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Environmental Policy Aid Under Uncertainty

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CHAPTER SIX

Environmental Policy Aid Under Uncertainty

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Contents

6.1. Introduction

Recent emphasis on uncertainty in environmental decision making reflects numerous changes in environmental science and policy making over the past few decades. Firstly, environmental policy problems increasingly involve large, interconnected and complex social choices. For example, climate change, ozone depletion, biodiversity loss, genetically-engineered crops, environment-related diseases and health risks involve large scale, long-term impacts, whose precise causes and consequences are often poorly understood. Given these uncertainties and the risk of irreversible environmental changes, different perspectives about the nature, policy implications, or even the existence of a problem, are inevitable (Rittel and Webber, 1973; Sarewitz, 2004).

Secondly, as a consequence, environmental policies have shifted to more precautionary (Tallacchini, 2005; van Asselt and Vos, 2005), non-structural (Faisal et al., 1999; Lu et al., 2001b) and demand-led approaches (Mohamed and Savenije, 2000).

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Thirdly, and also as a consequence of these new environmental problems, the process of policy making has increasingly favoured interdisciplinary, pluralistic and inclusive methodologies (Meppem, 2000; Shi, 2004), with scientists participating alongside other stakeholders in deliberative decision making (Renn, 2006), participatory assessment (Argent and Grayson, 2003) or group model building (Vennix, 1999).

These transformations are intertwined with a changing relationship between science and society, favouring greater openness and a dialogue between all knowledgeable parties (Fairhead and Scoones, 2005), often laying emphasis on multiple methods and perspectives in tackling these problems.

In this context, 'uncertainty' has become increasingly important in environmental science and policy making. One reason is that policy outcomes are only partly predictable and their associated uncertainties are large enough to sustain persistent conflicts and indecision. Related to this is the occasional tendency for scientists to conceal uncertainty for fear of diminishing their professional credibility and encouraging indecision (Bradshaw and Borchers, 2000). It is also because uncertainty provides a political resource, which can sustain personal beliefs and self-interest (Stirling, 2006; Weiss, 2002). Uncertainty poses various philosophical challenges regarding the origin, nature and value of knowledge, ethical challenges regarding acceptable levels of knowledge and risk, its distribution, and who has the mandate to decide, and political challenges regarding how to act when faced with substantial uncertainty. It also poses several practical challenges, in terms of identifying and describing (quantifying, qualifying) uncertainties, propagating them through decisions and communicating the results of an uncertainty analysis.

Recent emphasis on uncertainty within science has led to many perspectives on how risk and uncertainty should be defined and tackled (see for a review Brown, 2004; Brown et al., 2005; Refsgaard et al., 2005; Rotmans and van Asselt, 2001a; Rotmans and van Asselt, 2001b; van der Sluijs, 2007; Walker et al., 2003). Indeed, there is little consensus on how uncertainty should be defined, and no consistent, interdisciplinary framework in which to address it (although some attempts have been made, such as Walker et al., 2003). This reflects the complex nature of uncertainty and the diversity of disciplines in which it is a topic of research.

Harmonising these different concepts is not simply an issue of accepting terminology, but an issue of exploring the diversity of words and meanings associated with uncertainty as an "umbrella concept" (e.g. including terms such as imperfect, indeterminate, indecisive, ambiguous, imprecise, inaccurate, vague and ignorant). The differences between competing understandings of uncertainty (e.g. as a feature of real world systems versus a state of mind or some combination of the two) are deeply rooted in the methodological contexts in which uncertainty is conceptualised and debated. For example, while mathematicians agree on the basic principles of conditional probability, they may disagree on the range of applications in which Bayes' rule (of conditional probabilities) is appropriate, due to important philosophical differences on the nature of probability. In the context of this paper, the lack of a coherent understanding of uncertainty is only significant as far as it frustrates scientific policy advice. Indeed, in scientific research, the variety of competing views and interpretations of uncertainty (and scientific concepts in general) is favourable in the long term for encouraging debate and advancing knowledge. Policy-related research on the other hand is action-oriented and competing scientific interpretations prevent shared commitments and make scientific testimony increasingly politicised (Sarewitz, 2004; Weiss, 2002).

