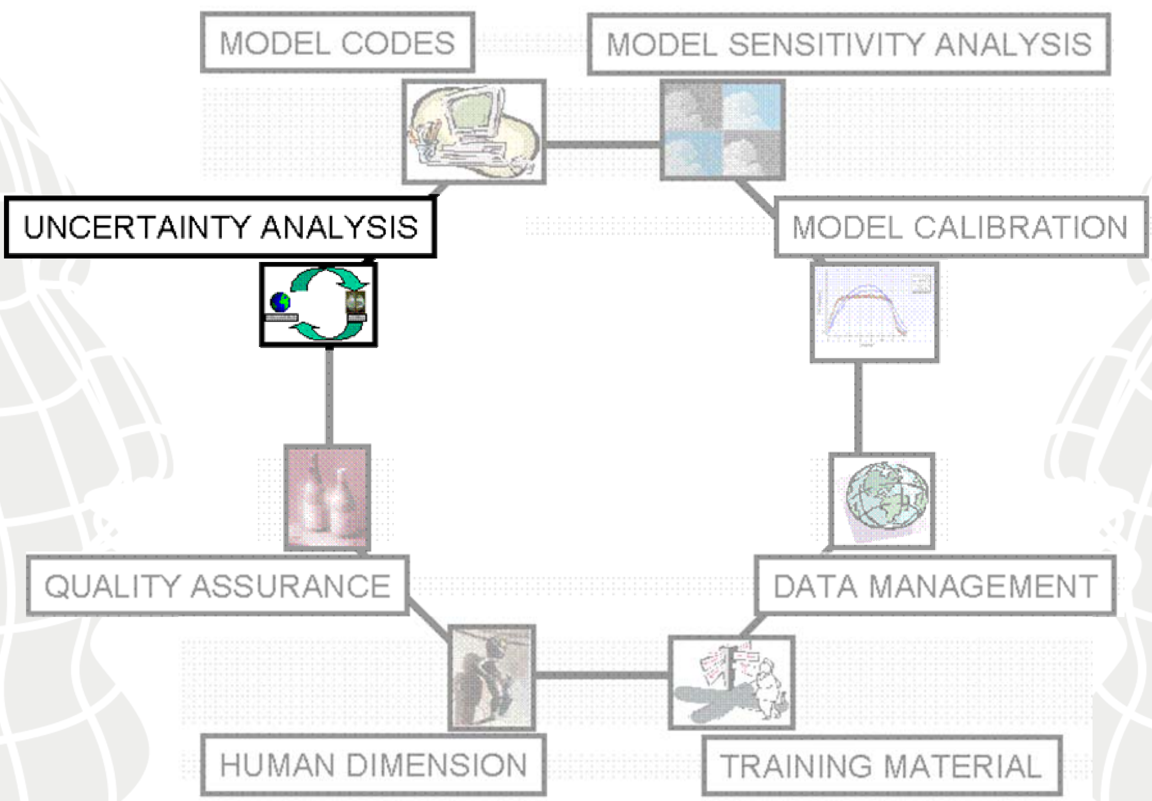
Harmoni-CA

Guidance

Uncertainty Analysis

Guidance 1



Contents

Jens Christian Refsgaard
Jeroen P. van der Sluijs
Anker Lajer Højberg
Peter Vanrolleghem

A research project supported by the European Commission under the Fifth Framework Programme and contributing to the implementation of the Key Action "Sustainable Management and Quality of Water" within the Energy, Environment and Sustainable Development.
Contract no: EVK1-2001-00192

Table of Contents

About this document

In order to support the implementation of the Water Framework Directive, the European Commission has established a cluster on Integrated Catchment Water Modelling (CatchMod). The objective of this cluster is the development of common harmonised modelling tools and methodologies for the integrated management of water at river basin or sub-basin scales, including the interface to the coastal zone.
Within the CatchMod cluster, the project Harmoni-CA has the objective to create a forum for unambiguous communication, information exchange and harmonisation of the use and development of ICT-tools relevant to integrated river basin management, and the implementation of the WFD.
Harmoni-CA is a large-scale concerted action, meaning that it does not carry out a research project, but synthesised available knowledge with the help of knowledge providers such as researchers. Typical actions of Harmoni-CA are meetings and workshops, leading to synthesis reports and guidances.
One of the tasks of the Harmoni-CA project, is defined within Harmoni-CA Work package 2 “TOOLBOX”. The objective of the "CatchMod Toolbox" is to provide easy and guided access to approved (benchmarked) ICT-tools necessary for the development of River Basin Management Plans in the form of an open, flexible, scientific sound toolbox for present and future integrated, harmonised ICT-tools. Easy access is not limited to technical access to resources through a web-site but also includes training material, demo case studies, protocols dealing with conditions for utilisation, rights of ownership, intellectual property rights and finance.

This document is the first of a row of harmoni-CA Guidance documents that are developed to support the CatchMod Toolbox.

Earlier versions of this document was presented and discussed at a CATCHMOD Technical Workshop, Copenhagen 16/11/2004. In this connection the document was formally reviewed by James Brown, Martin Krayer van Krauss, Bob Crabtree. Furthermor, constructive comments have been received from Simon Groot, Charles Perrin and Pasky Pascual.

1. Why is uncertainty assessment important

1.1 Uncertainty and risk in decision making

Integrated river basin management requires making a large number of decisions by operational agencies. A decision maker has to make decisions based on the available information. In most cases this information is deficient, incomplete and characterised by uncertainties of different kinds. How should this affect the decision making process? With increased uncertainty the chance of taking wrong decisions increases. Can the decision maker accept this? What can he or she do to make decisions that anticipate that outcomes can differ from what was expected? How should knowledge about the various uncertainties that characterise the available information be used to make better decisions? Nearly all information is uncertain. The main subject in this guidance document is methodologies and tools to characterise uncertainty and to assess the various sorts and sources of uncertainty, and the propagation of uncertainty through models to management information.

As one option, the decision maker may decide to postpone making a decision. This will allow more effort (money) to be put into collecting additional data or increasing modelling efforts, so as to improve the quality of information and, thereby, reducing the probability of taking a wrong decision. Further work on data collection and modelling involves costs in itself, and delays in the decision may also involve additional costs as well. The typical question "Do we have enough understanding to responsibly make a decision responsibly?" is thus in a rational sense a question on whether the risks of wrong decisions caused by imperfectness of the information are acceptable, or whether it is advisable to improve the quality of the information by, for instance, further data collection/modelling. One formal approach to address this question is through “value of information” analysis (VOI). Essentially, VOI encourages the prioritisation of research such that the expected value of additional information is compared against the opportunity costs of uncertainty, including the costs of making the wrong decision. This is sometimes difficult to do quantitatively in the environmental field because of problems associated with putting a value on natural resources. Nevertheless, even in the absence of explicit quantification, it is useful to remember that continuous attempts to reduce uncertainty by collecting additional information does not always make economic sense. Additional information—in the form of more data or more refined algorithms—almost always incurs costs. These costs must be balanced against the expected benefits of such information.

A note should be made here that higher quality of information does not automatically imply information with less uncertainty. It can also be information providing a richer insight in the sorts and magnitudes of uncertainty, so that the decision maker better understands what possible outcomes and risks to anticipate. This allows for contingent planning where options are kept open and flexible and where emergency risk management options can be prepared and kept on the shelf (compare to a fire extinguisher) so that they can be implemented immediately if that turns out to be necessary.

Another option open to the decision maker is to become risk-avers. This may result in incorporating a large safety margin or a ‘tolerance’, so that increased resources are spent on measures, such as clean-up of a site or water body, where there is a large probability that it may not be required to protect the water resources.

A decision maker can adopt one of the strategies developed in the field of decision theory if the ranges of outcomes for different options to choose from are known, but not the probabilities of each outcome. For instance, maximin is the strategy that chooses the option that has the best (that is: the least severe) worst case scenario. It makes sense if we have little to win and a great deal to loose, but it tends to prevent us from taking advantage of opportunities. Closely related to maximin is the difference principle: one society is better off than another if the worst-off members of the former do better than the worst-off in the latter. Maximin allows the most disadvantaged members of society to be harmed if the overall society benefits; the difference principle would forego an overall benefit to the society if it harmed the most disadvantaged members. The difference principle has been criticised for that it does not weigh limiting disadvantages to a subset of people against a possible increased average utility of society.

On the other extreme, maximax is the strategy that chooses the option that has the best best-case scenario. It is a risky strategy, often preferred by people with a risk seeking attitude that want to take advantage of opportunities and it makes sense if one has a great deal to gain and little to loose. Maximin can be seen as excessively pessimistic and maximax as excessively optimistic. An approach that attempts to balance between good and bad outcomes is the principle of insufficient reason: when we lack objective evidence to specify probabilities of outcomes, we should treat all outcomes as equally probable. (Resnik, 2003)

A widely advocated strategy is the Precautionary Principle if both the bounds on the outcomes and their probabilities are unknown. The Precautionary Principle grants greater benefit of doubt to the environment and to public health than to the activities that may be held to threaten these things (Stirling, 2003). Because the Precautionary Principle applies to those cases where serious adverse effects and surprises can occur with an unknown probability, it is rational to follow a better safe than sorry strategy. Failing to take precautionary measures in a timely manner could result in devastating and irreversible consequences (Harremoës et al., 2001). Such consequences might have been avoided by proactive and anticipatory interventions whose costs are justifiable in comparison to the damages and losses that could occur.

The above illustrates that decision makers should act differently under different situations of uncertainty. However, they will only be able to do this on a rational basis when they know how uncertain the available information is and when they know how to incorporate this in their decision making. Uncertainty is a difficult concept, and there is a need to educate and assist the decision maker working in a situation where there is uncertainty. In this document we will describe methodologies and tools for uncertainty assessment that may be used in the decision making process, allowing decision makers to take rational decisions on how to act under a situation of uncertainty.

1.2 Water Framework Directive - Requirements

The Water Framework Directive (WFD) provides a European environmental policy basis at the river basin scale. The river basin management and planning process prescribed in the WFD focuses on integrated management, involving all physical domains in water management, all sectors of water use, socio-economics and stakeholder participation. The planning process should move from a more rational-instrumental type of planning to an interactive planning with an open eye for the power of fundamental debate. The uncertainties present in such planning processes are judged of an increasing importance (EC, 2004a). An iterative planning process can deal with these uncertainties, for instance by revising the programmes of measures according to the circumstances (EC, 2004b). As such, the WFD poses new challenges to river basin managers. The traditional physical domain specific and sectoral approaches need to be combined and extended to fulfil the WFD requirements. In practise, the preparation of the river basin management plans prescribed in the WFD is in addition to these new challenges, influenced by uncertainties on the underlying data and modelling results.

A basic principle in EU environmental policy on which the WFD is based is ".. to contribute to the pursuit of the objectives of preserving, protecting and improving the quality of the environment in prudent and rational use of natural resources, and to be based on the precautionary principle ..[1]". Therefore, the holistic concept that is prescribed in the WFD with its integrated approach to natural resources and socio-economic issues requires that uncertainty be considered in the decision making process in order for it to become truly rational.

Uncertainty is addressed in several sections of the WFD document, (Blind and de Blois, 2003). For example, the WFD states with respect to monitoring that “Estimates of the level of confidence and precision of the results provided by the monitoring programmes shall be given ..”. In addition, most of the WFD guidance documents, being more specific than the WFD document itself, explicitly emphasise that uncertainty analyses should be performed. For instance, the guidance document on the planning process (EC,2004a) states: “Uncertainty can be defined as the occurrence of events that are beyond our control. Uncertainty is always an element in the planning process. It arises because the complexity of the many factors involved. In fact, meteorological, demographic, social, technical, and political conditions which will determine the planning process have behaviour patterns not always known with sufficient accuracy. Uncertainty arises mainly due to the stochastic nature of some key elements affecting these processes.” Similarly, the WATECO document on economic analysis states that “Uncertainty on costs, effectiveness and time-lagged effects of measures needs to be dealt with throughout the economic analysis process, and more generally throughout the process of identifying measures and developing the river basin management plan”. However, despite strong recommendations to consider uncertainty aspects, the guidance documents do not include recommendations on how to do so.

1.3 A motivating example

The problem is illustrated by an example from practise based on a study conducted by the County of Copenhagen (Copenhagen County, 2000; Refsgaard et al., 2000). The County of Copenhagen is the authority responsible for water resources management in the county where the city of Copenhagen abstracts groundwater for most of its water supply. According to a new Water Supply Act the county had to prepare an action plan for protection of groundwater against pollution. As a first step, in 2000, the county asked five groups of Danish consulting firms to conduct studies of the aquifer’s vulnerability to pollution in a 175 km^2 area west of Copenhagen, where the groundwater abstraction amounts to about 12 million m^3/year. The key question to be answered was: “which parts of this particular area are most vulnerable to pollution and need to be protected?” The five

[1] Directive 2000/60/EC, paragraph 11 in the introductory section.

consultants were selected from among the most well reputed consulting firms in Denmark, and they were known to have different views and preferences on which methodologies are most suitable for assessing vulnerability. As the job was one of the first consultancy studies in a new major market for preparation of groundwater protection action plans it was considered a prestigious job to which the consultants generally allocated some of their most qualified professionals.

The five consultants used significantly different approaches. One consultant based his approach on annual fluctuations of piezometric heads assuming that the larger the fluctuations the more interaction between aquifer and surface water systems and, hence, the larger vulnerability. Several consultants used the DRASTIC multi-criteria method (Aller et al., 1987), but modified it in different ways by changing weights and adding new, mainly geochemically oriented, criteria. One consultant based his approach on advanced hydrological modelling of both groundwater and surface water systems using the MIKE SHE code. Two other consultants used simpler groundwater modelling approaches. The three consultants applying modelling used simulated recharge as inputs to their respective DRASTIC approach. Thus, the five consultants used five different conceptual models to describe the possibility of groundwater pollution in the area. In addition, their different interpretations and interpolations made from a common data base resulted in significantly different figures; for example, for areal means of precipitation and evapotranspiration and the thickness of various geological layers (Refsgaard et al., 2000). Due to lack of concentration data in the aquifer system the methods could, mostly, not be tested against field data and their use could therefore be characterised as non-documented extrapolation. Such lack of rigorous validation tests is common in studies dealing with aquifer vulnerability towards pollution.

The conclusions of the five consultants regarding vulnerability to nitrate pollution are shown in Fig. 1. It is seen that the five estimates differ substantially from each other. In the present case, no data exist to validate the model predictions, because the five models have been used to make extrapolations towards unobservable futures. Thus, it is not possible, from existing field data, to tell which of the five model estimates are more reliable. The differences in prediction originate from two main sources: (i) data and parameter uncertainty and (ii) conceptual uncertainty. However, despite the significant data and parameter uncertainty, the main cause of the differences lies in the different conceptual models that were used by the five consultants.

Usually a water manager commissions only one study and bases his decisions on the conclusions from that study. The uniqueness of the present study was that five consultants were asked to answer the same question on the basis of the same data. In this respect the differences between the five best estimates are striking and clearly do not provide a sound basis for deciding anything about which areas should be protected. A worrying question, which is left unanswered, is whether the basis for decisions is just as poor in the many other cases where only a single conceptual model has been used and where, subsequently, a lot of money has been used to prepare and implement action plans.

