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Position paper

Selecting among five common 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 system 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, assess their outcomes, and communicate results in a transparent way. This paper reviews five common approaches or model types that have the capacity to integrate knowledge by developing models that can accommodate multiple issues, values, scales and uncertainty considerations, as well as facilitate stakeholder engagement. The approaches considered are: systems dynamics, Bayesian networks, coupled component models, agent-based models and knowledge-based models (also referred to as expert systems). 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 that aims to assist modellers and model users in the choice of an appropriate modelling approach for their integrated assessment applications and that enables more effective learning in interdisciplinary settings.

1. Introduction

Effective environmental management requires an understanding of the interactions between policy choice and complex social, economic, technical and environmental processes and related aims. 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 distributed 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 and more precisely estimated (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

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for such integrated assessment models or tools to enhance the effectiveness of decision-making and management has been widely acknowledged (see for example Bland, 1999; Voinov and Bousquet 2010; Carnevale et al., 2012; Hong et al., 2012; Jakeman and Letcher, 2003; Gough et al., 1998; Kragt et al., 2011; Liu et al., 2008; Oxley et al., 2004; Pahl-Wostl, 2007; Rotmans, 1998; Schneider, 1997; Zerger et al., 2011).

This paper reviews five broad classes of approaches that have the capacity to integrate knowledge (from various sources and of different types and forms) 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 in knowledge 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 but related 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:

i. **Integrated treatment of issues** – arises because management options for many natural resource problems have impacts on other social, economic and environmental issues. Concurrently considering the combined or integrated effects of management options may improve management decisions and reduce the occurrence of negative side effects. In this case integration is part of a system-wide 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. Voinov and Shugart (2013) distinguish between integrated and integral modelling, to stress that there may be different ways to conduct integration: in the former case, the system is considered as a collection of independent components, representing various subsystems (water, markets, agriculture, etc.); in the latter case integration is done at a lower level, when all the subsystems are described simultaneously as integral parts of the whole. This is an initial step in integration, which may involve stakeholders.

ii. **Integration with stakeholders**. The level and success at which model outputs are utilized will often depend on how connected stakeholders are to the model and how relevant model outputs are to policy and extension activities (Krueger et al., 2012; Voinov and Bousquet, 2010). Integration with and among stakeholders may vary from updating community groups of model outputs to large-scale inclusion of stakeholder views and knowledge at all stages of the modelling process. Various classifications of the types of integration between stakeholders and modellers have been given in the literature (e.g., Biggs, 1987; Martin and Sherington, 1997; Pretty, 1995). Integration of knowledge – sometimes known as participation or engagement – can be a side activity in the modelling process and may occur at any stage from elaboration of knowledge to use of models (Barreteau et al., 2013). It is also possible for modelling to be a side activity in the integration of knowledge. An example here involves scenario studies as carried out in the PRELUDE project (EEA, 2007) in which models contribute to participatory scenario development by providing quantitative information, insight in causal relations and side effects, consistency checks and/or visualisation.

iii. **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 (e.g. Barton et al., 2012).

iv. **Integration of processes** and models – requires combining two or more models of different systems or processes in a system (see Laniak et al., 2013 for a review). These processes may be biological, chemical, physical, economic or social. However, such integration may necessitate combining modelling techniques from disparate disciplines (e.g. Haapasaari et al., 2012). Here the target system is analysed with various lenses that all lead to a specific model.

v. **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 at 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). 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 (Welsh et al., 2013). 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. In integrated modelling for policy support, scale selection is a balancing act between: i) the scales of interest for end users or stakeholders; ii) the scale at which processes occur or can be represented; iii) the linkage between model components that represent processes across different scales; and iv) practical constraints such as data or computation limitations (Van Delden et al., 2011).

Of course, these five types of integration are not mutually exclusive. The integration of processes, disciplines or models may also involve the integration of different issues and scales (Kalaugher et al., 2013; Voinov and Shugart, 2013). Also, 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 assessment exercise.

Several modelling approaches can be 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 the incorporation of integrated knowledge and representations into models. Below in Section 3 we review some of the most relevant integrated modelling approaches before providing 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 questions: 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 and the impacts of alternative management actions. Predictive models may be very simple (often empirical, sometimes including theory to predict outliers) or may be more complex. Increased complexity of a model does not necessarily lead to improved predictive performance, so many successful predictive models, when judged with historical data only, have relatively simple structures that are well grounded in historical observations and mimic patterns or relationships observed (DePinto et al., 2004). Predictive models are generally required to have some level of accuracy in reproducing historic observations, and thus require data for calibration, and other independent data for validation.

Forecasting refers to predicting the value of a system variable in future time periods (short-, medium- or long-term), 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 et al., 1994). Forecasting can include likely or potential future scenarios, for example climate change and their impacts on biodiversity (Millennium Ecosystem Assessment, 2005). The accuracy of forecasting models is commonly tested by considering the difference between 'forecast' values and historic observations. With less information than that available for use in prediction, forecasting is typically more uncertain than contemporaneous prediction, unless coupled with real-time observational correction, with uncertainty typically growing with the length of the forecasting horizon (Alvisi and Franchini, 2011; Todini, 2004).

Management and decision-making under uncertainty often benefit from models, which are used in problem formulation and may be incorporated into 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-objective optimisation and multi-criteria analysis can provide insight into the trade-offs between competing objectives (Ascough et al., 2008; Maier et al., 2008) and can be coupled with simulation models (Gibbs et al., 2012). Management and decision-making models are usually needed to be able to differentiate between decision alternatives or management options (Ravalico et al., 2010). 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). Decision support models can be considered in terms of four main types of decision contexts (Barton et al., 2012; Sutherland, 1983): i) *directive*, where long-run options are explored, but the decision alternatives and causal structure for understanding their consequences are ambiguous and only likely directions of development can be predicted; ii) *strategic*, where focus is on evaluating alternatives to avoid medium-term future problems and to consider likely learning opportunities from policy; iii) *tactical*, where the models account for continuous observations and assist managers to react to short-term predictions; and iv) *operational*, where the causal structures are known and models are used to analyse and recommend alternative actions. There is a noticeable overlap between decision support models and those built for prediction; model purposes are clearly not mutually exclusive.

Social learning is increasingly acknowledged as a valuable output of building models. Social learning refers to the capacity of a social network to communicate, learn from past behaviour, and perform collective action, e.g. dealing with complex technical tasks and at the same time the social relational activities (Fraternali et al., 2012; Haapasaari et al., 2012). 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., 2007). In this case, models allow individuals to learn and experiment so as to inform their understanding of the way 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 often 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 (Levontin et al., 2011).

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 are fitted to their intended audience: some are 'research' models, accessible to the model builder and other researchers in order to explore their own assumptions; while others are stakeholder models that are generally developed with a large non-technical audience in mind, with the intention to open the black box such as with role playing games when the audience is not used to computer simulation (Barreteau et al., 2001). 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. Such information may be categorical in nature, e.g. yes/no, high/medium/low, but can also be descriptive or rule based. 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 (e.g. likelihood distribution assumptions) 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. System conceptualisation

When describing a system there are three major dimensions in which the system has to be conceptualised: space, time and structure.

