

The role of expert opinion in environmental modelling

Tobias Krueger^a, Trevor Page^b, Klaus Hubacek^c, Kevin Hiscock^a

^aSchool of Environmental Sciences, University of East Anglia, Norwich, NR4 7TJ, UK

^bLancaster Environment Centre, Lancaster University, Lancaster, LA1 4YQ, UK

^cSchool of Earth and Environment, University of Leeds, Leeds, LS2 9JT, UK; now at
Department of Geography, University of Maryland, 2181 LeFrak Hall, College Park MD
20742, USA

Corresponding author: Tobias Krueger, t.krueger@uea.ac.uk, +44 (0)1603 592922

Abstract

A case is made for a wider perspective on expert opinion in environmental modelling on the basis of the inevitable, though frequently informal, role of expert opinion in any model, the increasing number of models incorporating expert opinion formally, and the substantive value of non-scientific knowledge for modelling. Based on an extensive literature review, the paper exposes informal model assumptions and modeller subjectivity, examines in detail the formal uses of expert opinion and expert systems, and discusses the main concepts and issues of expert elicitation and the modelling of uncertainty. It is argued that superficial distinctions between experts and non-experts potentially discount valuable information and a definition of an expert as anyone with *the right kind of experience* is adopted, while it is crucial to demonstrate this experience as opinions are incorporated in models. In this respect, expert data should be treated as any other data, including propagation of associated uncertainties. The result is a broadening of the knowledge base which is expected to enhance the scientific enquiry and models, not least through creative conflict between scientific and non-scientific knowledge. It is here that the wider perspective on expert opinion is synergistic with participatory modelling and collaborative decision making. It is suggested that model scrutiny and the entry of expert opinion into models will benefit from a formal and transparent procedure that includes all stakeholders.

Keywords: subjectivity, uncertainty, expert system, expert elicitation, stakeholder, participatory modelling

1 Introduction

2 This paper aims to build a case for a wider perspective on expert opinion in environmental
3 modelling on the basis of the inevitable, though frequently informal, role of expert opinion
4 in any model, the increasing number of models incorporating expert opinion formally, and
5 the substantive value of non-scientific knowledge for modelling. All three points will be
6 substantiated in the course of the paper. This perspective offers a *substantive* rationale for
7 participatory modelling (Voinov and Bousquet, 2010, focussing on the instrumental
8 rationale), which will be discussed but is not the main focus of the paper.

9 Our main focus is to trace the elements of expert opinion in environmental models on a
10 fundamental level: what opinion is used for (the *location* of expert opinion in models),
11 whether this use is formal or informal, and whose opinion is used. Preliminary to this
12 analysis, we will clarify what other scholars mean by “opinion” (section 1.1) and “expert”
13 (section 1.2) and distil operational definitions. The backbone of the study is an extensive
14 literature review on the location of expert opinion in environmental modelling which is
15 synthesised in two tables (section 2). Part of this synthesis is a unifying classification of
16 expert systems (section 3). We will also discuss briefly how opinion may be elicited and
17 associated uncertainties modelled (section 4). The paper is as much about exposure of
18 model assumptions and modeller subjectivity as it is about the formal treatment of
19 uncertainties and the opportunity for expert systems and non-scientific knowledge.

20 Our intention is to bring some order to a varied and multidisciplinary body of literature as
21 well as our critical perspective, in the hope that this analysis will inform the formal use of
22 expert opinion in environmental models in the future. To limit the scope of the paper, we do
23 not deal with the role of opinion as used directly in environmental mapping and assessment
24 (e.g. Johnson and Gillingham, 2004; Geneletti, 2005; Clavel *et al.*, 2010) and more broadly in
25 environmental management (e.g. Otway and von Winterfeldt, 1992; Kangas and Leskinen,
26 2005), i.e. without or beyond formal models. We begin by deriving definitions of opinion
27 and knowledge and their relation with models.