In this chapter we discuss the role and value of uncertainty in environmental decision making, informed and aided by science. The paper is complementary to the discussion in Maier et al. (Chapter 5), focusing on uncertainties in scientific simulation models; and Brugnach et al. (Chapter 4), which describes various uses of models and associated uncertainties. For this reason, a detailed discussion of uncertainty in scientific models is avoided here. In Section 6.3, we briefly discuss cognitive biases and heuristics which influence perceptions of uncertainty. The link between a perceived level of uncertainty or confidence and a number of wider situational and personal factors is illustrated. In Section 6.4, we focus on uncertainties in decision models and decision frameworks, including their normative assumptions and ability to reduce judgemental biases. We argue that the large number of alternative frameworks can create confusion and encourage indecision, rather than reducing it, if the methodological diversity is not tackled sensibly. We show that perceptions and assessments of uncertainty are dependent on the formulation of policy problems and the extent to which a decision framework is embraced by policy makers. Finally, we provide several examples in which the problems of uncertainty in decision frameworks have been reduced through creative policy formulation – allowing resolution of hitherto intractable problems.

6.2. Factors Influencing Perceptions of Uncertainty

There is a vast body of literature in cognitive sciences, experimental psychology and behavioural decision theory dedicated to the study of inconsistencies underlying judgement and choice. Probably the best known are framing effects (Tversky and Kahneman, 1974), which refer to changing preferences in normatively equivalent situations. According to Tversky and Kahneman (1974) a decision frame refers to a "decision maker's conception of acts, outcomes, and contingencies associated with a particular choice." In a strict sense, the definition is applied to situations in which the presentation of a problem is slightly manipulated (e.g. half full versus half empty) but the prospects remain unchanged. In a loose sense the framing effects go beyond a simple semantic manipulation and include substantially different formulations of the 'same' problem (such as positive/gain vs. negative/loss frames), where 'same' is defined in the context of economic theory (Kuhberger, 1998). Describing identical problems in different frames can elicit different preferences: by highlighting the positive aspects of a problem, risk-aversion is encouraged; whereas negative framing encourages risk-seeking. Others suggest a typology of framing effects with different underlying mechanisms and consequences, distinguishing between risky choice, goal and attribute framing (Levin et al., 1998).

Tversky and Kahneman (1974) and Kahneman and Tversky (1996) suggest that intuitive judgement is mediated by a number of distinctive mental operations, called judgemental heuristics. Although practical, these heuristics lead to errors and inconsistencies in judgements. Their study is practically motivated (to recognise limitations of intuitive choices) and helps to understand psychological processes underlying perception and judgement. An availability heuristic, for example, refers to the positive weighting of an event that can be easily remembered (Alexander, 2002; Greening et al., 1996; Kahneman and Tversky, 1996). People tend to base their probabilistic assessments on the number of instances they can recall. Judgements are not simply retrieved from memory but are derived from a process that involves recalling memorable information (Carroll, 1978). Base-rate neglect reflects the tendency of people to base intuitive predictions and judgements of probability on similarity or representatives rather than explicitly-stated base rates of outcomes. Conjunction fallacy (see e.g. Fantino, 1998; Tversky and Kahneman, 1982) refers to the tendency of people to rate the probability of two events more likely to occur than one of them alone. Confirmation bias (Fiedler, 2000; Jonas et al., 2001) refers to selective information processing, favouring information which confirms rather than contradicts the belief and leads to all but one or two of the most important aspects to be disregarded. Overconfidence (Brenner and Koehler, 1996; Tversky and Kahneman, 1974) refers to the underestimation of uncertainties in some areas compared to the 'average response' whereas underconfidence refers to the exaggeration of some uncertainties. A good overview of these and other biases and heuristics can be found in Berthoz (2004) and Kahneman et al. (1982). Interestingly, despite a rich literature on expert elicitation of probabilities and risks (e.g. Ayyub, 2001; Moorthy and Fieller, 1998), few studies have attempted to integrate the social-psychological aspects of expert elicitation with the statistical aspects of defining uncertainty, although numerous researchers acknowledge this problem (see Moorthy and Fieller, 1998).

Opinions on risk and uncertainty are also associated with an individual's character and personality (Larichev, 1992; Lu et al., 2001a). Different cognitive styles have been employed to explain these phenomena (Blais et al., 2005), employing different measures of cognitive style, such as: the need for enjoyable and challenging cognitive activities; the need to impose structure to dispel doubt and uncertainty; fear of invalidity, information gathering (perception styles) and information evaluation (judgement styles). Numerous researchers (Nicholson et al., 2005; Simon et al., 2000) have found a positive association between risk behaviour and a number of distinctive personal characteristics.