In this case the uncertainty was so large that a basis for making a rationale decision did not exist. The conceptual uncertainty was discovered by chance, and the level of the uncertainty was a large, and uncomfortable, surprise to the water manager.

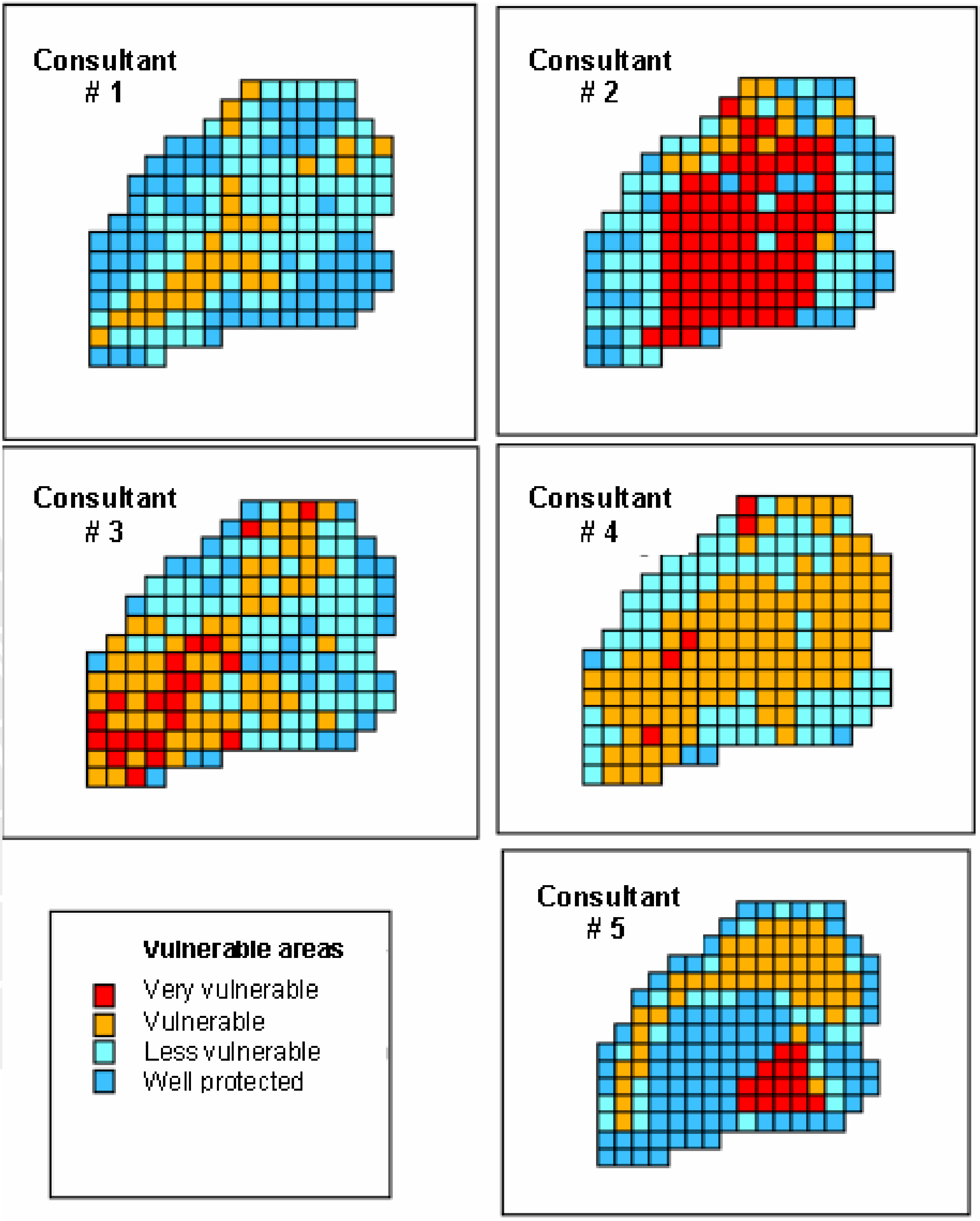


Fig. 1 Model predictions on aquifer vulnerability towards nitrate pollution for a 175 km^2 area west of Copenhagen (Copenhagen County, 2000).

1.4 Context and objective of this document

Models describing water flows, water quality, ecology and economy are being developed and used in increasing number and variety. With the requirements imposed by the WFD the trend in recent years to base water management decisions to a larger extent on model studies and to use more sophisticated models is likely to be reinforced. It is important to note that the modelling studies typically do not address the entire water resources management decision process, such as the WFD process, but rather support certain elements of the process.

The role of modelling as part of the WFD process may be illustrated schematically as in Fig. 2. The inner circle in Fig 2 depicts a simplified version of the WFD planning process (EC, 2004a) with the main elements:

- *Identification* including assessment of present status, analysis of impacts and pressures and establishment of environmental objectives. Here modelling may be useful for example for supporting assessments of what are the reference conditions, for assessment of the pressures and what are the impacts of the various pressures in combination to monitoring data and expert judgement (EC, 2004b).
- *Designing* including the set up and analysis of programme of measures designed to be able in a cost effective way to reach the environmental objectives. Here modelling will typically be used for supporting assessments of the effects and costs of various measures under consideration.
- *Implementing* the measures. Here on-line modelling in some cases may support the operational decisions to be made.
- *Evaluation* of the effects of the measures on the environment. Here modelling may support the monitoring in order to extract maximum information from the monitoring data, e.g. by indicating errors and inadequacies in the data and by filtering out the effects of climate variability.

This main WFD process is a participatory process with important elements of public participation.

Modelling can be used as a tool at various stages of the WFD process, as illustrated by the four smaller circles in Fig. 2. The typical steps and elements of a modelling process are illustrated in Fig. 3 and briefly described in Chapter 2. The most important interactions between the modelling process and the main planning process are:

- The modelling process starts with a thorough framing of the problem to be addressed and definition of modelling objectives and requirements for the modelling study (Step 1 in Fig. 3). Water managers and stakeholders dominate this step, which basically is identical to part of the broader planning process. A participatory based assessment of the most important sources of uncertainty for the decision (WFD) process should be used as a basis for prioritising the elements of the modelling study. The uncertainty assessments made at this stage will typically be qualitative.
- The main modelling itself is composed of steps 2,3 and 4 of Fig 3. Here the link with the main planning process consists of dialogue, reviews and discussions of preliminary results involving water managers and, according to decisions made at the start of the modelling, some stakeholders. As the modelling process proceeds uncertainty assessments are typically made more quantitative (rather than qualitative) and the uncertainties assessed by the modeller are confronted with the water manager and stakeholder expectations to accuracy.

- The finalisation of the modelling study (equivalent to the last step in Fig. 3), typically including scenario simulations. Here the water managers and the stakeholders again have a dominant role. The decisions made at the outcome of this step on the basis of modelling results are made in the context of the main planning process. Uncertainty assessment of model predictions is a crucial aspect of the modelling results and should be communicated in a way that is accessible for the stakeholders in the further WFD process.

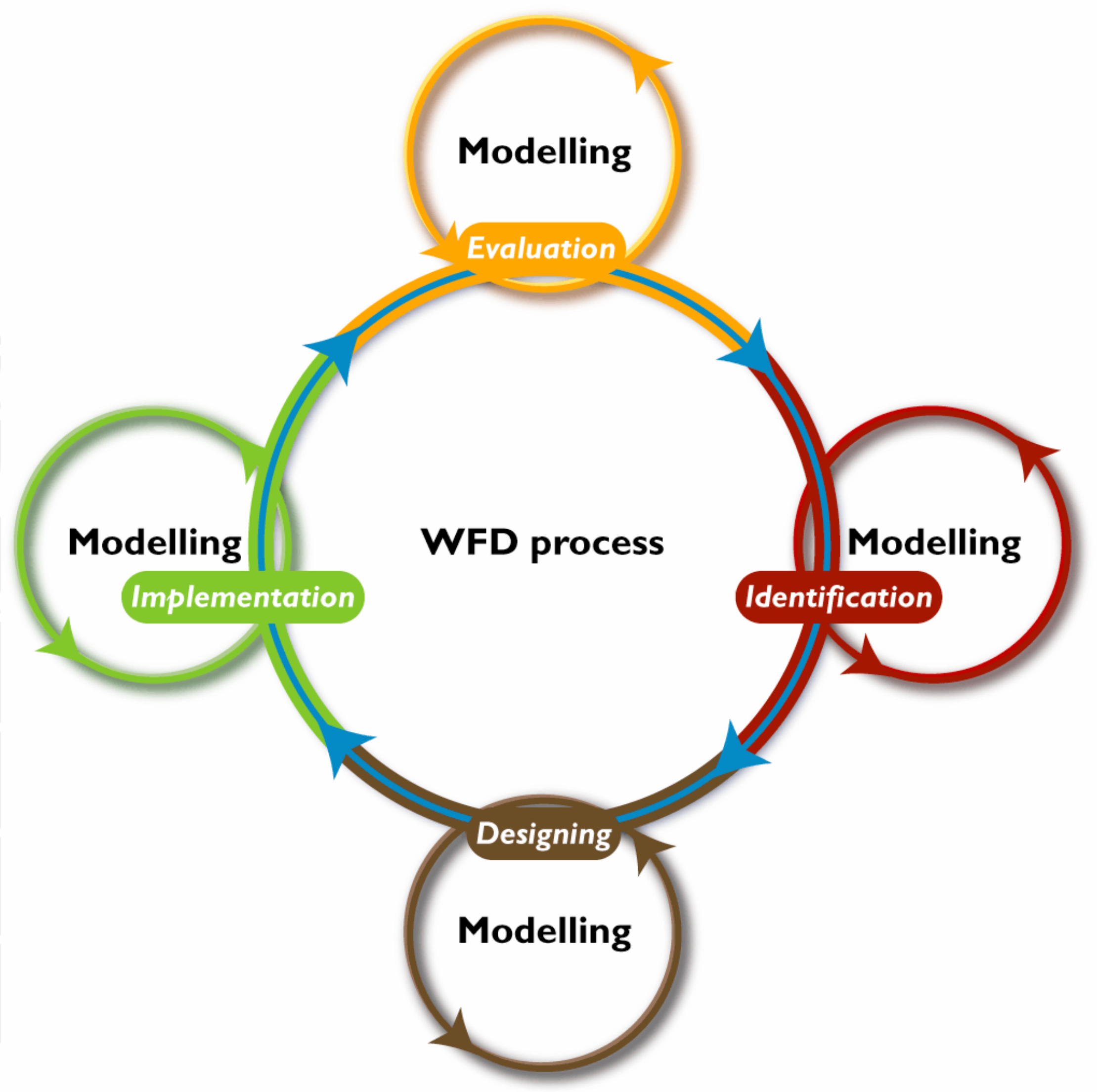


Fig. 2 The role of modelling in the water resources management process within the context of the Water Framework Directive (WFD).

The objective of this document is to provide guidance on uncertainty related to modelling in water resources management. Thus, the document does not focus on uncertainty related to the broader policy and public participation processes. The target audience for the document is professionals involved in modelling. This includes modellers themselves as well as the persons in the water manager's and stakeholders' organisations designated to interact with the modeller in the modelling process.

2. When is uncertainty assessment required

2.1 The modelling process

A modelling study will involve several phases and several actors. A typical WFD modelling study will involve the following four different types of actors:

- *The water manager*, i.e. the person or organisation responsible for the management or protection of the water resources, and thus of the modelling study and the outcome (the problem owner).
- *The modeller*, i.e. a person or an organisation that works with the model conducting the modelling study. If the modeller and the water manager belongs to different organisations, their roles will typically be denoted consultant and client, respectively.
- *The reviewer*, i.e. a person that is conducting some kind of external review of a modelling study. The review may be more or less comprehensive depending on the requirements of the particular case. The reviewer is typically appointed by the water manager to support the water manager to match the modelling capability of the modeller.
- *The stakeholders/public*. A stakeholder is an interested party with a stake in the water management issue, either in exploiting or protecting the resource. Stakeholders include the following different groups: (i) competent water resource authority (typically the water manager, cf. above); (ii) interest groups; and (iii) general public.

The WFD modelling process may, according to the HarmoniQuA project (Refsgaard et al., 2004; Scholten et al., 2004, www.harmoniqua.org), be decomposed into five major steps which again are decomposed into 45 tasks (Fig. 3). The contents of the five steps are:

- *STEP1 (Model Study Plan).* This step aims to agree on a Model Study Plan comprising answers to the questions: Why is modelling required for this particular model study? What is the overall modelling approach and which work should be carried out? Who will do the modelling work? Who should do the technical reviews? Which stakeholders/public should be involved and to what degree? What are the resources available for the project? The water manager needs to describe the problem and its context as well as the available data. A very important task is then to analyse and determine what are the various requirements of the modelling study in terms of the expected accuracy of modelling results. The acceptable level of accuracy will vary from case to case and must be seen in a socio-economic context. It should, therefore, be defined through a dialogue between the modeller, water manager and stakeholders/public. In this respect an analysis of the key sources of uncertainty is crucial in order to focus the study on the elements that produce most information of relevance to the problem at hand.
- *STEP 2 (Data and Conceptualisation).* In this step the modeller should gather all the relevant knowledge about the study basin and develop an overview of the processes and their interactions in order to conceptualise how the system should be modelled in sufficient detail to meet the requirements specified in the Model Study Plan. Consideration must be given to the spatial and temporal detail required of a model, to the system dynamics, to the boundary conditions and to how the model parameters can be determined from the available data. The need to model certain processes in alternative ways or to differing levels of detail in order to enable assessments of model structure uncertainty should be evaluated. The availability of existing computer codes that can address the model requirements should also be addressed.

- *STEP 3 (Model Set-up).* Model Set-up implies transforming the conceptual model into a site-specific model that can be run in the selected model code. A major task in Model Set-up is the processing of data in order to prepare the input files necessary for executing the model. Usually, the model is run within a Graphical User Interface (GUI) where many tasks have been automated. The GUI speeds up the generation of input files, but it does not guarantee that the input files are error free. The modeller performs this work.
- *STEP 4 (Calibration and Validation).* This step is concerned with the process of analysing the model that was constructed during the previous step, first by calibrating the model, and then by validating its performance against independent field data. Finally, the reliability of model simulations for the intended domain of applicability is assessed through uncertainty analyses. The results are described so that the scope of model use and its associated limitations are documented and made explicit. The modeller performs this work.
- *STEP 5 (Simulation and Evaluation).* In this step the modeller uses the calibrated and validated model to make simulations to meet the objectives and requirements of the model study. Depending on the objectives of the study, these simulations may result in specific results that can be used in subsequent decision making (e.g. for planning or design purposes) or to improve understanding (e.g. of the hydrological/ecological regime of the study area). It is important to carry out suitable uncertainty assessments of the model predictions in order to arrive at a robust decision. As with the other steps, the quality of the results needs to be assessed through internal and external reviews.

Each of the last four steps is concluded with a reporting task followed by a review task. The review tasks include dialogues between water manager, modeller, reviewer and, often, stakeholders/public. The protocol includes many feedback possibilities (Fig. 3).