1.1 Models, knowledge and opinion

Environmental models can be defined as formalisations of knowledge about the behaviour of environmental systems. We limit this paper to computer models and their various stages of development. Following the definition of *knowledge* based on evolutionary epistemology, knowledge of environmental systems behaviour is of the propositional type, i.e. a constantly evolving body of propositions that meet the conditions of justified true belief (e.g. Ayyub, 2010). Under this definition, propositional knowledge is created from information through investigation, study and reflection via the intermediate step of *opinion*, which can be defined as a preliminary proposition (Ayyub, 2010). Insofar as models are formalised knowledge, they are also subject to the evolutionary nature of knowledge (Ayyub, 2010, Fig. 2, p. 419), and thus reflect opinions as well as knowledge and various evolutionary stages in between.

In addition, as the level of formal abstraction of models increases, so does the level of simplifying assumptions (e.g. Haag and Kaupenjohann, 2001; Beven, 2009). These assumptions are to some extent arbitrary and hence have subjective components (e.g. van der Sluijs, 2002), i.e. they rely on opinion at least until tested against observations of systems behaviour. Note that the question of what constitutes a valid test of model assumptions is itself controversial (e.g. Jakeman *et al.*, 2006; Gupta *et al.*, 2008; Bellocchi *et al.*, 2009) and requires opinion again during model evaluation. Moreover, the classic separation of scientists from their objects of study has long been contested (with respect to environmental sciences see, for example, Funtowicz and Ravetz, 1993; van Asselt and Rotmans, 1996; Healy, 1997; Brown, 2004; Munnichs, 2004; Kolkman *et al.*, 2005; Fazey *et al.*, 2006; Fraser *et al.*, 2006; Lane *et al.*, 2006; Hulme, 2009) and knowledge claims (which we treat synonymously to opinions) seen as value-laden (e.g. Schneider, 1997; Huesemann, 2002; Kloprogge *et al.*, 2009).

This research ties in with a parallel strand of literature that has developed since the 1970s (e.g. Holling, 1973), suggesting that attempts to control highly complex and non-linear systems inevitably lead to unexpected outcomes and potentially crises (Holling and Meffe, 1996). In response, several alternative approaches to natural resource management have been developed including adaptive management (Holling, 1978), co-operative management

1 (e.g. Pinkerton, 1989), collaborative management (Wondolleck and Yaffee, 2000), and
2 adaptive co-management (e.g. Olsson *et al.*, 2004), with implications for knowledge
3 generation and its role in modelling and more recently participatory or mediated modelling
4 (e.g. van den Belt, 2004; Prell *et al.*, 2007; Voinov and Bousquet, 2010). We do not have to
5 digress further into philosophy and the history of these concepts here and enter the debate
6 about the relativist nature of knowledge itself (e.g. Brown, 2004; Munnichs, 2004;
7 Feyerabend, 2010), as we are only interested in opinions, i.e. those *claims* of knowledge
8 entering models that can justifiably be contested in any case. To some, and in principle, this
9 scope may include any element in a model.

10 In the environmental modelling literature, “expert knowledge”, “expert judgement” and
11 “expert opinion” seem to be used interchangeably (an observation shared by Meyer and
12 Booker, 2001, in the general context of expert elicitation). We will continue to use these
13 terms when citing the respective papers, but prefer to use the term opinion to emphasise
14 the subjective and preliminary nature of knowledge claims. Opinion being a preliminary
15 proposition in the evolutionary epistemology sense, we recognise that the transition to
16 actual propositional knowledge is fluent, and we refrain from deciding specifically at what
17 stage opinion might be called knowledge. The evolution of knowledge pertains to individuals
18 as well as the scientific community at large, although under different parameters. It is the
19 individual’s opinion that we are interested in here. However, we recognise that scientists
20 may tap simultaneously into personal (experiential) and collective (in this case mostly
21 documented) knowledge when forming opinions. In our experience, the documented
22 research base as a whole often dominates a scientist’s opinion. We now examine who may
23 qualify as an expert voicing opinions in modelling.

