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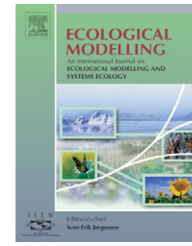

Review

Future research challenges for incorporation of uncertainty in environmental and ecological decision-making

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ABSTRACT

Environmental decision-making is extremely complex due to the intricacy of the systems considered and the competing interests of multiple stakeholders. Additional research is needed to acquire further knowledge and understanding of different types of uncertainty (e.g., knowledge, variability, decision, and linguistic uncertainty) inherent in environmental decision-making, and how these areas of uncertainty affect the quality of decisions rendered. Modeling and decision support tools (e.g., integrated assessment models, optimization algorithms, and multicriteria decision analysis tools) are being used increasingly for comparative analysis and uncertainty assessment of environmental management alternatives. If such tools are to provide effective decision support, the uncertainties associated with all aspects of the decision-making process need to be explicitly considered. However, as models become more complex to better represent integrated environmental, social and economic systems, achieving this goal becomes more difficult. Some of the important issues that need to be addressed in relation to the incorporation of uncertainty in environmental decision-making processes include: (1) the development of methods for quantifying the uncertainty associated with human input; (2) the development of appropriate risk-based performance criteria that are understood and accepted by a range of disciplines; (3) improvement of fuzzy environmental decision-making through the development of hybrid approaches (e.g., fuzzy-rule-based models combined with probabilistic data-driven techniques); (4) development of methods for explicitly conveying uncertainties in environmental decision-making through the use of Bayesian probability theory; (5) incorporating adaptive management practices into the environmental decision-making process, including model divergence correction; (6) the development of approaches and strategies for increasing the computational efficiency of integrated models, optimization methods, and methods for estimating risk-based performance measures; and (7) the development of integrated frameworks for comprehensively addressing uncertainty as part of the environmental decision-making process.

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Contents

1. Introduction

The public, industry, and government generally acknowledge that protecting, improving, and managing environmental resources is extremely important. Researchers have responded by designing and implementing experiments, collecting and analyzing data, and developing and parameterizing models in order to better understand and provide predictions about the nature of environmental and ecological systems. However, most of these efforts do not account for uncertainty and therefore fail to fully achieve their goals. In this paper, the authors present a review of the status of uncertainty analysis in environmental modeling and describe critical challenges that must be met in order to move forward. The conservation and management of biological systems – and the species that comprise them – is a daunting task because:

(1) Many systems are so complex and unpredictable that they are not well understood, and in fact defy the estimation of uncertainty.
(2) Environmental management problems and their solutions are often value-laden and subjective; consequently, standard or traditional decision-making approaches that rely on quantifiable and objective data often fail.
(3) A large number of organizations, institutions, and stakeholders, frequently with competing objectives, are responsible for policy analysis, regulatory decision-making, and priority setting for environmental actions and assessments. These groups invariably have different levels of expertise and knowledge that can lead to vastly different ways of understanding environmental management problems, thus often making negotiation a difficult process.
(4) There are typically a large number of potential management strategies or policy options, and unsuitable decisions can have profound ecological and environmental impacts, i.e., population crashes or ecosystem failures.
(5) While environmental decision-makers are usually aware that public confidence is the basis of successful policy, they have often failed to gain or preserve trust.

As a result of these difficulties, there has been an increase in the development and use of formal scientific approaches to assist with environmental management and decision-making. Jakeman and Letcher (2003) and Jakeman et al. (2006) have demonstrated the importance of integrated models (e.g., explicitly accommodating linkages between the natural and human environment) as a means of assessing the response of environmental systems to proposed management options. Gunderson and Holling (2000), Cowie and Borrett (2005), Curtis et al. (2005), and Pahl-Wostl (2005) have highlighted the need for the incorporation of social and institutional aspects into decision-making processes, and recently agent-based models have been used in an attempt to integrate social, economic, and environmental aspects in a single modeling framework (e.g., Bousquet and LePage, 2004). The field of multicriteria decision analysis (MCDA) attempts to combine social, environmental and economic assessment criteria into a single performance measure (e.g., David and Duckstein, 1976; Roy and Vincke, 1981; Janssen, 1996). Alternatively, in the instance where managers are faced with many management alternatives, Vasquez et al. (2000) and McPhee and Yeh (2004) have shown how environmental models can be linked with evolutionary optimization algorithms in order to obtain optimal tradeoffs between competing objectives to better inform management decisions. Lempert et al. (2006) demonstrated the use of robust decision-making (RDM) to reduce regret under "deep uncertainty", which is defined as the condition of being unable to construct a single satisfactory model describing an environmental decision-making situation, regardless of the manner in which parameter uncertainty is handled. The RDM approach has been suggested for use in evaluating complex policy situations involving short-term and long-term environmental, ecological, economic, and technological uncertainties, like climate policy and energy policy (Lempert et al., 2006).

As model complexity increases in order to better represent environmental and socio-environmental systems, there is a concomitant need to identify potential sources of uncertainty and to quantify their impact so that appropriate management options can be identified with confidence. Many studies have focussed on the identification and quantification of certain aspects of uncertainty, such as the development of risk-based performance measures (e.g., Hashimoto et al., 1982), and the incorporation of uncertainty into environmental models (e.g., Burges and Lettenmaier, 1975; Chadderton et al., 1982; Eheart and Ng, 2004), optimization methods (e.g., Cieniawski et al., 1995; Vasquez et al., 2000; Ciu and Kuczera, 2005), multicriteria methods (e.g., Rios Insua, 1990; Barron and Schmidt, 1988; Hyde et al., 2004), multi-period multicriteria model uncertainty analysis (e.g., Choi and Beven, 2007), decision-support tools (e.g., Pallottino et al., 2005; Reichert and Borsuk, 2005), and adaptive management systems (e.g., Prato, 2005). Only a few research studies have taken an integrated approach that identifies and incorporates all sources of uncertainty into the decision-making process (e.g., Maguire and Boiney, 1994; Reckhow, 1994; Labiosa et al., 2005), and several regional co-operative research efforts are underway to address this issue. These include the Harmoni-CA project in Europe (http://www.harmoni-ca.info/toolbox/Model_Uncertainty/index.php) and the eWater Co-operative Research Centre in Australia (http://www.ewatercrc.com.au).

In order to build upon these efforts, the authors of this review will:

(1) Discuss the major steps in the environmental decision-making process;
(2) Introduce a typology that identifies possible sources of uncertainty at each phase of the environmental decision-making process;
(3) Communicate current research progress; and
(4) Identify future directions and challenges in relation to the incorporation of uncertainty into the environmental decision-making process, including:
    (a) Quantifying uncertainty associated with human factors;
    (b) Developing appropriate risk-based assessment criteria;
    (c) Improving various techniques used in fuzzy environmental decision-making;
    (d) Demonstrating the efficacy of Bayesian decision-analysis tools in the environmental decision-making process;
    (e) Incorporating adaptive management practices into the environmental decision-making process, including model divergence correction;
    (f) Increasing the computational efficiency of models used in environmental decision analysis; and
    (g) Developing comprehensive, integrated frameworks for addressing uncertainty as part of the environmental decision-making process.

