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Complexity and Uncertainty: Rethinking The Modelling Activity

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CHAPTER FOUR

COMPLEXITY AND UNCERTAINTY: RETHINKING THE MODELLING ACTIVITY

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4.1. INTRODUCTION

Complexity and uncertainty have become critical considerations for environmental modelling applications, opening new avenues for the use and development of models. Increasingly models are being recognised as essential tools to learn, communicate, explore and resolve the particulars of complex environmental problems (Sterman, 2002; Van den Belt, 2004). However, this shift in the way in which models have been used has not always been accompanied by a concomitant shift in the way in which models have been conceived and implemented. Too often, models were conceived and built as predictive devices, aimed at capturing single, best, objective explanations. Considerations of uncertainty were often downplayed and even eliminated because it interfered with the modelling goals. This view did not take into account that other uses (see Chapter 2) may require models to be developed differently and thus required different ways for managing uncertainty.

For example, when building a predictive model the major goal is to closely replicate a phenomenon. In this context, uncertainty is considered something undesirable that needs to be eliminated or reduced as much as possible. To this end, there exist several methods and procedures of sensitivity and uncertainty analyses (see Chapter 5) that can be applied to quantify the uncertainty and determine which are the most important factors affecting model results. When a model is developed for exploration the aim is not so much mimicking reality but to elucidate general patterns of system behaviour. In this case, uncertainty can be considered a source of creative thought, and not necessarily something that ought to be avoided. Here, participatory procedures of uncertainty analyses can be used to develop different possible scenarios that allow investigation of alternative views of a system.

Chapter 2 raises this issue of the need to consider model purpose when developing and/or applying a model. Jakeman et al. (2006) list a comprehensive range of modelling purposes and Brugnach and Pahl-Wostl (2007) identify four major ones that are important for understanding and managing complex human environmental systems: prediction, exploratory analysis, communication and learning. Each of these purposes highlights different system characteristics, roles of uncertainty, the properties of the model and its validation. Here, we argue that uncertainty management has no meaning in isolation, but only relative to a particular modelling activity and the purpose for which a model is developed. In light of these concepts, the modelling activity is re-contextualised, from being a process that aims at objectively representing an external reality, to one that can only be defined according to the characteristics of the problem at hand: its level of complexity, the knowledge available, the purpose of the model and the modelling tools used (see also Chapter 2, Jakeman et al., 2006; Brugnach and Pahl-Wostl, 2007).
The purpose of this chapter is to show how these concepts can be made operational. Here, we apply a framework to different examples from various fields, highlighting its benefit and shortcomings. Using these examples, we illustrate the usefulness and importance of a coherent approach in dealing with different kinds of uncertainty. This chapter differs from and is complementary to Chapter 6 which focuses on the role and value that uncertainty has in environmental decision making. The main difference resides in that they investigate the relationship between uncertainty, which may come from models, and decisions, whereas we focus on the modelling process itself and how it is affected by uncertainty.

4.2. Uncertainty: Causes and Manifestations

In the modelling domain, uncertainty is commonly understood as an attribute that must be acknowledged and associated with the quality of the information used to build/run a model (Zimmermann, 2000). However, when modelling a complex system, the quality of information is not the only thing that matters; the modeller’s beliefs and experience also play an important role (Patt, 2007; Brugnach et al., 2006; Refsgaard et al., 2005; Klauser and Brown, 2004; Walker et al., 2003; Van Asselt and Rotmans, 2002; Pahl-Wostl et al., 1998). Even though a model can be based on sound process understanding, many unknowns about the system to be modelled generally remain (Brugnach, 2005). This forces the modeller to make assumptions and take subjective decisions about what and how a problem should be modelled, incorporating uncertainty in this way into the model through various stages of the development.

Here, we define uncertainty as the situation in which there is not a unique and objective understanding of the problem to be modelled.

Even though this situation may be due to deficiencies in information, i.e. inexactness, unreliability and ignorance (Walker et al., 2003), it also arises from the way in which this information is interpreted and framed (Patt, 2007; Dewulf et al., 2005). This means that there are many different sources from which uncertainty originates, and many different ways in which it gets manifested in a model, implying also different ways of dealing with it. This makes managing uncertainty a complex problem in itself, whose analysis and evaluation cannot be considered an external activity carried out after a model is built, but it must be embedded in the modelling process. We identify error in empirical observations, complex dynamics, ambiguity and conflicting knowledge, ignorance and values and beliefs as being the most relevant causes of uncertainty. Furthermore, these causes can affect the data, model structure or model framing.