24 **1.2 Who is an expert?**

25 We have presupposed that only the opinions of experts may be included in models.
26 However, for us an *expert* can be “anyone with the right kind of experience” (Collins and
27 Evans, 2007, p. 114), i.e. professionals such as scientists as well as experienced members of
28 the public. The book by Collins and Evans illustrates the difficulties in demarcating expertise
29 and the related ongoing debate in the social sciences. We do not need to enter this debate
30 as the experience-based definition provides, as will be seen, a satisfactory operational

1 meaning for the kind of expertise we are concerned with here. We suggest that it is more
2 important, as far as opinion in models is concerned, to demonstrate that opinion is backed
3 up by the right kind of experience in the topic that opinion is used for. We shall use the term
4 *expert opinion* to imply such experience. This definition has advocates also in the ecological
5 (e.g. Hamilton *et al.*, 2007; Murray *et al.*, 2009) and statistical (e.g. Morris, 1974; Garthwaite
6 *et al.*, 2005) literature. Of course, demonstrating that someone has the right kind of
7 experience is challenging, and requires a definition of what is the right kind of experience in
8 a specific context which may be contentious. But this is the discourse we should engage in
9 instead of a superficial distinction of experts and non-experts which potentially discounts
10 valuable knowledge.

11 In the environmental modelling literature, in the rare event that “expert” is defined
12 explicitly, the following definitions prevail: An expert is someone having specialist
13 knowledge acquired through practice (also called training), study (also called education) or
14 experience (e.g. Booker and McNamara, 2004; Kangas and Leskinen, 2005; O’Leary *et al.*,
15 2009; Kuhnert *et al.*, 2010). The experience-based definition of Collins and Evans (2007)
16 seems to encompass these three domains, but the authors dismiss training and education
17 credentials as reliable qualifiers if these are not accompanied by the right kind of
18 experience. In contrast, more restrictive definitions emphasise training as the prerequisite
19 of expertise (e.g. Ayyub, 2001).

20 Experts are frequently distinguished from the public (also called laypersons), i.e. people not
21 in possession of the knowledge of experts (implying some inferior knowledge base) or
22 possessing a different form of knowledge: “everyday knowledge” or “folk knowledge”
23 (Porsborg Nielsen *et al.*, 2007); “local knowledge” (Jonsson *et al.*, 2007); “contextual
24 knowledge” (Healy, 1997); “indigenous knowledge” or “traditional knowledge” (Hulme,
25 2009, speaking of “lay expertise” in this context). This superficial distinction between
26 experts and the public is in conflict with the experiential knowledge definition of experts of
27 Fazey *et al.* (2006) and the finding of Wynne (1996) that local knowledge can challenge
28 scientific knowledge (see Ravetz, 2006, p. 276, for further examples). Again, the definition of
29 experts of Collins and Evans (2007) allows for all these kinds of knowledge as long as the
30 right kind of experience can be demonstrated.

1 This definition also resonates with the concept of “extended peer communities” (Funtowicz
2 and Ravetz, 1993) which includes people in scientific quality control who are “particularly
3 affected by an issue but lying outside of traditional expertise” (Healy, 1997, p. 510). This
4 concept largely overlaps with a widely used definition of *stakeholder* as somebody who is
5 affected by a process or action or somebody who has the power to influence the outcome
6 (Freeman, 1984). Indeed, in many areas of environmental modelling, the people living,
7 working or recreating in a particular place will be the only ones having a clear sense and
8 appreciation of the history and interaction of events in that location, in addition to their
9 respective professional expertise, as argued by Lane *et al.* (2006) in the context of diffuse
10 pollution modelling (see Funtowicz and Ravetz, 1993; Brown Gaddis *et al.*, 2010, for similar
11 arguments). Lele and Allen (2006) expand the definition of “expert” further still by including
12 computer models, but this seems counter-productive given the role of opinion in
13 constructing models in the first place. *Expert system* seems a more appropriate term for a
14 computer model performing expert-like reasoning, see below, and we suggest reserving the
15 term expert for humans.