2. Environmental decision-making process

Several research traditions provide concepts, logic and modeling tools with the intent of facilitating better decisions about the environment (Jaeger et al., 2001). Policy analysis, which is built on the rational actor model, and includes both benefit–cost analysis and risk analysis, is the most elaborate of these efforts (Boardman et al., 2005; Dietz et al., 2001). Over the past two decades, a tradition of theory and research examining democratic deliberation as a basis for environmental decision-making has emerged (Renn et al., 1995). Discussions of sustainability, especially when linked to definitions of the concept and efforts to measure environmental performance, also can be viewed as attempts to improve environmental decision-making. In many of these traditional environmental decision-making approaches, the notion of what constitutes a "good" decision is fairly explicit. For example, many stakeholders or policy groups view good environmental decisions as utilitarian outcomes that provide the most satisfaction to a majority of people, typically through a participatory process of decision-making (Dietz, 2003). Advocates of sustainable, ecological, and environmental management usually note obligations to future generations, and most of them also voice concern for other species or for the biophysical environment. As illustrated above, a vast and diverse number of organizations and institutions are responsible for different aspects of environmental decision-making. Not surprisingly, numerous opinions have been voiced (as also evidenced by the contradictory nature of literature on the topic) as to the effectiveness of assorted approaches to environmental decision analysis and the types of tools, methods, criteria, etc. that best support the approaches. Discussion of the full spectrum of tools and criteria that could be considered in the environmental decision-making process is beyond the scope of this paper. Instead, we provide a general overview of the environmental decision-making cycle with an emphasis on the use of model-based decision support tools to generate optimal alternatives for environmental and ecological management.

Important factors that have an impact on whether and how environmental and ecological problems are addressed are shown in Fig. 1. Firstly, environmental problems need to be identified and brought to the attention of managers and decision-makers in the Problem Structuring phase. This can be done through the reporting of routine data, modeling efforts, or input from local stakeholders and/or lobby groups. Once a particular problem is on the agenda, a decision to take action has to be made. This decision will depend on factors such as the perceived importance and magnitude of the problem, as well as financial and possibly political considerations. Following a decision to act, the selection of appropriate assessment criteria and a list of alternative solutions have to be generated. Depending on the type of problem, there may be a small or very large number of alternatives. In order to determine which

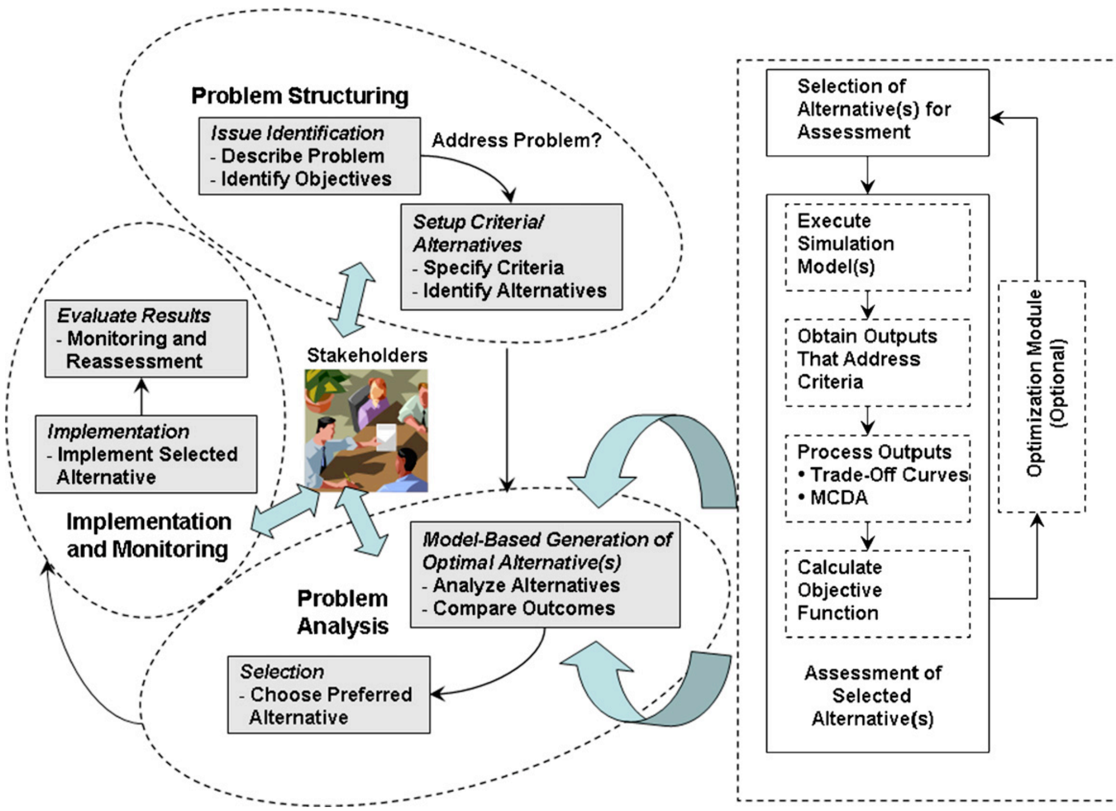

Fig. 1 – Schematic of the environmental decision-making process with an emphasis on model-based decision support tools to generate optimal alternatives.

alternative, or set of alternatives, is considered "optimal", analytical methods (e.g., integrated models), formal optimization techniques, and MCDA are generally used.

Traditionally, model-based decision-support tools have been used for identification and quantification of the severity of environmental problems, as well as helping to determine which subset of potential management alternatives can be considered optimal. These tools vary in complexity (and hence data requirements) and serve a variety of purposes. For example, models can be used to obtain a better understanding of complex systems or for prediction/forecasting to assist managers with assessing the utility of proposed management actions or the response of the system to other types of perturbations. Forecasting and prediction models are generally process-based (deterministic) or data-based (statistical), although the use of hybrid models is becoming increasingly popular. As shown in the Problem Analysis phase (Fig. 1), simulation models have a critical role in the evaluation of all, or a subset, of the potential alternatives against the assessment criteria. If the number of candidate solutions is limited, all options can be assessed. However, if a large number of options are available, formal optimization approaches, such as genetic algorithms, should be used to select a subset of the potential management alternatives. Assessment would generally be done with the aid of one or more (integrated) simulation models, comparing the performance of the proposed alternatives to the specified performance criteria. Usually, there will be a number of competing objectives, making it difficult to rank the candidate options. Where the number of proposed alternatives is limited, MCDA is often used to arrive at a single performance measure for each alternative. If the number of alternatives is large, and formal optimization algorithms are used, Pareto trade-off curves can identify a set of optimal alternatives. At this point, it is customary for the decision-maker to identify a particular optimal alternative. The third phase, Implementation and Monitoring, includes careful evaluation and reassessment of the implemented alternative, and further refinement in management practices if necessary (Fig. 1). Although the linkage is not explicitly shown, the Problem Structuring phase of the process can employ models to define the initial problem, decide whether to take action, and identify potential alternatives. Regardless of which phases of the environmental decision-making process are considered, various sources of uncertainty need to be dealt with explicitly in order to enable decisions to be made with confidence or a known level of certainty. Consequently, potential sources of uncertainty in the environmental decision-making process need to be identified, as discussed in Section 3.