2.2 Uncertainty aspects

Uncertainty aspects are important throughout the modelling process. Thus, uncertainty is considered explicitly in 14 out of the 45 tasks in Fig. 3. But uncertainty is treated in different ways at different stages of the process. The four main actions of dealing with uncertainty may be characterised as:

A. Identify and characterise sources of uncertainty (Fig 3)
The various sources of uncertainty need to be identified and characterised in connection with the tasks *Describe Problem* and Context and *Determine Requirements* in Step1 *Model Study Plan* (yellow arrows in Fig. 3). This should be done by the water manager but typically after a dialogue with relevant stakeholders. Depending on the framing of the model study some of these uncertainties may be located as external non-controllable sources. It is crucial that uncertainty is considered explicitly so early in the definition phase of the model study. Here uncertainties are seldom quantified. It is also at this early stage that the first analyses are made on the acceptable level of uncertainty and the expected model performance.

B. Modeller reconsiders uncertainty and performance criteria (Fig 3)
The modeller has to reconsider several times during the modelling process if the accuracy performance criteria formulated by the water manager are realistic for the particular model study. Most importantly (full green arrows in Fig. 3), the modeller has to do this in connection with preparation of a proposal, and when, after having made the first model test

run, s/he re-evaluates the performance criteria before the model validation tests in the next step. Furthermore (dotted green arrows in Fig. 3) in connection with reporting at the end of each step, the modeller has the opportunity to reconsider whether the originally promised performance criteria are still realistic, given the new information produced during the previous tasks in the respective step.

C. Reviews – dialogue- decisions (Fig 3)

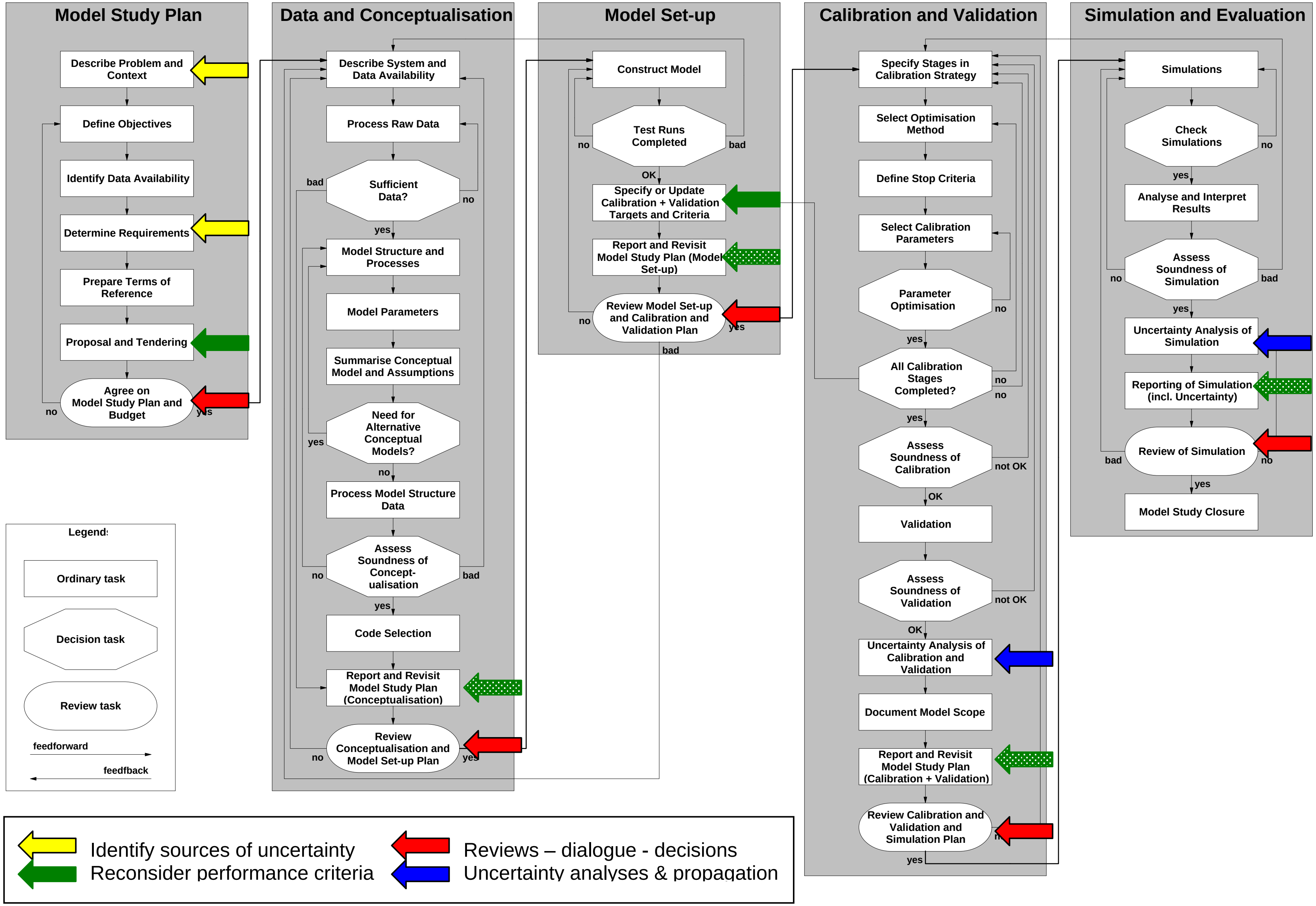
The last task in each step is a dialogue or decision task where a dialogue between water manager and modeller takes place. Often independent reviews are conducted as a basis for the decision and stakeholders and/or the general public are involved in the dialogue. As part of this dialogue, uncertainty aspects become important, e.g. when discussing whether there are sufficient data to proceed with the modelling, or whether the uncertainty of the model simulations are at a level where the results can be expected to be useful. The reviews and the stakeholder dialogues are also important platforms for a reflection on whether the assumptions made in the model are realistic and on how the study outcome may be influenced by the implicit and explicit assumptions made in the model. In many cases, more than one assumption is scientifically tenable. If such assumptions influence the model outcome, then the ignorance regarding which assumption is the best assumption can be an important source of uncertainty.

D. Uncertainty assessment and propagation (Fig 3)

Towards the end of the step Calibration and Validation and the step Simulation and Evaluation there are two tasks dealing exclusively with uncertainty assessment. In the first (Uncertainty Analysis of Calibration and Validation) an assessment is made of the model uncertainty related to simulations in the validation test cases. This is used for evaluating possible biases in model simulations and assessing if the model performance is good enough compared to the agreed accuracy requirements. In the second task (Uncertainty Analysis of Simulation) the uncertainties in the problem framing (the context) and the management scenarios are also taken into account.

The uncertainty assessment and propagation tasks (item D above) are the traditional uncertainty tasks often conducted in connection with model studies. These tasks are often comprehensive and may involve a lot of model calculations and are often limited to quantitative uncertainty. These tasks, which are both located towards the end of the modelling process, are very important. However, it is equally important to introduce uncertainty in the introductory phase of a model study. Therefore, the identification and characterisation of all uncertainty sources recommended in the task Determine Requirements under Step 1 (item A above) is crucial. The uncertainty aspects mentioned under items B and C are “less heavy” and may be seen as a follow up to item A.

Fig. 3 The five modelling steps and 45 tasks in the HarmoniQuA modelling protocol (Refsgaard et al., 2004)



3. What is uncertainty

3.1 Definitions

Uncertainty and associated terms such as error, risk and ignorance are defined and interpreted differently by different authors, see Walker et al. (2003) for a review. The different definitions reflect the underlying scientific philosophical way of thinking and therefore typically vary among different scientific disciplines. In addition they vary depending on their purpose. Some are rather generic, such as Funtowicz and Ravetz (1990), while others apply more specifically to model based water management, such as Beck (1987).

In this document we will use the terminology of Klauer and Brown (2003) that has emerged after discussions between social scientists and natural scientists specifically aiming at applications in model based water management. More details and discussion on the definitions given below can be found in Klauer and Brown (2003). By doing so we adopt a subjective interpretation of uncertainty in which the *degree of confidence* that a decision maker has about possible outcomes and/or probabilities of these outcomes is the central focus. For reasons of completeness and comparison we will also briefly sketch the objective interpretation of each form of uncertainty we discuss.

Uncertainty

The notion of uncertainty includes both subjective and objective aspects. Becoming confident or establishing lack of confidence is an act of subjective judgement about the validity of some information. However, the judgement might be supported and informed by the evaluation of 'objective' facts and other forms of evidence.

Definition (Uncertainty): A person is uncertain if s/he lacks confidence about the specific outcomes of an event or action. Reasons for this lack of confidence might include a judgement of the information as incomplete, blurred, inaccurate or potentially false or might reflect intrinsic limits to the deterministic predictability of complex systems or of stochastic processes.
Similarly, a person is certain if s/he is confident about the outcome of an event. It is possible that a person feels certain but has misjudged the situation (i.e. s/he is wrong).

Example: A person may be uncertain about the exact value of a river discharge value due to uncertainty related to the instruments used for measurements, representativeness of measurements and the method of transforming measurements (of often secondary variables) to discharge. Two different people may have different perceptions of the magnitude of this uncertainty.

Note that other authors define the term uncertainty not as a property (state of confidence) of the decision maker but as a property (state of perfection) of the total body of knowledge or information that is available at the moment of judgement. Uncertainty is then seen as an expression of the various forms of imperfection of the available information and depends on the state-of-the-art of scientific knowledge on the problem at the moment that the decision needs to be made (assuming that the decision maker has access to the state-of-the-art knowledge).

Ignorance

Awareness of the information on the potential outcomes of an event is a precondition for any grade of certainty or uncertainty. There are different, gradual stages of awareness starting from awareness of the existence of information to a deep understanding of the information.

Definition (ignorance): A person is ignorant with respect to an event if s/he is unaware of the (potential) outcomes of that event or of the event itself.

Examples: Oestrogens were not suspected of being harmful to fishes until a few decades ago. Clayey till was supposed to be virtually impermeable for pesticides and other contaminants and, therefore, provide good protection of groundwater until it was discovered 10-20 years ago that some clayey layers contain fractures through which pollutants can be transported very rapidly.

Note that ignorance refers to unawareness of the entire scientific community about potential outcomes of an event or side effects of an activity in the interpretation that sees ignorance as a property of the state of scientific knowledge rather than as the state of the individual decision maker.

Risk situations

If uncertainty is recognised as being an important issue, then the most common strategy to cope with this is to use probabilities. However, the use of probabilities presupposes a number of things about the available representation. First, it assumes that all potential outcomes of the event are known. In other words, that the event is properly characterised by the set of potential outcomes. Secondly, it assumes that the probabilities of each outcome are also known. We will call such a situation a risk situation.

Definition (risk situation): A risk situation is a person's representation of an event, where s/he assumes to know all potential outcomes as well as the probabilities of each outcome. In some disciplines risk is defined as being equivalent to probability, while in others it is defined as damage multiplied by probability. Our definition is compatible with the latter (but not the first) of these.

Example: A water manager has to decide whether to implement a certain measure; for example, cleaning a polluted aquifer or to make additional field measurements to improve the data basis and, thereby, reduce the uncertainty involved (i.e. two possible outcomes). The water manager believes s/he can calculate the uncertainty (in terms of a probability distribution function) for how polluted the aquifer is and how much this uncertainty will change in case of new data. At the same time s/he knows the costs of making a wrong decision and the costs of the additional field program.

Precaution

The Precautionary Principle (PP) has become an underlying rationale over the past decades for the satisfactory and ethically justified management of uncertain risks to public health, society or environment. The PP aims to protect humans and the environment against uncertain risks of human action by means of pre-damage control (anticipatory measures). The PP is to supplement, but not necessarily replace, other management strategies that fall short of being able to handle large scale scientific uncertainty and ignorance. It is incorporated in a large and increasing number of international treaties and declarations in the fields of, inter alia, sustainable development, environmental protection, health, trade, and food safety. The PP is on its way to becoming a widely accepted part of international law. In its basic form, the Precautionary Principle states that actions to protect human health and the environment against possible danger of severe and irreversible damage, need not wait for rigorous scientific proof (Weiss, 2003).

Definition (precautionary principle): In order to protect the environment, the precautionary approach shall be widely applied by States according to their capabilities. The lack of full scientific certainty shall not be used as a reason for postponing cost-effective measures to prevent environmental degradation where there are threats of serious or irreversible damage.
The triple negative notion in this definition stemming from the Rio Declaration(1992), that the absence of rigorous proof of harm does not justify inaction, is perceived as being weak. It forces the consideration of proactive intervention but does not require such intervention. Other definitions are stronger and put the burden of proof on the proponent of an action to show that it does not pose a danger of environmental harm. For examples, the Wingspread Statement on the Precautionary Principle defines it as follows: *"When an activity raises threats of harm to human health or the environment, precautionary measures should be taken even if cause and effect relationships are not fully established scientifically . . .[The] proponent of the activity, rather than the public, should bear the burden of proof."*

3.2 Taxonomy of imperfect knowledge

There are many different decision situations, with different possibilities for characterising our confidence in the available information or in other words the uncertainty. A first distinction is between ignorance as a lack of awareness about imperfect knowledge and uncertainty as a state of confidence about knowledge. Our state of confidence may range from being certain to admitting that we know nothing (of use), and uncertainty may be expressed at a number of levels in between. Regardless of our confidence in what we know, ignorance implies that we can still be wrong ('in error'). In this respect Brown (2004) has defined a taxonomy of imperfect knowledge as illustrated in Fig. 4.

It is useful in evaluating scientific uncertainty to distinguish between uncertainty about the 'outcomes' or scenarios, as possible states of 'reality' (mechanisms, events, observations), and uncertainty in terms of 'probability' (chance, likelihood, plausibility) for each outcome to occur. If one throws a perfect dice, the outcome is uncertain, but the 'draw' of a perfect dice is certain: we know precisely the probability for each of the 6 outcomes, each being 1/6. This is what we mean by 'uncertainty in terms of probability'. However, the estimates for the probability of each outcome can also be uncertain. If a model study says: "there is a 30% probability that this area will flood two times in the next year", there is not only 'uncertainty in terms of probability' but also uncertainty regarding whether the estimate of 30% is a reliable estimate.

Secondly, it is useful to distinguish between bounded uncertainty, where all possible outcomes are deemed 'known' (they can be distinct or indistinct) and unbounded uncertainty, where some or all possible outcomes are deemed unknown. Since quantitative probabilities require 'all possible outcomes' of an uncertain event and each of their individual probabilities to be known, they can only be defined for 'bounded uncertainties'. If probabilities cannot be quantified in any undisputed way, we often can still qualify the available body of evidence for the possibility of various outcomes. Inspired by legal practices, Weiss (2003a, 2003b, + personal communication 2004) developed the following 12 point subjective scale for qualifying evidence that can be used for this purpose:

- Impossible
- Hunch
- Reasonable suspicion
- Reasonable belief
- Reasonable indication
- Preponderance of the evidence
- Substantial and credible
- Clear indication
- Clear showing
- Clear and convincing
- Beyond a reasonable doubt
- Beyond any doubt

If outcomes but no probabilities are known we have to rely on 'scenario analysis'.