4.2.1 Causes of uncertainty

*Error in empirical observations* refers to the deviation that exists between the real value of a quantity and the one that is used in the model. This category includes errors in measurements that are used to describe a system, due to failures or limitations
in the instruments or technologies used for measuring, or to the procedures followed.

Complex dynamics refers to the fact that complex systems are open systems whose
behaviour is highly variable in space and time depending on context and history. They may express nonlinear or sometimes chaotic behaviour. Furthermore, these systems are constantly learning, evolving and adapting to new conditions. This variable behaviour makes it difficult to describe and predict system states and processes, showing a high sensitivity to boundary and initial conditions.

Ambiguity and conflicting knowledge refers to the situation in which information
(e.g. linguistic) can be associated with entirely different meanings, or when it can be understood as explaining contradictory facts. The reason may derive from different origins (e.g. different disciplinary fields), or different interpretations (e.g. it means different things to different people).

Ignorance indicates that some aspects of the system (e.g. elements, relationships, sub-systems, present or future states) are not known or ignored, i.e. recognised and total ignorance (Walker et al., 2003) is due to lack of information or to a lack of understanding about the system's behaviour.

Value and beliefs refer to the situation in which the interpretation of the information about the system to be modelled is not objective, but depends on the values and beliefs of the modeller.

4.2.2 Manifestation of uncertainty

Data, parameter values. This is uncertainty associated with the input data or parameter values used in a model.

Structure. This type of uncertainty refers to model structure or process understanding. It points out deficiencies in knowledge or contradicting theories on the behaviour of modell components and their interactions.

Framing. This type of uncertainty refers to the modelling process in which the model is embedded. It reflects the subjectivity incorporated in defining the modelling activity, as filtered through the experience, interest, values and beliefs of the modeller. For example: Why do we choose a specific modelling approach? Why do we consider a particular problem worth modelling?

4.3. A Conceptual Approach to Deal with Uncertainty and Complexity in Modelling

Even though determining how the various causes of uncertainty affect the resulting representation is an important step, this does not suffice to capture the complexity of the situation. During the modelling process the different causes of uncertainty affect the data, structure and framing of the model. How this happens, how relevant this may be regarding the modelling goals and how the situation should be handled, depends entirely on what the goals of the modelling exercise are. In this
regard, uncertainty and its effects cannot be considered in absolute terms, but only relative to the purpose of a particular modelling setup.

The approach presented here is based on the rationale that the purpose for which a model is built has implications for the way in which uncertainties are addressed and included in a model (Brugnach and Pahl-Wostl, 2007). Using this idea as a baseline, a categorisation of models proposed by Brugnach and Pahl-Wostl (2007) is adopted and then used to determine the role and management of uncertainties. Four different purposes are identified: prediction, explanatory analysis, communication and learning. Depending on the purpose the major priorities to address uncertainties are highlighted.

### 4.3 Prediction

In complex, adaptive systems prediction of the trajectories of individual state variables in a specific system is not very meaningful. Models are particularly suited to produce general insights about regularities in system behaviour. Hence, prediction refers here to the ability to foresee properties and relationships at the level of the overall system behaviour as, for example, the effect of increasing diversity on the adaptive capacity of a system or the influence of network structure on the spread of innovation in a social system (e.g. see the review by Levin, 1998; Pahl-Wostl, 1995). Such modelling exercises can generate global insights and support the development of guidelines for integrated system design (e.g. the role of centralised versus de-centralised control in resource management regimes). When models are used for prediction, they are expected to capture the essential characteristics of the modelled system and to produce sufficiently close realisations of future system behaviour in some sense. Among other aspects, modellers should then consider the main uncertainties that could conspire against reasonable outcomes. Then, uncertainties can be reduced and explicitly accounted for in the model results. Measurement errors, input errors and the model structure itself are particularly important sources of uncertainty in predictive models. Uncertainty acknowledgement may result in setting the boundaries at which model results are not valid. Table 4.1 summarises how to address uncertainties when the modelling purpose is prediction.

