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Uncertainty in integrated coastal zone management

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Abstract. Uncertainty plays a major role in Integrated Coastal Zone Management (ICZM). A large part of this uncertainty is connected to our lack of knowledge of the integrated functioning of the coastal system and to the increasing need to act in a pro-active way. Increasingly, coastal managers are forced to take decisions based on information which is surrounded by uncertainties. Different types of uncertainty can be identified and the role of uncertainty in decision making, scientific uncertainty and model uncertainty in ICZM is discussed. The issue of spatial variability, which is believed to be extremely important in ICZM and represents a primary source of complexity and uncertainty, is also briefly introduced. Some principles for complex model building are described as an approach to handle, in a balanced way, the available data, information, knowledge and experience. The practical method of sensitivity analysis is then introduced as a method for a posterior evaluation of uncertainty in simulation models. We conclude by emphasising the need for the definition of an analysis plan in order to handle model uncertainty in a balanced way during the decision making process.

Keywords: Coastal management; Coastal system; Keystone process; Model; Simulation.

Introduction

In order to carry out a successful Integrated Coastal Zone Management (ICZM), a thorough understanding of the functioning of the coastal system is required. This can be achieved by studying the relevant processes in geomorphology, ecology, coastal land use, and socio-economy, and especially their interdependencies, within the coastal zone. Currently there is a lack of understanding of the integrated functioning of the coastal system. Perhaps equally significant is that at present the elementary knowledge for a truly interdisciplinary approach is also still lacking.

The development of integrated models can help to investigate the processes and feedback mechanisms between geomorphology, ecology, coastal land use, and socio-economy. The development and also the use of these models is, however, surrounded by uncertainties. These uncertainties may already originate in the initial phases of the model building processes, for instance when considering the choice of key variables or key processes. The search for key processes in the complex issue of integrated assessment draws on Holling's (1992) argument that the dynamic behaviour of many ecosystems can be explained by a few driving forces, namely the keystone processes. Other matters of uncertainty concern the choice of temporal and spatial aggregation levels. One of the major difficulties in the linking of different processes in integrated assessment and integrated modelling is the linking of the available information and the process knowledge both in space and time. Different systems work along different time scales (Costanza 1991), for example biology, economics and geology work from seasons to millions of years. Spatially, processes may display an equally large variability. The linking of processes in space and time basically corresponds to defining the mechanisms of downscaling and upscaling of processes.

Uncertainty is also produced by the lack of knowledge about the external influences that the coastal system is subject to. Both natural and human-induced influences can affect the functioning of coastal systems. There is always uncertainty surrounding the predictions for change and of the rates of change, for instance in the context of climatic change related forces (possible relative sea level change, change of storminess, etc.) and in the context of future coastal land use settings and socio-economic scenarios.

Other sources of uncertainty arise from the institutional settings in which the Integrated Coastal Zone Management action is undertaken. Such settings are hardly ever optimal. There are many different actors involved, who have very diverse interests, are distributed in space and act on different scales during the various phases of problem analysis, planning, implementation and evaluation. The various actors further complicate the problem of evaluating the modelling results by imposing their subjective interpretations or specific interests upon the model outputs eventually presented by the coastal scientists.

All such sources of uncertainty are investigated here with reference to the coastal area and Integrated Coastal Zone Management. The aim is to make the model utilization more and more generally applicable, so that it becomes less dependent on the specific model to which it is applied. This can be achieved by introducing, and using, principles and guidelines for systematic analysis and communication of uncertainty.

The existence of uncertainty cannot be a justification for not undertaking Integrated Coastal Zone Management. At the same time, however, representing, qualifying, and quantifying uncertainty is central to support a proper and robust decision making. A model-based assessment may use heuristic schemes to communicate uncertainties, for instance by assigning degrees of confidence to the main concluding statements that result from the model runs. However, more systematic analysis and communication of uncertainty should also be possible by defining scenarios of change and undertaking guided sensitivity analyses.

Types of uncertainty

On the sources of uncertainty

The literature provides an extensive overview of different classifications of uncertainties. This is not surprising, since the issue of uncertainty has invariably been an important one in (physical) science (Morgan & Henrion 1990). Science and the role of science, however, evolve with developments in society. The emergence of large scale environmental problems and the public concern over these issues has changed the tasks for scientists.