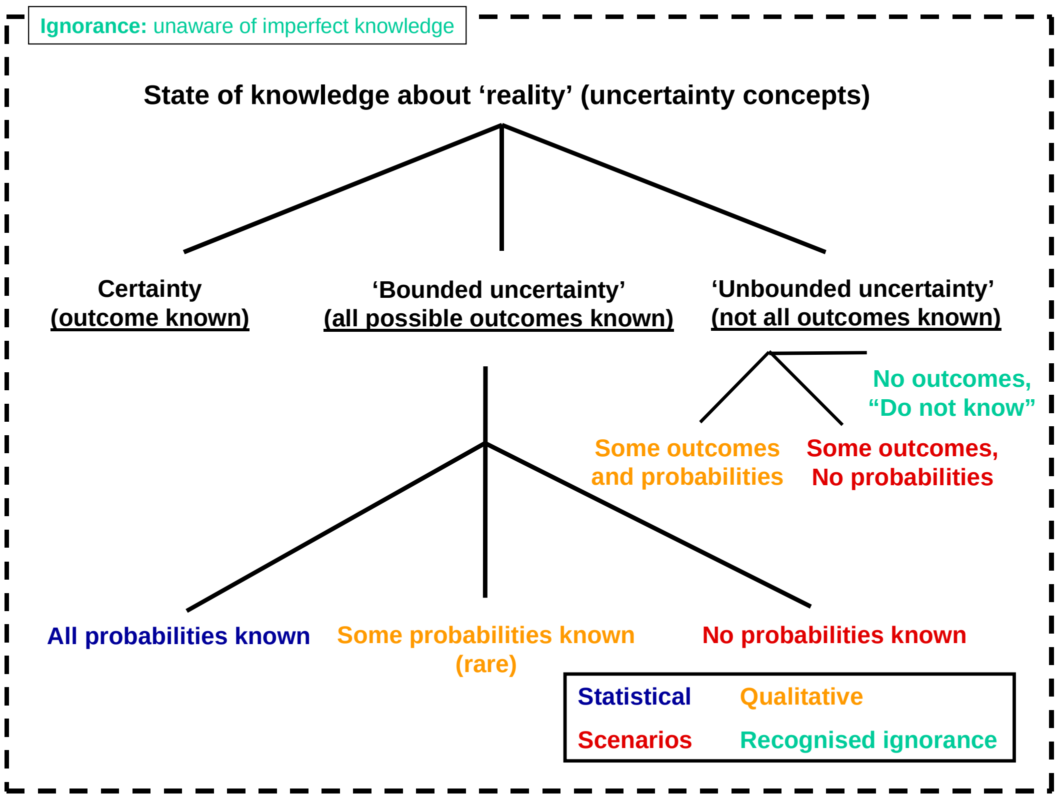


Fig. 4 Taxonomy of imperfect knowledge resulting in different uncertainty situations (Brown, 2004)

The bounded uncertainty where all probabilities are assumed known (the blue case in Fig. 4) is often denoted 'statistical uncertainty' (e.g. Walker et al., 2003). This is the case that is traditionally addressed in model based uncertainty assessments. It is important to note that this case only constitutes one of many of the decision situations outlined in Fig. 4, and, in many situations, the main uncertainty in a decision situation cannot be characterised quantitatively.

3.3 Sources of uncertainty

Walker et al. (2003) describes the uncertainty as manifesting itself at different locations in the model based water management process. These locations, or sources, may be characterised as follows:

- *Context*, i.e. at the boundaries of the system to be modelled. The model context is typically determined at the initial stage of the study where the problem is identified and the focus of the model study selected as a confined part of the overall problem. This includes, for example, the external economic, environmental, political, social and technological circumstances that form the context of problem.
- *Input uncertainty* in terms of external driving forces (within or outside the control of the water manager) and system data that drive the model such as land use maps, pollution sources and climate data.
- *Model structure uncertainty* is the conceptual uncertainty due to incomplete understanding and simplified descriptions of processes as compared to nature.
- *Parameter uncertainty*, i.e. the uncertainties related to parameter values.
- *Model technical uncertainty* is the uncertainty arising from computer implementation of the model, e.g. due to numerical approximations and bugs in the software.
- *Model output uncertainty*, i.e. the total uncertainty on the model simulations taken all the above sources into account, e.g. by uncertainty propagation.

3.4 Nature of uncertainty

Walker et al. (2003) explain that the *Nature* of uncertainty can be categorised into:

- *Epistemic uncertainty*, i.e. the uncertainty due to imperfect knowledge.
- *Stochastic uncertainty*, i.e. uncertainty due to inherent variability, e.g. climate variability.

Epistemic uncertainty is reducible by more studies: e.g. comprising research and data collection. Stochastic uncertainty is non-reducible.

Often the uncertainty on a certain event includes both epistemic and stochastic uncertainty. An example is the uncertainty of the 100 year flood at a given site. This flood event can be estimated: e.g. by use of standard flood frequency analysis on the basis of existing flow data. The *(epistemic)* uncertainty may be reduced by improving the data analysis, by making additional monitoring (longer time series) or by a deepening our understanding of how the modelled system works. Note that this does not imply that data collection and further research automatically leads to a reduction of epistemic uncertainty. More research sometimes increases epistemic uncertainty in the short term. For instance, the recognised epistemic ignorance has temporary increased if new data show that our mechanistic understanding of the system (as represented in a model structure) cannot be right and science has not yet discovered what mechanisms or internal system feedbacks, or other factors were overlooked. The epistemic uncertainty is reduced only after we have discovered what was wrong about our earlier mechanistic understanding of the system. However, no matter how perfect both the data collection and the mechanistic understanding of the system are, and, no matter for how long historical data time series exist, there will always be some (*stochastic*) uncertainty inherent to the natural system, related to the stochastic and chaotic nature of several natural phenomena, such as weather. Perfect knowledge on these phenomena cannot give us a deterministic prediction, but would have the form of a perfect characterisation of the natural variability; for example, a probability density function for rainfall in a month of the year.

3.5 The uncertainty matrix

The uncertainty matrix in Fig. 5 can be used as a tool to get an overview of the various sources of uncertainty in a modelling study. The matrix is modified after Walker et al. (2003) in such a way that it matches Fig. 4 and so that the taxonomy now gives 'uncertainty type' in descriptions that indicate in what terms uncertainty can best be described. The vertical axis identifies the location or source of uncertainty while the horizontal axis covers the level and nature of uncertainty.

It is noticed that the matrix is in reality three-dimensional (source, type, nature). Thus, the categories Type and Nature are not mutually exclusive, and it may be argued that the matrix should be modified in such a way that the two uncertainties within Nature (epistemic and variability) should become subcells within the Type categories. This is not done for graphical reasons.

An inventory can be made of where the uncertainties are located and how they can be characterised by filling out all the cells in the matrix.

Source of uncertainty		**Taxonomy (types of uncertainty)**				**Nature**	
		Statistical uncertainty	Scenario uncertainty	Qualitative uncertainty	Recognised ignorance	Epistemic uncertainty	Stochastic uncertainty
Context	Natural, technological, economic, social, political						
Inputs	System data						
	Driving forces						
Model	Model structure						
	Technical						
	Parameters						
Model outputs							

Fig. 5 The uncertainty matrix (modified after Walker et al., 2003).

4. Methodologies for uncertainty assessment

In general, transparency and reporting are essential for a good uncertainty assessment. Many methodologies and tools suitable for supporting uncertainty assessment have been developed and reported in the scientific literature. No methodology is applicable to address all the different aspects of uncertainty assessment. In this chapter some important methods are briefly described in one-page summaries:

- Data Uncertainty
- Error Propagation Equations
- Expert Elicitation
- Extended Peer Review (review by stakeholders)
- Inverse modelling (parameter estimation)
- Inverse modelling (predictive uncertainty)
- Monte Carlo Analysis
- Multiple Model Simulation
- NUSAP
- Quality Assurance
- Scenario Analysis
- Sensitivity Analysis
- Stakeholder Involvement
- Uncertainty Matrix

References to more detailed descriptions and to supporting software tools are provided in the summary descriptions. For several of the methodologies more extensive descriptions are available in the RIVM/MNP Tool Catalogue, that served as a starting point for the overview presented here (van der Sluijs et al., 2004).

The methods can roughly be divided in three groups that differ slightly in purpose:

1. *Methods to characterise and prioritise uncertainty:*
   This includes methods for handling data uncertainty, methods of expert elicitation, parameter estimation through inverse modelling, sensitivity analysis, the NUSAP method and the uncertainty matrix.
2. *Methods aiming to increase the quality of information:*
   This includes procedures for quality assurance, extended peer review and stakeholder involvement.
3. *Methods to quantify and propagate uncertainty in model calculations to produce uncertainty in model outcome:*
   This includes the error propagation equations, Monte Carlo analysis, inverse modelling (parameter estimation and predictive uncertainty), multiple model simulation, various forms of sensitivity analysis and scenario analysis.

The methods are not necessarily valid for only one of the listed groups. Sensitivity analysis may, for instance, be used both to identify the importance of a given uncertainty source at an early stage in the modelling process, and again at a later stage to quantify the uncertainty with respect to the model results. Each of the methods will be reviewed in the following sections.

4.1 Data Uncertainty

Description

Uncertainty in data may be described in 13 uncertainty categories depending on how data varies in time and space (Brown, 2004; Brown et al., 2005).

Space-time variability	Measurement scale			
	Continuous numerical	Discrete numerical	Categorical	Narrative
Constant in space and time	**A1**	**A2**	**A3**	**4**
Varies in time, not in space	**B1**	**B2**	**B3**	
Varies in space, not in time	**C1**	**C2**	**C3**	
Varies in time and space	**D1**	**D2**	**D3**	

Each data category is associated with a range of uncertainty models, for which more specific probability density functions (pdfs) may be developed with different simplifying assumptions (e.g. Gaussian; second-order stationarity; degree of temporal and spatial autocorrelation). Furthermore, correlation in time and space is characterised by correlogram/variogram functions. Categorical data (3) differ from numerical data (1, 2), because the categories are not measured on a numerical scale.

A software tool for supporting the assessment of data uncertainty within the above framework is being developed within the EU FP5 project HarmoniRiB. This tool will become publicly available by 2006.

Resources required

Assessment of uncertainty requires a basic understanding of uncertainty concepts such as probability distribution and correlogram functions and their relation to the scale of measurement.

Uncertainty assessment deduced from specific information on the individual sources of uncertainty or from data analysis is a laborious and difficult task requiring substantial resources. This approach requires a specific knowledge on the various sources of uncertainty such as instrument accuracy (http://www.harmonirib.com) transformation functions from variable actually measured (e.g. water table) to variable of interest (e.g. discharge), aggregation in time and/or space, representativeness of sampling, etc.

Assessments based on expert judgements and literature values from similar settings are often the only feasible way in practice. Such assessments may be supported by guidelines for assessing uncertainty in various types of data originating from meteorology, soil physics and geochemistry, hydrogeology, land cover, topography, discharge, surface water quality, ecology and socio-economics (Van Loon and Refsgaard, 2005). This report has been prepared on the basis of literature reviews.

Strengths and limitations

+ Important input when assessing uncertainty of model output
+ Useful feedback information to design of monitoring programmes
– May require a lot of work
– Complex issue with many possibilities to make theoretically inconsistent assessments. Especially the correlation structure and its link with the scale of support may be difficult to understand

References

http://www.harmonirib.com
http://www.swift-wfd.com
Brown JD (2004) Knowledge, uncertainty and physical geography: towards the development of methodologies for questioning belief. Transactions of the Institute of British Geographers, 29(3), 367-381.

Brown JD, Heuvelink GBM and Refsgaard JC (2005) An integrated framework for assessing and recording uncertainties about environmental data. Accepted for publication in Water Science and Technology.

Refsgaard JC, Nilsson B, Brown J, Klauer B, Moore R, Bech T, Vurro M, Blind M, Castilla G, Tsanis I and Biza P (2005) Harmonised Techniques and Representative River Basin Data for Assessment and Use of Uncertainty Information in Integrated Water Management (HarmoniRiB). Accepted for publication in Environmental Science and Policy.

Van Loon E and Refsgaard JC (eds.) (2005) Guidelines for assessing data uncertainty in hydrological studies. First draft version prepared September 2004. Final version to be published beginning of 2005 on http://www.harmonirib.com

4.2 Error Propagation Equations

Description

The error propagation equations (e.g. Mandel, 1984, Bevington and Robinson, 1992) are widely used in the experimental and measurement sciences to estimate error propagation in calculations. The error propagation equations are valid only if the following conditions are met:

- The uncertainties have Gaussian (normal) distributions;
- The uncertainties are relatively small: the standard deviation divided by the mean value being less than 0.3;
- The uncertainties have no significant covariance.

The error propagation equations for the most common operators are (σ is the standard deviation):

Addition and Subtraction: $z = x + y + ..$ or $z = x - y - ..$

$$\sigma_z = \sqrt{(\sigma_x{}^2) + (\sigma_y{}^2) + ..}$$

Multiplication by an exact number: $z = c\,x$

$$\sigma_z = c\sigma_x$$

Multiplication and Division: $z = x\,y$ or $z = x/y$

$$\frac{\sigma_z}{z} = \sqrt{\left(\frac{\sigma_x}{x}\right)^2 + \left(\frac{\sigma_y}{y}\right)^2 + ..}$$

The method can be extended to allow non-Gaussian distributions and to allow for covariances (see e.g.: http://www.itl.nist.gov/div898/handbook/mpc/section5/mpc55.htm

Resources required

The error propagation equations require no specific hardware or software and can typically be applied on the back of the envelope or on an ordinary scientific calculator, or using a spreadsheet.

Most of the time will be consumed by quantifying the uncertainties in the parameters and inputs, which can be derived from statistics if available or otherwise can for instance be obtained by means of expert elicitation.

Strengths and limitations

\+ Requires very little resources and skills (but the choice of the aggregation level for the analysis is an important issue that does require skills)

\+ Quick (but can be dirty)

– Has a limited domain of applicability (e.g. near-linearity assumption)

– The basic error propagation equations cannot cope well with distributions with shapes other than normal (but the method can be extended to account for other distributions).

– Leads to a tendency to assume that all distributions are normal, even in cases where knowledge of the shape is absent and, hence, a uniform distribution would be a better reflection of the state of knowledge.

– Cannot easily be applied in complex calculations.

References

Bevington PR and Robinson DK (1992) Data Reduction and Error Analysis for the Physical Sciences, WCB/McGraw-Hill Boston USA, p.328.

IPCC (2000) Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories, IPCC.

Ku H (1966). Notes on the Use of Propagation of Error Formulas, J Research of National Bureau of Standards-C. Engineering and Instrumentation, 70C, 4, 263-273.

Mandel J (1984) The Statistical Analysis of Experimental Data, Dover Publications New York, USA, p.410.

4.3 Expert Elicitation

Description

Expert elicitation is a structured process to elicit subjective judgements from experts. It is widely used in quantitative risk analysis to quantify uncertainties in cases where there are no or too few direct empirical data available to infer on uncertainty. Usually the subjective judgement is represented as a 'subjective' probability density function (PDF) reflecting the expert's degree of belief.

Expert elicitation in the context of uncertainty quantification aims at a credible and traceable account of specifying probabilistic information regarding uncertainty, in a structured and documented way. Typically it is applied in situations where there is scarce or insufficient empirical material for a direct quantification of uncertainty, and where it is relevant to obtain inscrutable and defensible results (Hora, 1992).