### 4.3.2 Exploratory analysis

When models are used for exploratory analysis, their emphasis is placed not so much on predicting future states or mimicking reality, but on observing possible system development trajectories and detecting extreme behaviour patterns or drastic changes. Since we are dealing with complex systems it may not be possible to attach a given probability to a certain outcome, but simply to provide evidence that it is possible and what might be the implications. This can be very useful in participatory settings given the diversity that characterises human societies and thus also the range of plausible scenarios that may be envisaged (Pahl-Wostl, in press; Van der Heijden, 1996). In these cases, uncertainties do not necessarily need to be eliminated, but included to produce alternative scenarios that can be explored.
Table 4.1  Strategies to address uncertainties when the model purpose is prediction

<table>
<thead>
<tr>
<th>Errors in empirical observations</th>
<th>Uncertainty bounds in parameter values to be able to define robustness of model simulations given an uncertain database</th>
<th>Complex Systematic variation of structural dimensions such as heterogeneity, linkage between elements, individual properties to explore origins of variability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ambiguity and conflicting knowledge</td>
<td>If appropriate choose more than one interpretation</td>
<td>Choose several model structures</td>
</tr>
<tr>
<td>Ignorance</td>
<td>Test sensitivity to ignorance in knowledge</td>
<td></td>
</tr>
<tr>
<td>Beliefs and values</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Ignorance can be turned into creativity, and beliefs and values can be used to define internally consistent pathways. Table 4.2 shows some suggestions on how to deal with uncertainties when the modelling purpose is exploratory analysis.

4.3.3 Communication

Models may serve the purpose of communicating knowledge about complex systems to decision makers, stakeholder groups and/or the general public. In this case models can be seen as educational tools, or as ways to challenge inadequate beliefs or assumptions. For example, these models may help to build understanding of the implications of positive feedback cycles or abrupt changes brought about by threshold effects (Carpenter et al., 1999; Schlumpf et al., 2001). Uncertainty is part of the model structure itself and serves to indicate knowledge deficiencies, and the presence of values embedded in the model. Thus, uncertainty needs to be explicitly included in model communication. Table 4.3 shows some ways to handle uncertainties in these cases.
### Table 4.2  Strategies to address uncertainties when the model purpose is exploratory analysis

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Structure</th>
<th>Framing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Errors in empirical observations</td>
<td>Include average</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Complex dynamics</td>
<td></td>
<td>Source of innovation</td>
<td></td>
</tr>
<tr>
<td>Ambiguity and conflicting knowledge</td>
<td>Development of more than one scenario in participatory setting</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ignorance</td>
<td>Test sensitivity to ignorance in knowledge</td>
<td></td>
<td>Creative input from participatory process</td>
</tr>
<tr>
<td>Beliefs and values</td>
<td>Base for the development of different model structures – correspondence with framing important</td>
<td>Base for the development of different consistent scenarios in terms of coherence in perspective – should be made explicit</td>
<td></td>
</tr>
</tbody>
</table>

### Table 4.3  Strategies to address uncertainties when the model purpose is communication

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Structure</th>
<th>Framing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Errors in empirical observations</td>
<td>Explain origin</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Complex dynamics</td>
<td>Educational implementation of implications of different model structures with reasoning why this is possible</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ambiguity and conflicting knowledge</td>
<td>Interactive implementation of different interpretations</td>
<td>Illustrate role of framing for choosing one of several possible interpretations</td>
<td></td>
</tr>
<tr>
<td>Ignorance</td>
<td>Implement different model structures derived from different beliefs and values</td>
<td>Address role of science and expert knowledge in providing “truths”</td>
<td></td>
</tr>
<tr>
<td>Beliefs and values</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 4.4 Strategies to address uncertainties when the model purpose is learning

<table>
<thead>
<tr>
<th>Errors in empirical observations</th>
<th>Complex dynamics</th>
<th>Ambiguity and conflicting knowledge</th>
<th>Ignorance</th>
<th>Beliefs and values</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Participatory model development to develop more than one structural implementation</td>
<td>Elicit cognitive maps and framing and make them explicit in a group</td>
<td>Include knowledge from participatory settings</td>
<td>Elicit role of beliefs and values influencing frames and make this explicit with interactive methods</td>
</tr>
</tbody>
</table>

4.3.4 Learning

Learning as a modelling purpose is used in the sense of utilising, not just the model as a final product, but the model building process itself as a means of understanding the system. Here the stakeholders are involved in the model construction in a process described as social learning. The model is part of the system it intends to represent (Pahl-Wostl, 2002). Model builders or “experts” are not external observers as in previous model purposes, but facilitators of a participatory process (Vennix, 1996; Checkland, 1999; Sterman, 2000; Pahl-Wostl, 2007). Modelling as a process and its product, the model, are both used as an opportunity to exchange ideas and knowledge, using participatory approaches to uncover mental models and frames (Hare and Pahl-Wostl, 2002; Vennix, 1996). Table 4.4 summarises ways to address uncertainties when the modelling purpose is learning. The shaded areas are of particular importance because they refer to uncertainties about the overall framing of the model and the modelling process. Frames are a key element of social learning processes (Bouwen and Taillieu, 2004; Pahl-Wostl and Hare, 2004).
4.4. **EXAMPLES**

4.4.1 **Prediction: model use in the development of the US clean air mercury rule**

4.4.1.1 **Model description and purpose**

The US Environmental Protection Agency issued the Clean Air Mercury Rule (CAMR) on March 15, 2005 after more than a decade of discussion to permanently cap and reduce mercury emissions from coal-fired power plants. Federal agencies in the United States are required to prepare regulatory impact analyses (RIAs) for every major regulatory action they undertake. The use of models is a crucial component in conducting these complex regulatory impact analyses.