3. Typologies and sources of uncertainty

Although many sources of uncertainty are recognized, there is still a lack of information and agreement on their characteristics, relative magnitudes, and available means for dealing with them. In addition, many typologies have been developed for different purposes, as pointed out by Walker et al. (2003): "within the different fields of decision support

Table 1 – Uncertainty typologies from the literature—1990 to present

Reference from literature	Types of uncertainty considered
US-EPA (1997)	Scenario uncertainty, parameter uncertainty, model uncertainty
Morgan and Henrion (1990); Hofstetter (1998)	Statistical variation, subjective judgment, linguistic imprecision, inherent randomness disagreement, approximation
Funtowicz and Ravetz (1990)	Data uncertainty, model uncertainty, completeness uncertainty
Bedford and Cooke (2001)	Aleatory uncertainty, epistemic uncertainty, parameter uncertainty, data uncertainty, model uncertainty, ambiguity, volitional uncertainty
Huijbregts et al. (2001)	Parameter uncertainty, model uncertainty, uncertainty due to choices, spatial variability, temporal variability, variability between sources and objects
Bevington and Robinson (2002)	Systematic errors, random errors
Regan et al. (2002)	Epistemic uncertainty, linguistic uncertainty
Walker et al. (2003)	*Location*: context uncertainty, model uncertainty (input, structure, technical, parameter, outcome); *level*: statistical uncertainty, scenario uncertainty, recognized ignorance, total ignorance; *nature*: epistemic uncertainty, variability uncertainty
Maier et al. (2008)	Data uncertainty, model uncertainty, human uncertainty

(policy analysis, integrated assessment, environmental and human risk assessment, environmental impact assessment, engineering risk analysis, cost–benefit analysis, etc.), there is neither a commonly shared terminology nor agreement on a generic typology of uncertainties." This point is illustrated in Table 1, which shows both divergence and overlap in classifying uncertainties according to various literature sources over the past two decades.

Uncertainty is a non-intuitive term that can be interpreted differently depending on the discipline and context where it is applied. In a simple definition, uncertainty is defined as "incomplete information about a particular subject", where total ignorance (i.e., indeterminacy) is considered an extreme form of uncertainty (Harwood and Stokes, 2003; Walker et al., 2003). Funtowicz and Ravetz (1990) describe uncertainty as a situation of three kinds of inadequate information: inexactness, unreliability, and border with ignorance. They link the degree of uncertainty to the stakes of the decision—the uncertainties in small systems with low stakes are largely due to scientific judgments but these uncertainties surrender to a broader lack of knowledge when the systems are large and the stakes are high. In this paper, we offer a composite typology of uncertainty that borrows from Morgan and Henrion (1990), NRC (1994), Walker et al. (2003), and many of the other typologies listed in Table 1. Following the classification of Walker et al. (2003), we distinguish between lack of knowledge and the uncertainty resulting from intrinsic variability in the system(s) or processes under consideration (Fig. 2).

Following commentary by Norton et al. (2006), our typology also includes uncertainty associated with the selection of a particular decision-making approach (i.e., uncertainty in establishing appropriate goals and objectives, assessment or evaluation criteria, and performance measures), and linguistic uncertainty that surfaces because our natural language is vague, ambiguous, and context dependent. As might be expected, Fig. 2 shows that decision-making uncertainty is strongly impacted by variability in the system of interest, particularly for human behavior and institutional (e.g., social and economic) dynamics. Basic definitions and components associated with each of the four main uncertainty terms in Fig. 2 are given as follows.

3.1. *Knowledge uncertainty*

This refers to the limitation of our knowledge, which may be reduced by additional research and empirical efforts. It is also known as epistemic or epistemological uncertainty. Knowledge uncertainty can have process understanding and model (i.e., parametric/data, structure, technical, and output) components.

3.1.1. *Process understanding*

This is strongly related to the limits of scientific understanding, such as what knowledge is lacking or what temporal or spatial scale mismatches exist among disciplines. This type of uncertainty is closely related to the "structure of knowledge" discussed by Benda et al. (2002). They include the following categories which limit our understanding of phenomena across different disciplines: (1) disciplinary history and attendant forms of available scientific knowledge; (2) spatial and temporal scales at which that knowledge applies; (3) precision (i.e., qualitative versus quantitative nature of understanding across different scales); and (4) availability of data to construct, calibrate, and test predictive models. It is important to note that new knowledge on complex processes may reveal the presence of uncertainties that were previously unknown or were understated (Walker et al., 2003). In this way, additional knowledge reveals that our understanding is more limited or that the processes are more complex than previously thought (van der Sluis, 1997).

3.1.2. *Parametric/data*

Data are used extensively in the environmental decision-making process. For example, data may be used to highlight an environmental problem that needs to be addressed, to determine the magnitude of a particular problem, to help with the selection and screening of potential alternative solutions, to assist with the development of system models (e.g., calibration and validation) and to identify appropriate performance values in multicriteria decision analyses. Data uncertainty arises from measurement error (e.g., type of instrument used, quality and frequency of instrument calibration, data reading/logging, user-error and biases in sampling or data retrieval,

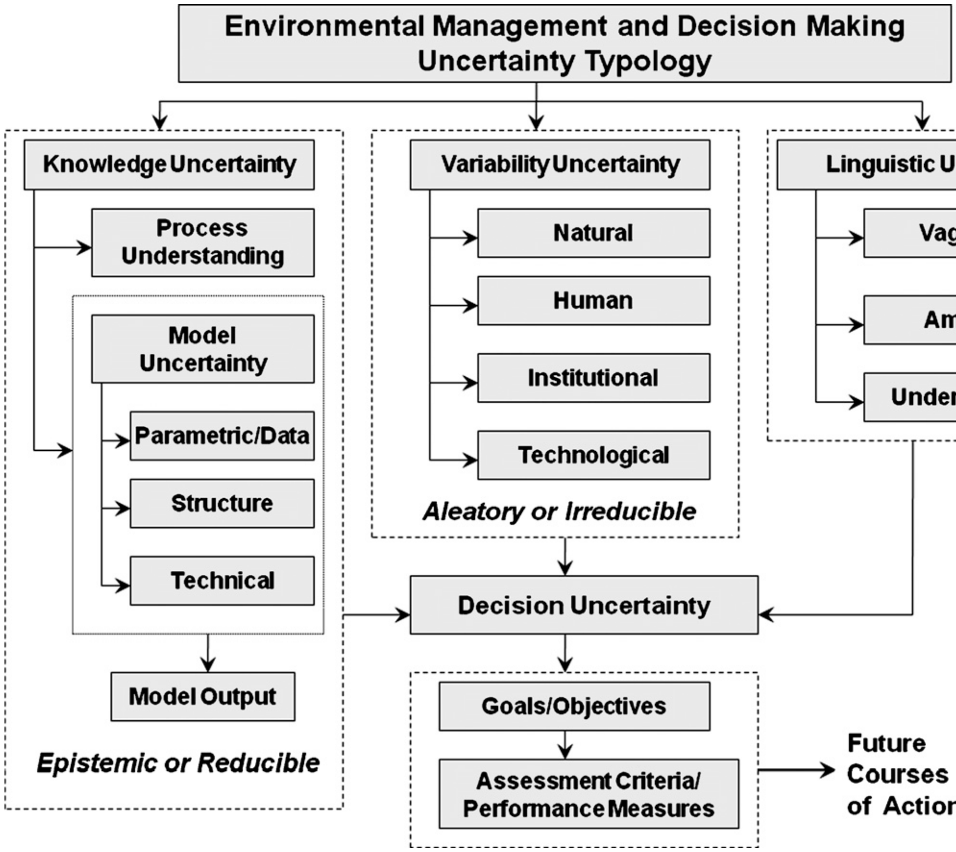

Fig. 2 – Description of uncertainty in environmental management and decision-making based on knowledge uncertainty, system variability uncertainty, linguistic uncertainty, and decision-making uncertainty.

and data transmission/storage), type of data recorded and length of record, type of data analysis/processing, and the method of data presentation (Maier et al., 2008). Walker et al. (2003) recognize the importance of data uncertainty; however, they classify data uncertainty under the category of model inputs, i.e., uncertainty associated with data that describe the reference (base case) system and the external driving forces influencing the system and its performance.