2.3.1. Treatment of space

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

i. **Non-spatial models** do not make reference to space. For example a predator-prey model may not refer to any particular spatial scale (Atanasova et al., 2011; Ramos-Jiliberto, 2005).
ii. **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 (as in the examples in iii below) and the interactions between parts of the lake system are not considered explicitly.
iii. **"Region"-based, compartmental spatial models** provide outputs (and calculate internal states) for homogeneous sub-areas of the total area modelled. These sub-areas are defined as homogeneous in a key characteristic(s) relevant to the model, e.g. homogeneous soil types, similar production systems or belonging to the same administrative region. For example a lake system may be disaggregated into areas within 1–2 m 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.
iv. **Grid, cell or element-based spatial models** provide outputs (and calculate internal states) on a uniform or non-uniform grid- or vector-based representation (see for example Brown Gaddis et al., 2010; Laughlin et al., 2007; Pausas and Ramos, 2006; Rasmussen and Hamilton, 2012; Schaldach and Alcamo, 2006). Neighbouring grid elements or cells may have some of the same characteristics but will still be modelled separately, as opposed to homogeneous region-based spatial models where these areas would be lumped. 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.
v. **Continuous space models** like partial differential equations are typically discretised in environmental modelling into one of the above, though in some cases their direct analytical treatment can produce interesting theoretical results about system performance (Vanhatalo et al., 2012).

2.3.2. Treatment of time

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

i. **Non-temporal, static/steady state 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.
ii. **Lumped, discrete temporal/transient 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; Lynam et al., 2010; Shrestha et al., 2006; Wilkinson et al., 2009).
iii. **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.
iv. **Continuous models** result when the time-step becomes infinitesimally small and the discrete (difference equations) model becomes formulated in terms of ordinary differential equations. Such models are sometimes treated analytically as in the case of the Lotka–Volterra or other theoretical models of ecological communities (Svirezhev and Lofoget, 1983).

For integrated models, the entire model may not employ a single spatial or temporal scale or resolution, 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 conceptualisation of interactions and choice of aggregation or disaggregation level is subjective and is likely to affect model outputs. Sensitivity to such a choice should be considered eventually by alternative conceptualisations 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).

2.3.3. Treatment of entities or structure

Some models are designed to estimate average, aggregated or distributional characteristics of a population or phenomenon, while others, such as agent-based models, simulate autonomous groups like population settlements (Sanders et al., 1997) or individuals as 'agents' and their (preferential/behavioural) interactions with each other and their environment (see for example Filatova et al., 2011; Gao and Hailu, 2012; Hood, 1999; Schreinemachers and Berger, 2011; van der Veen and Otter, 2001). 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 socioeconomic applications in which agents represent humans or non-human animals. See Section 3.4 for further discussion on agent-based models.

Among aggregated models we also find many ways to treat system structure. Depending upon the level of detail that is justified or can be afforded we can find models that operate with just a few most important variables, compared to models that describe the system structure in terms of dozens or even hundreds of variables.

2.4. 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 different processes interact), from uncertainties in interpretation of data in relationship to the variables of interest (e.g. Linden and Mäntyniemi, 2011) and measurements used to parameterise the model or from uncertainty in the inputs or conditions used for model runs. Uncertainty may also be related to issues of complexity, e.g. ambiguities that often exist in the different perceptions of system definition and alternative causal structures (Mäntyniemi et al., 2013), or in the conceptualisation and problem framing due to multiple knowledge frame uncertainties (Brugnach et al., 2011; Henriksen et al., 2012). For models aiming at providing an integrated representation, 'validating' their predictive accuracy is generally not straightforward due to a lack of appropriate data for 'validation', especially for future predictions.

Some modelling approaches, such as Bayesian networks (Section 3.2), are able to explicitly deal with uncertainty in interpretation of data, measurements or conditions. Other approaches, such as system dynamics (Section 3.1), coupled components models (Section 3.3), and agent-based models (Section 3.4) require comprehensive testing of the model to allow this understanding to be developed. The level of testing required to develop this understanding (which is dependent on the modelling objective) 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 Norton and Andrews, 2006; Norton et al., 2006; Refsgaard et al., 2006). Modern Bayesian parameter estimation procedures (Gelman et al., 2004; Mäntyniemi et al., 2013) account for the mutual dependencies of parameters (variance–covariance structures of parameters) that are key for predictions of future states given historical data; however Bayesian methods remain underutilised in practice (Kuikka et al., 2013).

Requirements regarding model uncertainty are often associated with the purpose of the model. For example, the variation of a system output from observed values may be very important for forecasting models, but may be much less critical for social learning models, where the emphasis is more on stakeholders exchanging ideas and knowledge. In a management model, the user may be more concerned with being able to estimate the magnitude, or merely the direction, of impacts from two alternative management options (or scenarios) rather than precise prediction values (Reichert and Borsuk, 2005).

2.5. Resolving the model

There are four main approaches for generating output from environmental 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 or policies and the effects and associated trade-offs.

The second approach is solving the model equations analytically. This is of course possible only for models that are sufficiently simple, usually with just several variables and no spatial representation. In this case we can get a full description of the parameter space and know what the system behaviour will be under all possible combinations of parameters. This approach gives us an ultimate understanding of system performance, but the limits on model complexity are quite restrictive.

The third 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 fourth 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 multi-objective requirements (Carnevale et al., 2012; Farmani et al., 2009).

The choice of one approach over others is often imposed by computational, theoretical and end user considerations. For example, optimisation often requires an extensive search of the space of alternatives, which for complex and large integrated models, can be prohibitively expensive from a computational perspective. A possible solution is to simplify the model by use of a metamodel (Piñeros Garcet et al., 2006; Ratto et al., 2012), 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 (Farmani et al., 2012) and in many cases not even desirable.

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 five model types for integrated assessment before providing an overview of applications of each approach. These are Systems Dynamics (SDs), Bayesian Networks (BNs), Couple Component Models (CCMs), Agent-Based Models (ABMs) and Knowedge-Based Models (KBMs). It concludes with a framework for choosing the appropriate approach, given requirements placed on the model and type of applications defined by system definition and as part of development of terms of reference for the modelling project. 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 (Lehikoinen et al., 2013) or even an expert system if the structure of the network and the information that populates it are derived from expert opinion (e.g. Lecklin et al., 2011).

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 2 are 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 system dynamics?

System dynamics (SD) modelling represents a set of conceptual and numerical methods that is 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 a philosophy, paradigm, or methodology), and its epistemological and ontological stance (positivist or interpretivist) (Lane, 2001; Lane and Oliva, 1998).

There is much written about the philosophy of system dynamics, but in essence it boils down to system formalism based on ordinary differential (or rather difference) equations, which is formulated when the modeller converts the dynamic hypothesis into a "stocks and flows" representation. A dynamic hypothesis is a

Table 1
Summary of the five approaches to integration.