In the example considered, the development of the CAMR RIA, a chain of models was applied to assess the impacts of proposed regulation of mercury on the dispersion, deposition and uptake of mercury, its associated health effects and valuation (US EPA, 2005). The analysis presented here focuses only on one step within this chain of models, namely the Mercury Maps (MMaps) approach, used to estimate how changes in atmospheric deposition translate into changes in methylmercury concentration in fish tissue. The model is based on the assumption of a linear, steady-state relationship between changes in concentrations of methylmercury in fish and changes in atmospheric deposition of mercury and assumes that atmospheric deposition is the principal source of mercury to waterbodies.

4.4.1.2 **Causes and manifestations of uncertainty and how they were handled**

As shown in the RIA, the use of the MMaps model in the CAMR was subject to several sources of uncertainty. Uncertainties manifested in the data and model structure were the ones that received most attention and were explicitly noted in the RIA.

*Error in empirical observations.* The major causes of uncertainty considered in relation with model data were errors and gaps of knowledge in both the model parameters and input data. The MMaps model relies on records of fish tissue mercury concentrations from the Fish Tissue Database of the National Listing of Fish and Wildlife Advisories. The fish tissue data may not represent average, steady-state concentrations. In estimating the changes in freshwater fish methyl-mercury concentrations resulting from changes in mercury deposition, uncertainty was reduced by supplementing site-specific data with knowledge from the scientific literature.

*Complex dynamics.* The processes of transportation, methylation and bioaccumulation of mercury in watersheds are complex and are influenced by the characteristics of the watersheds. The simple relationship assumed in the MMaps model does not reflect these complex dynamics. To supplement the MMaps model, examples of five case studies of a range of ecosystem types were used to explore the range in temporal responses of different ecosystems following reductions in atmospheric mercury emissions by coupling outputs from atmospheric fate and transport models with a set of watershed and water body models that are calibrated with site-specific...
monitoring data from the ecosystems in the case studies. This approach helped to cope with the structural variability of ecosystems and with uncertainty within the MMaps approach by providing a semi-quantitative uncertainty envelope for temporal responses of the various ecosystems.

Ambiguity and conflicting knowledge. Another source of uncertainty in the MMaps forecasts are the atmospheric deposition rates used to forecast changes in fish mercury concentrations. Comparison between the outputs of air dispersion models and deposition rates observed at selected sites revealed that the model outputs were somewhat less than those observed, which may result in an overestimate of the relative change in atmospheric deposition and changes in fish mercury concentration by the MMaps model. Incomplete and conflicting knowledge on model process description exist and has been accounted for by including case studies for in-situ observations and data from the literature.

Ignorance. The US EPA also noted that epistemic uncertainty about key process variables, such as the functional form of equations used to quantify methylation rate constants, is a major contributor to overall uncertainty that cannot be quantified at this time. Ignorance on model structure was thus considered, but could not be quantified. This cause of uncertainty was handled by five case studies which were set up to explore the range of model responses in different ecosystems. The results were used to estimate confidence bounds for model outputs.

4.4.1.3 Discussion
This example illustrates the complexities involved in the use of models for regulatory purposes especially those of a national nature. While obliged to assess the impacts of regulation of mercury, the US EPA is aware of the difficulties of predicting changes in complex systems. Hence the RIA for the CAMR clearly outlines the assumptions, limitations and uncertainties associated with the models used. When the US EPA concurs that “observed datasets are always incomplete and uncertain and represent only a snapshot of the real system” (US EPA, 2005) it acknowledges uncertainties rooted in errors and variability of data used. It further recognises that “irrespective of the quality of their process algorithms, none of the models can be considered a priori predictive tools” (US EPA, 2005), i.e. uncertainty related to the structure of models used is acknowledged. Given the uncertainties associated with the model used in this regulation development and the evolving and complex nature of the science of mercury, the US EPA views this study as part of an iterative modelling exercise. It intends to conduct a post-auditing of the models used by monitoring the impact of the adoption of CAMR on mercury deposition and fish tissue, and to continue to evaluate and refine, as necessary, mercury estimation tools and models.