Differences in opinion or 'biases' on risk and uncertainty vary systematically between groups of scientists and policy makers, as well as between individuals. For example, scientists tend to overestimate the uncertainties associated with research from competing groups. An inability to listen carefully or a lack of critical investigation, including its deliberate suppression, may decrease group performance and conviction. Janis (1972) identified several symptoms or biases applicable to group performance (Turner and Pratkanis, 1998). These symptoms are especially apparent in highly cohesive, isolated groups with a dominant leader. In such situations, groups tend to perform poorly in terms of surveying alternatives and objectives and appraising uncertainty and risk, leading to poor decision making (McCauley, 1998). Hodson and Sorrentino (1997) suggested that uncertainty-oriented groups are less susceptible to these problems, especially under open-leadership and when a variety of opinions are heard.

Cognitive modelling is used in a number of fields such as system dynamics, decision support systems and computer science. It attempts to facilitate enrichment and validation of human beliefs and perceptions (mental models) and encourage backward and forward thinking. Intuitive decision making involves deeply held beliefs and assumptions through which reality is constructed (Chen and Lee, 2003). Knowledge in human brains is embodied in cognitive structures, referred to as mental models, which are powerful in facilitating learning and qualitative reasoning but less efficient at handling large amounts of data, representing complex phenomena, or capturing non-linear feedback processes. These models are incomplete and imprecisely stated, implicit, intuitive, and often wrong. The term 'mental model' is itself ill-defined, being used for a wide variety of mental constructs, but intuitively understandable and thus favoured in a number of scientific disciplines.

A comprehensive discussion of the individual and social factors that govern the quality of intuitive decision making and perceptions of uncertainty is beyond the scope of this chapter. Nevertheless, this short review illustrates how perceptions or beliefs are translated into weight attached to uncertainty or lack of confidence. Furthermore, while it is difficult to assess uncertainty resulting from these biases and heuristics, it is important to acknowledge them in policy processes.

6.3. Uncertainty in Decision Models

Choosing one policy measure from a set of mutually exclusive alternatives is limited by our capacity to process all important factors when tackling large environmental problems, such as biodiversity conservation, water and soil degradation, and climate change. In addition to these cognitive limitations, people hold different views about what is important and worthy of pursuit. Competing goals and different underlying values attached to outcomes of policies are yet another source of disagreement and uncertainty in decision making.

Decision analysis helps to avoid biases in judgement and make decisions more compatible with normative axioms of rationality for situations involving multiple, conflicting interests and beliefs. Decision models (DMs) result from the systematic exploration and negotiation of a 'problem,' including its existence, boundaries and structure. DMs comprise alternative courses of actions (policies or policy measures); decision goals – translated into more tangible evaluation criteria – against which the policies are weighed; and preferences, which describe how well the policies satisfy the objectives. There are normally several candidate policies; for example, high nitrate pollution can be tackled by introducing financial incentives, changing nutrient management in farms, protecting littoral vegetation and favouring phytodepuration, or improving the effectiveness of waste water treatment plants (WWTP). Binary (yes/no) choices, such as whether to adhere to the Kyoto protocol for reducing greenhouse gas emissions are frequently indicative of escalating conflicts due to incommensurable ethical principles, values and interests. Goals may refer to competing targets, e.g. macroeconomic developments vs. social impact; favouring different policies so that no single option outperforms all others. In these situations, decision makers may be a priori uncertain (undecided) about what policy action is most appropriate. This indecisiveness is a result of the diversity of decision outcomes, which are not uniformly distributed in space and time (e.g. different policy impacts on upstream vs. downstream water users; WWTP extensions may have an earlier impact on nitrate concentration than land use changes) or the values attached to them. Uncertainty in the outcomes of a choice poses yet another challenge for decision making.

The tradeoffs or preferences are value judgements, which are frequently not observable and must be revealed or approximated. Such uncovered preferences are context specific and depend on the description and framing of a problem, and how the questions are formulated. For example, to assess the environmental costs of irrigation, one must consider the value of wetlands and riverine ecosystems deprived by water abstraction. These values, regardless of whether they are in monetary terms or relative utility, may be difficult to approximate as the results depend on the respondents' prior knowledge, or on what they think others would approve. In situations involving uncertainty, preferences are formed over probabilities of possible outcomes of the policies and integrated into the decision model. These preferences embody attitudes towards risk (risk aversion vs. risk seeking vs. risk neutrality), defined according to the value individuals attach to the uncertain outcomes of a decision. This mixing of probability and utility is also found in the formulation and estimation of statistical models in the physical sciences (Moorthy and Fieller, 1998).