Approach	Typical applications (in approx. order)	Types of data	Treatment of space	Treatment of time	Treatment of uncertainty in inputs/parameters	Treatment of uncertainty in model structure	Optimisation or scenario-based
System dynamics	• System understanding/experimentation • Social learning	Quantitative mainly	Limited to date – lumped 'regions', and non-spatial, more common	Routine	Challenging but possible through Monte Carlo (MC) runs. Scenarios to simulate plausible range of inputs and other drivers	Requires comprehensive discrimination tests between alternatives	Scenario-based (also refers to simulation-based)
Bayesian networks	• Decision-making and management • Social learning • System understanding/experimentation • Prediction	Both	Limited to date – lumped 'regions', and non-spatial, more common	Limited – lumped temporal, or non-temporal, more common	Explicit by assigning probabilities to the links between the states of variables. Scenarios to simulate plausible range of inputs and other drivers	Structural learning from data and knowledge is possible	Both
Coupled component models	• Prediction, forecasting • System understanding/experimentation • Decision-making and management	Quantitative mainly but qualitative possible	Comprehensive set of options	Routine though component models may be limited eg if BN	Challenging through MC and/or Bayesian inference if model run-time not a constraint. Scenarios to simulate plausible range of inputs and other drivers	Requires comprehensive discrimination tests between alternatives	Both
Agent-based models	• Social learning • System understanding/experimentation	Quantitative mainly	Limited	Limited	Challenging but possible through MC runs. Scenarios to simulate plausible range of inputs and other drivers	Requires comprehensive discrimination tests between alternatives	Scenario-based
Knowledge-based models	• Decision-making and management • Prediction • Forecasting	Both	Limited – lumped, non-spatial more common	Various - usually non-temporal but rules can be 'forecast' based	Can be explicit	Requires comprehensive discrimination tests between alternatives	Scenario-based

conceptualisation of the causal relationships, feedback loops, delays, and decision rules that are thought to generate system behaviour. Stocks (also known as accumulators or levels) represent the system state variables (Sterman, 2000). Flows (also known as rates) are the processes that influence change in the stock levels (the right-hand side of equations). A simulation engine is used to run the numerical model, and simulate the change in the values of stocks and flows over time.

In many SD applications (particularly those using tools such as Stella, Vensim and Powersim), 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) (Costanza and Ruth, 1998). Based on these ideas, a number of SD-based modelling approaches have emerged, such as: mediated modelling (Metcalf et al., 2010; van den Belt, 2004) and Group model building (Vennix, 1996). Note, however, that there have been questions about the empirical evidence for the effectiveness of SD approaches for social learning (Qudrat-Ullah, 2008).

3.1.2. How do system dynamics approaches deal with model considerations?

In system dynamics we usually deal with discrete time and, particularly when using tools such as mentioned above, quite limited treatment of space. Either the model is spatially aggregated or at best it deals with a few spatial compartments. Uncertainty in data and input values must be considered by comprehensive testing of the model; that is, neither data nor parameter uncertainty are 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). Indeed, as with most integrated modelling approaches, BNs being an exception, treatment of uncertainty requires Monte Carlo type simulations for assumptions about errors in inputs and parameters, and comprehensive discrimination tests between alternative model structure assumptions.

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 addressed quite early in the 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 are often used throughout the modelling process (Luna-Reyes and Andersen, 2003), incorporating qualitative data into system dynamics models and assessing the impacts of soft variables is challenging. A number of methods have been developed to address this requirement (e.g. Ford and Sterman, 1998; McLucas, 2003).

SD models are most useful for social learning and enhancing system understanding or for experimentation applications (e.g. Hare, 2011; Seppelt and Richter, 2005; Sterman et al. 2013; Yeh et al., 2006).

3.1.3. Advantages and disadvantages of system dynamics models

Aside from the capacity to model feedbacks, delays, and nonlinear effects, using SD provides several advantages to the modelling process and end users. First, SD models (even just as 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

Table 2
Selected applications of integration approaches.

Reference	Management problem	Study area	Components	Optimisation/scenario	Uncertainty
System dynamics					
Chang et al., 2008	Coastal zone management	Kenting, Taiwan	Socioeconomic (tourism, land development) Environmental (sediment, wastewater) Ecological (coral reef, fish, algae) Management	Scenario-based	Sensitivity analysis
Fernández and Selma (2004)	Water resource management	Irrigated lands of Mazarrón and Aguilas, SE Spain	Agriculture Socioeconomic Water resources Pollution	Scenario-based	N/A
Hilty et al. (2006)	Impact of Information and Communication Technologies on environmental sustainability	European Union	ICT industry ICT use Energy Transport Goods and Services Waste	Scenario-based	Model output generated for each scenario was compared with qualitative estimation and validation from experts
Janssen (2001)	Lake eutrophication	Not implemented for a specific case – exploratory model	Lake ecosystem model (movement of phosphorus through the system – soil, water, mud) Human system model (behaviour of agents –farmers)	Scenario-based	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
Kuper et al. (2003)	Water resource management	Niger River delta – Mali	Human migration, population increase Land degradation Population dynamics (fish) Economic	Scenario-based	N/A
Lauf et al. (2012)	Urban development	Berlin metro region	Household structure Population dynamics Urban development	Scenario-based	N/A
Qin et al. (2011)	Water resource management	Shenzhen River, China	Socioeconomic (population, gross regional production, water demand, pollution generation) Water infrastructure (water supply, wastewater treatment) Receiving water system (hydrodynamics, water quality)	Scenario-based	Scenario analysis Qualitative assessment/ discussion of uncertainties
Saysel et al. (2002)	Water resource management	Numerous provinces in Turkey involving dam projects on the Euphrates and Tigris Rivers	Socioeconomic Land degradation (erosion, salinity) Water quality and quantity Institutional	Scenario-based	N/A
Settle et al. (2002)	Exotic species invasion	Yellowstone Lake, WY, USA	Aquatic ecology Socioeconomic	Scenario-based	N/A
Yeh et al. (2006)	Soil erosion and nutrient pollution	Keelung River, Taipei, Taiwan	Soil erosion Sediment transportation Runoff Nutrient Economic	Scenario-based	N/A

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Table 2 (*continued*)