While the US EPA attempted to qualify the results by analysing the sources of uncertainty in the analysis, the use of the framework proposed in this paper may help to simplify the communication of the different sources of uncertainties in the modelling exercise and allow comparison between different models which may be used. However, it must be made clear that not all aspects of the framework are applicable to all instances of model use. In particular, in this example, the sources of uncertainty due to values and beliefs were not relevant given the scope of the analy-
sis. The modelling exercise was used to analyse the impacts of the implementation of a chosen policy. The framing of the problem (need to reduce mercury emissions from coal fired power plants) involved making a policy decision to assess the impacts of a specific type of regulatory approach (cap and trade) on specific end points of interest. In this case the end points are the IQ of children born to women who consume fish, which the regulators considered to be the most sensitive segment of the population, as well as the economic impact of the regulation. While this assumption is made clear in the RIA, the use of the framework to highlight this framing of the modelling exercise may further clarify the decision-making process used to select this particular approach. The issue here is the decision making behind the selection of a particular policy, not just the modelling used to evaluate the impacts of this policy.

4.4.2 Exploratory analysis: microeconomic modelling of land use change in a coastal zone area

4.4.2.1 Model description and purpose
This example presents a spatially-explicit, agent-based model which simulates urban development in the coastal zone area in the Netherlands (see Filatova and van der Veen, 2006 for a detailed description). The modelling is focused on individual stakeholder behaviour. Perception of risk of flooding is introduced in the micro model of individual location choice. The purpose of this model is to explore possible outcomes of coastal policy decisions on land use patterns. It investigates how individual location decisions, influenced by spatial planning and coastal management policies, lead to the emergence of macroeconomic phenomena and affect risk of flood in the area.

4.4.2.2 Causes and manifestations of uncertainty and how they were handled
*Complex dynamics.* This cause of uncertainty was mainly associated with the description of stakeholder behaviour, a process that evolves and adapts to new conditions resulting in complex social dynamics. It was also associated with the representation of the natural and socioeconomic systems, through the consideration of climate change factors (sea level rise or erosion), economic shocks and policy changes. This cause of uncertainty manifested itself in model data, structure and framing. It was managed by constantly updating and refining the data using the latest information about the beliefs, values and intentions of human agents. At the structural level, it was handled by including, in the description of the socioeconomic system, behavioural models for the micro and macro scales. In the case of natural systems, different potential forcing factors were hypothesised (such as sea level rise and erosion) and they were parameterised in the model. When associated with model framing, this cause of uncertainty constituted a source of innovation, since it forced the modeller to look at the research problem from different conceptual points of view enriching their vision of the problem and the results obtained.

*Ambiguity and conflicting knowledge.* One cause of ambiguity and conflicting knowledge was the discrepancy about the future developments of the system (fu-
ture land use, coastal management decisions, people's perception of risk of flood, etc.), which manifested in the model structure. To that end, the development of more than one scenario in the participatory setting helped determine potential future developments. Another issue was the variety of, and some times contradictory, views that different disciplines and theories held on the system. Such was the case of the theoretical approach chosen (e.g. game theory, spatial econometrics, prospect theory of decisions under risk). This cause of uncertainty directly affected model framing, discussions with specialists who use different modelling tools applicable to the problem, as well as discussions within trans-disciplinary research groups that were carried out to deal with this situation.

**Ignorance.** The lack of empirical information about profits and investments of the firms and their levels of risk aversion constituted a cause of uncertainty that directly affected the data. Further on, lack of microeconomic information about some elements of the system and their interactions, such as households and firms and the form of their goal functions, affected the structure of the model. When dealing with a deficit of information in the data, sensitivity analyses tests were carried out, to determine the importance of the situation. To deal with the lack of information in model structure, a review of the existing knowledge about the system was undertaken at an early stage of model construction. Key processes were defined in the context of the case-study problem. Discussions with stakeholders through role playing games were carried out to elicit knowledge about the problem.

**Beliefs and values.** This cause of uncertainty played an important role in the interpretation of factors, such as the influence that economic agents may have in making land use decisions in the coastal area, the perception of risk of flooding, or risk communication. It was the modeller who, based on their beliefs and values about the problem, re-interpreted these factors affecting the structure and framing of the model. To cope with this situation, different model structures were implemented which were based on alternative socioeconomic concepts of location behaviour. When dealing with framing issues, the exploration of implications of a range of plausible assumptions and differences in risk perception served as a base to structure a risk dialogue.