Several elicitation protocols have been developed amongst which the much-used Stanford/SRI Protocol is the first (Spetzler and von Holstein, 1975; see also Morgan and Henrion, 1990; chapter 6 and 7).

Expert elicitation typically involves the following steps: (1) Identify and select experts; (2) Explain to the expert the nature of the problem and the elicitation procedure. Create awareness of biases in subjective judgements and explore these. (3) Clearly define the quantity to be assessed and chose a scale and unit familiar to the expert. (4) Discuss the state of knowledge on the quantity at hand (strengths and weaknesses in available data, knowledge gaps, qualitative uncertainties). (5) Elicit extremes of the distribution. (6) Assess these extremes: could the range be broader than stated? (7) Further elicit and specify the distribution (shape and percentiles or characterising parameters). (8) Verify with the expert that the distribution that you constructed from the expert's responses correctly represents the expert's beliefs. (9) Decide whether or not to aggregate the distributions elicited from different experts (this only makes sense if the experts had the same mental models of the quantity for which a distribution was elicited).

Resources required

Typically performing a formal expert elicitation is a time and resource intensive activity. The whole process of setting up a study, selecting experts, preparing elicitation questions, performing expert training, expert meetings, interviews, analyses, writing rationales, documentation etc. can easily stretch over months or years. The choice of whether to perform a formal or a more informal elicitation (NCRP, 1996) depends on the price one is willing to pay for more inscrutable and defensible results, and will be influenced by the relevance and controversies regarding the problem area.

One needs to have good interviewing skills and a reasonable understanding of the field under consideration. A good understanding of biases in subjective judgements by experts is required to avoid these biases to the maximum extent possible. Skills are needed to draft a good questionnaire or template for the elicitation. Training in elicitation techniques may be needed.

Strengths and limitations

- \+ It has the potential to make use of all available knowledge including knowledge that cannot be easily formalised otherwise.
- \+ It can easily include views of sceptics and reveals the level of expert disagreement on certain estimates.
- – The fraction of experts holding a given view is not proportional to the probability of that view being correct.
- – One may safely average estimates of model parameters, but if the expert's models were incommensurate, one may not average models (Keith, 1996).
- – If differences in expert opinion are irresolvable, weighing and combining the individual estimates of distributions is only valid if weighted with competence of the experts regarding making the estimate. There is no good way to measure competence.
- – The results are sensitive to the selection of the experts whose estimates are gathered.

References

Ayyub BM (2001) Elicitation of Expert Opinions for Uncertainty and Risks, CRC Press, Florida.
Hora SC (1992) Acquisition of Expert Judgement: Examples from Risk Assessment. Journal of Energy Engineering, 118, 136-148.
Meyer MA and Booker JM (1991) Eliciting and Analyzing Expert Judgement: A practical Guide, Academic Press, London
Morgan MG and Henrion M (1990) Uncertainty, A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis, Cambridge University Press.
Spetzler CS and von Holstein S (1975) Probability Encoding in Decision Analysis. Management Science, 22(3).
http://legacy.ncsu.edu/classes/ce456001/www/Background1.html.

4.4 Extended Peer Review (review by stakeholders)

Description

Extended peer review is the involvement of non-scientific actors in the quality assurance processes of knowledge production and assessment for policy making and risk management. Extended peer review can include all stakeholders engaged in the management of the problem at hand. Stakeholders are those actors who are directly or indirectly affected by an issue and who could affect the outcome of a decision making process regarding that issue or are affected by it.

Stakeholders' reasoning, observation and imagination are not bounded by scientific rationality. This can be beneficial when tackling ill-structured, complex problems. Consequently, the knowledge and perspectives of the stakeholders can bring in valuable new views on the problem and relevant information on that problem. The latter is known as “extended facts”. Stakeholders can contribute to the quality of knowledge in a number of ways. These include improvement of the quality of the problem formulation and the questions addressed by the scientists; the contribution of knowledge on local conditions which may help determine which data are strong and relevant or which response options are feasible; providing personal observations which may lead to new foci for empirical research addressing dimensions of the problem that were previously overlooked; criticism of assumptions made by the scientist, which may lead to changes towards assumptions that better match real life conditions; and, creative thinking of mechanisms and scenarios through which projected environmental and hydrologic changes may affect different sectors of society.

Resources required

Extended peer review requires well-developed communication and group moderation skills, along with a good understanding of public perceptions of risks and of science in general. Didactic skill is also required to help stakeholders to understand the sometimes complex and abstract concepts used in scientific assessments. Involving social scientists in the design and implementation of extended peer review processes is recommended.

Strengths and limitations

+ Allows for the use of extra knowledge from non scientific sources
+ Increases the level of public accountability in knowledge production
+ Promotes a development from knowledge consumption towards knowledge co-production
– Scientific and non-scientific participants are often not reciprocally accountable
– Public tends to get co-opted according to dominant view
– May reproduce power asymmetries.

References

Funtowicz SO and Ravetz JR (1996) Risk Management, post-normal science, and extended peer communities. In: Hood C and Jones DKC, Accident and Design, Contemporary debates in Risk Management. UCL Press, 172-182.

Healy S (1999) Extended peer communities and the ascendance of post-normal politics. Futures, 31, 655–669.

Fuller S (2003) On the need to extend peer review: A reply to Kihara. Social Epistemology, 17 (1), 74-78

Kihara H (2003) The Extension of Peer Review, How should it or should not be done? Social Epistemology, 17 (1), 65–73.

Pellizzoni L (1999) Reflexive Modernization and Beyond: Knowledge and Value in the Politics of Environment and Technology. Theory, Culture & Society 16(4): 99-125.

4.5 Inverse Modelling (parameter estimation)

Description

Parameter values are often optimised through inverse modelling. This is also denoted as automatic calibration (Duan et al, 1994; Hill, 1998; Doherty, 2003). An optimal parameter set is sought "automatically" by minimising an objective function, often defined as the summed squared deviation between the calibration targets (field data) and their simulated counterparts.

Most inversion techniques have the benefit that they in addition to optimal parameter values also produce calibration statistics in terms of parameter- and observation sensitivities, parameter correlation and parameter uncertainties. As the model calibration is based on a single model (with one possible model structure), errors in the model structure will be propagated to the model parameter uncertainties. The estimated parameter uncertainties are thus uncertainties for the effective model parameter given both the model structure and available observations (number, location and types of observations). This also means that estimated parameter uncertainties will not compensate adequately for the model structure uncertainty, when the model is used for prediction of conditions beyond the calibration base (e.g. when calibrating on groundwater flow and subsequently using the model to simulate groundwater transport and concentrations). Unless the model structure uncertainty is somehow considered the resulting simulation uncertainty will be significantly underestimated.

A different approach to autocalibration has been developed by Beven (Beven and Binley, 1992; Beven 2002) in the Generalised Uncertainty Likelihood Estimation (GLUE) method. Beven argues that one optimal set of parameter values does not exist (equifinality concepts), and that many likely sets therefore should be included in model simulations. Thus modelling is carried out in a Monte Carlo framework, where a large number of realisations of parameter sets are sampled from a broad a priori space of possible parameter values. By adopting threshold values for acceptable simulation accuracy, and rejecting parameter combinations for non-behavioural models, it is then possible to estimate the space of plausible parameter values and hence make inferences about the parameter uncertainty.

Resources required

Many software tools support inverse modelling, which often requires only moderate resources and skills to operate. Good modelling skills and comprehensive experience are, however, required to understand and analyse the results properly.

Universal optimisation routines can be downloaded as freeware, e.g. PEST (http://www.sspa.com/pest) and UCODE (http://water.usgs.gov/software/ucode.html).

Strengths and limitations

\+ Gives an objective estimate of parameter uncertainty based on information in available field data
\+ Most methods gives information on correlation between parameters
\- Most methods rely on assumptions, e.g. linearity as well as random and normally distributes residuals
\- Parameter uncertainties are computed for the specific model structure and available observations. The uncertainties may thus not be valid for conditions beyond the calibration base.

References

Beven K and Binley AM (1992) The future role of distributed models: model calibration and predictive uncertainty. Hydrological Processes, 6, 279-298. (See also http://www.es.lancs.ac.uk/hfdg/glue.html for further information on GLUE)

Beven K (2002) Towards a coherent philosophy for modelling the environment. Proceedings of the Royal Society of London, A, 458 (2026), 2465-2484.

Doherty J (2003) Ground water model calibration using pilot points and regularization. Ground Water, 41(2), 170-177. (See also http://www.sspa.com/pest for further information/download of PEST)

Duan Q, Sorooshian S and Gupta VK (1994) Optimal use of the SCE-UA global optimization method for calibrating watershed models. Journal of Hydrology 158, 265–284.

Hill MC (1998) Methods and guidelines for effective model calibration. U.S. Geological Survey, Water-Resources Investigations Report 98-4005. Denver CO (document available at http://pubs.water.usgs.gov/wri984005/).

4.6 Inverse modelling (predictive uncertainty)

Description

In addition to parameter estimation some of the inverse optimisation routines include the ability to estimate predictive uncertainties. The method by which the predictive uncertainty is derived varies among the inversion routines. But common to many of the local optimisation routines based on non-linear regression, is that the prediction of interest is treated as an observation, and the regression algorithm is then used to quantify the effect of the parameter uncertainty on this "observation". Some methods rely on a semi-analytical solution in which the regression algorithm is used to compute either a predictive uncertainty interval for the output variable or uncertainty in the difference between a reference case and a scenario simulation. Other methods use the regression to seek the maximum or minimum value of the prediction under the constraint that the model must be calibrated at an acceptable level, which is defined by some predefined acceptance level of the objective function.

Resources required

If inverse optimisation is used for calibration, the extra resources required to run the predictive mode is very limited. Some methods may need a considerable number of model evaluation and thereby long execution times.

Strenghts and limitations

\+ Gives an objective estimate of the predictive uncertainty given the applied model structure

\- Most methods rely on assumptions, e.g. linearity as well as random and normally distributes residuals

\- The predictive uncertainty are often limited to data types that can be defined as observations, this means that uncertainties on variables that are interpolated or extrapolated compared to the available field data can not be quantified by these methods.

References

Doherty J (2003) Ground water model calibration using pilot points and regularization. Ground Water, 41(2), 170-177.

Hill MC (1998) Methods and guidelines for effective model calibration. U.S. Geological Survey, Water-Resources Investigations Report 98-4005. Denver CO (document available at http://pubs.water.usgs.gov/wri984005/).

Tonkin MJ, Hill MC and Doherty JE (2004) MODFLOW-2000, the U.S. geological survey modular ground-water model -- Documentation of mod-predict for predictions, prediction sensitivity analysis, and enhanced analysis of model fit. Open-File Report 03-385 (document available at http://water.usgs.gov/nrp/gwsoftware/modpredict/modpredict.html).

4.7 Monte Carlo Analysis

Description

Monte Carlo Simulation is a statistical technique for stochastic model-calculations and analysis of error propagation in calculations. Its purpose is to trace out the structure of the distributions of model output. In it's simplest form this distribution is mapped by calculating the deterministic results (realisations) for a large number of random draws from the individual distribution functions of input data and parameters of the model. Advanced sampling methods have been designed such as Latin Hyper Cube sampling to reduce the required number of model runs needed to get sufficient information about the distribution in the outcome (mainly to save computation time). Latin Hyper Cube sampling makes use of stratification in the sampling of individual parameters. As in random Monte Carlo sampling, pre-existing information about correlations between input variables can be incorporated. Monte Carlo analysis requires the analyst to specify probability distributions of all inputs and parameters, and the correlations between them. Both probability distributions and correlations are usually poorly known. Ignoring correlations and co-variance in input distributions may lead to substantial under- or over-estimation of uncertainty in model outcome.

Monte Carlo analysis is a skill, and when it is used without following some basic principles of good practice it may lead to meaningless results. A good primer for responsible use of Monte Carlo Analysis is, for instance, the EPA "Guiding Principles for Monte Carlo Analysis" (EPA, 1997).

Most Monte Carlo analysis software offers the possibility to determine the relative contribution of uncertainty in each parameter to the uncertainty in a model output, e.g. by sensitivity charts, and can be used for a sophisticated analysis of trends in the presence of uncertainty.

Resources required

A number of commercial and free software packages (@Risk, Crystal Bal, SimLab) are available to do Monte Carlo analysis. Another commercial package is Analytica (http://www.lumina.com), which is a quantitative modelling environment with built-in Monte Carlo algorithms. Packages such as Crystal Ball are very easy to learn. If you are familiar with Excel it takes less than one hour to get proficient with Crystal Ball. It takes more time to get proficient with SimLab and requires more skills because one has to interface SimLab with one's own model.

Performing Monte Carlo Analysis on complex models with long computation times and many variables requires major computer resources and computation time. Software solutions to combine PCs in a network to create a super computer capacity can be an outcome (e.g. the Super Muse software from the US-EPA: http://www.epa.gov/athens/research/modeling/supermuse/supermuse.html)

Strengths and limitations

+ Provides comprehensive insight in to how specified uncertainty in inputs propagates through a model.
+ Forces analysts to consider uncertainty and interdependencies among different inputs explicitly.
+ Is capable of coping with any conceivable shape of PDF and can account for correlations.
+ Can be used in 2-dimensional models to assess variability and epistemological uncertainty separately.
– Monte Carlo assessment is limited to quantifiable uncertainties.
– One may not have any reasonable basis on which to ascribe a probability distribution to parameters
– May take large run-time for computational intensive models. This can partly be remedied by using more efficient sampling techniques (e.g. Latin Hypercube Sampling).
– The interpretation of a probability distribution of the model output by decision makers is not always straightforward. There is no single rule arising out of such a distribution that can guide decision-makers.

References

EPA (1997) Risk Assessment Forum, Guiding Principles for Monte Carlo Analysis, EPA/630/R-97/001. (http://www.epa.gov/NCEA/pdfs/montcarl.pdf)

Crystal Ball 2000, User Manual Decision Engineering Inc., Denver.

Palisade Corporation (2000) Guide to Using @RISK - Risk Analysis and Simulation Add-in for Microsoft Excel, Version 4, March 2000.

Saltelli A, Chan K and Scott M (2000) Sensitivity Analysis John Wiley & Sons publishers, Probability and Statistics Series.

Saltelli A, Tarantola S, Campolongo F and Ratto M (2004) Sensitivity Analysis in Practice: A Guide to Assessing Scientific Models, John Wiley & Sons publishers.

Vose D (2000) Risk Analysis – A quantitative guide, 2nd edition. John Wiley & Sons, Ltd. Chichester.

4.8 Multiple Model Simulation

Description

Multiple Model Simulation is a strategy to address uncertainty about model structure. Instead of doing an assessment using a single model, the assessment is carried out using different models. For instance, this can be realised by having alternative model codes with different process descriptions (Linkov and Burmistrov, 2003; Butts et al., 2004) or, in the groundwater case, by having different conceptual models based on different geological interpretations (Troldborg, 2000, Selroos et al., 2001).

The strategy of applying several alternative models based on codes with different model structures is also common in climate change modelling. Thus in its description of uncertainty related to model predictions of both present and future climates the IPCC Special Report on Emission Scenarios (IPCC, 200x) bases its evaluation on scenarios of many (up to 35) different models.