Reference	Management problem	Study area	Components	Optimisation/scenario	Uncertainty
Bayesian networks					
Bacon et al. (2002)	Land use change	Wales	Land use change Agriculture Socioeconomic	Scenario-based	First stage of model acknowledges that findings are not absolute and estimates errors
Borsuk et al. (2004)	Eutrophication	Neuse River estuary, NC, USA	Water quality Aquatic ecology	Scenario-based	Probability distributions propagated to model endpoints
De Santa Olalla et al. (2007)	Aquifer planning	Eastern Mancha, Spain	Water inputs Environmental restrictions Urban consumption Agricultural consumption	Scenario-based	Each node has a conditional probability table, which quantifies how much that node is related to its parent nodes in probabilistic terms
Dorner et al. (2007)	Non-point source pollution	Stratford Avon upper watershed, Southern Ontario, Canada	Erosion and sediment transport Economic	Scenario-based	Monte Carlo simulation to compute probability distributions for the model's outputs, using probability density functions from other studies.
Henriksen et al. (2007)	Groundwater contamination	Havelse Creek catchment, Denmark	Groundwater flow and transport Urban and rural pesticide sources Farm economics Ecological and sociological impacts	Scenario-based	
Kuikka et al. (1999)	Fisheries management	Baltic Sea	Mesh size Exploitation level Fish recruitment and growth rates	Both scenario- and optimal-based	Monte Carlo simulations; Scenarios for different growth rates
Lehikoinen et al. (2013)	Oil combating fleet locations	Gulf of Finland	Recovery efficiency of vessels Location of vessels Weather impact	Both scenario- and optimal-based	Uncertainty in parameters reflected in conditional probabilities; sensitivity analysis (value of information)
Levontin et al. (2011)	Fisheries management	Baltic Sea	Bioeconomic Sociological (commitment to management, compliance) Biological	Scenario-based	Uncertainty in parameters reflected in conditional probabilities
Molina et al. (2010)	Water resources management	Altiplano region, Murcia, Spain	Hydrogeology Socioeconomic	Scenario-based	Comparison with results from parallel studies; Stakeholder review
Pérez-Miñana et al. (2012)	Greenhouse gas emissions management	UK (agricultural sector)	Fertiliser, crops and land use change Farm livestock emissions Farm energy emissions Carbon sequestration	Scenario-based	N/A
Pollino et al. (2007)	Decline in native fish communities	Goulburn Catchment, Victoria, Australia	Water quality Hydraulic habitat Structural habitat Biological potential Species diversity	Scenario-based	Uncertainty in parameterization through expert elicited and data-based conditional probabilities. Sensitivity analysis helped identify errors in the network structure or CPTs.
Rieman et al. (2001)	Land management	Columbia River Basin, USA	Population dynamics (salmonids) Aquatic ecology	Scenario-based	N/A

Sadoddin et al. (2005)	Salinity management	Little River catchment, Macquarie River Basin, Australia	Social acceptability Terrestrial ecology Economic impacts (agricultural returns) Hydrological Stream ecology	Scenario-based	Uncertainty in parameterization through conditional probabilities, no estimate of structural uncertainty
Ticehurst et al. (2011)	Natural Resource management	Wimmera catchment, Victoria, Australia	Socioeconomic (landholder values/attitudes, knowledge, income/funding, farm practices)	Scenario-based	Sensitivity analysis; Comparison of BN analysis results with that from a conventional analysis based on same data; Expert review
Ticehurst et al. (2007)	Management of coastal lakes and estuaries	Various, NSW Australia	Impacts on economic production Water quality Terrestrial habitat Social acceptability and cultural values Aquatic habitat, flora and fauna	Scenario-based	Uncertainty in parameterization through conditional probabilities, no estimate of structural uncertainty
Coupled component models					
Fischer and Sun (2001)	Analysing and projecting regional land use	China	Terrestrial ecology Economics	Optimisation	N/A
Krol et al. (2001)	Semi-arid regions and vulnerability to climate change	North East Brazil	Water resources Agriculture Socioeconomic	Scenario-based	N/A
Lehtonen et al. (2007)	Agricultural development	Ylaneenjoki and Taipaleenjoki regions, Finland	Nutrient leaching Economic	Scenario-based	N/A
Letcher et al. (2004)	Water allocation, access and pricing	Namoi River Basin, NSW, Australia	Hydrology Farm returns and decision-making Policy and access arrangements	Scenario-based	Limited analysis of parameter sensitivity conducted.
Letcher et al. (2006a,b)	Integrated Water Resources Management	Numerous small catchments, northern Thailand	Hydrology Crop growth Household returns and making Erosion	Scenario-based	Detailed analysis of parameter sensitivity conducted.
Matthies et al. (2006)	Water quality management	Elbe River basin, Germany	Precipitation-runoff Nutrient loads Hazardous substance loads	Scenario-based	N/A
Münier et al. (2004)	Agricultural land use change	Denmark	Economic Terrestrial ecology	Scenario-based	N/A
Prato (2005)	Landscape change	Rock Mountain West, USA	Economic Land use change Ecological assessment Policy	Scenario-based	N/A
Rivington et al. (2007)	Climate change impact	‘Hartwood farm’, Scotland and ‘Agrichiana farm’, Italy	Biophysical systems model Management systems model	Scenario-based	N/A However, authors identified uncertainty as the principal limitation of their approach.
Rutledge et al. (2008)	Regional development	Waikato region, New Zealand	Climate change Hydrology Water quality Demographics Economics, Land use Terrestrial biodiversity	Scenario-based	N/A
Schluter and Ruger (2007)	Water management	Amudarya river delta, Central Asia	Water allocation Changes to major environmental variables Habitat suitability	Scenario-based	The scenario analysis itself was used as a means to assess uncertainties in future water availability

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Table 2 (*continued*)

Reference	Management problem	Study area	Components	Optimisation/scenario	Uncertainty
Turner et al. (2000)	Wetland management and policy	Not specified	Wetland ecology	N/A	N/A
Van Delden et al. (2004); Van Delden et al. (2007)	Catchment management and regional development	Mediterranean catchments (generic model)	Climate and weather Hydrology Sedimentation Salinisation Water demands and usage Water resources Land use Profit and crop choice Dynamic suitability Plant growth Natural vegetation Land management	Scenario-based	Behavioural tests/sensitivity analysis
Van Delden et al. (2008)	Spatial planning, policy impact assessment	Puerto Rico	Climate change Economic Demographic Transport Regional interaction Land use	Scenario-based	Behavioural tests and where possible comparison of model output with data
Van Delden et al. (2009)	Desertification, water resource management, land degradation, land use planning, land management	Countries and regions (generic model)	Climate and weather Hydrology Plant growth Erosion Regional interaction Land use Crop choice Dynamic suitability	Scenario-based	Model output compared with data and expert validation
Van Delden et al. (2010)	Impact assessment of (agricultural) EU policies	EU-27	Climate change Agricultural economics Demographics Land use Crop choice Dynamic suitability and yield	Scenario-based	Model output compared with data, behavioural tests
van der Veeren and Lorenz (2002)	Catchment management Nutrient abatement	Rhine River Basin	Nutrient generation and transport Water quality model Environmental indicators Economic model	Scenario-based	N/A
Voinov et al. (1999)	Catchment management	Patuxent watershed, Maryland, USA	Economic (land use) module Hydrology Socioeconomic Aquatic ecology Water quality	Scenario-based	N/A
Agent-based models					
Filatova et al. (2011)	Coastal zone land use	Not specified (theoretical application)	Socioeconomic (land characteristics, demand/supply, land market dynamics)	Scenario-based	N/A
Gao and Hailu (2012)	Recreational fishing management	Ningaloo Marine Park, Western Australia	Econometric models (Trip demand, Site choice, Trip timing, Trip length, Catch Rate) Trophic-dynamic model (algae, fish, coral)	Both scenario-based and optimization-based (using AHP to rank options)	Integrated with fuzzy logic to incorporate uncertainties over the preferences of outcomes or criteria
Gross et al. (2006)	Rangeland management	North-east Australia	Plant and livestock dynamics Management actions and characteristics	Scenario-based	N/A