DMs resemble scientific simulation models (SMs) in terms of their structure, and tendency to abstract and simplify phenomena deemed important for a particular case. For this reason, attempts have been made to classify the types and sources of uncertainty that arise in DMs (Basson and Petrie, 2007; French, 1995) in a similar way to SMs. Important sources of uncertainty in a DM include: the extent to which decision criteria approximate the goals and objectives of a study; redundancy within criteria and subsequent overestimation of some aspects; coherence and consistency of preferences; predictability of policy outcomes; representativeness of actors invited to deliberate on policy choices; ambiguity of policies/objectives and expectations about their implementation. Uncertainties can also be classified by the different stages of a decision process, including: boundary negotiation; model development; use of models to challenge thinking and interpretation of the results from modelling. Yet there are important differences between DMs and SMs which limit the practical value of such typologies in DMs, as discussed below.

Numerous decision frameworks are available to (more or less explicitly) elicit the preferences of individuals and to aggregate them across different objectives (intra-personal aggregation) and across different actors (inter-personal aggregation). The extent to which specific DMs are considered consistent and 'rational' depends on the compliance of the elicited preferences with the model's assumptions and its ability to outplay cognitive biases. The models differ considerably in terms of: (i) the underlying theory and assumptions (e.g. monetary valuation; utility theory; value function approaches; outranking techniques; Bayesian statistics; participatory deliberation); (ii) the approach pursued (e.g. generation of tradeoffs versus elicitation of value judgements; a priori methods versus progressive or interactive methods, etc.); (iii) the assumed form of preference function (e.g. non-additive versus additive, linear versus non-linear); (iv) the way value judgements are elicited (e.g. direct assessment versus elicitation of tradeoffs); and (v) the extent to which the method accommodates different perspectives and problem structures.

Although DMs vary in purpose, any given decision problem can typically be addressed with more than one DM. As such, DMs act as "lenses" through which the policy problem is viewed, and different DMs may (frequently do) lead to different conclusions. More detailed discussions about the strengths and flaws associated with specific DMs can be found in Bell et al. (2001), French (1995), Kangas and Kangas (2004), Mingers and Rosenhead (2004), Poyhonen and Hamalainen (2001) and Ryan (1999).

The process of eliciting preferences can also introduce uncertainty into a DM. In this context the description and framing of a problem, as well as the formulation of specific questions, can influence the preferences elicited, and hence the reliability of the results. Prior knowledge, preconceived options, levels of understanding of the issues, composition of the interviewed group, levels of income and education and the time spent considering a problem all influence the elicited preferences. Thus, the 'true' beliefs of the individuals may not be elicited, especially if people find value judgements difficult and, in this case, they may adjust their reply to conform with what they believe the interviewer, or the group, finds most acceptable (compliance biases). As a result, the respondents may ultimately feel manipulated by the method or interviewer, and have limited confidence in the results obtained. These problems are greatest when (i) the goods or benefits are unique and cannot be substituted or replaced, or when it is an important component of the respondents endowment; and (ii) too many alternatives/criteria are presented (Jia and Fischer, 1993) or differences in values are high (Bell et al., 2003; Hobbs and Horn, 1997; Hobbs and Meier, 1994).

The variety of different decision frameworks is problematic, as different methods may, and normally do, yield different results and hence the decision may depend on the methods selected. Given the large number of methods available, choosing the most appropriate one is difficult and, typically, only a small number of well-known methods are applied. There is no simple criterion for preferring one technique over another in any given situation. Unsurprisingly, most scientific studies show strong partiality for whichever technique conforms best to the world view of the policy adviser. The choice of method is frequently influenced by the beliefs of those identifying policy options, scientists being no exception. The disputes regarding the use of alternative approaches are sometimes based on prejudices, misconceptions or oversimplifications of the criticised methods, while intentionally concealing the weaknesses of the preferred methods. In other cases, alternative decision methods are ignored, and hence the impacts of selecting a specific method are not considered. Clearly, the subjective choices of scientists and decision makers are an important component of decision making, but the impacts of methodological diversity, namely the availability of multiple candidate methods (sometimes referred to as 'equifinality' in the physical sciences), has received relatively little attention in decision making.