Funtowicz & Ravetz (1990) introduce the term 'post-normal science' which indicates the passing of Kuhnsian 'normal science' associated with puzzle-solving. In the post-normal era, scientific problems are introduced through policy issues. The issues of risk and environment impose new tasks on those scientists and experts who provide information and advice on policy problems, the so-called policy related research (Funtowicz & Ravetz 1990; Funtowicz & Ravetz 1991; Morgan & Henrion 1990). Despite the progress in technology and science we now have to cope with increasing uncertainties surrounding complex environmental problems and threats. Dealing with these uncertainties involves a new challenge for scientists.

The relationship between policy and science has changed over the years. In the past science provided the 'hard' (numerical) facts and handed them over to the 'soft' (interest driven) politics (Funtowicz & Ravetz 1990). Nowadays policy makers more often have to make 'hard' decisions based on 'soft' scientific information. Furthermore, the view of policy makers taking over to make decisions after scientists have finished their job of providing the facts, is no longer satisfactory. If the policy making process is going to make adequate use of science, a careful and iterative process of analysis and interpretation is required.

Policies can no longer be assumed to be based on scientific information which has a high degree of certainty (Funtowicz & Ravetz 1990). A common response of decision makers and the public is to demand at least the appearance of certainty. Problems arise, however, when policy and decision makers do ask scientists for 'certain' information (Capobianco & Otter 1997). In many cases policy makers expect straightforward information as input into their decision making process. In other words, the 'politically correct' way of presenting model results to the end-user (e.g. decision-maker) is to produce a single value answer. Thus, if a model is calibrated and validated it is considered to be reliable and to add an uncertainty interval would be equivalent to doubting the results (Cunge 1998).

In this context, Funtowicz & Ravetz (1990) assert that "our culture invests a quality of real truth in numbers...". The reliance on numbers, which are not only considered necessary, but also generally sufficient, can easily lead to the conviction that all problems will be solved with bigger and faster computers. But, bigger is not necessarily better and small improvements will eventually require increasingly large efforts. The term 'appropriate models' can be used (analogous to appropriate technology) to indicate models in which the various degrees of accuracy, reliability and uncertainty are tuned to one another (Vreugdenhil 1997). The 'tuning' of the various aspects determines the quality of the model.

A very general typology of uncertainties, based on the division into a natural system and a human system, is given by Rotmans et al. (1994). They distinguish:

- Scientific uncertainties: occurring in the environmental system and which arise from the degree of unpredictability of global environmental change processes and may be narrowed as a result of further scientific research or more detailed and appropriate modelling;
- Social and economic uncertainties: occurring in the human system and which arise from the degree of unpredictability of future geopolitical, socio-economic and demographic evolution and which are inherently 'unknowable' or in practice unpredictable.

The first statement, however, is in conflict with the observation that non-linear systems can exhibit deterministic chaos and thus become inherently unpredictable.

Funtowicz & Ravetz (1990) distinguish between three sorts of uncertainty, namely technical, methodological and epistemological uncertainty. Technical uncertainty relates to inexactness of data or the spread of data sets. Methodological uncertainty corresponds to

Table 1. Sources of uncertainty with respect to planning phases (modified from EPA; Anon. 1996).

Activity	Source of uncertainty	Solution
Data collection	Unclear communication	• Contact principal investigator or other study participants if objectives and methods of studies are unclear • Document decisions made during the course of the assessment
	Descriptive errors	• Verify that data sources have followed appropriate Quality Assurance/Quality Control (QA/QC) procedures
	Variability and definition of representative values	• Describe heterogeneity using point estimates (e.g. central tendency and high end) or by constructing probability or frequency distributions • Differentiate from uncertainty due to lack of knowledge
	Uncertainty about a quantity's true value	• Use standard statistical methods to construct probability distributions or point estimates (e.g. confidence limits) • Evaluate power of designed experiments to detect differences • Consider taking additional data if sampling error is too large • Verify location of samples or other spatial features
	Data gaps	• Describe approaches used for bridging gaps and their rationales • Promote the routine application of synoptic and long-term monitoring techniques • Differentiate science-based judgements from policy-based judgements
System analysis	Model structure uncertainty (process models)	• Beware of the problem of practical identifiability and of the problem of overcalibration • Discuss key aggregations and model simplifications • Compare model predictions with data collected in the system of interest
	Uncertainty about a model's form (empirical models)	• Evaluate whether alternative models should be combined formally or treated separately • Evaluate the practical applicability of empirical models in the context of interest
	Uncertainty about model and data integration	• Compare model predictions with data collected in the system of interest • Evaluate their degree of balance
Decision making	Uncertainty related to the attribution of values	• Distinguish different classes of values • Consider the possibility for values to change in time • Update values regularly
	Uncertainty related to intercomparison of values	• Consider the need to deal with 'monetary' and 'non-monetary' values • Distinguish between 'use' and 'non-use' of natural resources
	Uncertainty related to scale effects of decisions	• Consider that the implementation of one decision on a certain spatial scale produces effects at larger as well as shorter spatial scales