Janssen et al. (2000)	Rangeland management	Not specified	Socioeconomic Agriculture Rangeland ecology	Optimisation	N/A
Kaufmann and Gebetsroither (2004)	Sustainable use of renewable resources	Not specified	Socioeconomic Forest processes	Scenario-based	N/A
Le et al. (2012)	Land-use change	Hong Ha watershed, Vietnam	Socioeconomic (human population) Biophysical (landscape) Land-use related policies	Scenario-based	Independent replications method which calculates the mean values of the impact indicators and their confidence intervals
Mathevet et al. (2003)	Conservation management	Camargue, France	Socioeconomic	Scenario-based	N/A
Parrot et al. (2011)	Marine wildlife protection (maritime traffic management)	St Lawrence River Estuary, Canada	Whales Environment (bathymetry, navigational charts, tides, visibility) Boat	Scenario-based	Results validated against real scenarios
Schreinemachers and Berger (2011)	Agricultural system management	Various	Investment (land, livestock, technology, crops, conservation) Productivity and consumption Resource dynamics (soil, water, nutrients)	Scenario-based	Sensitivity analysis; Comparison to other simulators
van der Veen and Otter (2001)	Land use change	Not specified	Socioeconomic Spatial heterogeneity	Scenario-based	N/A
Zhang et al. (2011)	Emissions trading policy design	Jiangsu Province, China	Emission abatement costs and discharge tax Transaction costs Market efficiency	Scenario-based	N/A
Knowledge-based models					
Booty et al. (2009)	Environmental effects monitoring (industry/mining)	Canada	Effluent Fish community Benthic community	Scenario-based	N/A
Chevalier et al. (2012)	Frost damage to agricultural crops	Georgia, USA	Weather (air temperature, dew point temperature, wind speed) Agrometeorology (frost/freeze risk levels for specified crops)	Scenario-based	Fuzzy logic to handle imprecise nature of frost risk levels
Dai et al. (2004)	Water quality	Noyo River catchment, California, USA	Water pollution Water quality Catchment management	Scenario-based	N/A
Ferraro (2009)	Soil condition	Inland Pampa, Argentina	Crop management (tillage, harvest, yields, fertilization) Physical soil degradation Chemical soil degradation	Scenario-based	Sensitivity analysis to assess the relative importance of input variables; Fuzzy logic to handle imprecise nature of the indicators
Fleming et al. (2007)	Cholera health risk	South Africa	Risk of algal bloom Socioeconomic model	Scenario-based	Fuzzy logic was applied to deal with uncertainties in the environmental variables
Giordano and Liersch (2012)	Soil salinity	Lower Amudarya River Basin, Uzbekistan	Plant growth Groundwater Soil/surface characteristics Drainage Irrigation	Scenario-based	Fuzzy logic to handle vague linguistic variables; Experts evaluated the reliability of model outputs
Lam et al. (2004)	Watershed management	Lake Seymour, British Columbia	Turbidity Erosion	Scenario-based	N/A
Marsili-Libelli (2004)	Eutrophication	Orbetello lagoon, Italy	Water quality	Scenario-based	N/A

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Table 2 (*continued*)

Reference	Management problem	Study area	Components	Optimisation/scenario	Uncertainty
Regan et al. (2004)	Threatened species conservation	Snake River, USA	Conservation biology	Scenario-based	Uncertainty in the input parameters is carried through to the final output value in that the resulting bounds reflect the full extent of the uncertainty in the input parameters
Vellido et al. (2007)	Water management	Numerous streams across 7 European countries and Israel	Climate Land use Nutrients relative status Reach location (position from a wastewater treatment plant)	Scenario-based	N/A

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, an SD model makes a useful distinction between the *true* and *perceived* system conditions. This distinction is essential for modelling decision-making and social responses.

Secondly, due to advances in the development of high level dynamic modelling software platforms, such as ithink (isee systems, www.iseesystems.com), Vensim (Ventana Systems, www.vensim.com) and Powersim Studio (Powersim Software AS, www.powersim.com), 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 contributions 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., 2007). Central to these contributions is the work done on Group Model Building (GMB): a SD-based approach that brings together users, decision makers, and modellers through a facilitated process to develop conceptual and numerical models. Over the last 30 years and more, work on GMB has resulted in developing and evaluating standardized sets of modelling activities, known as scripts to be used in participatory modelling and collaborative planning (Hovmand et al., 2012).

The flipside of user-friendly and efficient model-building tools, like Stella (isee systems, www.iseesystems.com) or Simile (Simulistics, www.simulistics.com), is that it becomes relatively simple to add variables and interactions to the model, 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 these user-friendly graphic interfaces has in some cases been a disservice by offering the 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 ensue from 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 also very limited in the above-mentioned model building tools, although this is not due to a limitation in the method but rather the nature of these tools. Probably only Simile provides some functionality for that, but not the other software platforms. This has been partially compensated for by add-on software packages, such as the Spatial Modeling Environment (SME; Maxwell et al., 2003) or StellaR (Naimi and Voinov, 2012) that link system dynamics software to more powerful spatial engines. Besides these model building tools, software environments such as Geonamica facilitate developing and integrating spatially explicit SD models (Hurkens et al., 2008). However, working with these environments requires software development capabilities of the modeller.

3.1.4. Brief overview of applications

Some examples of how the SD approach has been utilised to investigate complex interactions between humans and ecosystems are summarised in Table 2. 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 the case study differ widely, 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 (BNs) are most commonly used in modelling for decision-making and management applications in which uncertainty is a key consideration (see for example Ames, 2002; Bromley et al., 2005; Jenson, 1996; Kuikka et al., 1999; Newton, 2010; Pearl, 1990; Varis, 2002; Varis and Kuikka, 1999). 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 but time steps can be used to describe such effects (e.g. Borsuk et al., 2006).

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, including expert opinion and survey data, are available (e.g. Chen and Pollino, 2012; Richards et al., 2013; Sadoddin et al., 2005; Ticehurst et al., 2011). 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 (see Fernandes et al., 2012). BNs are capable of incorporating qualitative state variables, for example 'river health is better' or 'river health is worse', strengthening their 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 and uncertainty theory, BNs are especially useful for management and decision-making purposes in a wide range of applications where uncertainty is pervasive (e.g. Castelletti and Soncini-Sessa, 2007; Pérez-Miñana et al., 2012; Ticehurst et al., 2007). 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 with management targets. This makes BNs very accessible to decision-makers. Also, their relatively straightforward, cause-effect structure facilitates involvement of non-technical stakeholders in the design, development and application of the model (Haapasaari et al., 2012; Mäntyniemi et al., 2013).