The same strategy is followed in the Dialogue Model (Visser et al. 2000). Dialogue simulates the cause effect chain of climate change, using mono-disciplinary sub-models for each step in the chain. The chain starts with scenarios for economic growth, energy demand, fuel mix etc., leading to emissions of greenhouse gasses, leading to changes in atmospheric composition, leading to radiative forcing of the climate, leading to climate change, leading to impacts of climate change on societies and ecosystems. Rather than picking one main-stream mono-disciplinary sub-model for each step, Dialogue uses multiple models for each step (for instance, three different carbon cycle models, five different GCM model-outcomes, etc.), representing the major part of the spectrum of expert opinion in each discipline. This multiple model approach facilitates the inclusion of new alternative models in each step to accommodate new scientific ideas on the structure of a given sub-model.

Refsgaard et al (submitted) present a new framework for dealing with uncertainty due to model structure error, based on alternative conceptual models and assessment of their pedigree and adequacy.

Resources required

Multiple model simulation requires modelling skills to design and implement the various model structures. Varying model structure is a much more complex task than varying parameters and there are no ready to use software solutions available. The required resources will further depend on the complexity of the model and the required time for each model run. If models developed and run by different modelling groups are used, a substantial part of the resources will be required for co-ordination and project management.

Strengths and limitations

+ The effects of alternative model structures can be analysed explicitly.
+ It makes it possible to include expert knowledge on plausible model structures.
+ It substantially reduces the chances that the assessment overlooks important aspects of the problem compared to the use of single models only. In that sense it may reduce surprises.
– We cannot be sure whether we have adequately sampled the relevant space of plausible models. Important plausible model structures could be overlooked.
– Often we do not know the plausibility and even less the probability of each conceivable model structure.
– The expert knowledge on which the formulations of the alternative conceptual models have to be based has an unavoidable subjective element.

References

Butts MB, Payne JT, Kristensen M and Madsen M (2004) An evaluation of the impact of model structure on hydrological modelling uncertainty for streamflow simulation. Journal of Hydrology, 298, 242-266.

Linkov I and Burmistrov D (2003) Model uncertainty and choices made by the modelers: lessons learned from the international atomic energy agency model intercomparisons, Risk Analysis 23(6), 1297-1308.

Nakicenovic N, Alcamo J, Davis G, de Vries B, Fenhann J, Gaffin S, Gregory K, Grübler A, Jung TY, Kram T, La Rovere EL, Michaelis L, Mori S, Morita T, Pepper W, Pitcher H, Price L, Riahi K, Roehrl A, Rogner H-H, Sankovski A, Schlesinger M, Shukla P, Smith S, Swart R, van Rooijen S, Victor N, Dadi Z (2000) IPCC Special Report on Emissions Scenarios. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. 599pp.

Refsgaard JC, van der Sluijs JP, Brown J and van der Keur P (submitted) A Framework For Dealing With Uncertainty Due To Model Structure Error.

Selroos JO, Walker DD, Strom A, Gylling B and Follin S (2001) Comparison of alternative modelling approaches for groundwater flow in fractured rock. Journal of Hydrology, 257, 174-188.

Troldborg L (2000) Effects of geological complexity on groundwater age prediction. Poster session 62C, AGU. EOS Transactions, 81(48), F435.

Visser H, Folkert RJM, Hoekstra J and De Wolff JJ (2000) Identifying key sources of uncertainty in climate change projections. Climatic Change 45, 421-457.

4.9 NUSAP

Description

The NUSAP system for multidimensional uncertainty assessment (Funtowicz and Ravetz, 1990) aims to provide an analysis and diagnosis of uncertainty in science for policy. The basic idea is to qualify quantities using the five qualifiers of the NUSAP acronym: Numeral, Unit, Spread, Assessment, and Pedigree. NUSAP complements quantitative analysis with expert judgement of reliability (Assessment) and systematic multi-criteria evaluation of the different phases of production of a given knowledge base (Pedigree). Pedigree criteria can be: proxy representation, empirical basis, methodological rigor, theoretical understanding, and degree of validation. Pedigree assessment can be further extended to also address societal dimensions of uncertainty, using criteria addressing different types of value weighting, quality of problem frames etc. NUSAP provides insight on two independent properties related to uncertainty in numbers, namely spread and strength. Spread expresses inexactness whereas strength expresses the methodological and epistemological limitations of the underlying knowledge base. The two metrics can be combined in a Diagnostic Diagram mapping strength of for instance model parameters and sensitivity of model outcome to spread in these model parameters. Neither spread alone nor strength alone is a sufficient measure for quality. Robustness of model output to parameter strength could be good even if parameter strength is low, if the spread in that parameter has a negligible effect on model outputs. In this situation our ignorance of the true value of the parameter has no immediate consequences. Alternatively, model outputs can be robust against parameter spread even if its relative contribution to the total spread in the model is high provided that parameter strength is also high. In the latter case, the uncertainty in the model outcome adequately reflects the inherent irreducible uncertainty in the system represented by the model. Uncertainty then is a property of the modelled system and does not stem from imperfect knowledge on that system. Mapping components of the knowledge base in a diagnostic diagram thus reveals the weakest spots and helps in the setting of priorities for improvement.

Resources required

Resources required for assessing the Spread qualifier depend on the method chosen (some form of Sensitivity Analysis or Monte Carlo analysis usually in combination with expert elicitation will be needed).

For the assessment of Pedigree, many resources (pedigree matrices, pedigree calculator, kite diagram maker, elicitation protocol and questionnaires) are freely available from http://www.nusap.net. Basic skills of Expert Elicitation are required.

Basic skills for facilitating structured group discussions are needed if one uses an expert workshop. In addition, skills are needed to arrive at a balanced composition of the workshop audience to minimise biases.

Time required per expert elicitation in a one to one interview depends on the number of parameters and the complexity of the case. Typically, it may vary between 1 and 5 hours. A substantial amount of time may be needed for a good preparation of the elicitation interviews.

Recommended length for a NUSAP expert elicitation workshop is between one and one and a half days

Strengths and limitations

- \+ Identifies both quantitative and qualitative uncertainty in quantitative information and enables them to be displayed in a standardised and self-explanatory way
- \+ Promotes criticism by clients and users of all sorts, both expert and lay, and will thereby support extended peer review processes
- \+ It is flexible in its use and can be used on different levels of comprehensiveness: from a 'back of the envelope' sketch based on self elicitation to a comprehensive and sophisticated procedure involving structured, informed, in-depth group discussions on a parameter by parameter format
- – The scoring of pedigree criteria is to a large extent based on subjective judgements. Therefore, outcomes may be sensitive to the selection of experts involved in the scoring.
- – It is hard to apply the method to complex models with large numbers of parameters.

References

Www.nusap.net

Funtowicz SO and Ravetz,JR (1990) Uncertainty and Quality in Science for Policy. Dordrecht: Kluwer.

Craye M, van der Sluijs JP and Funtowicz SO (2004) A reflexive approach to dealing with uncertainties in environmental health risk science and policy, International Journal for Risk Assessment and Management 5 (2).

Van der Sluijs JP, Craye M, Funtowicz SO, Kloprogge P, Ravetz JR and Risbey J (2005) Combining Quantitative and Qualitative Measures of Uncertainty in Model based Environmental Assessment: the NUSAP System, Risk Analysis, 25 (2).

Van der Sluijs JP, Risbey J and Ravetz JR (in press) Uncertainty Assessment of VOC emissions from Paint in the Netherlands, Environmental Monitoring and Assessment.

4.10 Quality Assurance

Description

Quality assurance (QA) may be defined as protocols and guidelines to support the proper application of models. Important aims of QA are to ensure the use of best practise and to ensure that the expected accuracy and model performance are in accordance with the project objectives. Uncertainty and QA are intimately linked as uncertainty plays a very important role throughout the modelling process.

Many QA guidelines exist such as Middlemis (2000), Van Waveren et al. (1999) and Scholten et al. (submitted). Most guidelines have been prepared for a single modelling domain, such as groundwater and for use in a particular, confined, market such as a single country (Refsgaard, 2002; Refsgaard et al., 2004).

Key elements of QA procedures include:

- Definition of the purpose of the modelling study, including translation of the water manager and stakeholder needs to preliminary performance criteria.
- Establishment of performance criteria. The accuracy of the model predictions has to be established via a trade off between the benefits of improving the accuracy in terms of less uncertainty on the management decisions and the costs of improving the accuracy through additional model studies and/or collection of additional field data.
- Reviews carried out by independent auditors with subsequent consultation between the modeller, the water managers and possibly the stakeholders at different phases of the modelling project. Important aspects of the reviews are to ensure that good practise has been followed and to evaluate if the uncertainty assessments made by the modeller are credible and adequate.
- Performance of model validation tests, i.e. testing of model performance against independent data that have not been used for calibration in order to assess the accuracy and credibility of the model simulations for situations comparable to those where it is intended to be used.

The HarmoniQuA project has developed a comprehensive set of QA guidelines for multiple modelling domains combined with a supporting software tool, MoST (downloadable via www.harmoniqua.org). In addition to the software tool, the HarmoniQuA guidelines are unique in their dedication aspects, namely that different tasks and responsibilities are described for different users, different modelling domains and different levels of modelling job complexity.

Resources required

For QA to become successful it is required that both the modeller and the water manager are motivated and active in supporting its use. The water manager has a particular responsibility, because they have the power to request and pay for adequate QA in modelling studies. Therefore, QA guidelines can only be expected to be used in practice, if the water manager prescribes their use. In this respect, it is essential that the water manager has the technical capacity to organise the QA process.

Strengths and limitations

+ Improves the chances that best practise is used
+ Improves the quality of the work and the credibility of the results
+ Makes it possible to include stakeholders into the modelling process in a formalised framework, either as information, consultation or involvement.
+ Improves the transparency and reproducibility of the modelling work.
- To be done properly it requires resources and adds to the cost of a modelling study.
- May become a ‘rubber stamp’ and generate a false credibility if not designed and performed thoroughly.

References

Middlemis H (2000) Murray-Darling Basin Commission. Groundwater flow modelling guideline. Project no. 125, Aquaterra Consulting Pty Ltd., South Perth. Western Australia.

Refsgaard JC, Henriksen HJ, Harrar WG, Scholten H and Kassahun A (2004) Quality assurance in model based water management – review of existing practice and outline of new approaches. Environmental Modelling and Software. Accepted.

Refsgaard, JC (Ed) (2002) State-of-the-Art Report on Quality Assurance in modelling related to river basin management. Report from the EU research project HarmoniQuA. www.harmoniqua.org. 18 chapters, 182 pp. Geological Survey of Denmark and Greenland, Copenhagen.

Scholten HS, Kassahun A, Refsgaard JC, Kargas T, Gavadinas C and Beulens AJM (submitted) The HarmoniQuA methodology to support multidisciplinary model-based water management.

Van Waveren RH, Groot S, Scholten H, Van Geer F, Wösten H, Koeze R and Noort J (1999) Good Modelling Practice Handbook, STOWA, Utrecht, The Netherlands (in Dutch). English version from http://www.landandwater.tudelft.nl/Downloads/GMP-uk.pdf.

www.harmoniqua.org from where the supporting tool MoST can be downloaded.

4.11 Scenario Analysis

Description

Scenario Analysis aims to describe logical and internally consistent sequences of events to explore how the future may, could or should evolve from the past and present. The future is inherently uncertain. Different alternative futures can be explored through scenario analysis. As such, scenario analysis is also a tool to deal explicitly with different assumptions about the future. A definition is “Scenarios are descriptions of journeys to possible futures. They reflect different assumptions about how current trends will unfold, how critical uncertainties will play out and what new factors will come into play” (UNEP, 2002). Another definition is: “A scenario is a description of the present state of a social and or natural system (or a part of it), of possible and desirable future states of that system along with sequences of events that could lead from the present state to these future states.” Other definitions also include the purposes of the use of scenarios.

Different types of scenarios can be distinguished. For instance, Alcamo (2001) discerns baseline vs. policy scenarios, exploratory vs. anticipatory scenarios and qualitative vs. quantitative scenarios.

Baseline scenarios present the future state of society and environment in which no (additional) environmental policies do exist or have a discernible influence on society or the environment. Policy scenarios depict the future effects of environmental protection policies. Exploratory scenarios start in the present and explore possible trends into the future. Anticipatory scenarios start with a prescribed vision of the future and then work backwards in time to visualise how this future could emerge. Qualitative scenarios describe possible futures in the form of narrative texts or so-called “story-lines”. Quantitative scenarios provide tables and figures incorporating numerical data often generated by sophisticated models.

Finally, scenarios can be surprise-free or trend scenarios, that extend foreseen developments, on the one hand or include surprises and exploring the extremes (e.g. best case / worst case) on the other hand.

Resources required

Scenario analysis requires creativity and ability to think outside the scope of the familiar and the present. Furthermore, it requires insight in dynamics, relationships, in synergies of systems and their environment and thus it requires a broad knowledge of the field involved. Therefore, scenarios analysis should take place in an interdisciplinary team.

In the case of a quantitative approach, computer models or spreadsheets or other software are needed to run/visualise scenarios. Access to relevant data is important in order to be able to construct the scenarios.
In the case of a qualitative approach, input has to be collected from experts, stakeholders or users in workshops with stakeholders to be able to develop storylines. Basic skills for facilitating groups are required. Both approaches are time and resource consuming.

Strengths and limitations

+ Scenarios are often the only way to deal with the unknown future;
+ Assumptions about future developments are made transparent and documented
+ Gives insight in key factors that determine future developments;
+ Creates awareness on alternative development paths, risks, and opportunities and possibilities for policies or decision-making.
– The analysis is limited to those aspects of reality that can be quantified (quantitative scenarios);
– Difficult to test underlying assumptions (qualitative scenarios);
– Frequently scenarios do not go beyond trend extrapolation (quantitative scenarios) and are surprise-free;
– Frequently models used contain only one view, which will make the outcomes narrow in scope, thus not doing justice to the wish to explore fundamentally different futures.

References

Alcamo J (2001) Scenarios as tools for international environmental assessments. Environmental issues report. Experts corner report. Prospects and Scenarios No.5, European Environment Agency, Copenhagen
Van Der Heijden K (1996) Scenarios: The Art of Strategic Conversation, John Wiley & Sons; ISBN: 0471966398
UNEP (2002) Global Environmental Outlook 3: Past, present and future perspectives, Earthscan.

4.12 Sensitivity Analysis

Description

Sensitivity analysis (SA) is the study of how the variation in the output of a model (numerical or otherwise) can be qualitatively or quantitatively apportioned to different sources of variation, and of how the outputs of a given model depend upon the information fed into it (Saltelli et al., 2000, 2004).

Depending on the complexity of a model's output space SA methods may range from the simple to the relatively complex. If a model's output space is linear or approximates a hyperplane, SA may be conducted through a straightforward application of differential analysis. This is typically done by taking partial derivatives of the output with respect to one input, holding all other inputs constant.

If a model's output space is nonlinear (or does not approximate a hyperlplane) then the assumptions for differential analysis do not hold. Differential analysis may be conducted, but the analyst should be aware that the results may apply only to a narrow range of the output space. For this reason, differential analysis in this situation is referred to as Local SA.

If the analyst wishes to conduct Global SA (i.e. SA across the model's entire output space) for nonlinear (non-hyperplaner) models, then other analytical methods should be used. These include such methods as Monte Carlo Analysis, Morris' One-at-a-time method and various variance based methods such as Fourier Amplitude Sensivity Test (FAST).