the unreliability or the level of confidence to be placed in a quantitative statement. Epistemological uncertainty is connected to ignorance and represents all the different gaps in our knowledge not encompassed in the previous sorts of uncertainty.

Morgan & Henrion (1990) list three types of uncertainty about which analysts should be explicit:

- uncertainty about technical, scientific, economic and political quantities;
- uncertainty about the appropriate functional form of technical, scientific, economic and political models;
- disagreements among experts about the value of quantities or the functional form of models.

The US Environmental Protection Agency (Anon. 1996) discusses sources of uncertainty that arise during the evaluation of information and conceptual model development (combined under the subject of scenario uncertainty), when evaluating the value of a parameter (e.g. an environmental measurement), and during the development and application of models. Many of the sources of uncertainty discussed by EPA (Anon. 1996) are relevant to characterising both exposure and environmental effects. The sources and example strategies for the analysis phase are shown in Table 1.

Each of the phases which can be discerned in Integrated Coastal Zone Management (ICZM) involves a certain degree of uncertainty related to the various activities. In Fig. 1 a non-exhaustive overview is given of possible uncertainties. The type of uncertainties we are most interested in, are those related to problem recognition and analysis and to the planning activities where the decision making process has its central moment. ICZM may require sequential decisions to be undertaken and methodologies to formulate and solve sequential decision making problems under uncertainty with continuous decision and/or random variables are increasingly being developed (Stonebraker & Kirkwood 1997).

We do not discuss here in detail the uncertainty for all phases. We aim to make clear that a fully deterministic approach cannot handle uncertainty related to the various phases of a generic coastal zone management task.

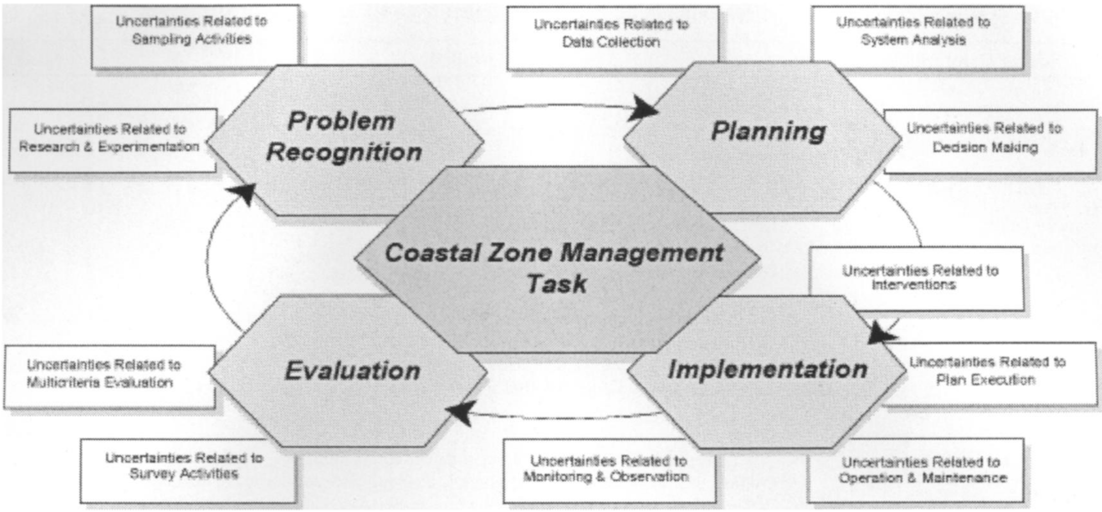

Fig. 1. Uncertainties in coastal zone management.

