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Uncertainty in Environmental Decision-Making: Issues, Challenges and Future Directions

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Uncertainty in Environmental Decision-Making: Issues, Challenges and Future Directions

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Abstract: Environmental decision-making is complicated by the complexity of natural systems and the often competing needs of multiple stakeholders. Modelling tools are often used to assist at various stages of the environmental decision-making process. If such models are to provide effective decision support, the uncertainties associated with all aspects of the decision-making process need to be taken into account explicitly. However, as models become more complex in order 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 (i) the development of appropriate risk-based performance criteria that are understood and accepted by a range of disciplines, (ii) the development of methods for quantifying the uncertainty associated with human input, (iii) 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 (iv) the development of an integrated framework that enables all sources of uncertainty to be incorporated in the environmental decision-making process.

Keywords: Environmental decision-making; Environmental models; Uncertainty

1. INTRODUCTION

Environmental management presents significant challenges, as:

- It is concerned with highly complex systems that are generally not well understood;
- It generally involves a large number of stakeholders, often with competing objectives; and
- There are generally a large number of potential management options.

As a result, there has been an increase in the use of formal approaches to environmental management. Jakeman and Letcher [2003] and Jakeman et al. [2006] have demonstrated the importance of integrated models 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 modelling framework (e.g. Bousquet and LePage, 2004). Much work has also been done in the field of multi-criteria decision analysis (MCDA) in order 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 a large number of potential alternatives, Vasquez et al. [2000] and McPhee and Yeh [2004] have shown how environmental models can be linked with evolutionary optimisation algorithms in order to obtain optimal tradeoffs between competing objectives to better inform management decisions.

As model complexity increases in order to better represent environmental and socio-environmental systems, there is an increased 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), optimisation methods (e.g. Cieniawski et al., 1995; Vasquez et al., 2000; Ciu and Kuczera, 2005), multi-criteria methods (e.g. Rios-Insua, 1990; Barron and Schmidt, 1988; Hyde et al., 2004), and decision-support (e.g. Pallotino et al., 2005; Reichert and Borsuk, 2005) and adaptive management (e.g. Prato 2005) systems. However, there is a need to examine the decision-making process in an integrated fashion, in order to identify all sources of uncertainty and ways of incorporating them into the decision-making process. At present, several regional, co-operative research efforts are underway to address this problem as part of the Harmoni-CA project in Europe (http://www.harmoni-ca.info/toolbox/Model_Uncertainty/index.php), the eWater Co-operative Research Centre in Australia (http://www.ewatercrc.com.au/researchprograms.html) and the Interagency Steering Committee on Multimedia Environmental Models - Workgroup 2: Uncertainty Analysis and Parameter Estimation (http://www.iscmem.org/WorkGroup_02.htm) in the United States. In order to build on these efforts, the purpose of this paper is to:

- Discuss the major steps in the environmental decision-making process;
- Identify possible sources of uncertainty at each stage of the environmental decision-making process; and
- Discuss current progress and identify some of the remaining issues, challenges and future directions in relation to the incorporation of uncertainty into the environmental decision-making process, including the development of:
  - Appropriate risk-based assessment criteria;
  - Methods for quantifying uncertainty associated with human input;
  - Approaches for increasing computational efficiency; and
  - An integrated framework for addressing uncertainty as part of environmental decision-making processes.

2. ENVIRONMENTAL DECISION-MAKING PROCESS

In order to develop model-based decision-support tools for environmental management and policy analysis, one or more of the steps in the environmental decision-making process need to be considered. The main factors that have an impact on whether environmental problems are addressed, and how this is done, are shown in Figure 1. Firstly, environmental problems need to be identified and brought to the attention of environmental managers / decision-makers. This can be done through the reporting of routine data, modelling efforts, or input from local stakeholders and / or lobby groups. Once a particular problem is on the agenda of environmental managers, a decision has to be made whether action should be taken to address the problem. This decision will depend on a number of factors, such as the perceived importance and magnitude of the problem, as well as financial considerations. If it is decided to address the problem, a list of alternative solutions has 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 alternative, or set of alternatives, is considered “optimal”, analytical methods, such as integrated models, formal optimisation techniques and multi-criteria decision analysis are generally used. Finally, the decision-maker has to decide which option will be implemented.