16 Table 1 lists some types of experts in the context of environmental modelling. The
17 description of experts, i.e. the scientist expert, the farmer expert and so on, which is taken
18 with some shortening from the original papers, provides a *necessary* indication of the right
19 kind of experience but not a *sufficient* one, for which additional qualifiers and discussions
20 would be needed. In this context, there remains much to be researched about the nature
21 and kinds of expertise (Collins and Evans, 2007). See Ericsson *et al.* (2006) for a display of
22 research methods from multiple disciplines. We suggest that the selection of experts and
23 the demonstration of experience will benefit from a formal and transparent procedure that
24 includes all stakeholders, a point that will be discussed in sections 2.2 and 4.

25 **2 Location of expert opinion in environmental modelling**

26 We distinguish between *informal* (implicit, unstructured, undocumented) and *formal*
27 (explicit, structured, documented) use of expert opinion in models (after Otway and von
28 Winterfeldt, 1992). The *types* of information (Knol *et al.*, 2010) that an expert might provide,
29 i.e. quantitative, qualitative or conceptual (or causal) information, will be clear from the
30 locations.

2.1 Informal use of expert opinion

When constructing environmental models, many choices about process representations (model structure), parameter values and boundary conditions must be made using scientific expertise, and uncertainty remains as to whether a model is an adequate representation of the scientists' understanding of the system under study (Hargreaves, 2010, for the case of climate models). Van der Sluijs (2002) argue that Integrated Assessment Models of climate change are largely based upon uncertain, incomplete and provisional knowledge, and involve, often implicit and hidden, subjective choices and value-laden assumptions that modellers are often not fully aware of. Arhonditsis *et al.* (2008, p. 2) come to a similar conclusion for ecological models, stating that "even the most well studied ecological processes can be mathematically described by a variety of relationships that entail different assumptions". Kloprogge *et al.* (2009) give examples of model assumptions for assessing human health impacts of tropospheric ozone exposure. In all these cases expert opinion enters the respective models implicitly, unstructured and undocumented, i.e. informally. This role of expert opinion is fundamental, but has implications for the utilisation of models. Hence the specific nature of informal expert opinion in models is examined next.

2.1.1 Model structure

In relation to model structure, expert opinion enters the translation of a perceptual model into a formal model and subsequently a procedural model which has a specific time and space discretisation¹. Besides some level of perceptual ignorance, both the perceptual and the formal model draw on scientific knowledge from disparate temporal and spatial scales (Beven, 1989; Kloprogge *et al.*, 2009) which do not connect unambiguously. The formal and procedural models, in turn, rely on further assumptions to simplify calculations and on choices of numerical techniques to solve equations. Decisions to include, exclude or simplify processes are to some extent arbitrary and hence have subjective components (van der Sluijs, 2002). Inappropriate numerical choices can lead to artefacts in model simulations (Seppelt and Richter, 2005; Kavetski *et al.*, 2006).

¹ The distinction of perceptual, formal and procedural models is made following standard terminology of the modelling process (Beven, K. J. (2009). Environmental Modelling: An Uncertain Future? Oxon, Routledge.).

1 The predictions of a model structure as a whole can, of course, be tested against
2 observations of system behaviour, but it is not clear, unless all elements of expert opinion
3 are made explicit, exactly which set of knowledge and opinion is being assessed. Besides, an
4 evaluation of the aggregated model behaviour will not be sensitive to all assumptions. There
5 is, therefore, a case for more detailed means of model scrutiny, which we will turn to in
6 section 2.1.3.

