, Various, Optimisation
N/A

Gross et al. (2006)
Rangeland management, North-east Australia, Plant and livestock dynamics, Various, Various, Scenario-based
N/A

Kaufmann and Gebetsroither (2004)
Sustainable use of renewable resources, Socio-economic, Various, Various, Scenario-based
N/A

Mathevet et al. (2003)
Conservation management, Socioeconomic, Regional, Seasons, Scenario-based
N/A

Moreno et al. (in press)
Deforestation, Socioeconomic (settler, concessionaire and government agents), 4 ha cells, Half-yearly, Scenario-based
N/A

Van der Veen and Otter (2001)
Land use change, Socio-economic, Various, Various, Scenario-based
N/A

Expert Systems
Dai et al. (2004)
Water quality, Various, Scenario-based
N/A
<table>
<thead>
<tr>
<th>Study</th>
<th>Methodology</th>
<th>Location</th>
<th>Variable(s)</th>
<th>Scenarios</th>
<th>Uncertainty</th>
<th>Notes</th>
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<tbody>
<tr>
<td>Fleming et al. (in press)</td>
<td>Cholera health risk</td>
<td>South Africa</td>
<td>Risk of algal bloom Socio- economic model</td>
<td>Various</td>
<td>N/A</td>
<td>Not specified Scenarios-based Fuzzy logic was applied to deal with uncertainties in the environmental variables</td>
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<tr>
<td>Regan et al. (2004)</td>
<td>Threatened species conservation</td>
<td>Snake River, USA</td>
<td>Conservation biology</td>
<td>Various</td>
<td>N/A</td>
<td>Various Scenarios-based Uncertainty in the input parameters is carried through to the final output value that the resulting bounds reflect the full extent of the uncertainty in the input parameters</td>
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<tr>
<td>Vellido et al. (in press)</td>
<td>Water management</td>
<td>Numerous streams across 7 European countries and Israel</td>
<td>Climate Land use Nutrients relative status Reach location (position from a wastewater treatment plant)</td>
<td>Stream</td>
<td>N/A</td>
<td>Various Scenarios-based</td>
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</tbody>
</table>


Table 3. Appropriate use of integrated modelling techniques

<table>
<thead>
<tr>
<th>What is your reason for modelling/type of application?</th>
<th>System dynamics</th>
<th>Bayesian Networks</th>
<th>Meta Modelling</th>
<th>Coupled component Models</th>
<th>Agent based Models</th>
<th>Expert Systems</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predictive</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
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<tr>
<td>Forecasting</td>
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<td>X</td>
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<td>X</td>
<td></td>
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<tr>
<td>Decision-making</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
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<tr>
<td>System understanding</td>
<td>X</td>
<td></td>
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<tr>
<td>Social learning</td>
<td>X</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>What types of data do you have available/want to use to populate your model?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Qualitative and quantitative data</td>
</tr>
<tr>
<td>Quantitative data only</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Do you want your model to focus more on a complex description of specific processes in the system or have a greater breadth of coverage of interactions in your system?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depth of specific processes</td>
</tr>
<tr>
<td>Breadth of system</td>
</tr>
<tr>
<td>Compromise</td>
</tr>
<tr>
<td>Both</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Do you want your model to provide explicit information about uncertainty caused by model assumptions?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
</tr>
<tr>
<td>No</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Are you interested in investigating the interactions between individuals and their impact on the system, or only the aggregated effects behaviour?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interactions</td>
</tr>
<tr>
<td>between individuals</td>
</tr>
<tr>
<td>Aggregated effects</td>
</tr>
</tbody>
</table>