Uncertainty in decision making

Risk can be defined as an exposure to a chance of injury or loss and since risk involves chance or probability it thus also needs to deal with uncertainty (Morgan & Henrion 1990).

Risk assessment has become the central guiding principle at environmental management agencies (see, for instance the American EPA) but true uncertainty has yet to be adequately incorporated into environmental protection strategy. Even the most recent and advanced initiatives for the adoption of environmental management standards avoid tackling the problem of uncertainties (Anon. 1995a, b). The reason why our current approaches to environmental management and policy making have difficulty in handling uncertainty may be clear. The goal of decision makers is to make unambiguous, defensible policy decisions. Often these decisions are codified in the form of laws, regulations, and procedures. While legislative language is often open to interpretation, regulations are much easier to write and enforce if they are stated in clear and absolutely certain terms. But many scientific studies come to just conclusions in terms of probability (or conditional probabilities) because that is the nature of the phenomenon.

When trying to enforce the regulations after they have been drafted, the problem of true uncertainty about the impacts remains. As they are currently set up most environmental regulations demand certainty and the absence of certainty may lead to frustration and poor communication. Because of uncertainty, environmental issues can often be manipulated by political and economic interest groups. Uncertainty about global warming is perhaps the most visible current example of this effect.

One way in which the environmental regulatory community has begun to deal with the problem of true uncertainty, is through the 'precautionary principle'. The principle states that rather than await certainty, regulators should act in anticipation of any potential environmental harm in order to prevent it. The precautionary principle is so frequently invoked in international environmental resolutions that it has come to be seen by some as a basic normative principle of international environmental law. The principle, however, offers no guidance as to what precautionary measures should be taken. It 'implies the commitment of resources now to safeguard against the potentially adverse future outcomes of some decision', but does not tell us how many resources or which adverse future outcomes are most important (Funtowicz et al. 1995).

Scientific uncertainty

Science treats uncertainty as a characteristic of all information that must be honestly acknowledged and communicated. Over the years scientists have developed increasingly sophisticated methods to measure and communicate uncertainty arising from various causes. Progress has been made in the sense that the occurrence of many types of events can be predicted with a certain degree of confidence. At the same time, however, science has uncovered even more uncertainty, rather than leading to the absolute precision. In this case the scientific method can only set boundaries to the limits of our knowledge (Capobianco 1998). It can define the boundaries of what is known. For instance, science can tell us the range of uncertainty about global warming and relative sea level rise, and maybe something about the relative probabilities of different outcomes. In most important cases, however, it cannot tell us which of the possible outcomes will occur with any degree of accuracy. In that case the definition of ranges or limits can already provide a very important result.

One of the principal reasons for the problems with current methods of Integrated Coastal Zone Management, and of Environmental Management in general, is scientific uncertainty which can be defined here as the uncertainty surrounding our integral understanding of the coastal system. Especially in the context of sustainable development, uncertainty is mainly related to the long time horizon and the economic-ecological interactions (van den Bergh & Nijkamp 1991). Much uncertainty emerges from unforeseeable qualitative changes in a system, which are due to integral shifts in behavioural patterns, exogenous impacts or changes in policy institutions. Some problems with temporal scale in the linking of human and biophysical processes concern the discounting of the future, depreciating natural assets, the existence of cumulative change (Lonergan & Prudham 1994), etc.

The differences in handling temporal aspects in the various disciplines becomes explicit when comparing models of economic and ecological systems. Economic data is usually aggregated over time, so that models are developed to represent what happens during a calendar year. In ecology, processes are simulated at short time scales and treated entirely as recursive and consequently high time resolution models are adopted (Bockstael 1996). In addition, ecologists are also interested in long time horizons and especially the long-term implication of human action (Bockstael et al. 1995). Economists, however, tend to ignore the very long run because of the inherent unpredictability of the future.

Similar difficulties are encountered when linking processes operating at different spatial scales. Land resources vary in space and this spatial variability represents an important source of complexity and uncertainty (Costanza et al. 1993). In addition, space is one of the neglected areas in economics (Nijkamp 1986; Armstrong & Taylor 1995). Economists are not used to working with the concept of space. When human behaviour is studied or modelled, the focus is on informational flows such as money and prices and (virtual) markets which have no geographical dimensions. Natural scientists concentrate on actual flows of physical quantities. Ecologists, for example, think in terms of water, biomass and energy flows which all have spatial characteristics. Consequently, ecologists have made great progress in the development of spatial models while economists have not (Bockstael et al. 1995).