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 (Aguilera et al., 2011; Chen and Pollino, 2012; 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. 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 through stakeholder dialogues, 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. Assessment of structural uncertainty is often neglected, but can be addressed by building and comparing outputs from alternative models based on different hypotheses about the system. This can be done within a single modelling framework, with the alternative hypotheses represented in a parent node for those nodes dependent on the hypotheses (Kuikka et al., 1999). Practical implementation of BNs often requires discretization of continuous variables. This may add substantial imprecision to variable relationships and model predictions, and may produce misleading results where extremes cases (i.e. tails of the distribution) are of interest (Nash and Hannah, 2011). Finally, as mentioned above, BNs are not capable of adequately considering feedback loops.

As with system dynamics, there are now numerous software platforms available for developing and applying BNs, including the more commonly used Netica (Norsys Software Corp., www.norsys.com), Analytica (Lumina Decision Systems, www.lumina.com), GeNIe and SMILE (University of Pittsburgh, genie.sis.pitt.edu), and Hugin Expert (Hugin, www.hugin.com). Some BN software platforms have been developed to overcome limitations of the modelling approach; for example BNT (K. Murphy, bnt.googlecode.com) and DBmcmc (D. Husmeier, www.bioss.ac.uk/~dirk/software/DBmcmc) handle dynamic BNs, and BUGS (MRC and Imperial College, www.mrc-bsu.cam.ac.uk/bugs) supports continuous variables.

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 or temporal, although lumped representations of space and time are occasionally used (e.g. object oriented Bayesian networks as in Molina et al., 2010). This is not necessarily due to a limitation in the method; it has more to do with the nature of applications to 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. (2007) and Farmani et al. (2009) demonstrate that this is not a true limitation of the technique. They 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 under uncertainty and management purposes, and there is a strong focus on stakeholder participation in model development.

3.3. Coupled component models

3.3.1. What are coupled component models?

The approach of coupling component models (CCMs) involves combining models from different disciplines or sectors to come up with an integrated outcome (see for example Drobinski et al., 2012; Fennessy and Shukla, 2000; Grant et al., 2002; Laniak et al., 2013; Letcher et al., 2004; Matthies et al., 2006; Prato, 2005; Rivington et al., 2007; Schneider et al., 1999; Van Delden et al., 2007, 2011). This can include the hybridisation of ABMs, SDs, KBMs, BNs and/or other modelling approaches. The combination of these approaches is especially seen when integrating social, economic and biophysical components. In such cases, the biophysical models are often the process-based computationally intensive models and distributed in time and space, while the social and economic models are often the ABM, BN, SD or KBM models (e.g. Van Delden et al., 2007).

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 CCM 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 often able to incorporate feedback.

3.3.2. How do coupled component models deal with model considerations?

CCMs 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 2.3. 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 temporal and spatial 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 (see Van Delden et al., 2011 for further discussion on scaling issues).

CCMs typically only incorporate quantitative data in model parameterisation, however this depends on the models that are integrated. 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.

3.3.3. What types of applications are coupled component models used for?

These models can be useful for prediction, forecasting, management and decision-making, developing system understanding/ experimentation and, if they are not overly complex, social learning. However, added model complexity can make these models inappropriate or difficult to use successfully in prediction applications for which uncertainty assessments are required (Voinov and Cerco, 2010). On the other hand, there is a tendency to assume to include all relevant processes in CCMs; these processes are made explicit and uncertainties can be specified for them. As in all modelling approaches choosing a level of detail appropriate for a specific purpose is something that lies with the modeller and is not a characteristic of an approach.

3.3.4. Advantages and disadvantages

A CCM can explore dynamic feedbacks, for example between socioeconomic change and ecological perturbations (Schreinemachers and Berger, 2011) and can incorporate very detailed representations of system components and their links. However, there may be difficulty in conceptually linking legacy models, as they were not built for integration but rather for in-depth understanding of a specific discipline. While it is preferred that the modelling process begins with the conceptual integration of processes followed by the development of models that fit the conceptual understanding, this is often not feasible due to time and other resource constraints (Van Delden et al., 2011). Despite being less than ideal, the integration of these legacy models seems to be common practice due to the large investments made in developing these models, and because they have been calibrated and people are already familiar with them.

When compared to other simpler approaches, coupled component models allow for more depth in the representation of individual components. Some 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 to estimate their uncertainty (Voinov and Shugart, 2013). Other approaches focus on a balance in the level of detail of the various models and, in such cases, individual components usually have a less detailed representation. When CCMs feature an ad hoc integration, whereas the other approaches tend to provide a shell to implement an integrated representation, they do not benefit from the interfaces available for SD, BN or ABM. Hence normally they do not facilitate participatory model development.

3.3.5. Brief overview of applications

Coupled component modelling is historically one of the most commonly used approaches to integrated modelling. Applications vary greatly in terms of spatial and temporal scales, the system components considered, the types of problems being addressed and the approach required (Akbar et al., 2013; Bergez et al., 2013; Mohr et al., 2013). This can be seen clearly from the breadth of examples provided in Table 2. CCMs can contain meta-modelled elements, or even components, which mix the other integrated modelling approaches. The examples provided demonstrate that a large range of component models focus on depth of description for a few system components rather than on breadth of description of the entire system, but others can have a broader focus and include less detail in the individual components. 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.

3.4. Agent-based models

3.4.1. What are agent-based models?

Agent-based models (ABMs) focus on representation of the interactions between autonomous entities in a system representing most often humans (see for example Bousquet et al., 1999; Filatova et al., 2011; Janssen, 2002; Lansing and Kremer, 1994; Le et al., 2012; Monticino et al., 2007; Moss et al., 2001; Pahl-Wostl, 2002;

Smajgl et al., 2011; Znidarsic et al., 2006) but also groups (Sanders et al., 1997), animals (Drogoul and Ferber, 1994) or biophysical entities such as water (Servat et al., 1998). 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 made up of two or more agents that exist at the same time, share common resources and eventually communicate with each other. Agents are typically able to react to perceived changes in their environment through action on the environment or internal adaptation. ABMs are able to represent agents' behaviour with a rule based approach.

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 individual entities. ABMs are sometimes developed and applied to incorporate complex cognitive representations of individuals' mental models, behaviours and choices, such as with the BDI (Belief, Desire, Intention) model (Rao and Georgeff, 1995). Thanks to such features, ABMs can explore, for example, how the attitudes of individuals or the institutional setting can affect system-level outcomes (Pahl-Wostl, 2005). For this reason they are particularly useful for social learning applications. The conceptual framework for an agent-based model usually describes the interaction of autonomous entities, as well as their links and their behavioural patterns.

3.4.2. How do agent-based models deal with model considerations?

ABMs handle spatial features well and are tailored to represent individuals. They are able to deal with elementary (spatial, organisational) level dynamics, as well as aggregated ones, such as farmers and villages, fields and river catchments (Becu et al., 2003). 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 components and nice visualisation features such as in Cormas (Cirad, cormas.cirad.fr), NetLogo (CCL, ccl.northwestern.edu/netlogo), and Repast (Argonne National Laboratory, repast.sourceforge.net). These platforms lead to use of ABMs for scenario exploration rather than for optimisation. They also include features for sensitivity analysis. However, it is still very difficult to address uncertainty in most ABMs and their simulation outputs.