Traditionally, model-based decision-support tools have been used to help determine which subset of potential alternatives can be considered “optimal” (i.e. Figure 1, Step 4). As shown in Figure 1 (Steps 4.1 – 4.3), this would require the selection of appropriate assessment criteria, followed by the assessment of all, or a subset of, the potential alternatives identified in Step 3 against these criteria. If the number of candidate solutions is limited, all options can be assessed. However, if a large number of options is available, formal optimisation approaches, such as genetic algorithms, should be used to select which subset of the potential alternatives to assess. The assessment process would generally be done with the aid of one or more (integrated) simulation models, which enables the performance of the proposed alternatives to be assessed against the specified performance criteria. In general, there will be a number of competing objectives, making it difficult to rank the candidate options. In cases 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

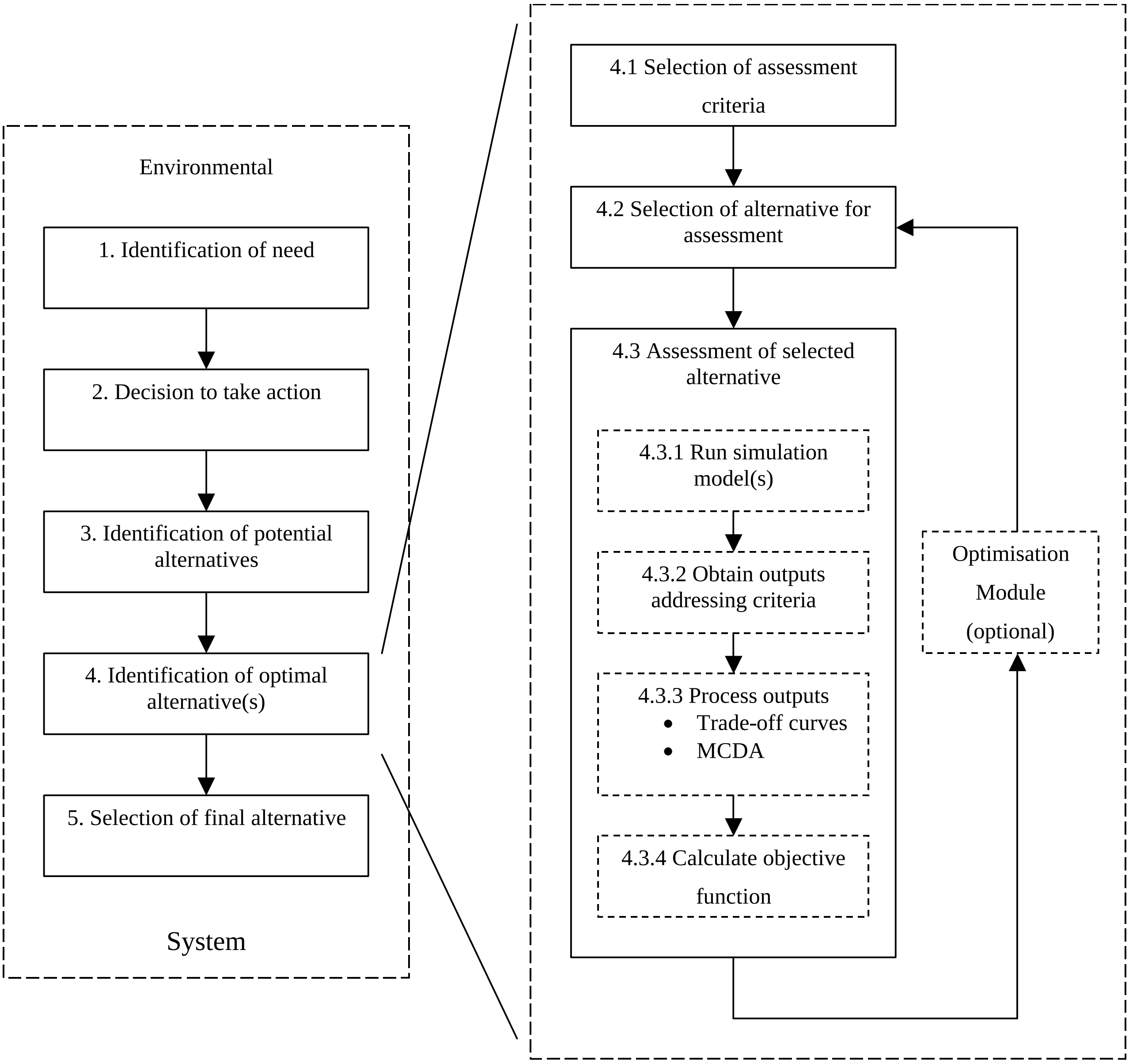

Figure 1. Process for arriving at a chosen development / management alternative.

optimisation algorithms are used, Pareto optimal trade-off curves can be developed to identify a set of "optimal" solutions.