There is a strong relationship between data uncertainty and parameter uncertainty, which refers to uncertainty associated with model parameters that generally have to be obtained directly from measured data or indirectly from measured input–output data by calibration. Other potential sources of uncertainties in estimates of parameters include misclassification and estimation of parameters through non-representative samples caused by time, space, or financial limitations. Even though many parameters obtained directly from data can be measurable up to very high precision (at least in principle), some of the uncertainties associated with data and discussed previously still come into play. If parameters are obtained by calibration, the length, quality and type of available data records can have a significant impact. In addition, the type of calibration method employed can have a marked influence on the model parameters obtained (e.g., whether calibration is conducted manually or using a sophisticated optimization algorithm). Harremoës and Madsen (1999) highlight the relationship between model structure uncertainty (described below) and calibration parameter uncertainty: "There is in principle an optimum combination of model complexity and number of parameters as a function of the data available for calibration and the information contained in the data set used for calibration. Increased model complexity with an increased number of parameters to be calibrated may in fact increase the uncertainty of the model outcomes for a given set of calibration data."

3.1.3. *Model structure*

Models are necessarily simplified representations of the phenomena being studied and a key aspect of the modeling process is the judicious choice of model assumptions. The optimal model will provide the greatest simplifications while providing an adequately accurate representation of the processes affecting the phenomena of interest. Hence, the structure of models employed to represent "real-world" systems is often a key source of uncertainty. In addition to the significant approximations inherent in modeling, often times competing models may be available. Consequently, uncertainty about the structure of the system that we are attempting to model implies that multiple model formulations might be a plausible representation of the system, or that none of the proposed system models is an adequate representation of the real system (Walker et al., 2003). Model structure uncertainty arises from the use of surrogate variables, the exclusion of variables, the relationship between variables and input/output, and from approximations and functional forms, equations, and mathematical expressions used to represent the physical and biological world. To select the best environmental management strategies, models of the underlying physical processes that take into account the best scientific knowledge (and the uncertainties associated with this knowledge) need to be available to test the robustness of different management strategies (Harwood and Stokes, 2003). It is important to note that the "best" model may not be the most complex or "complete", in the sense that quantitatively incorporating every aspect of the system under study may result in more uncertainty than if only the salient processes (if known) are considered. A "reductionist" approach, where every minute detail is represented in a model's structure, may be capable of reproducing the real system, while an understanding of dynamical mechanisms important to environmental decision-making may still be lacking. This leads us to envelope uncertainty pertaining to modeling philosophy as an important component to model structural uncertainty.

3.1.4. *Technical*

Walker et al. (2003) categorize model technical uncertainty as the uncertainty generated by software or hardware errors, i.e., hidden flaws in the technical equipment. Software errors arise from bugs in software, design errors in algorithms, and typing errors in model source code. Hardware errors arise from bugs, such as the bug in the early version of the Pentium processor, which gave rise to numerical error in a broad range of floating-point calculations performed on the processor. It is also possible for the number of significant figures represented in floating-point calculations (e.g., *float* versus *double* parameter types) to lead to changes in model outcome where sensitivity to initial conditions (a hallmark of chaotic systems) is a factor.

3.1.5. *Model output*

This is the accumulated uncertainty (i.e., propagated through the model) caused by all of the above sub-categories (i.e., data, parameters, structure, and technical) and is reflected in the resulting outcomes of interest. It is sometimes called prediction error, since it is the discrepancy between the true value of an outcome and the model predicted value. If the true values are known then a formal validation exercise can establish the prediction error; however, practically all simulation models are used to extrapolate beyond known situations to estimate outcomes for situations that do not yet exist. In this case, in order for the model to be useful in practice, it may be necessary to build the credibility of the model with its users and with consumers of its results (Beck, 1987).

3.2. *Variability uncertainty*

This type of uncertainty is also referred to as external, objective, random or stochastic. It is related to the inherent variability manifested in natural and human (i.e., social, economic, and technological) systems. This type of variability is critical in management decisions since it is usually poorly understood and confused with knowledge uncertainty as a result of "ignorance" by managers, lawyers, and stakeholders (Rose and Cowan, 2003). Components of variability uncertainty include natural, human, institutional, and technological (Fig. 2).

Natural variability is related to the inherent randomness of nature, i.e., the chaotic and unpredictable quality of natural processes. The uncertainty associated with human input has received limited attention in the literature; however, this type of uncertainty can have a significant impact at all stages of the environmental decision-making process. For example, the values and attitudes of the environmental manager/decision-maker, as well as the current political climate, can influence whether an environmental problem is addressed, which alternative solutions will be considered, which assessment criteria will be used, and which alternative is ultimately selected. The knowledge base, education, attitudes, and political "clout" of stakeholder and lobby groups can also have a major influence on the final outcome. For example, whether a particular environmental problem is drawn to the attention of the environmental manager/decision-maker, and how seriously it will be treated, can be a function of the above factors. Similarly, stakeholder groups can have an input into the choice and screening of potential solutions, as well as the assessment process via the development of appropriate assessment criteria and the provision of weightings (if multicriteria decision approaches are utilized). Even the more "technical" aspects of the decision-making process are not immune from uncertainty due to human input. Refsgaard et al. (2005) found that the results of a modeling exercise varied significantly when different modelers were presented with the same problem and data, i.e., the knowledge, experience and preferences of the modelers significantly impacted the modeling outcomes. Institutional uncertainty is represented by social, economic, and cultural dynamics (societal variability). The need to consider societal and institutional processes as a major contributor to uncertainty due to variability can be inferred from Funtowicz and Ravetz (1990) and De Marchi et al. (1993). New developments or breakthroughs in technology or unexpected consequences ('side-effects') of technologies contribute to technological uncertainty.

All of the above sources can contribute to variability uncertainty, but it may be difficult to identify precisely what is reducible through investigations and research and what is irreducible (i.e., an inherent property of the phenomena of concern). Either way, it is important to make an assessment, because the information may be essential to the evaluation process.

3.3. *Decision-making uncertainty*

Finkel (1990) makes an important distinction between the aforementioned types of uncertainty, and decision uncertainty, which enters quantitative policy analysis after the estimation of risk has been generated. He states that "this type of uncertainty arises whenever there is ambiguity or controversy about how to quantify or compare social objectives." Decision uncertainty is also related to what Morgan and Henrion (1990) and others refer to as "value" uncertainty. Most descriptions of incorporating uncertainty into analysis consider the modeling aspect of physical systems and therefore exclude discussions of uncertainty pertaining to the decisions about valuing social objectives. In analyses that estimate the economic costs and benefits of policy changes, however, decision uncertainties are extremely important because they go to the heart of how these social objectives are determined. Decision uncertainty may also be strongly related to the way model predictions are interpreted and communicated, especially with regard to future courses of action. When high uncertainty is not properly explained or understood, it can delay action or cause the selection of values at the "extreme of the ranges that result in highly risky (or overly conservative) management decisions" (Frederick and Peterman, 1995; Rose and Cowan, 2003).