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

ABMs are primarily used for policy and institutional analysis, and for simulating socioeconomic or socioecological processes to improve understanding of the dynamic interactions between agents and their settings. 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 collections of applications with target systems emanating from current (Gilbert, 2007) or ancient social issues (Kohler and Gumerman, 2000), as well as environmental ones (Janssen, 2002). ABMs are well suited to social learning, experimentation or management support. However, some are simple enough to be used for forecasting or prediction (e.g., Duriez et al., 2009; Schmitz, 2000).

3.4.4. 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, however omitting them may lead to much worse results and limit their ability for social learning.

The structures of ABMs are generally highly complex, incorporating not only local interactions but also variability among individuals and behaviour that adapts to the changing environment. Consequently, many ABMs tend to have high numbers of parameters and significant computational resource requirements, and their simulation results may not be easily reproduced. ABMs are quite a good candidate for several dimensions of integration with stakeholders thanks to ease of translation in role playing games (Bousquet et al., 2002; Le Page et al., 2012), but also integration of issues or disciplines. Although real-world processes can often be easily communicated with ABMs, the results are often not, especially when the model shows unexpected and/or emergent behaviour.

3.4.5. Brief overview of applications

As far as environmental issues are concerned, ABMs have mainly been used for three purposes: as part of an exploratory participatory modelling process with relatively smaller numbers of stakeholders considering resource competition problems at local scales; as a group decision or management support tool 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 (e.g. Smajgl et al., 2011).

3.5. Knowledge-based models

3.5.1. What are knowledge-based models?

Traditionally, in this type of model knowledge is encoded into a knowledge base and then an inference engine uses logic to infer conclusions (Chen et al., 2008; Davis, 1995; Davis et al., 1992). Knowledge-based models (KBMs) can be divided into rule-based models, where the models are formalised by a set of "if-then-else" rules, and logic-based models, where the models are expressed as a series of logic statements, called facts, formalised according to a logic system.

KBMs need to be 'learned' based on the experience of the user and the knowledge inputs to the system, through a process called 'knowledge elicitation'. This process is supervised by a human being, in opposition to other types of models, such as Artificial Neural Networks and to a lesser extent, Bayesian Networks, where the knowledge is often learnt directly from data. The main resulting difference is that the knowledge elicited from the expert is explicitly encoded in facts and rules and it can be also used to explain deductions based on chains of rule applications, something which is not trivially available in data-centric models.

KBMs are typically used in Expert Systems which, according to Haan et al. (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).

3.5.2. How do knowledge-based models deal with model considerations?

KBMs 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 by the definition of certainty factors associated with the rules and the effects of these on the certainty of the recommendation to be considered (see for instance, Heckermann and Shortliffe, 1992). In particular, the use of Fuzzy Set Theory (Klir and Yuan, 1995) in Expert Systems allowed considerable improvements in the ability to both represent uncertainty, and also to process it and make inferences, by means of fuzzy inference engines. The application of the so-called Fuzzy Expert Systems (Kandel, 1991) in various domains of Environmental Sciences has been particularly successful (Chevalier et al., 2012; Dokas et al., 2009; Lukasheh and Warith, 2001).

Most KBMs 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). An example is provided by Metternich (2001) on the design of an expert system to assess temporal and spatial changes of salinity. Spatial rule-based models have been prototyped, but are less commonly applied than non-spatial systems, even if we can remark that Cellular Automata can be based on simple spatial rules, which are often a combination of expert knowledge and historic calibration (e.g. Ravazzani et al., 2011). Rule-based models provide scenario-based outcomes using 'what if' rules, and are therefore not appropriate for optimisation-based applications. Finally, logic-based models have also been used to improve the rigour in the construction of models (Muetzelfeldt et al., 1989), and strictly related to such attempts are declarative models (Muetzelfeldt, 2007). The aim of declarative models 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.

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

The operation of KBMs by expert systems is useful for all purposes but they are most commonly used for management and decision-making applications. For some systems, such as wastewater treatment plants, the diagnostic capabilities of expert systems (rule backtracking) are also useful. Expert systems have also been proven useful in the analysis of outputs from large and complex models (Lam et al., 1988). A KBM can also be used, as shown by Herrero-Jiménez (2012), in place of quantitative models in the assessment of environmental impacts. KBMs are often used as a component with other types of approaches (e.g. Roetter et al., 2005; Sojda, 2007), in most cases to incorporate qualitative and difficult to formalise knowledge into technical systems.

3.5.4. Advantages and disadvantages

There are many advantages in using KBMs. 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 KBMs, provide a comprehensive knowledge base (Hart, 1986). Since an expert system is essentially a program, it is consistent. Mistakes can occur, but it is rare. KBMs have several disadvantages. The knowledge must be kept up to date in order to incorporate new findings which might overturn or improve previous knowledge. All knowledge must be acquired before it can be represented (Hart, 1986), and therefore the approach is not suitable for problems where knowledge of the relevant processes is uncertain or incomplete. Some problems can be too complex to be formalised using a KBM, containing too many rules or facts that can be time consuming for the inference engine to process. In the case of rule-based models the order in which rules are presented in the system is very important to ensure the best 'diagnosis' is retrieved (Gruber and Olsen, 1994).

3.5.5. Brief overview of applications

KBMs 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.

A relevant body of applications has been developed in the field of wastewater treatment, where the design and implementation of decision support systems take advantage of the ability of KBMs to represent human expertise that is difficult to formalise otherwise (Sànchez-Marré et al., 2008). In particular, they have proven useful for problem diagnosis for wastewater treatment plants, as recently shown by Aulinas et al. (2011). In the case of wastewater treatment plants there are many complex issues pertaining to non-linearities in biochemical processes that cannot be simply formalised by a traditional modelling approach. However, KBMs can be used to elicit the experience of plant operators and therefore incorporate 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 soil (Ferraro, 2009; Giordano and Liersch, 2012), total maximum daily loads for sediment (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.

4. Selecting the appropriate modelling approach

The attributes of each of the different modelling approaches described in Section 3 have been used to develop a guiding framework for selecting an appropriate approach for new applications (see Table 3). This table allows modellers and model users to choose an appropriate model type for their application considering 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. The following conclusions can be drawn from this table and the applications presented in Table 2:

- Systems dynamics and agent-based models are similar in being well suited for the purpose of improving system understanding and social learning. This is because the emphasis of these methods is on exploring the plausibility of assumptions and outcomes, rather than on accurate prediction, forecasting or decision-making. Such models are often developed to allow decision-makers and stakeholders to experiment with the model and try out differing assumptions about poorly understood processes. These models do not tend to be highly prescriptive about policy implications.
- Bayesian networks and, to a lesser extent, knowledge-based models are typically used to directly inform decision-making under uncertainty. They accomplish this by incorporating both qualitative and quantitative data to generate predictions (in the case of Bayesian networks often probabilistic) about the outcomes of candidate actions or policies. Neither focuses on a deep representation of processes, but rather provides a greater breadth of coverage, including explicit information about uncertainty at an aggregate level. BNs are also valuable for social learning.