There are various ways to account for spatial variability, each having its advantages and drawbacks. A fundamental problem is how to estimate the value of a certain piece of land, based on a set of existing samples of nearby locations. The variation is not completely random over space, but very often exhibits spatial dependence. This implies that knowing the value of a land characteristic at a certain point already provides information about non-sampled points nearby.

Interest in quantifying spatial uncertainty has increased with the increasing use of geographic information systems and the development of modelling approaches that can be directly integrated with them (Engelen et al. 1995). Major advances have been made in general computer hardware and software capabilities, which have facilitated far more sophisticated geographic data bases and manipulation possibilities (Martin 1996). Strategies include verifying the locations of remotely sensed features, ensuring that the spatial resolution of data or a method is commensurate with the needs of the assessment, and using methods to describe and use the spatial structure of data.

Model uncertainty

Models can be used to develop our understanding of integrated coastal systems. We distinguish between different classes of models that can be developed and applied to a variable extent in the phases of problem analysis, planning, implementation, and evaluation (see Fig. 1) of Integrated Coastal Zone Management. An important aspect of the decision making process is risk assessment, concerning the risk of not taking action as well as that of taking action.

Conceptual model development, in the sense of building a qualitative, schematic model, may account for one of the most important sources of uncertainty in a risk assessment. A conceptual model may precede the building of a quantitative model or be a model in its own right.

If important relationships are missed or specified incorrectly, risks could be seriously under- or overestimated in the planning phase. Uncertainty can arise from lack of knowledge on how the coastal system functions, failing to identify and interrelate temporal and spatial parameters, not describing influencing factors and driving forces, or not recognising secondary effects. In the context of changes in coastal land use and land cover it has been recognised that the interdependencies among human behaviours, land cover and the state of the environment should be studied and modelled (Rayner 1994). There is considerable speculation about the importance of various human factors as drivers of land use and they are less systematically described and investigated than the biogeophysical factors. Uncertainty also still remains about some of the biogeophysical processes involved (Veldkamp & Fresco 1996; Rayner 1994).

Uncertainty associated with conceptual models can be reduced by developing alternative conceptual models for a particular assessment to explore possible relationships. In cases where more than one conceptual model is plausible, the risk assessor must decide whether it is feasible to follow separate models through the analysis phase or whether the models can be combined into a better conceptual model. Developing models is an iterative process and it is important to revisit, and if necessary revise, conceptual models during risk assessments to incorporate new information and re-check the rationale. It is valuable to present conceptual models to risk managers to check for completeness and clarity and to ensure the models address the key concerns that the managers have.

Sources of uncertainty that arise primarily during the development and application of models originate from the structure of process models and the description of the relationship between two or more variables in empirical models. Especially the choice for so called 'key variables' or 'key processes' is surrounded by uncertainty. Uncertainty in process or empirical models can be quantitatively estimated by comparing model results to measurements taken in the system of interest or by comparing the results obtained using different model alternatives.

In the practical application of a generic coastal zone model like that of Fig. 2 (Capobianco & Otter 1996), links will be further detailed between all the subsystems used to describe the coastal area. Links can be indicated in qualitative terms, but also be represented by:

- *One mathematical formula*, describing the functional dependencies of the link. Uncertainty here can be such that various mathematical formulas can be equally justified.
- *A series of possible values*, e.g.: the height of the embankments, the monthly or yearly fluxes of water required to irrigate or drain an agricultural field. Uncertainty here can be reduced by more detailed or more prolonged field data acquisition.
- *A series of if-then conditions*, which describe the management practices as well as the regulatory system and which are linked to possible expert systems based approaches. Uncertainty here is often related to the possible unknown or hidden practices as well as to the problem of scales.
- *The indication of a 'submodel'*, which can handle downscale transitions leading to a higher resolution. More than one submodel, with different parameterizations, can be applied here.
- *Other*, in the sense that we do not expect to have solved all the possible situations, even with such a general framework.