In summary, disagreements are inevitable when multiple possible methods are available to address any given decision problem. To overcome this, different methods could be applied in parallel, thereby identifying similarities and highlighting inconsistencies between methods. This could be seen as an educational exercise, whereby the decision maker learns more about their own preferences (Hobbs and Horn, 1997). Indeed, according to French (1995), critical self-reflection is at least as important as the outcome reached through DM. This approach has also been suggested in the physical sciences, where multiple possible explanations of physical data and processes are common (e.g. Refsgaard et al., 2005). However, given the practical problems of comparing methods (time, resources, expertise), as well as the problems of selecting an appropriate range of 'candidate methods,' further evidence is required on the practicality and value of this approach.

6.4. Uncertainty in Practical Policy Making

At some point the scientists involved in the development of environmental policies have to convey the uncertainty associated with the most promising policy options to the decision makers, who are responsible for making the final choice, and defend it in the public debate. Even if in the process of policy development, the uncertainties are reduced as much as possible, there often remains a substantial level of uncertainty with respect to the effectiveness and outcomes of the proposed policy. In tackling this problem, policy makers often shift the focus from uncertainty to risk.

A systematic elaboration of 'risk' is beyond the scope of this paper, but also see Chapter 5. We will show some cases in which scientists and decision makers interacted in the decision-making process in uncertain and 'risky' situations. The cases are positioned in a general framework about the concept of risk that comes from the managerial sciences. The development and implementation of a new environmental policy shows similarities with the development and market introduction of a new product. The latter has been studied extensively in business administration and managerial sciences (Sitkin and Pablo, 1992; Smith, 1999).

In Keizer et al. (2002) a product innovation is labelled risky if: (1) the likelihood of a bad result is large; (2) the ability to influence it within the limits of time and resources is small; (3) its potential consequences are severe. Often risk analysis focuses exclusively on either technological, organisational, market or financial factors. The success of product innovation, however, is determined by external and internal forces in which all these factors interact. The similarities with innovations in environmental policies are outlined below.

- Technology: the policy is based on sufficient scientific insight into the measures and the resulting environmental (and other) effects.
- Market: policy is accepted by the public and other stakeholders (companies, NGOs and governmental organisations with a specific interest in the policy).
- Finance: sufficient funds for implementation of the policy and low likelihood of negative effects with high financial consequences.

- Operations: good internal organisation and co-operation with external parties in the implementation and maintenance of the policy.

In the following cases uncertainties in the domain of science (technology) resulted in possible risks in the domains of market, finance and operations. These risks have been tackled in interaction between scientists and decision makers aiming at a decrease of the likelihood of unexpected effects; a decrease of the potential damage and an increase of the abilities for 'damage control.'

6.5. Reducing Uncertainty Through Innovative Policy Interventions

In the preceding we lamented the fact that it was difficult to completely eliminate uncertainty from the process of decision making. However good environmental outcomes can sometimes result from a reduction of perceived uncertainty below a certain qualitative threshold. In other instances a transformation of the nature of uncertainty in a manner that relieves apparent stressors, imposed by discipline-induced cognitive biases and perceptions, can similarly result in a positive outcome.

A practical example of this comes from the Bay-Delta region of California where water exports from the Delta were suspected as the cause of the anadromous fishery. Water exports to coastal cities and agriculture were curtailed at the behest of biologists based on perceived risk to the fishery, which caused hostility between water agencies and the resource agencies responsible for the fishery. Existing policy was too cumbersome to develop multiobjective optimal solutions to the problem. Innovative policy makers created an "environmental water account" – a bank account of water supply designated for fish and wildlife uses. Biologists could spend the resource as they might money in a bank account and were allowed to save a portion of that unused one year for the next. When exports were curtailed to municipal, industrial and agricultural customers, water was drawn from the account according to the length of time the curtailment occurred and the flow reduction required. The net effect was to reframe the issue – creating a new decision space which constrained the options available to fish agencies while providing the water agencies with reduced risk of what had been perceived as arbitrary curtailments in water exports. This example illustrates how changing the mix and weighting of the previously described risk vectors in decision space – technology, market inducements, finance and operation – can lead to more stable, sustainable and environmentally sound policies.