Models can also be used in other steps of the process outlined in Figure 1, such as the identification of the initial problem, the decision whether to take action, and the identification of potential alternatives. In addition, there may be a need to model all, or various subsets, of the process shown in Figure 1. For example, if the objective is to assess the impact of alternative policy directions on the degree to which different types of environmental problems are being addressed over an extended period of time, all of the steps outlined in Figure 1 would need to be modelled. However, regardless of which steps of the environmental decision-making process are considered, all sources of uncertainty need to be modeled 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. SOURCES OF UNCERTAINTY

Various forms of uncertainty are associated with each of the steps in the environmental decision-making process outlined in Figure 1, as summarised in Table 1. Traditionally, the focus has been on uncertainty in data and environmental models. However, there is an increasing recognition that the uncertainties associated with "human" factors also need to be taken into consideration.

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, validation) and to identify appropriate performance values in multi-criteria decision analyses. Uncertainties in data include:

- Measurement error: This could be due to the type of instrument used (e.g. measurement precision), how well the instrument is calibrated, how the data are read (e.g. automatic logging, manual reading), how frequently the data are measured and recorded (e.g. are all major system variations captured) and how the data are transmitted and stored.
- Type of data recorded: In many instances, not all relevant data are recorded. Consequently, the data may present an incomplete or skewed picture of the state of a system. However, such data can be the basis of decisions made.
- Length of data record: The length of the data record is likely to have an impact on the types of events that have been captured, and can therefore have a significant impact on decisions made and models calibrated and validated using these data.
- The way the data are analysed / processed and presented: The way raw data are analysed / processed can have a significant impact on decision-making processes, as this may highlight certain factors in preference over others and can affect the strength of the argument made to environmental managers / decision-makers.

Table 1: Example sources of uncertainty in the environmental decision-making process.

Category	Example Sources of Uncertainty

Data	• Measurement error
	   o Type of instrument
	   o Quality and frequency of calibration of instrument
	   o Data reading and logging
	   o Data transmission and storage
	• Type of data recorded
	• Length of data record
	• Type of data analysis / processing
	• The way the data are presented

Models	• Modelling method used • Type, quality and length of record of available data • Calibration method and data used • Validation method and data used • Input variability
Human	• Knowledge, experience and expertise of modeller • Political "clout" and perceived importance of stakeholder(s) • Knowledge, values and attitudes of stakeholders • Strength of argument presented by stakeholders • Values and attitudes of managers / decision-makers • Current political "climate"

Models can play an important role at a number of stages of the environmental decision-making process, including identification and quantification of the severity of environmental problems, as well as the identification of potential and optimal solutions. Models can vary significantly in complexity (and hence data requirements) and can serve a variety of purposes. For example, models can be used for simulation purposes in order 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 / prediction models are generally process based (deterministic) or data based (statistical), although the use of hybrid models is becoming increasingly popular. Models can also be used for optimisation or to conduct multi-criteria decision analysis.

It is well-recognized that predictive models are generally subject to input, model and parameter uncertainty (e.g. Loucks and Lynn, 1966; Burges and Lettenmaier, 1975; Vicens et al., 1975). Uncertainties in model inputs are due to measurement errors and / or natural variability (e.g. using a single, critical input, rather than a distribution of extreme inputs). The term model uncertainty is generally used to describe the uncertainty associated with the inability of the developed model to represent the system it attempts to model. This may be due to the choice of a sub-optimal model type or structure, the lack of representative data (in the case of data-driven models, where the selection of an appropriate model structure is a function of the available data) or the lack of existence of a representative model type and / or structure (e.g. in the case where the system to be modelled in insufficiently well understood). Parameter uncertainty refers to the uncertainty associated with model parameters, which generally have to be obtained directly from measured data or indirectly from measured input-output data by calibration. If parameters are obtained directly from measured data, some of the uncertainties associated with data discussed previously come into play. If parameters are obtained by calibration, the length, quality and type of available data records discussed previously 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 optimisation algorithm).

One type of uncertainty that has received limited attention in the literature is the uncertainty associated with human input. 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 significantly impact on 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 of the decision-making process. 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 alternatives, as well as the assessment process via the development of appropriate assessment criteria and the provision of weightings, if multi-criteria decision approaches are utilized.

Even the more "technical" aspects of the decision-making process are not immune from uncertainty due to human input. For example, Refsgaard et al. [2005] found that the results of a modelling exercise varied significantly when different modellers were presented with the same problem and data. The knowledge, experience and preferences of the modellers were found to have a significant impact on the results obtained. For example, if modellers have experience with a particular modelling approach and / or software package, they are more likely to utilize this approach / package, in preference to a, perhaps, more appropriate modelling tool. Similarly, the way a particular modelling approach is applied (e.g. what calibration method is used, how the available data are used) can also vary from modeller to modeller, based on their knowledge, experience and preferences.