Dynamic simulation models can easily have a large number of parameters. Each of these must be established

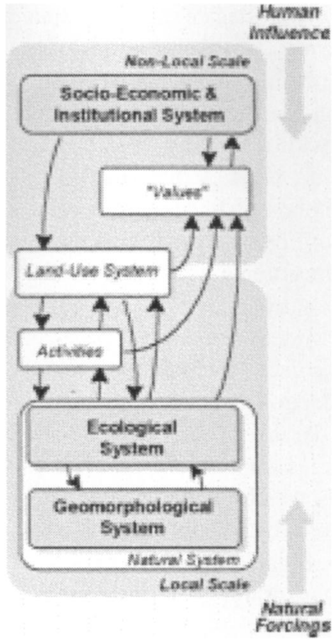

Fig. 2. Generic conceptual model for a coastal system.

by calibration based on available data or derived from 'first' principles. A major problem is that very often parameters are linked, while the possible interactions are unknown. Also, many adjustments of parameters can lead to the same final results. What is needed is insight into the natural and human processes and their interactions, many of which are poorly understood. Understanding the interactions between natural and human processes is indeed a fundamental aspect of integrated modelling. The integration is however still faced with unresolvable problems, partly because natural sciences and human sciences are based on conflicting epistemologies.

Together with the rapid growth in integrated analyses and the development of integrated models, the critique on these integrated approaches has also grown. Especially the large scale integrated models, which use scenarios to provide predictions or projections of the future, are under fire. Sometimes a number of these unverified models are linked to each other which leads to speculations without an empirical check. Such an approach is sometimes considered as being unscientific (see also Funtowicz & Ravetz 1990).

Principles for complex model building

Considering the uncertainties in decision making, in scientific knowledge, and especially in model building, it is worth following some fundamental principles in the model building process to deal with these uncertainties (see Table 2). We expect the application of such

Table 2. Principles for complex model building.

Principle	Description	Explanation
The principle of balance	The available knowledge and representation of forcings, processes & output must be compatible.	They should not be 'unrealistically' unbalanced. Particularly the problem of balancing available information with model complexity should be handled here. Nevertheless, at same time it is important to take into account the possible utilisation of new technologies and methodologies, such as the use of remote sensing or radiometric analysis techniques to quantify processes that could not be otherwise detected.
The principle of indeterminacy	We have to accept that there are aspects of the forcings, processes & output that cannot be determined on a certain time and space scale.	In quantum physics the principle recognises that, on the atomic level, any measuring process involves energy which by necessity interferes with the energy measured. This is something that we cannot avoid and we just must accept. The practical problem consists in the identification of the balance between processes on certain scales and observables on the same scales.
The principle of parsimony	The number of unknown parameters must be kept at the minimum possible to reproduce the forcings, processes and output.	In such a way we can aim to understand the dynamics and not introduce useless and dangerous mechanisms of complication. In cybernetics and systems science[1] this is also known as Occam's Razor: 'one should not increase, beyond what is necessary, the number of entities required to explain anything'.
The principle of complexity	Complexity can only be handled in a simple way.	This principle is connected to the Principle of parsimony. We should aim to handle the emerging simple features rather than reproduce the complex, potentially chaotic, dynamics. We would end into other complex and chaotic dynamics.
The principle of uncertainty invariance	When transforming a system, the amount of information in the resulting system should be as close as possible to the original.	In other words, when transforming or translating a system or a problem formulation from one representation to another, we should aim at neither gaining nor losing any information. This can, of course, be difficult to achieve if uncertainty and information are represented in different ways in the different representation frames.

[1]In cybernetics and systems science the principle of parsimony can be related to the principle of uncertainty maximization in inductive reasoning (use all but not more of the available information) and the principle of uncertainty minimisation in deductive reasoning (lose as little information as possible).

principles to allow for balancing the available data, information, knowledge and experience both during the model building process and during the model utilization phase.

Table 2, which contains a description and short explanation of the principles of complex model building, is followed by some background information about each principle.

The principle of balance recalls the need to consider forcing factors, processes, and output in their relation. Dealing with integrated modelling of complex environmental systems, it would be extremely inefficient and potentially dangerous to look at them in a completely independent way, simply because they are never fully independent. This also implies that there should be a balance between available data and modelled processes, starting from the consideration that both data and models are just a limited representation of reality. Cunge (1998) work, along this line of thinking.