### 4.4.2.3 Discussion

The main cause of uncertainty in this model is associated with the dynamics of complex adaptive systems. This issue was addressed by investigating the system at different scales. In particular, emergent macro phenomena, such as land use and prices on the land market, were derived from simulating the interactions of individual land users. The current framework was useful to identify the main sources of uncertainty and possible ways to handle them in exploratory models. This case study gives a sense of how the proposed framework can be applied, but the particular strategies of addressing uncertainty might vary with the specific case-studies. In general, the revealed causes of uncertainty might be used to run alternative scenarios and to observe certain dynamics of the whole system in these cases (for example, a sea level rise scenario or an increase in the perception of the flooding risk scenario).
4.4.3 Communication: modelling water quality at different scales and different levels of complexity

4.4.3.1 Model description and purpose
In this example a water quality model is applied to two sections of the Saale River in Germany (see Lindenschmidt, 2006a, 2006b, for more detailed information). Different complexity levels are used to provide insights about the applicability of the model in simulating water quality at two different spatial and temporal scales (90 km and daily time steps compared to 2 km and hourly time steps). The purpose of the modelling exercise sketched here is to communicate the relationship of scale and level of complexity chosen in modelling water quality. Its target audience will mainly be within the scientific community.

The two most important constituents representing water quality here are suspended sediments and zinc. The model simulates the transport of particulate and dissolved zinc, a mass balance for all materials entering and leaving the system, sedimentation, resuspension, sorption and diffusion from bottom sediments. The most sensitive process for zinc transport and fate is sorption of its dissolved fraction to suspended particulate matter (Lindenschmidt et al., 2006). However, modelling this process is not a straightforward issue. While there exists a widely shared agreement and little doubt about the importance of this process, there are strong controversies about the level of complexity at which sorption should be modelled, as well as how it should be modelled.

By comparing the modelling results from two different scales, in which different levels of complexity for the sorption process were used, it was shown that the choice of a level of complexity of a model structure cannot be made independent from the scale to which the model will be applied. On the smaller scale, coupling a geochemical model to the modelling system to include substance turnover in the bottom sediments is essential, which is not the case on the larger scale. Comparing complexities and scales allowed a useful communication of the uncertainty, in particular the importance of sediment “memory” in the transport of metals in the river system.

4.4.3.2 Causes and manifestations of uncertainty and how they were handled

Error in empirical observations and complex dynamics. The largest variation in the input data was found in the little amount of sediment coring data that was available, which also showed a broad range of concentrations. Given the paucity of data available, it is difficult to distinguish errors in measurement from natural variability in bottom sediments. To deal with this situation, it was checked whether simulation outcomes are sensitive to values of parameters derived from this data.

Ambiguity and conflicting knowledge. For the sorption of zinc’s dissolved fraction to particular matter, several process descriptions of varying complexity exist. This cause of uncertainty manifested in the model structure and was handled by implementing different process descriptions of varying complexity at different scales.

Ignorance. Lack of knowledge in the transport and turnover processes in the bottom sediments and the interaction of substances between these sediments and the overlying water column became quite evident when modelling sediment and
heavy metal transport for the small-scale study. This cause of uncertainty affected model data, structure and framing. Increasing complexity for the smaller scale model required additional data sampling, especially of the bottom sediments. To cope with this problem, it was possible to set reasonable values for the initial concentrations in the water and bottom sediments coupled to a geochemical model. With respect to model framing, it was realised that for applications at the smaller scale a geochemical model is needed for the bottom sediment component of the modelling system.

Beliefs and values. Modelling water quality was framed based on the belief that the most important constituents are suspended sediments and zinc; and that sorption of zinc’s dissolved fraction to particulate matter is the most sensitive process. This cause manifested in the framing of the model. Literature on the topic was consulted, indicating that the problem was framed in a sound way.

4.4.3.3 Discussion
The purpose of the modelling exercise sketched here is to communicate the relationship of scale and level of complexity chosen in modelling water quality. Its target audience will mainly be within the scientific community. The purpose of this case deviates slightly from the notion of “communication” as introduced earlier in the chapter, assuming the models are being used for communication of the different viewpoints and opinions of the various interest groups (in this case scientists). Nevertheless, the example highlights the importance of explicitly communicating the scientific uncertainty associated with the scale and level of complexity within the scientific community. To illustrate and communicate implications of this uncertainty, various possible implementations were realised and compared. The application of the framework showed that it might be difficult to distinguish causes of uncertainty manifesting themselves in the same way in a model. In this example, data used for parameter estimation showed high variation; it could not be identified whether this variation was due to natural variability or due to errors in measurement.