The extent to which the above uncertainties have been incorporated into modelling frameworks, and the remaining and emerging challenges of developing model-based decision support tools for integrated environmental management, are discussed in Section 4.

4. PROGRESS, CHALLENGES AND FUTURE DIRECTIONS

4.1 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 (expected length 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). 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.

4.2 Uncertainty in Human Input

Uncertainties associated with data, as well as model inputs and parameters, have been recognized for some time, and much work has been done to incorporate these types of uncertainty into modelling frameworks (e.g. Thyer et al., 2002). However, because the significance of the impact human input can have on the environmental decision-making process has only been recognised relatively recently, methods for dealing with the uncertainty associated with this factor are still in their developmental stages. Significant advances have been made in relation to developing models of human behaviour 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 et al., 2004). However, although these models generally allow for heterogeneity in human behaviour, they do not model uncertainty in the various model components. 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 for 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 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 multi-criteria 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 alternatives is large, multi-objective optimisation approaches (e.g. Deb et al., 2002) can be used to obtain Pareto optimal tradeoffs 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 multi-criteria decision-analysis. However, such an approach is yet to be tested.

4.3 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:

- <u>The use of more efficient methods for estimating risk-based performance measures:</u> 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 (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.
- <u>The skeletonisation of complex models via innovative sensitivity analysis methods:</u> 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].
- <u>The use of metamodels to replace all, or portions of, computationally inefficient process models:</u> 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.

4.4 Integrated Uncertainty Framework for Decision Making

As discussed in Section 2 and illustrated in Figure 1, many of the issues and challenges discussed in Sections 4.1-4.3 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 a holistic, integrated uncertainty framework to support the development, evaluation and utilization of models for effective environmental decision-support. Some of the issues that should be addressed by such a framework include explicit incorporation 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 behaviour of variables across space and time. Such a framework should also tie together uncertainty related to multi-criteria tradeoffs and combined measures of model fit and complexity and also discuss 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?

In addition, there is also a need to expand the framework to incorporate sensitivity analysis. Although sampling-based uncertainty and sensitivity analysis is a fairly established area of study, a number of important challenges and areas for additional study remain. For example, there is a need for sensitivity analysis procedures that are more effective at revealing nonlinear relations than those currently in use. Candidates include procedures based on complete variance decomposition (Li et al., 2001), tests for non-monotonic relations (Hora and Helton, 2003), nonparametric regression (Bowman and Azzalini, 1997), and the two-dimensional Kolmogorov-Smirnov test (Garvey et al., 1998). Furthermore, sampling-based procedures for uncertainty and sensitivity analysis typically use probability as the model, or representation, for uncertainty. However, when incomplete information is available with which to characterize uncertainty, probabilistic characterizations can give the appearance of more knowledge than is really present (Helton et al., 2004). Alternative representations for uncertainty such as evidence theory and possibility theory merit consideration for their potential to represent uncertainty in situations where sparse information is available (Helton et al., 2004). Finally, a significant challenge is the communication to potential users of uncertainty and sensitivity analysis about: (i) the significance of such analyses, and their role in both large- and small-scale analyses; (ii) the need for an appropriate delineation of uncertainty due to lack of knowledge and uncertainty due to variability (Hoffman and Hammonds 1994); (iii) the importance of avoiding excessively conservative assumptions if meaningful uncertainty and sensitivity analysis results are to be obtained; and (iv) the need for a concise conceptual blueprint of what an analysis is intended to characterize, and a computational design consistent with that blueprint.

5. SUMMARY AND CONCLUSIONS

Environmental decision-making is extremely complex due to the complexity of the systems considered and the competing interests of multiple stakeholders. In order to improve the quality of decisions made, formal decision support tools, such as integrated models, optimisation algorithms and multi-criteria decision-analysis, are being used increasingly. In addition, the need to consider environmental, social and economic systems in an integrated fashion has also received increased attention. However, as decision-support tools increase in complexity, the need to consider uncertainty at all stages of the decision-making process becomes more important, so that decisions can be made with confidence or known certainty. Some of the important areas that need to be addressed in relation to the incorporation of uncertainty in environmental decision-making processes include:

- The development of appropriate risk-based performance criteria that are understood and accepted by a range of disciplines.
- The development of methods for quantifying the uncertainty associated with human input.

- The development of approaches and strategies for increasing the computational efficiency of integrated models, optimization methods and methods for estimating risk-based performance measures.
- The development of an integrated framework that enables all sources of uncertainty to be incorporated in the environmental decision-making process.

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