Table 3
Appropriate use of integrated modelling approaches (X = common feature, * = possible feature).

		System dynamics	Bayesian networks	Coupled component models	Agent based models	Knowledge based models
Reason for modelling/type of application	Prediction	*	X	X	*	X
	Forecasting			X		X
	Decision-making under uncertainty	*	X	*	*	X
	System understanding	X	X	X	X	
	Social learning	X	X		X	
Type of data available to populate model	Qualitative and quantitative data	*	X	*	*	X
	Quantitative data mainly	X		X	X	
Model focus on a complex description of specific processes or greater breath of coverage of interactions in system?	Depth of specific processes	*		X	X	X
	Breadth of system	X	X	X	*	X
Model to provide explicit information about uncertainty caused by model assumptions?	Yes		X			
	No	X		X	X	X
Interest in investigating the interactions between individuals and their impact on the system, or only the aggregated effects behaviour?	Interactions between individuals				X	
	Aggregated effects	X	X	X	*	X

- Coupled component models are often regarded as capable of describing complex interactions among detailed processes for the purposes of prediction, forecasting and system understanding. They deal with space and time. They are, however, not necessarily better than SD, BN or ABM models for prediction. Larger, more detailed models often behave poorly as far as uncertainties are concerned because they are more likely to be over-parameterised and uncertainties become difficult to explore.
- The ability of coupled component models to describe complex interactions and the fact that it is sometimes convenient to couple existing complex models, is the likely reason for their popularity. However, they can also be the most time-intensive type of integrated model to set-up and may not provide the broad overview, uncertainty information, or decision-support capabilities that stakeholders may require. On the other hand, coupled component models, especially if built in a top-down integrative way, can be hybrids of many of the other

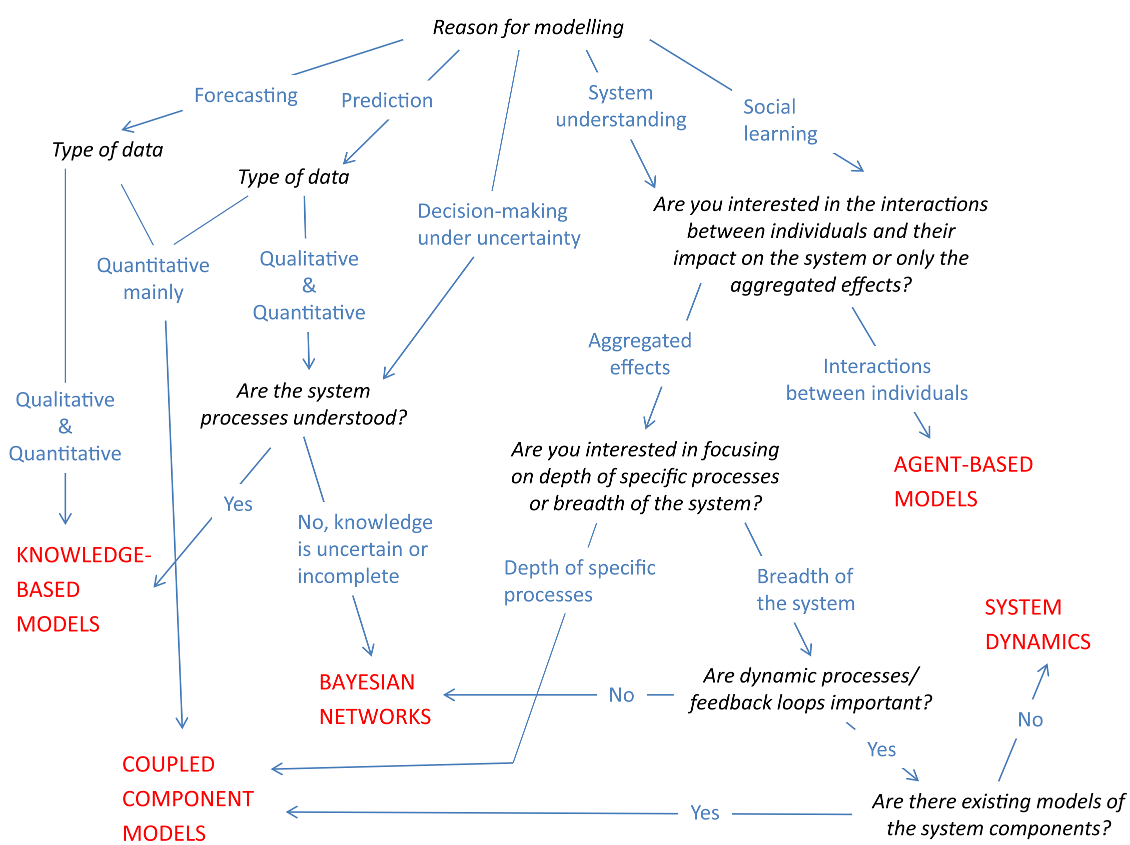

Fig. 1. Decision tree for selecting the most appropriate integrated modelling approach under standard application.

model approaches and balance complexity with the knowledge available to calibrate them.

- Agent-based models have proven to be of high utility for social learning in a wide range of settings where assumptions about processes and interactions are explored and shared. They can consider individual and/or aggregated effects.
- Knowledge-based, or conceptual models for any of the approaches can be a good entry point into the problem to refine the goals, understand the most important system features, and identify the key variables and factors.

The guiding framework for selecting the most appropriate modelling approach is also represented in the form of a decision tree in Fig. 1. The decision tree and Table 3 are limited to considering only the five broad approaches, their standard modelling applications and the selection criteria discussed in this paper. In Table 3, crosses denote the standard practices and uses, but nonstandard practice and future developments could enhance the properties of the modelling methods. When deciding on an approach for a new application, other approaches, including hybrid forms (i.e. coupled component models), which use a variety of approaches to knowledge integration, should also be considered. For example, there are already attempts to couple ABMs with system dynamics (Baki et al., 2012; Haase et al., 2012), use Bayesian methods with ABMs (Parry et al., 2013) or use SD as a technique to couple complex models, including ABM, knowledge-based models and cellular automata models (Van Delden et al., 2007, 2009). As coupled component models are able to combine any type of model, all types of applications are theoretically possible, depending on the models included. For example, although coupled component models are typically built to investigate the aggregated effects of system behaviour, they can be applied to explore interactions between individuals if one of the model components is an ABM.

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; Hare, 2011). 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 (Henriksen et al., 2007) 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 (Hare, 2011). It is crucial that the performances of models built for management and decision-making are appropriately evaluated to establish a level of confidence in the use of their outputs (see Bennett et al., 2013). 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 five 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 purpose 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.

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 or modelling of the target system.

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