Resources required

Sensitivity Analysis (SA) requires basic computer skills and basic knowledge of statistical concepts. Software for SA is available both as freeware (such as SIMLAB) and commercial. SIMLAB: http://www.jrc.cec.eu.int/uasa/prj-sa-soft.asp and http://sensitivity-analysis.jrc.cec.eu.int/default2.asp?page=SIMLAB

Commercial packages for Monte Carlo analysis such as @Risk (http://www.palisade.com) and Crystal Ball (http://www.decisioneering.com/crystal_ball) include options for sensitivity analysis. @Risk and Crystal Ball are designed as fully integrated MS-Excel add-in programs with their own toolbar and menus.

The precise requirements depend on the complexity of the model to which one applies the Sensitivity Analysis and the number of factors one wants to include in the analysis. It may be necessary to program an interface between the model and the Sensitivity Analysis software.

Strengths and limitations

+ Gives insight in the potential influences of all sorts of changes in inputs
+ Helps discrimination across parameters according to importance for the accuracy of the outcome
+ Software for Sensitivity Analysis is freely available
+ SA can help in evaluating the fit-for-purpose of a model
– Has a tendency to yield an overload of information.
– SA does not require one to assess how likely it is that specific values of the parameters will actually occur.
– Commercial software packages for SA can be used with minimal knowledge on the sampling and calculations techniques itself, which allows incompetent use.
– In practice SA often takes the model structure and system boundaries for granted

References

Saltelli A, Chan K and Scott M (2000) Sensitivity Analysis John Wiley & Sons publishers, Probability and Statistics Series.

Saltelli A, Tarantola S, Campolongo F and Ratto M (2004) Sensitivity Analysis in Practice: A Guide to Assessing Scientific Models, John Wiley & Sons Publishers.

Campolongo F, Tarantola S and Saltelli A (1999) Tackling quantitatively large dimensionality problems. Computer Physics Communication, 117, 75-85.

Morris MD (1991) Factorial sampling plans for preliminary computational experiments. Technometrics, 33(2)

Http://sensitivity-analysis.jrc.cec.eu.int/default.htm

4.13 Stakeholder Involvement

Description

Stakeholder involvement in not only the decision making process but also in knowledge production and knowledge use, can help to assess and manage complex (environmental) problems in a better way. This potential can be tapped in three ways:

(1) By enabling them to articulate issues of concern and to improve the problem framing for research and policy;
(2) By utilising their own (non scientific) knowledge and observations and their capacity to invent new options; and
(3) By involving them actively in the quality control of the operational knowledge that is co-produced (extended peer review).

By engaging stakeholders into the risk management process it is likely that they will not only contribute to future risk management decisions but also support their implementation.

We have another concern as well when addressing complex environmental policy issues in a participatory way. The scientific soundness of the presumed causal mechanisms underlying alternative problem definitions needs to be warranted if we want to base our policies on scientifically sound underpinnings. Although there is more than one legitimate interpretation of the science, this plurality of perspectives does not deny the special competence of scientists. It does mean that there is a mixing and blending of skills, partly technical and partly personal, of all those engaged that can enrich the comprehension of the whole.

The RIVM/MNP Guidance for Uncertainty Assessment and Communication (Van der Sluijs et al. 2004) has a useful section on stakeholder involvement, including an instrument for discourse analysis.

Stakeholders can also be used in environmental monitoring, as is done for instance in the European Phenological Data Platform for Climatological Applications and other initiatives where citizens provide observations on effects of climate changes on nature (e.g. first day in the year that a bird species is observed).

The HarmoniCOP project has developed a typology to characterise tools to support the public participation process in relation to implementation of the Water Framework Directive (Maurel, 2003).

Resources required

Stakeholder involvement in knowledge production requires very good communication and deliberation skills and the involvement of social scientists is recommended. It also puts high requirements on the infrastructure through which stakeholders can contribute their knowledge and on the quality assurance of the knowledge provided, especially if this infrastructure has to function during a long period of time (as with environmental monitoring systems).

Strengths and limitations

+ Increases the level of public accountability in knowledge production
+ May increase the public support for the knowledge base that is co-produced
– There are many unresolved challenges regarding the quality control of knowledge produced by non scientific actors

References

Kloprogge P and van der Sluijs JP (forthcoming) The inclusion of stakeholder knowledge and perspectives in integrated assessment of climate change. Climatic Change.

Maurel P (Ed.) (2003) Public participation and the European Water Framework Directive. Role of Information and Communication Tools. Workpackage 3 Report of the HarmoniCOP Project. Cemagref, Montpellier, www.harmonicop.info.

Osidele OO and Beck MB (2002) Integrating Stakeholder Imagination with Scientific Theory: A Case Study of Lake Lanier, USA, Proceedings of the IEMSS, 31-36

Stern PC and Fineberg HV (eds.) (1996) Understanding risk, informing decisions in a democratic society, Washington DC: National Research Council, National Academy Press.

van der Sluijs JP, Risbey JS, Kloprogge P, Ravetz JR, Funtowicz SO, Quintana SC, Guimarães Pereira Â, De Marchi B, Petersen AC, Janssen PHM, Hoppe R and Huijs SWF (2003) RIVM/MNP Guidance for Uncertainty Assessment and Communication: Detailed Guidance Utrecht University & RIVM (available from www.nusap.net).

Yosie FT and Herbst TD (1998) Using stakeholder processes in environmental decision-making. An evaluation of lessons learned, key issues and future challenges, Ruder Finn Washington, ICF Inc., http://www.gdrc.org/decision/nr98ab01.pdf

4.14 Uncertainty Matrix

Description

The uncertainty matrix (Walker et al, 2003, Janssen et al., 2003) can be used to identify and prioritise the most important uncertainties in a given model study. The matrix shown below is an example of a project specific adaptation of the more general uncertainty matrix shown in Fig. 5, above.

Source of uncertainty	Type of uncertainty				Importance	
	Statistical uncertainty	Scenario uncertainty	Qualitative uncertainty	Recognised ignorance	Weight-ing	(uncertainty x weight)
Problem context						
- future agritultural practise		medium	medium	medium	large	medium
- future climate		medium	medium	large	medium	medium
Input data						
- catchment data	medium			small	large	medium
- nitrate load from agriculture	small			small	large	small
Parameter uncertainty						
- water quantity	small			small	medium	small
- water quality	medium			medium	medium	small
Model structure (conceptual)						
- geology		large	large	medium	large	large
- nitrate reduction in underground		medium	medium	large	large	large
Model technical uncertainty						
- numerical approximation	small			small	medium	small
- bugs in software				medium	medium	small
					SUM:	

For a specific application the different sources of uncertainty are listed in the rows and the type of uncertainty associated to each source is noted and characterised. This may be done either quantitatively or, as shown in the above figure, qualitatively. The importance of each source may then be characterised by a weighting depending on its impact on the modelling study in question. The Sum of uncertainty may then be assessed, e.g. by use of the error propagation equation (Section 4.2).

It may not be possible to identify all sources of uncertainty and/or assigning correct weightings from the project start. The matrix may thus be used interactively by adding or reassigning weights during the modelling process as more insight into the system is gained.

Resources required

The uncertainty matrix can be used as a heuristic instrument and screening tool. One can draft a gross list of uncertainties to be addressed and give a priority (e.g. high, medium, low) to each cell by going over all the cells of the matrix systematically and reflecting on the question whether that cell may be relevant to include in an uncertainty assessment of the case at hand. This can be done by an individual researcher; in a dialogue in a research team; or in a dialogue between a research team and the client; or, in a wider dialogue between the research team, the client and a group of stakeholder representatives.

The resources required will depend on the way the matrix is used in the process. The broader the dialogue is in which the tool is used, the more resources will be required.

Strengths and limitations

+ Forces the analyst to systematically consider a broad range of possible sources and types of uncertainty. It thereby reduces the chance that important uncertainties are overlooked.
+ Can be used quick and dirty/back of the envelope or more sophisticated and comprehensive
+ Facilitates and structures a dialogue on uncertainty, both within a research team and in communication with clients, peers and stakeholders
– Strongly relies on expert judgement, the result is likely to be sensitive to the composition of the group of analysts involved in applying the matrix
– Yields mainly qualitative insights, has limited value if it is not complemented by some form of quantitative analysis

References

Walker WE, Harremoës P, Rotmans J, Van der Sluijs JP, Van Asselt MBA, Janssen P and Krayer von Krauss MP (2003) Defining Uncertainty A Conceptual Basis for Uncertainty Management in Model-Based Decision Support, Integrated Assessment, 4(1), 5-17.

Janssen PHM, Petersen AC, van der Sluijs JP, Risbey JS and Ravetz JR (2003) RIVM/MNP Guidance for Uncertainty Assessment and Communication: Quickscan Hints & Actions List. RIVM/MNP, ISBN 90-6960-105-2, 2003 (available from www.nusap.net)

5. How to select the appropriate methodology for uncertainty assessment

5.1 Introduction

Some of the more important types of methodologies and associated tools that may be applied for assessing uncertainties are listed and briefly described in Chapter 4. The next question is which methodology should be selected for a particular purpose and task of the modelling process.

The selection of an adequate methodology depends on:

- Where in the modelling process the analysis should be carried out, cf. Chapter 2.
- The type, nature and source of uncertainty, cf. Chapter 3.
- The priority that addressing each of the identified sources of uncertainty has, according to their importance for the decision-making process ("policy relevance").
- The available resources and level of ambition with respect to completeness of the analysis.

Guidance regarding the selection of appropriate methodologies/tools for different purposes is provided in the following two sections.

5.2 Methodologies according to modelling process and level of ambition

Table 1 provides a list of applicable methodologies that are considered to be adequate for the different tasks/steps in the modelling process described in Chapter 2 and Fig. 3. Furthermore, it includes hints for which methodologies are more suitable for comprehensive analysis with relatively large economic resources for the study and which methodologies correspond to a lower level of ambition (denoted as "basic" in the Table).

Table 1 Suitable methodologies to deal with uncertainty at various stages of a modelling process

<table>
<tr><th rowspan="2">Type of uncertainty aspect</th><th rowspan="2">Task in the modelling process (cf. Fig. 2)</th><th colspan="2">Level of ambition/available resources</th></tr>
<tr><td>Basic</td><td>Comprehensive</td></tr>
<tr><td rowspan="2">Identify and characterise sources of uncertainty</td><td>Describe Problem and Context (Step 1)</td><td rowspan="2">UM</td><td rowspan="2">EPE, SI, UM</td></tr>
<tr><td>Determine Requirements (Step 1)</td></tr>
<tr><td rowspan="6">Modeller reconsiders uncertainty and performance criteria</td><td>Prepare and Evaluate Tender (Step 1)</td><td colspan="2" rowspan="7">(Update of) UM
+
Common sense</td></tr>
<tr><td>Reporting (Step 2)</td></tr>
<tr><td>Reporting (Step 3)</td></tr>
<tr><td>Reporting (Step 4)</td></tr>
<tr><td>Reporting (Step 5)</td></tr>
<tr><td>Specify or Update Calibration and Validation Targets and Criteria (Step 3)</td></tr>
<tr><td rowspan="5">Reviews-dialogue-decisions</td><td>Agree on Model Study Plan and Budget</td></tr>
<tr><td>Review of Step 2</td><td>QA</td><td>EPR, QA</td></tr>
<tr><td>Review of Step 3</td><td>QA</td><td>EPR, QA</td></tr>
<tr><td>Review of Step 4</td><td>QA</td><td>EPR, QA</td></tr>
<tr><td>Review of Step 5</td><td>QA</td><td>EPR, QA</td></tr>
<tr><td rowspan="2">Uncertainty assessment and propagation</td><td>Uncertainty Analysis of Calibration and Validation (Step 4)</td><td>DA, EPE, SA</td><td>DA, EPE, EE, IN-PA, IN-UN, MCA, MMS, NUSAP, SA</td></tr>
<tr><td>Uncertainty Analysis of Simulation (Step 5)</td><td>DA, EPE, SA</td><td>DA, EPE, EE, IN-UN, MCA, MMS, NUSAP, SC,SA, SI</td></tr>
</table>

Abbreviations of methodologies:

DA Data Uncertainty
EPE Error Propagation Equations
EE Expert Elicitation
EPR Extended Peer Review (review by stakeholders)
IN-PA Inverse modelling (parameter estimation)
IN-UN Inverse modelling (predictive uncertainty)
MCA Monte Carlo Analysis
MMS Multiple Model Simulation
NUSAP NUSAP
QA Quality Assurance
SC Scenario Analysis
SA Sensitivity Analysis
SI Stakeholder Involvement
UM Uncertainty Matrix

5.3 Methodologies according to source and type of uncertainty

Table 2 provides a list of applicable methodologies for addressing uncertainty of different types and originating from different sources. Note that the nature of uncertainty (epistemic or stochastic) has been omitted as compared to the uncertainty matrix in Fig. 4. The reason for this is that this is a third dimension and that each of the cells below may be divided into reducible (epistemic) and irreducible (stochastic) uncertainty.

Table 2 Correspondence of the methodologies with the source and types of uncertainty distinguished in the uncertainty taxonomy (inspired by van der Sluijs et al., 2004).

Source of uncertainty		**Taxonomy (types of uncertainty)**			
		Statistical uncertainty	Scenario uncertainty	Qualitative uncertainty	Recognised ignorance
Context	Natural, technological, economic, social, political	EE	EE, SC, SI	EE, EPR, NUSAP, SI, UM	EE, EPR, NUSAP, SI, UM
Inputs	System data	DA, EPE, EE, MCA, SA	DA, EE, SC	DA, EE	DA, EE
	Driving forces	DA, EPE, EE, MCA, SA	DA, EE, SC	DA, EE, EPR	DA, EE, EPR
Model	Model structure	EE, MMS, QA	EE, MMS, SC, QA	EE, NUSAP, QA	EA, NUSAP, QA
	Technical	QA	QA	QA	QA
	Parameters	IN-PA, SA, QA	IN-PA, SA, QA	QA	QA
Model outputs		EPE, EE, IN-UN, MCA, MMS, SA	EE, IN-UN, MMS, SA	EE, NUSAP	EE, NUSAP

Abbreviations of methodologies:

DA Data Uncertainty
EPE Error Propagation Equations
EE Expert Elicitation
EPR Extended Peer Review (review by stakeholders)
IN-PA Inverse modelling (parameter estimation)
IN-UN Inverse modelling (predictive uncertainty)
MCA Monte Carlo Analysis
MMS Multiple Model Simulation
NUSAP NUSAP
QA Quality Assurance
SC Scenario Analysis
SA Sensitivity Analysis
SI Stakeholder Involvement
UM Uncertainty Matrix

6. Illustrative cases

The following cases aim to illustrate which uncertainty methods typically might be selected in different types of modelling studies. With reference to Fig. 2 above the first two cases address model application to design programme of measures, while the last two cases deals with implementation and monitoring, respectively. The main difference between the two first cases lies in the level of ambition/available resources, cf. Table 1 above. The cases are hypothetical.