4.4.4 Learning: modelling for strategic river planning in the Maas, the Netherlands
4.4.4.1 Model description and purpose
River management projects often involve a multitude of actors and stakeholders and a variety of interests to be taken into account (e.g. Clark and Richards, 2002; Ward et al., 2006). Particularly in the early phases of such a project, when the management alternatives are still numerous, a ‘learning’ model can be beneficial to help river managers and policy makers in understanding one another and the system. From recent practise we can begin to appreciate how to approach the utilisation of such learning models. The Integrated Explorative Study on the Maas (IVM) is an example of a project in which numerous management options were evaluated using a model during stakeholder workshops. From this project we could derive a number of uncertainty elements in situations where stakeholders and modellers were learning from one other. In the workshops within the IVM framework the Planning Kit Maas (Dutch: Blokkendoos Maas) was used. One of the purposes of
this model was to understand how the system works, and which effects different
management alternatives have on the system. Simultaneously, we aimed to learn
from this exchange between model and stakeholders for the development of a new
river model.

4.4.4.2 Causes and manifestations of uncertainty and how they were
handled

Complex dynamics. In the Planning Kit Maas, margins for uncertainty due to natural
variability were indicated. This was much to the discomfort of some of the present
decision makers, because it gave them a feeling of ’inaccuracy.’ Specifically, they feared
that finding local support for measures would be hard. This cause of uncertainty
manifested in model structure. It served to increase the knowledge of the decision
makers by involving them in a learning process during model construction. This
led to more confidence and support in the eventual choice process.

Ambiguity and conflicting knowledge. Regardless of the calculations made, the effect
of some of the proposed measures remained uncertain. Inhabitants of the area for
instance claimed that the effect of some measures in the Grensmaas would be much
lower than that calculated due to local gravel soils. Disclosure of this type of local
knowledge helped the experts in making more accurate predictions of measured
effects. This is a clear example of the mutual learning that can be established during
workshops. This cause of uncertainty manifested in model framing, and could be
addressed using a model which allows iteration and which enables working with
ranges of variables. A promising approach is the fuzzy set theory, in which ranges
of variable values and linguistic knowledge rules can be registered (Janssen et al.,
2006).

Beliefs and values. The main constraint of the project, being the preservation of
current safety levels, was disputed. However, the effects of a different choice of safety
level were not clear either. There clearly was a difficulty in framing the problem due
to different beliefs and values. Hence incorporation of the people’s thoughts and
knowledge on this aspect clarified the constraints of the project and the possibilities
to widen these. The work sessions in this project provided a good ‘tool’ to elicit
and discuss such knowledge. Specifically, ex ante discussion of the beliefs and values
led to a consensus before proceeding to the next step in the process. This cause
of uncertainty was manifested in the model framing. Open discussion, and possibly
the use of mind mapping, were the suggested approaches for dealing with it.

4.4.4.3 Discussion

The presented framework helps identify possible relevant causes of uncertainties
and makes appropriate, yet rather abstract, suggestions on how to deal with these
uncertainties. It is doubtful whether the framework would allow more concrete
guidelines, because it might reduce its applicability since every situation demands
a particular implementation. The causes of uncertainties suggested by the frame-
work, as the most relevant in learning models, were indeed the ones emerging in
the example. Moreover, applying the framework brought into attention the many
difficulties associated with the issue of problem framing, suggesting that the mod-
elling work may still not be suitable for developing a predictive model.
On the other hand, if all relevant stakeholders would have agreed on framing and structure before the modelling exercise was undertaken, it would not have been necessary to develop a learning model. In the case addressed, it was clear that a learning model was much needed, since there was no common understanding about the system. Hence, a learning model can help to achieve a common understanding about a problem, to then proceed (if necessary) with the development of a different type of model, built for a different purpose and conditions.

4.5. CONCLUSIONS

In the presence of complexity, uncertainty is recognised as an intrinsic and unavoidable component of modelling. To deal with uncertainty it is not only necessary to know from where the uncertainty stems and how it is manifested, but also to consider it in the context of the purpose for which a model is built. Different modelling purposes highlight different modelling characteristics and ways in which uncertainties should be regarded and treated and lead to an improved understanding of the concept. The different purposes are not mutually exclusive when models are used in dealing with understanding and managing environmental problems. However, it is a real challenge and a responsible task of the modeller to make explicit and eventually combine different purposes in a scientifically credible and transparent way and to choose, design and apply the model according to the purpose it is supposed to serve.