3.4. *Linguistic uncertainty*

Regan et al. (2002) define linguistic uncertainty as uncertainty that arises because our natural language is vague, ambiguous, and context dependent, and because the precise meaning of words can change over time. Elith et al. (2002) emphasize that linguistic as well as epistemic uncertainty can be present in model predictions and provide further elucidation of the linguistic uncertainty typology shown in Fig. 2. Vagueness is a type of linguistic uncertainty that arises because natural and scientific language allows cases where a precise description of a quantity or entity is not available, i.e., a "borderline" case that does not exactly fit into a category. Vagueness can be found in concepts with a natural numerical ordering (i.e., growth stages for a soybean plant) but also in concepts without a numerical order, such as vegetation classes (Elith et al., 2002). Ambiguity arises because some words have more than one meaning and it is not clear which meaning is intended. Ambiguity can be a problem in modeling when records from a number of sources are being used and the original researcher is not accessible for, or cannot help with, clarification of the record. Underspecificity is present where there is unwanted generality in data, i.e., the original data on which a data record is based were more exact than a newer and less precise version. Underspecificity can also arise as a result of epistemic uncertainty, i.e., if data are measured using GPS in a precise location in an agricultural field but recorded generally (e.g., the location is in the northwest corner of the field).

Models used in ecosystem management approach linguistic uncertainty in different ways. For example, rule-based models in ecosystem management are commonly derived from: (1) expert knowledge and/or ecological (monitoring) data that are available in a linguistic format (Salski, 1992), and (2) the necessity for decision support to be interpretable and transparent. Because of these aspects, approaching ecosystem management by reasoning according to the principles of fuzzy logic and fuzzy-rule-based models is becoming more common. Further discussion on fuzzy logic approaches in environmental decision-making is presented in Section 4.3.

4. Directions and challenges for future research

In the following sections, the extent to which the above uncertainties have been incorporated into modeling frameworks and the remaining and emerging challenges of developing model-based decision support tools for integrated environmental management are discussed.

4.1. *Uncertainty in human factors*

Significant advances have been made in relation to developing models of human behavior and linking them with ecological, environmental and economic models for the purposes of environmental management and policy assessment (e.g., Anderies, 2000; Bossel, 2000; Janssen et al., 2000; Peterson, 2000; Walker et al., 2002; Bousquet and LePage, 2004; McNamara and Werner, 2004; Werner et al., 2004; McNamara and Werner, 2005). However, although these models generally allow for heterogeneity in human behavior, they do not model uncertainty in the various model components. The significant impact that human input can have on the environmental decision-making process has only been recognized relatively recently. Consequently, one of the upcoming challenges is to develop frameworks that enable the uncertainties associated with human inputs to be accounted for explicitly. This includes the development of uncertainty analysis methods that are able to cater to subjective and non-quantitative factors (e.g., van der Sluijs et al., 2005), human decision-making processes (which may be influenced by political and other external factors), and uncertainties associated with the model development process itself (e.g., Refsgaard et al., 2006).

Uncertainty due to human input also has a role to play in the ranking of potential management alternatives in accordance with the selected assessment criteria. Assessment criteria generally address competing objectives, which complicates the ranking of proposed alternatives. If there are a limited number of alternatives, some form of multicriteria decision analysis can be used to rank the potential alternatives, such as value-focused approaches [e.g., Weighted Sum Method (WSM) (Janssen, 1996) or Analytic Hierarchy Process (AHP) (Saaty, 1977)] and outranking methods [e.g., PROMETHEE (Brans et al., 1986) or ELECTRE (Roy, 1991)]. All of these approaches rely on the provision of relative weightings of the assessment criteria (performance values) by actors representing stakeholder groups. A number of distance-based sensitivity analysis and probability-based uncertainty analysis methods have been developed to take account of potential uncertainties in the weightings provided by the actors (e.g., Barron and Schmidt, 1988; Butler et al., 1997). This provides decision-makers with information on the impact of uncertainties in the weightings on the ranking of alternatives. However, the above approaches generally do not consider uncertainties associated with the assessment criteria. Recently, Hyde et al. (2003) have demonstrated that uncertainties in the assessment criteria can have a significant impact on the rankings of alternatives, and concluded that it is desirable to jointly consider uncertainties in the assessment criteria and the weightings provided by stakeholders. If values of the assessment criteria are obtained using models that take into account uncertainty, and appropriate risk-based performance measures are used, this issue is addressed automatically. However, if uncertainties have not been considered when obtaining values of the assessment criteria (e.g., by using deterministic models or the input of experts), methods such as that proposed by Hyde et al. (2003) have to be used.

If the number of potential management alternatives is large, multi-objective optimization approaches (e.g., Deb et al., 2002) can be used to obtain Pareto-optimal trade-offs between competing assessment criteria (e.g., Vasquez et al., 2000). Such trade-off curves can be used by decision-makers to choose the most appropriate alternative. Recently, the use of clustering techniques, such as self-organising maps (Kohonen, 1982), have been proposed as a means of extracting solutions from Pareto trade-off curves that are representative of areas of the solution space with different characteristics (e.g., low cost solutions with high associated risks of failure and vice versa) (Shie-Yui et al., 2004). This reduces the number of potential Pareto-optimal solutions that have to be considered by decision-makers. In addition, if the resulting number of characteristic solutions is relatively small, they could be considered as potential solutions as part of a multicriteria decision analysis. However, such an approach is yet to be tested.

4.2. *Risk-based assessment criteria*

If uncertainty is incorporated into models explicitly, the criteria used to assess the performance of alternative solutions need to reflect this. A number of risk-based performance criteria have been proposed for environmental models, which generally relate to the concept of the likelihood, the likely magnitude, and the likely duration of failure, where failure is defined as the inability of an environmental system to perform its desired function. For example, Hashimoto et al. (1982) introduced three risk-based performance measures for water resources systems, including reliability (likelihood of failure), vulnerability (degree of failure) and resilience (inverse of the expected duration of failure). However, even though the above concepts are widely accepted, the terminology used to describe them, and their exact definition, tend to vary between, and even within, discipline areas. One example of this is the term resilience, which has been defined in a variety of ways (e.g., Holling, 1996; Hashimoto et al., 1982; Fiering, 1982; Batabyal, 1998). Furthermore, the inapplicability of the "factor of safety concept" to modeling natural environmental systems (Haff, 1996) suggests that the performance of alternative solutions be cast in terms of a "worst case scenario." In addition, concepts related to the stability of systems and the ability of systems to move between multiple stable states are also common in other disciplines, such as economics and control engineering.

Given (i) the increased recognition for the need to incorporate uncertainty into decision-support models; (ii) the increase in the utilization of integrated models, which are generally developed by multidisciplinary teams; and (iii) the diversity of, and confusion surrounding, the definition and estimation of risk-based performance measures, there is a need to develop a common lexicon in relation to risk-based performance criteria across disciplines. There have been some attempts to develop classification systems for risk-based performance criteria (e.g., Maier et al., 2002), but more work is required in this area. In addition, it is timely to re-visit the question of whether the types of performance criteria currently in use are appropriate for complex environmental problems. This is particularly relevant in relation to appropriate performance measures related to sustainability goals.