The principle of indeterminacy introduces some conceptual limitations to the type of scale transitions that can be resolved in practical applications. There are limits to the resolution that can be achieved for certain processes in the real world. The difficulty we are facing is the quantitative determination (even if expressed in a fuzzy way) of such limits (Capobianco 1998).

The principle of parsimony represents, in practice, a way to prioritize the selection of possible theories or models. This is extremely important especially for those situations where different parameter sets produce the same observable response. The more parameters there are in a model, the easier it could be to fit a given set of 'calibration data'. On the other hand a large parameter set could also result in a greater uncertainty and a larger sensitivity of the model output to variations of the input.

The principle of complexity can be considered as a corollary to the principle of parsimony. In practice, if the occurrence of a feature is a recognised character of the system under given conditions, it is easier to describe its behaviour rather than try to describe its formation and its behaviour together. Practically speaking such a principle is being implicitly used in theoretical morphodynamics to describe the occurrence of morphological patterns (e.g. Hulscher et al. 1993).

The principle of uncertainty invariance is extremely useful while trying to build integrated models when models for non-integrated processes already exist. In other words, if the aim is to keep information, every action is justified if it does not increase uncertainty.

Sensitivity analyses

Integrated modelling can be achieved by setting up a problem specific model in an intrinsically integrative way. More often, however, integrated modelling of complex coastal systems is attained by linking formal disciplinary models. In dealing with the integration of different formal model structures, the evaluation of sensitivity of model outputs is essential for the quantification of uncertainty.

Sensitivity analysis can be used to evaluate how model output changes with changes in input variables, and uncertainty propagation can be analysed to examine how uncertainty in individual parameters can affect the overall uncertainty of the assessment. The availability of software for Monte Carlo analysis[1] has greatly increased the use of probabilistic methods (see Meeuwissen 1996, for a formal treatment of the problem). Other methods (such as for example fuzzy mathematics and Bayesian methodologies) are available, but have not yet been extensively applied to ecological risk assessment. No matter what technique is used, all the sources of uncertainty discussed above should be addressed.

Simulation modelling requires a large number of model parameters (calibration values) and input data. An important issue in modelling is the sensitivity of the model to variations in parameters or data. Sensitivity analysis allows us to see where the model is most sensitive, thus on which aspects the calibration and modelling efforts should be concentrated. The basic method for sensitivity analysis requires the parameter to be varied in some predictable way, subsequently the model is run and the output recorded.

Sensitivity analysis is a very powerful and flexible technique. It is applicable to variables with and without known probability distributions (i.e., frequency distributions are acceptable). Without modern computers it would be impossible. Some tricky points are establishing the distributions of the input variables, designing a sampling strategy that will give reliable results in a reasonable number of simulations (typically in the order of 1000), making sure we have examined enough simulations, quantifying the true distribution of the output errors.

Kinzelbach & Kunstmann (1998) discuss the quantification of uncertainty arising from the imperfect knowledge of the input parameters for groundwater flow and transport models. They recall computationally efficient approaches such as Gaussian Error Propagation and the First Order Second Moment technique (FOSM). Generally speaking, the more information is available about the model formulation and the more it is possible to work analytically on the linearized system, the more efficient the process of sensitivity analysis turns out to be.

Non-linearity represents both a problem and an opportunity. Non-linear behaviour typically occurs around 'working points' or 'attractors'. Around given working points the evolution of the system and the model output may be relatively insensitive to variations of certain inputs or parameters until a certain 'threshold' is reached and the transition from one attractor state to another is achieved. Such 'thresholds' prevent sensitivity to certain inputs or to certain parameters, but at the same time they may cause large variations to occur from small modifications of the inputs if the working point is at the edge of rapid transition (catastrophic behaviour). These are important aspects in a sensitivity analysis and directly connected to the issue of risk assessment in environmental management (i.e. the system can be relatively insensitive to certain actions but highly sensitive to certain other actions that cause a transition to occur).

Analysis plan in the decision making process

In the decision making process, ambiguities, errors, and disagreements will occur, all of which contribute to uncertainty. Wherever possible, these sources of uncertainty should be eliminated through better planning. Not all uncertainty can be eliminated, and therefore a clear description of the nature of the uncertainties should be made from the initial steps of problem analysis onwards. Problem analysis should be considered as a formal process for generating and evaluating preliminary questions about why environmental effects have occurred, or may occur, as a result of natural forces as well as human activities.