4.5.1 Models for prediction purposes

Environmental models are used to support decision making by operational agencies. This is accomplished by selecting appropriate models for a particular task, and subsequently applying them for calculation of the effects of relevant measures upon which the decision makers can base their decision strategy. In this context it is important for the decision maker to be aware of uncertainties associated with the results on which decisions are based. A predictive model is assumed to be valid within the spatial and temporal domain for which the model has been calibrated and validated. For the model to be valid outside this domain, it must be assumed that the conceptual basis is valid. Hence, using models in predictive mode with limited knowledge of model structure is fraught with substantial uncertainty (Refsgaard et al., 2006) which must be reduced or at least be known in order to be useful for supporting policy making. In the case where ambiguity and/or conflicting knowledge is present several model structures can be selected for modelling, and sensitivity to model structure on the consequences for policy making can be assessed. The role of uncertainty in predictive modelling as a result of incomplete knowledge of the system under observation is illustrated by an example from the US EPA. In this example uncertainty related to model structure is addressed, where ignorance on this structure necessitated use of a multiple model framework for resolving the uncertainty due to the model concept. Thus, when models are used for prediction
purposes, uncertainties ought to be explicitly recognised and their effect evaluated as they are propagated into the model predictions affecting the validity of the results. Instead of stretching the boundaries of using models for prediction too far, it may in some cases be more appropriate to explicitly use models for exploratory analysis if warranted by the knowledge base and the complexity of the system under investigation.

4.5.2 Models for exploratory purposes
Models used for exploratory purposes support the mapping of a whole range of possible development pathways of the system under investigation. Such activities can inform policy development and implementation processes about potential risks as well as potential opportunities and the conditions under which certain outcomes are most likely to occur. Thus, when models are used for exploration, uncertainty may be regarded as a source of innovation. Participatory processes contribute to the acknowledgement of multiple views on incomplete knowledge and using models for exploratory analysis is then useful for testing of sensitivity resulting from uncertain model input information. This is demonstrated by the example of micro-economic modelling of land use change in a coastal zone area in the Netherlands. A model is used to explore how the outcomes of policy making may affect land use patterns and addresses ambiguity and conflicting knowledge in the structure of the model, including uncertainty in beliefs and values of stakeholders.

4.5.3 Models for communication purposes
In models for communication purposes, uncertainty is generally implemented in the model structure and framing. Hence, each different theory on the modelled system can be analysed by varying the model structure. These models enable comparison of several theories and the impact of these theories on model outcome. Hence, this approach could be considered as a specific type of sensitivity analysis which is not varying model parameters but model structure. This implementation of uncertainty is indispensable for communicative models since it allows bridging the gap between different stakeholder beliefs. This was illustrated in a water quality model applied on two sections of the River Saale in Germany. Different model structures were created to compare the impact of complexities and scales on the performance of zinc sorption modelling. Implementing uncertainty in the model structure and framing could elucidate the appropriate scale and complexity for modelling this sorption process despite the persisting ambiguity and conflicting knowledge on this issue.

4.5.4 Models for learning purposes
When the model purpose is learning, stakeholders and model builders should both be able to learn from the model building process. Both the model and the model building process are opportunities to exchange ideas and knowledge, to understand and respect alternative views and to become more explicit and reflect on one's
own perceptions. Models are thought to be a device to learn about a particular phenomenon, and in that case uncertainty can highlight different viewpoints and opinions. Hence, uncertainty for this model purpose should be implemented in the model structure and framing. This should lead to flexible models which can deal with various insights. To generate such models, a fuzzy logic approach was applied in the presented example. Stakeholder knowledge and insights are often formulated in qualitative or linguistic terms. The fuzzy method can implement these knowledge formulations and hence it allows construction of flexible models. Since the method is straightforward and easily interpretable, it structures knowledge and enhances learning of both stakeholders and model builders.

The approach discussed here provides general guidance to deal with the various sources of uncertainties that relate to the data, structure and framing of a model, taking into account that model purpose is what determines the way in which uncertainty should be conceptualised. The examples showed that identification of the model purpose is an essential starting point for determining how uncertainty is handled. However, the presented framework should be applied with caution and in a flexible way. Specifically, each modelling case objective must be carefully analysed as to how uncertainty related to modelling the case can support the modelling process in a meaningful way. In this chapter a process is presented to facilitate matching the uncertainty related to specific human-environment model cases at an appropriate temporal and spatial scale to the purpose for which the models are built. Hence, this paper provides a standardised framework for reflection on how different models support dealing with uncertainty depending on the purpose of the modelling work. This could also assist modellers in identifying and implementing uncertainties in the development of models.

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