4.3. *Fuzzy environmental decision-making*

The potential of the fuzzy system approach for modeling uncertainty in environmental decision-making lies in several critical features including (i) fuzzy logic as a method to capture the imprecision associated with everyday reasoning; and (ii) the representation of human judgment models as fuzzy rules (Dorsey and Coovert, 2003). Furthermore, fuzzy systems offer opportunities to model environmental processes for which only a linguistic description is available; non-fuzzy techniques (e.g., probabilistic tools and Monte Carlo simulation) cannot handle the imprecision and vagueness of semantic aspects which are inherent in linguistic uncertainty. Central to applications of fuzzy systems is the concept of a fuzzy set. Fuzzy sets, as opposed to crisp or classical sets, have a gradual transition from membership to non-membership in the set. Membership degree in a fuzzy set is specified as a real number on the interval [0, 1] where 0 indicates that the element does not belong to the set and 1 indicates that the element completely belongs to the set. Essentially, the membership function defines the shape of the fuzzy set.

The ability to integrate expert knowledge (structured mainly by means of linguistic expressions) concerning environmental and ecological relationships, as well as the availability of qualitative data (e.g., habitat variables), are frequently cited as important reasons to use fuzzy system tools (e.g., fuzzy-rule-based models for decision support and predictive modeling) to deal with uncertainty inherent in ecosystem management. Fuzzy sets and rules have been constructed for implementation in integrated environmental management (Enea and Salemi, 2001), sustainable development (Ducey and Larson, 1999; Cornelissen et al., 2001), threatened species classification (Regan and Colyvan, 2000), and groundwater management (Lee et al., 1994). Fisher (2003, 2006) offers a methodology for applying concepts from fuzzy set theory to environmental decision-making, with examples in human health assessment and air quality/pollution forecasting. Tesfamariam and Sadiq (2006) incorporated fuzzy arithmetic operations to modify the traditional AHP for risk-based environmental decision-making. The resulting fuzzy AHP was used to evaluate vagueness uncertainty in selection of drilling fluid/mud for offshore oil and gas operations. Fuzzy set theory has also been used to characterise uncertainty in engineering design calculations (Kraslawski et al., 1993), wastewater sludge disposal (Crump et al., 1993), and solute transport modeling (Dou et al., 1999).

By addressing areas of uncertainty, ambiguity, and dissent in the decision process, fuzzy set techniques provide the opportunity to improve both immediate short-term decisions and the strategic aspect of environmental management. However, a number of problems remain to be solved in future research including:

(1) Exploring the meaning of linguistic terms and assigning fuzzy values to linguistic terms are essential in resolving vagueness, fuzziness, uncertainty and imprecision in decision-making problems. There are few practical systems to capture linguistic terms from decision-makers and systematically convert them into fuzzy sets.

(2) New methods for generating reasonable membership functions are needed, especially those that are intuitive, simple to use, and based on input from decision-makers or historical resources.
(3) A significant amount of fuzzy set application to environmental decision-making in the literature is based on hypothetical information or test cases. Applications of fuzzy systems to real environmental decision-making problems with real decision-makers are urgently needed to demonstrate the efficacy of the fuzzy systems approach for solving real-world problems.
(4) Validation and optimization problems have resulted in numerous non-reliable models. This problem can be overcome through the development of hybrid approaches combining fuzzy-rule-based models with probabilistic data-driven techniques. Hopefully, more reliable modeling results will convince environmental managers and policy makers to apply fuzzy models in practice.

4.4. *Bayesian approaches to modeling and communicating uncertainty*

A central assumption underlying the calculation of simple (i.e., sample mean, variance, and standard deviation) and more complex statistical parameters is known as the frequentist assumption (e.g., Efron, 1978): a true, fixed, value for each parameter of interest exists, the expected value of this parameter is obtained by random sampling repeated ad infinitum, and the underlying parameter distribution is known. Ellison (1996) points out problems with this assumption from an ecological perspective: (1) within experiments, true randomization is difficult and replication is often small or nonexistent (Reckhow, 1990); and (2) ecological experiments are rarely repeated independently and organisms within a population are not alike nor will their future offspring be alike. Therefore, the likelihood is extremely low that true, fixed values for ecologically meaningful statistical parameters exist (Ellison, 1996).

The alternative to the frequentist paradigm is Bayesian inference. Bayesian inference provides a mechanism to quantify uncertainty in parameter estimates, and to determine the probability that an explicit scientific hypothesis is true, given (i.e., conditional upon) a set of data. Bayesian inference begins with the observation that the joint probability of two parameters, P(a,b), equals the product of the probability of one of the parameters and the conditional probability of the second parameter given the occurrence of the first one:

$$P(b)\cdot P(a|b) = P(a, b) = P(a)\cdot P(b|a) \tag{1}$$

The terms in Eq. (1) can easily be rearranged to yield an expression (known as Bayes' theorem) for P(a|b), the posterior probability of obtaining the parameter 'a' given the data at hand. In this expression, P(a) is the prior probability, i.e., P(a) is the expected probability before the experiment is conducted. Thus, Bayesian inference treats statistical parameters as random variables, and uses the expected value of the likelihood function P(b) to act as a scaling constant that normalizes the sum or integral of the area under the posterior probability distribution (Ellison, 1996). Bayesian probability statements can be made for alternative possible values for the actual abundance and status of a natural ecosystem population. For example, there is a probability of 0.20 that the actual abundance is less than some critical cutoff value such as 30% of system carrying capacity. This allows conceptually consistent statements about risk to be computed.

Bayesian probability can also provide clear statements about the plausibility of alternative ecological hypotheses for processes that may be structuring ecological communities, such as the responses of populations to exploitation (McAllister and Kirchner, 2002). Applications of Bayesian statistical methods (e.g., hierarchical modeling, decision trees, influence diagrams, and belief networks) are rapidly expanding in the environmental and resource management arena (Varis and Kuikka, 1999; Wade, 2000) including: (1) fisheries management science (Kuikka et al., 1999; McAllister and Kirchner, 2002); (2) forestry and forest ecology (Crome et al., 1996; MacFarlane et al., 2000); (3) environmental policy decision-making (Ellison, 1996; Wolfson et al., 1996); (4) integrated water resource planning (Bromley et al., 2005); (5) integrated ecological modeling (Borsuk et al., 2004; Lamon and Stow, 2004); and (6) informing adaptive resource management (Prato, 2000). A few of the above studies in particular demonstrate the efficacy and potential of Bayesian methods as a rigorous and conceptually intuitive approach to dealing with model uncertainty (e.g., Crome et al., 1996; Wade, 2000; McAllister and Kirchner, 2002). In particular, Bayesian data analysis permits the relative credibility of each alternative model to be evaluated against the data, taking into account uncertainty over the range of values for the parameters in each model.