The problem analysis phase, being the first stage of an environmental risk assessment, provides the foundation on which the entire assessment depends. Therefore, it is important to acknowledge and communicate data, information, and knowledge gaps. Any deficiencies in problem analysis will compromise all subsequent work on the uncertainty evaluation and risk assessment.
At the end of the problem analysis phase there are three products that determine its success:

- adequate reflection of management goals and the environmental system they represent;
- conceptual models that describe key relationships between sources of impact or disturbance and the management goals;
- an analysis plan (to drive model building, sensitivity analysis, and decision making).

[1]Stochastic modelling by Monte Carlo simulation can be used to asses error propagation through the model and to identify the distribution function of the outcome of an integrated model that results from the distribution functions of the input data, the model parameters and the model relations. Due to its resource consuming character and due to lack of information on the distribution functions of all individual model constituents, Monte Carlo simulation is not common practice.

Essential in the development of these products is the effective integration and evaluation of the available information and knowledge. An analysis plan can be a final stage of problem analysis, particularly in the case of complex assessments. The analysis plan can also delineate the assessment design, data needs, measures, and methods for conducting the analysis phase of the risk assessment. It may be relatively brief or extensive depending on the nature of the assessment. Furthermore it includes the most important pathways and relationships identified during the problem analysis phase and which will be pursued further. An important issue for the risk assessor is to describe what will be done and, in particular, what will not be done. Another concern is determining the level of confidence needed for the management decision relative to the confidence that can be expected from an analysis, in order to determine data needs. When new data are needed to conduct analyses, the feasibility of obtaining the data should be taken into account.

In situations where data are few and new data cannot be collected, it should be possible to combine existing data with extrapolation models so that alternative data sources may be used. This allows the use of data from other locations or on other organisms where similar problems exist and data are available. When using data that require extrapolation, it is important to identify the source of the data, justify the extrapolation method and discuss major uncertainties apparent at this point.

Where data are not available, recommendations for new data collection should be part of the problem analysis. An iterative approach to the risk assessment may be selected to provide an opportunity for early management decisions using newly available data. A decision to conduct a new iteration is based on the results of any previous iteration and proceeds using new data collected as specified in the analysis plan. When new data collection cannot be obtained, pathways that cannot be assessed are a source of uncertainty and should be described in the analysis plan.

Conclusion

We have discussed the problem of dealing with uncertainty in decision making, with scientific uncertainty, and with model uncertainty in Integrated Coastal Zone Management. We can conclude that the knowledge and the understanding of the (interacting) processes in the coastal zone is incomplete and characterised by large uncertainties and limits to predictability. The uncertainties affect the estimates of future states of key variables and the future behaviour of system constituents. Some of these uncertainties are both potentially reducible, for instance when coming from incomplete information, incomplete understanding or lack of quality in data and models. Others are probably irreducible, coming from undeterministic system elements, practical unpredictability of chaotic system components, limits to our ability to know, understand and handle complexity.

Uncertainty evaluation is an ongoing theme throughout the various phases of the Coastal Zone Management Task. The objective is to describe, and, where possible, quantify what is known and not known about exposure and effects in the coastal system of interest. Uncertainty analyses increase credibility by explicitly describing the magnitude and direction of uncertainties.

It is important to discriminate between the potentially solvable and the currently unsolvable uncertainties. Coastal management has to be robust towards the currently unsolvable uncertainties, whereas adequate research programs should be designed to reduce the potentially solvable uncertainties. Further, the methodology has the potential to assess the quality of model output and to identify the parts of the model whose individual lack of quality contributes the most to the overall lack of quality. The latter information is very useful for setting research priorities.

A set of principles for complex model building was introduced which is believed is helpful in dealing with uncertainty. Particular attention is given to the aspect of balancing available information with model complexity. Complexity can only be handled in a simple way and therefore we aim to fully understand and be able to reproduce the emerging simple features. 'As the complexity of a system increases, our ability to make a precise and yet significative statement about its behaviour diminishes until a threshold is reached beyond which precision and significance (or relevance) become almost mutually exclusive characteristics' (Zadeh 1973).

We conclude by underlining the need for the definition of an analysis plan in order to handle model uncertainty in the decision making process.

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