Environmentally sound and politically innovative policy can sometimes be achieved as a result of a more linear, progressive erosion of uncertainty – where this uncertainty is often used for political ends to perpetuate a status quo and induce inertia to change. A good example of this, also from California, was the Mono Lake controversy. Declining water levels in a high-Sierran terminal lake caused by over-diversion of streamflow by the Los Angeles Department of Water and Power threatened unique tufa formations, gull and shorebird communities within the Pacific Flyway and had eliminated several native fisheries. Grassroots activism and development of core science from field data collected at the lake eventually showed a defensible relationship between lake level and ecosystem health. Activism of the policy front combined with the emerging science brought the issue to the attention of the general public and helped to convince legislators to align against a very powerful water agency. Legislation finally passed that forced Los Angeles to manage the watershed in an environmentally responsible manner and give up a portion of their acquired water right. This is an example of a process where the scientific method of collecting and interpreting data and developing progressively better ecosystem models whittles away uncertainty where finally the weight of evidence tips the scales against a formidable opponent. Policy can then be crafted, that is congruent with the new paradigm of uncertainty, to optimally reapportion the resource among competing uses in multiobjective decision space. This last process sometimes takes time as a common universe of discourse is developed between former adversaries.

Another example of progressive erosion of uncertainty by interaction between scientists and policy makers comes from The Netherlands. The Dutch Environmental and Nature Policy Assessment Agency (MNP) is a centre of expertise for the national government in the development, monitoring and assessment of policies for the quality of environment and nature. Models and databases on various environmental topics are important instruments in the MNP-toolbox. In a comprehensive study (Jansen et al., 2004), 27 models and databases frequently used by MNP were audited. Uncertainty was an important aspect in the audits. The outcomes of the study created among policy makers a 'willingness to invest' in improvement of the MNP-toolbox. This raised the question where to invest, in order to get an optimal contribution to future decision making. At this point the focus changed from uncertainty to risk. The models and databases were grouped in categories according to the political perception of the risks:

(1) Low: instruments for the design of generic policies (affecting many interest groups) on issues that are generally accepted by the Dutch society.
(2) Medium: instruments for the design of generic policies on issues which are controversial in Dutch society (raise a lot of political debate).
(3) High: instruments for the design of specific policies with a large potential effect on the (financial) interests of certain stakeholder groups or individuals (farmers, companies).

Based on this risk-analysis the MNP decided to invest substantially in quality improvement of the models and databases in category 3 and 2. After this first-order selection based on risks, a further second-order selection and design of improvement measures was carried out on the basis of the scientific uncertainties in the individual models and databases.

6.6. Discussion and Conclusions

It is apparent that perceptions of uncertainty, scientific or otherwise, depend strongly on the context in which they were developed, and that any treatment of uncertainty in policy-related research must acknowledge this. If uncertainty is viewed as a level of confidence, and thus dependent on the beliefs of individuals and groups of people, there is a clear correspondence between a decision maker's perceived uncertainty and their level of satisfaction, trust and acceptance of the resulting decisions. However, establishing confidence (reducing uncertainty) is less straightforward, since the main sources of uncertainty are case-specific and vary with the decision problem, levels and access to information, the expertise, interest, and personalities of those involved and the methods used to elicit preferences. In practice, these sources of uncertainty are difficult to specify precisely and cannot be quantified numerically in an operational way. This stems from the inherent difficulty of identifying subtle changes in personal relations, perceptions and level of trust, all of which are central to decision making. Thus, while it may be possible to develop classifications of uncertainty, such as lists of cognitive biases and heuristics, it is likely that such attempts will improve the qualification of uncertainties in specific cases. This points to an important difference between decision models, whose principal aim is to establish values and preferences (which are strongly dependent on the act of observing) and scientific simulation models, where values and preferences are secondary, and results are (presumed) only weakly dependent on the act of observing. These differences are important in understanding the difficulties of communication between scientists and decision makers on issues of uncertainty.

Despite these differences, scientific models and decision models are complementary. The former improve our ability to store and process large volumes of data and analyse complex patterns and non-linear feedbacks, which are beyond our visual and mental capacity. The latter enhance our ability to make coherent choices and comply with assumed axioms of rational behaviour. In both cases, there are strong links between model structures and normative frameworks (defining what is rational and desirable), although they are more apparent in decision modelling. It is difficult, therefore, to compare models without considering the appropriateness of their normative assumptions.

This chapter does not include a deeper reflection about the role of epistemological frameworks in informing environmental policy making or in prompting divergent understandings of uncertainty. Indeed, this is partly because the authors hold different opinions on the extent to which they hamper progress. However, it is clear that particular conceptions of uncertainty are influenced by the wider context in which research is conducted, including its social, political and ethical frameworks.

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