Overall, Bayesian decision analysis has provided a systematic and intuitive approach to guiding the decision-making process by allowing use of the best available information in a rigorous statistical framework, involving stakeholders at several stages of the evaluation, taking into account the key uncertainties affecting management decisions, and conveying explicitly the uncertainties in the potential decision outcomes with the use of Bayesian probability statements. However, Bayesian inference has been criticized for its subjectivity and apparent lack of explanatory power (Dennis, 1996), and in some cases it may indeed be difficult to use true Bayesian methodologies. For example, we may not be sufficiently skilled at translating our subjective prior beliefs into a mathematically formulated model and prior probabilities. Further research is needed to address this difficulty, particularly when dealing with models that have an extremely large number of parameters. Modern methods of Bayesian statistics can employ highly computationally intensive Markov chain Monte Carlo techniques to draw inferences and identify sources of uncertainty (e.g., Lee and Kim, 2007). Increased computational efficiency (discussed in Section 4.6) is crucial to further application of these techniques and to the emerging success of the Bayesian approach in environmental decision analysis.

4.5. *Adaptive management and model divergence correction*

In general, adaptive management (e.g., Holling, 1978) incorporates initial uncertainty, treats decisions as hypotheses to be tested, and demands that managers learn from the consequences of their decisions and alter their decisions (or implement new decisions) accordingly. A major hurdle in reducing uncertainty in model predictions used for environmental management activities is convincing both scientists and policy-makers to follow through with research by performing adaptive management and consistent monitoring and comparison between model outcome(s) and the trajectory of target natural systems. For example, periodic data collection following management activities fed back into a reconfigured or re-parameterized model can facilitate "running predictions" that can reduce uncertainty (Haff, 1996) and achieve realization of the management objectives (e.g., Florsheim and Mount, 2002). These techniques (e.g., Kalman filtering) can be used to control divergence between model predictions and target systems over time. In addition, if adaptive management activities can be accomplished within a divergence time scale (Haff, 1996), defined as the time scale over which uncertainty in model predictions result in irreconcilable divergence between predictive capability and system trajectory, uncertainty may be mitigated by corrective action. Interestingly, adaptive management is precisely analogous to an iterative Bayesian learning and decision process. Prior information is specified, decisions are made, and consequences are observed. The consequences are not treated as final events, but as new sources of information (new prior probability functions) that can lead to modifications in management practices (e.g., new decisions).

4.6. *Computational efficiency*

Historically, the inclusion of uncertainty in even relatively simple simulation models has been a problem from the perspective of computational efficiency. This is because the evaluation of risk-based performance measures generally requires simulation models to be run repeatedly (e.g., as part of Monte Carlo methods). Advances in computing power have made the estimation of risk-based performance measures possible for models with relatively short run times. However, as models are becoming increasingly complex in order to model environmental systems in a more realistic fashion, issues related to computational efficiency are likely to be exacerbated to the point where run times are infeasible. Although processor speed is increasing rapidly, this is unlikely to outweigh the impact of the increased computational requirements of more complex models. Past experience indicates that, as computational power increases, so does the difficulty and complexity of the problems being tackled. Consequently, there is a need to develop alternative means of addressing the problems posed by excessive computer run times.

In order to increase computational efficiency, a number of different approaches can be taken, including:

(1) *The use of more efficient methods for estimating risk-based performance measures*: There have been many attempts to speed up Monte Carlo methods, including the use of more efficient stratified sampling methods, e.g., random, importance, Latin Hypercube, and Hammersley sampling (e.g., McKay et al., 1979; Helton and Davis, 2003). In addition, first- and second-order approximations can be used (e.g., Maier et al., 2001). More recently, alternative methods of estimating risk-based performance measures have been introduced in order to increase computational efficiency (e.g., Babayan et al., 2005), and work in this area is ongoing.

(2) *The skeletonization of complex models via innovative sensitivity analysis methods*: Sensitivity analysis methods can be used to identify parts of integrated models to which model outputs are relatively insensitive. This enables insensitive model components to be treated as deterministic or, alternatively, to be removed from the model altogether. However, one problem with this approach is that traditional sensitivity analysis methods, such as the Morris method (Morris, 1991), are ill-equipped to deal with the high degree of non-linearity and interaction that characterise integrated models. Monte-Carlo methods overcome these problems, but are generally too computationally expensive. More computationally efficient alternatives include the Extended Fourier Amplitude Sensitivity Testing (FAST) method (Saltelli et al., 1999) and the new sensitivity analysis approach proposed by Norton et al. (2005).

(3) *The use of metamodels to replace all, or portions, of computationally inefficient process models*: An alternative to using computationally expensive process models is the use of data-driven metamodels. Metamodels, first proposed by Blanning (1975), are models of simulation models. They serve as a surrogate, or substitute, for more complex and computationally expensive simulation models. While it takes time to develop metamodels, this is offset by the considerable time savings achieved when they are required to be run repeatedly. Recently, artificial neural network models have been used successfully as metamodels (e.g., Broad et al., 2005a), and are well-suited to act as metamodels for integrated environmental models due to their ability to deal with highly non-linear data. Once developed, artificial neural network metamodels can be used to estimate a range of risk-based performance measures (e.g., Broad et al., 2005b). However, the metamodeling approach assumes that the metamodel is valid with respect to the simulation model it is approximating and that, in turn, the simulation model is valid with respect to the system it is designed to model. This raises the issue of how to take into account any uncertainties associated with the simulation model and its representation by the metamodel. As metamodels are data-driven, their parameters generally do not have any physical meaning. Consequently, incorporation of parameter uncertainty is not an easy task. Methods such as those discussed in Lampinen and Vehtari (2001) and Kingston et al. (2005) go partway towards addressing this problem by enabling metamodel parameter uncertainty to be taken into account explicitly. However, this issue needs to be explored more fully.

4.7. *Integrated uncertainty frameworks for environmental decision-making*

Many of the issues and challenges discussed in Sections 4.1–4.6 are highly interrelated and need to be addressed in an integrated fashion and in the context of environmental decision-making. Consequently, there is a need to develop holistic, integrated uncertainty frameworks to support the development, evaluation and utilization of models for effective environmental decision-support. Renschler (2006) proposed an integrated framework combining a scaling theory, a geospatial data management tool, and a GIS-based environmental modeling interface, allowing interdisciplinary collaborators to efficiently handle and communicate the transformation of geospatial information of properties and processes across scales. The framework integrates our fundamental understanding and ability to communicate how we: (1) represent spatial/temporal variability, extremes, and uncertainty of environmental properties and processes in the digital domain; (2) transform their spatial/temporal representation across scales during data processing and modeling in the digital domain; and (3) design and develop tools for standardized geo-spatial data management and process modeling and implement them to effectively support decision- and policy-making in natural resources and hazard management at various spatial and temporal scales of interest. It should be noted that a standard definition of uncertainty does not neccessarily imply intercomparibility of model uncertainty analysis results. The reason for the lack of intercomparibility lies in the heterogeneity in both structure and the fundamental principles upon which models are based. In order to better achieve intercomparability, Wattenbach et al. (2006) have proposed a web-based client–server architecture approach to framework development (Fig. 3) based on the following principles:

- Standardized methods for uncertainty and sensitivity analysis for ecosystem models, including techniques for cross-site comparison;
- Standardized datasets to allow inter-model comparison of uncertainty and sensitivity measures;
- Standardized software interfaces for ecosystem models to allow access to databases for model experiments and results; and
- Databases for model evaluation results to allow scientists, stake-holders and policy-makers easy access to information concerning model quality and uncertainty.