6.1 Case 1: Designing measures – nutrient load/comprehensive modelling

This case resembles some of the problems typically encountered in some central and northern European river basins with eutrophication of surface water bodies caused by nutrient loads primarily from agriculture but also to some extent from industry and urban areas. The conditions can furthermore be characterised by:

- There is a good amount of high quality data.
- Modelling studies have regularly been carried out during the past 10 years for various water management purposes.
- The river basin authority (water manager) has a large and highly professional staff with comprehensive experience in handling modelling projects.
- Some of the key stakeholders are very well organised and have professional support (e.g. agricultural advisory service and green NGOs) that are able to evaluate and challenge any possible scientific weaknesses of modelling studies.

In this case the river basin authority has to select the most appropriate measure or combination of several measures required in order to achieving the objectives of good ecological status. The possible measures may include some with various kind of restrictions on agricultural management, some focussing on removal of nutrients from industrial and urban point sources and some resulting in restoration of nature areas, e.g. with more frequent inundation and associated restrictions on land use.

A typical selection of uncertainty methods is illustrated in Table 3.

6.2 Case 2: Designing measures – water scarcity/basic modelling

This case resembles some of the problems typically encountered in some Mediterranean river basins with water scarcity and competing demand from different stakeholders for urban water supply, irrigation and nature. The conditions can furthermore be characterised by:

- There are relatively few data.
- Previously modelling studies have only been carried out for research purposes.
- The river basin authority (water manager) has a professional staff with little experience in handling modelling projects.
- The key stakeholders are very well organised but they do not have access to professional support that can assist them in evaluating and challenging the possible scientific weaknesses of modelling studies.

In this case the river basin authority has to select the most appropriate measure or combination of several measures required to solve the water scarcity problem and at the same time achieving the objectives of good ecological status. The possible measures may include some on water savings and demand management and some involving additional supply (e.g. from desalination, from a new reservoir or from new groundwater abstraction).

A typical selection of uncertainty methods is illustrated in Table 4.

6.4 Case 3: Implementation – Real-time forecasting (of Case 2)

This case can be seen as a continuation of Case 2 above. Assume that the measures designed in Case 2 has included a reservoir with a condition on a certain downstream flow regime to be maintained, e.g. in terms of required minimum flows and/or water quality criteria. In order to ensure the downstream flow regime and at the same time minimise the release from the reservoir real-time forecasts on the future flows (up to a week) is performed.

In this case the hydrological model setup and applied during Case 2 will typically be extended and used in real-time operation. Most of the model can be used directly, but it needs to be tailored to run operationally in a real-time environment, implying a modification to use input data from only on-line stations and development of an updating routine to enable feed-back from real-time flow data.

A typical selection of uncertainty methods is illustrated in Table 5.

6.4 Case 4: Evaluation - Post project appraisal (of Case 1)

This case can be seen as a continuation of Case 1 above. Assume that the measures designed in Case 1 have been implemented and that a monitoring programme has been established to monitor to which extent the measures have had the desired effect. In case of nutrient loads from agriculture, this is known to show large temporal variations generated by climate variability. Thus winters with more rainfall and higher temperatures will give larger nutrient load than winters with less rainfall and/or lower temperatures. This temporal variability is usually much larger than the change in average load that is the objective of the designed programme of measures. Such climatically generated variance in a monitoring time series appears as noise if a statistical test is performed to identify a possible trend or a step change in the data.

In this case a dynamic model driven by climate input may be used to simulate the variation generated by the climate alone. By filtering out part of the climatically generated noise it may then be possible to identify changes in nutrient loads caused by the WFD measures (Refsgaard et al, 1989; Lørup et al., 1998). As the basic model has been established in Case 1 this model application can be seen as a post project appraisal. It will therefore typically not be required to start from scratch, but rather to re-use the already calibrated/validated model – just with new input data.

A typical selection of uncertainty methods is illustrated in Table 6. It is noted that, due to the re-use of an existing model, the modelling steps 2, 3 and 4 are not performed here.

Table 3 Example of methods selected in Case 1: Design measures – nutrient load/comprehensive modelling

Modelling process			Link to decision (WFD) process
Modelling Step (Fig. 3)	**Uncertainty method**	**Content**	
STEP 1 Framing of modelling study	UM	Identification and characterisation of sources of uncertainty used as a basis for prioritising what should be done in the modelling study	Stakeholders and water manager are key players in the WFD process and are continuously involved in this modelling step translating the needs in the decision process to modelling objectives and requirements
	SI	Stakeholders express their interests and wishes with respect to objectives of modelling and requirements to accuracy	
STEPs 2, 3, 4 Conceptualise, set up and document model	UM	Update of uncertainty matrix	These steps in the modelling process are driven by the modeller. Stakeholders and water managers follow the modelling process through reports and meetings. The link to the WFD process is ensured by a formalised dialogue in connection with reviews at the end of each step, where decisions on approval of past work and possible adjustments of future project works are made
	DA	Assessment of data uncertainty done by modeller	
	SA	Sensitivity analysis to identify most important parameters for calibration	
	IN-PA	Assessment of uncertainty of model parameter values	
	MCA	Monte Carlo analysis to investigate whether the model results obtained during calibration and validation possibly can be explained by the assessed uncertainty on input data and parameter values	
	QA	Peer review of modelling work done by an external modelling expert	
	EPR	Stakeholder reviews of technical elements with special emphasis on the relevance and quality of the modelling study evaluated on the basis of the knowledge and interests possessed by the stakeholders	
STEP 5 Model application	EE	Expert elicitation on likely elements in scenarios for future developments	The main part of the work in this final step is done by the modeller, but in a close dialogue with stakeholders and the water manager, who carry the results of the modelling study back into the WFD decision process.
	SC	Scenario analysis	
	MCA	Comprehensive Monte Carlo analysis with propagation of uncertainties on data and parameter values to assess uncertainty of model outcome	
	MMS	Formulation of multiple model structures to encapsulate the uncertainty on process equations, hydrogeological interpretations, etc.	
	QA	Peer review of modelling work done by an external modelling expert	
	EPR	Stakeholder reviews of technical elements with special emphasis on the relevance and quality of the scenario analysis and uncertainty assessments	

Table 4 Example of methods selected in Case 2: Design measures – water scarcity/basic modelling

Modelling process			**Link to decision (WFD) process**
Modelling Step (Fig. 3)	**Uncertainty method**	**Content**	
STEP 1 Framing of modelling study	UM	Identification and characterisation of sources of uncertainty used as a basis for prioritising what should be done in the modelling study	Stakeholders and water manager are key players in the WFD process and are continuously involved in this modelling step translating the needs in the decision process to modelling objectives and requirements
STEPs 2, 3, 4 Conceptualise, set up and document model	UM	Update of the uncertainty matrix	These steps in the modelling process are driven by the modeller. Stakeholders and water managers follow the modelling process through reports and meetings. The link to the WFD process is ensured by a formalised dialogue in connection with reviews at the end of each step, where decisions on approval of past work and possible adjustments of future project works are made
	DA	Assessment of data uncertainty done by modeller	
	SA	Sensitivity analysis to investigate whether the model results obtained during calibration and validation possibly can be explained by reasonable uncertainty assumptions on input data and parameter values	
	QA	Peer review of modelling work done by an external modelling expert	
STEP 5 Model application	SC	Scenario analysis	The main part of the work in this final step is done by the modeller, but in a close dialogue with stakeholders and the water manager, who carry the results of the modelling study back into the WFD decision process.
	SA	Sensitivity analysis to investigate the robustness of the model outputs to uncertainty in input data and model parameters	
	QA	Peer review of modelling work done by an external modelling expert	

Table 5 Example of methods selected in Case 3: Implementation – real-time forecasting (of Case 2)

Modelling process			**Link to decision (WFD) process**
Modelling Step (Fig. 3)	**Uncertainty method**	**Content**	
STEP 1 Framing of modelling study	UM	Identification and characterisation of sources of uncertainty used as a basis for prioritising what should be done in the modelling study	Stakeholders and water manager are key players in the WFD process and are continuously involved in this modelling step translating the needs in the decision process to modelling objectives and requirements
STEPs 2, 3, 4 Conceptualise, set up and document model	UM	Update of the uncertainty matrix	These steps in the modelling process are driven by the modeller. Stakeholders and water managers follow the modelling process through reports and meetings. The link to the WFD process is ensured by a formalised dialogue in connection with reviews at the end of each step, where decisions on approval of past work and possible adjustments of future project works are made
	DA	Assessment of data uncertainty done by modeller	
	SA	Sensitivity analysis to investigate whether the model results obtained during calibration and validation of the new model elements (new on-line stations, data assimilation algorithm) possibly can be explained by reasonable uncertainty assumptions on input data and parameter values	
	QA	Peer review of modelling work done by an external modelling expert	
STEP 5 Model application	DA	Assessment of data uncertainty done by modeller	The main part of the work in this final step is done by the modeller, but in a close dialogue with stakeholders and the water manager, who carry the results of the modelling study back into the WFD decision process.
	MCA	Assessment of uncertainty of forecasted flows/water quality. This may for instance be done by Ensemble Kalman Filtering, which includes Monte Carlo techniques	
	QA	Peer review of modelling work done by an external modelling expert	

Table 6 Example of methods selected in Case 4: Evaluation – post project appraisal (of Case 1)

Modelling process			**Link to decision (WFD) process**
Modelling Step (Fig. 3)	**Uncertainty method**	**Content**	
STEP 1 Framing of modelling study	UM	Identification and characterisation of sources of uncertainty used as a basis for prioritising what should be done in the modelling study	Stakeholders and water manager are key players in the WFD process and are continuously involved in this modelling step translating the needs in the decision process to modelling objectives and requirements
STEPs 2, 3, 4 Conceptualise, set up and document model			These steps are not performed in this case, because the model from Case 1 is re-used.
STEP 5 Model application	DA	Assessment of data uncertainty done by modeller	The main part of the work in this final step is done by the modeller, but in a close dialogue with stakeholders and the water manager, who carry the results of the modelling study back into the WFD decision process.
	SA	Sensitivity analysis to investigate the robustness of the model outputs to uncertainty in input data and model parameters	
	QA	Peer review of modelling work done by an external modelling expert	
	EPR	Stakeholder reviews of technical elements with special emphasis on the relevance and quality of the scenario analysis and uncertainty assessments	

7. References

The references below do not include the references in 14 tables in Chapter 4.

Aller LT, Bennet T, Lehr JH and Petty RJ. DRASTIC: A Standardized System for Evaluating Ground Water Pollution Potential Using Hydrogeologic Setting, U.S. EPA Robert S. Kerr Environmental Research Laboratory, EPA/600/287/035, Ada, OK; 1987.

Beck MB (1987) Water Quality Modelling: A Review of the Analysis of Uncertainty. Water Resources Research, 23(8), 1393-1442.

Blind M and de Blois C (2003) The Water Framework Directive and its Guidance Documents – Review of data aspects. Chapter 5 in Refsgaard JC and Nilsson B (Eds.) Requirements Report. Geological Survey of Denmark and Greenland, Copenhagen. Available on http://www.harmonirib.com.

Brown JD (2004) Knowledge, uncertainty and physical geography: towards the development of methodologies for questioning belief. Transactions of the Institute of British Geographers. *Accepted.*

Copenhagen County (2000) Pilot project on establishment of methodology for zonation of groundwater vulnerability. Proceedings from seminar on groundwater zonation, November 7, 2000. County of Copenhagen. (In Danish).

EC (2004a) Common Implementation Strategy for the Water Framework Directive (2000/60/EC) Guidance Document No 11, Planning Processes. European Communities. Available on http://forum.europa.eu.int/Public/irc/env/wfd/library?l=/framework_directive/guidance_documents/0publishedsguidancesdocu&vm=detailed&sb=Title

EC (2004b) Common Implementation Strategy for the Water Framework Directive (2000/60/EC) Guidance Document No 3, pressures and impactes, IMPRESS. Available on http://forum.europa.eu.int/Public/irc/env/wfd/library?l=/framework_directive/guidance_documents/0publishedsguidancesdocu&vm=detailed&sb=Title

Harremoës P, Gee D, MacGarvin M, Stirling A, Keys J, Wynne B, and Guedes Vaz S (eds.) (2001) Late lessons from early warnings: the precautionary principle1896–2000, Environmental issue report no. 22. Copenhagen. European Environment Agency.

Funtowicz SO and Ravetz J (1990) Uncertainty and Quality in Science for Policy. Kluwer Academic Publishers, Dordrecht.

Healy S (1999) Extended peer communities and the ascendance of post-normal politics. Futures, 31, 655–669.

Klauer B and Brown JD (2003) Conceptualising imperfect knowledge in public decision making: ignorance, uncertainty, error and ‘risk situations’. Environmental Research, Engineering and Management.

Lørup JK Refsgaard JC and Mazvimavi D (1998) Assessing the effect of land use change on catchment runoff by combined use of statistical tests and hydrological modelling: Case studies from Zimbabwe. Journal of Hydrology, 205, 147-163.

Refsgaard JC, Alley WM and Vuglinsky VS (1989) Methodology for Distinguishing Between Man's Influence and Climatic Effects on the Hydrological Cycle. IHP-III Project 6.3. Technical Documents in Hydrology, UNESCO.

Refsgaard JC, Hansen LK and Vahman M (2000) Groundwater zonation in Copenhagen County – Intercomparision of thematic results from different consultants. Seminar on groundwater zonation, November 7, 2000. County of Copenhagen. (In Danish).

Refsgaard JC, Henriksen HJ, Harrar WG, Scholten H and Kassahun A (2004) Quality Assurance in Model Based Water Management – Review of Existing Practise and Outline of new Approaches. Environmental Modelling & Software, *Accepted.*

Resnik DB (2003) Is the precautionary principle unscientific? Studies in History and Philosophy of Biological and Biomedical Sciences, 34, 329–344.

Rio Declaration on Environment and Development, 1992. In Brown Weiss, Edith et al. (1999), International Environmental Law: Basic Instruments and References, 1992–1999. Ardsley NY: Transnational Press.

Scholten H, Refsgaard JC and Kassahun A (2004) Structuring Multidisciplinary Knowledge for Model Based Water Management; The HarmoniQuA Approach. In: Pahl C, Schmidt S, Jakeman T. (Eds.), iEMSs 2004 International Congress: "Complexity and Integrated Resources Management". International Environmental Modelling and Software Society, Osnabrück, Germany, June 2004.

Stirling, A, The Precautionary Approach To Risk Appraisal, NWMO Background Paper, Sussex, 2003, 29 pp.

Walker WE, Harremoës P, Rotmans J, Van der Sluijs JP, Van Asselt MBA, Janssen P and Krayer von Krauss MP (2003) Defining Uncertainty A Conceptual Basis for Uncertainty Management in Model-Based Decision Support, Integrated Assessment, 4(1), 5-17.

Weiss C (2003) Expressing scientific uncertainty, Law, Probability and Risk, 2, 25–46.

Weiss C (2003) Scientific Uncertainty and Science Based Precaution. International Environmental Agreements: Politics, Law and Economics, 3, 137-166.

Van der Sluijs JP, Janssen PHM, Petersen AC, Kloprogge P, Risbey JS, Tuinstra W and Ravetz JR (2004) RIVM/MNP Guidance for Uncertainty Assessment and Communication Tool Catalogue for Uncertainty Assessment. Utrecht University. (Downloadable from http://www.nusap.net/sections.php?op=viewarticle&artid=17)