Other frameworks have been developed to increase the usefulness of integrated assessment models in policy analysis. Kann and Weyant (2000) categorize types of uncertainty analyses that can be performed on large-scale energy/economic policy models, and develop a unifying framework (based on a stochastic dynamic optimization approach) for comparing uncertainty analyses containing different objective functions (e.g., single-period versus multi-period decision analysis). Mostashari and Sussman (2005) advocate the engagement of stakeholders from the inception of the environmental planning and policy analysis process, and propose a stakeholder-assisted modeling and policy design process (SAM-PD). System dynamics simulation is used to illustrate complex interactions in the environmental decision-making process and improve representation of the system in the model through stakeholder input and feedback.

While not an uncertainty framework per se, van der Sluijs et al. (2004) describe the tool catalog of the RIVM/MNP guidance for uncertainty assessment and communication. The

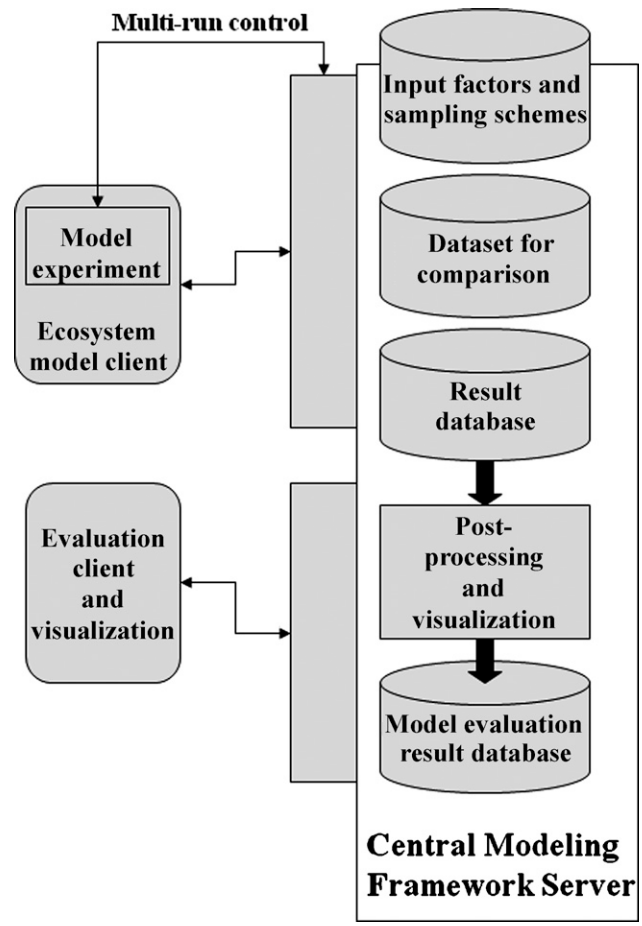

Fig. 3 – Web-based client–server uncertainty framework approach (adapted from Wattenbach et al., 2006).

uncertainty assessment toolbox includes tools for sensitivity analysis, error propagation, Monte Carlo analysis, NUSAP (Numeral Unit Spread Assessment Pedigree) analysis (van der Sluijs et al., 2005), and scenario analysis. Many of the approaches (e.g., NUSAP) are “meta-methods” integrating other tools in the toolbox. van der Sluijs et al. (2004) also provide detailed descriptions of the tools, discuss the types of uncertainty the tools address (including the advantages and disadvantages of each tool), and list references to web sites, handbooks, and user guides for each tool.

The above examples incorporate some of the significant criteria that should be addressed when developing integrated uncertainty frameworks for decision-making. These include explicit treatment of uncertainties arising from incomplete definitions of the model structural framework, spatial/temporal variations in variables that are either not fully captured by the available data or not fully resolved by the model, and the scaling behavior of variables across space and time. Such frameworks for decision-making should also tie together uncertainty related to multicriteria trade-offs and combined measures of model fit and complexity, as well as discussing data collection needs, i.e., when to stop collecting data and refine the model and, if additional data need to be collected, what should be collected in order to materially reduce model uncertainty.

5. Summary and conclusions

Environmental decision-making is extremely complex due to the intricacy of the systems considered and the competing interests of multiple stakeholders. Additional research is needed to acquire further understanding of knowledge, variability, decision, and linguistic uncertainty in environmental decision-making, and how these areas of uncertainty affect the quality of decisions rendered. Developing acceptable and efficacious environmental decision-making approaches requires improvement of uncertainty analysis techniques, concepts, and assumptions in pertinent research, with subsequent implementation, monitoring and auditing, and possible modification of selected environmental management practices.

Many sophisticated approaches to environmental decision-making contain a modeling or some other type of formal decision support component. In this paper, we have focused on the use of decision support tools, such as integrated models, optimization algorithms and multicriteria decision analysis, which are being used increasingly for comparative analysis and uncertainty assessment of environmental management alternatives. In this context, modeling for environmental decision support should provide decision-makers with an understanding of the meaning of predictive uncertainty in the context of the decisions being made. To a decision-maker, the possible outcomes resulting from a course of action are of main interest, where an "outcome" is defined in terms of the variables of interest to the decision-maker. As previously stated, predicting outcomes involves the integration of all sources of uncertainty, including uncertainty in model parameter, structure, and output, system variability, decision-making criteria, and linguistic interpretation. These sources of interest can include social and economic endpoints and other variables outside the expertise of ecologists and environmental scientists which often contribute to some of the difficulties associated with transmitting and translating scientific information into policy and decisions. Nevertheless, these variables may be of primary importance for aiding decision-makers in choosing between alternatives.

In summary, uncertainty must be addressed in any comprehensive and defendable environmental decision-making situation. Failure to do so invites potential unreliability of the results with consequential loss of public trust and confidence. There also exists a need to consider environmental, social and economic systems in an integrated fashion, particularly for dealing with community- or regional-based environmental problems or issues addressing ecosystem variability. We have discussed some of the important areas that need to be considered in relation to the incorporation of uncertainty in environmental decision-making processes including:

(1) Development of methods for quantifying the uncertainty associated with human input;
(2) Development of appropriate risk-based performance criteria that are understood and accepted by a range of disciplines;
(3) Improvement of fuzzy environmental decision-making through the development of hybrid approaches (e.g., fuzzy-rule-based models combined with probabilistic data-driven techniques);
(4) Explicit conveyance of the uncertainties in environmental decision-making through the use of Bayesian probability approaches;
(5) Incorporation of adaptive management practices including correcting model divergence;
(6) Development of approaches and strategies for increasing the computational efficiency of integrated models, optimization methods and methods for estimating risk-based performance measures; and
(7) Development of integrated frameworks for comprehensively addressing uncertainty as part of the environmental decision-making process.

Obviously, the above list is not all-inclusive and leaves room for other existing techniques or approaches. The type or quality of the uncertainty assessment, and the scientific tools employed in that assessment, must be decided pragmatically as part of the infrastructure (including cost) and system dynamics of the decision-making process. In addition, unfounded certainty about a perceived problem (particularly those shaped by normative assumptions and societal beliefs) may far outweigh technical or scientific uncertainty in the decision-making process. Rauscher (1999) quite rightly points out that the sharing of decision-making power between representatives of technical, social, political, economic, and legal interests "creates tensions which help make ecosystem management a very wicked problem." We reassert the importance of developing innovative methods for quantifying the uncertainty associated with human input by noting that human attitudes, beliefs, and behavior provide a large area beyond scientific and technical uncertainty in the ultimate solution to environmental problems.

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