7 **2.1.2 Model parameterisation and boundary conditions**

8 In relation to model parameterisation, expert opinion enters the estimation of parameter
9 values by, again, drawing on scientific experience and previous studies from different
10 temporal and spatial scales. The subjectivity of this estimation was demonstrated by Brown
11 *et al.* (1996) and Boesten (2000) for the case of pesticide fate modelling. Their findings are
12 exemplary for all areas of environmental modelling. In the study of Boesten (2000),
13 subjectivity means selective ignorance of parts of available laboratory data (including the
14 definition of outliers), and the choice of intermediary methods, models and “default”
15 parameters. The resulting prediction uncertainty was of similar magnitude as that resulting
16 from using generic parameters from the literature. Brown *et al.* (1996) show prediction
17 uncertainty resulting from modeller subjectivity of similar magnitude to the variation in field
18 measurements. A similar study by Gonzales and Gergel (2007) demonstrates the sensitivity
19 of an invasive species model to competing parameter assumptions.

20 It is possible, of course, to standardise parameter estimation using formal inference
21 methods that combine prior information and observed system responses, and associated
22 uncertainties can be quantified. However, when analysing model uncertainty, more choices
23 still must be made regarding error characteristics and numerical methods which may often
24 rely on a scientist’s subjectivity as well as introducing significant 2nd order uncertainty, i.e.
25 uncertainty about the extent and formalisation of uncertainty (e.g. Eduljee, 2000; Beulke *et al.*,
26 2006). Numerical methods can be justified by analysing convergence, but error
27 assumptions eventually require independent data for justification. As these data have
28 usually limited availability, subjective simplifications and choices are inevitable, yet should
29 be made explicit to allow peer review (as in Krueger *et al.*, 2009, for example). Brown *et al.*

1 (2004) go further by arguing for a plurality of uncertainty models as well as environmental
2 models.

3 Lastly, in relation to boundary conditions, expert opinion enters the translation of data
4 sources to the scale of model discretisation and the estimation of future conditions. Scaling
5 involves interpolation or disaggregation while future conditions may be estimated on a
6 continuous scale from extrapolation to imagination.

7 **2.1.3 Scrutinising model assumptions**

8 Funtowicz and Ravetz (1993, p. 743) argue that computers have become “substitutes for
9 disciplined thought and scientific rigour”. Indeed, it is difficult to obtain detailed and
10 complete descriptions of the process representations of published models, and this limits
11 the extent to which peer review can be an effective part of the modelling process (Risbey *et al.*,
12 1996; Lane *et al.*, 2006). Moreover, scientific peer review itself reaches its limits as
13 “model predictions become more public, as members of the public themselves are able to
14 be more reflexive and as the kinds of doubts expressed about models take on forms that are
15 outside the conventional scientific training of modellers” (Lane *et al.*, 2006, p. 250). In
16 realisation of this fact, many have argued that the elements of expert opinion entering
17 modelling (and decision making for that matter) should be made identifiable and reviewable
18 by all stakeholders through stating and documenting them more explicitly (e.g. Healy, 1997;
19 Kangas and Leskinen, 2005). Van Asselt and Rotmans (1996) argue for a plurality of models
20 (structures and parameterisations) to represent contrasting scientific opinions in a
21 systematic and reproducible way. Van der Sluijs and co-authors, in a series of papers (van
22 der Sluijs, 2002; van der Sluijs *et al.*, 2005; Kloprogge *et al.*, 2009, to name the most relevant
23 for our discussion), developed a method for analysing the value-ladenness of model
24 assumptions on the basis of the NUSAP² methodology (Funtowicz and Ravetz, 1990).
25 Following NUSAP, the knowledge base, production process, scientific status and
26 underpinning behind key assumptions (collectively called “pedigree”) is scored by analysts,
27 peers and stakeholders on a set of criteria (Kloprogge *et al.*, 2009, Tab. 1, p. 4). This method
28 can lead to analysing the sensitivity of model outputs to assumptions, revising assumptions

29 ² NUSAP is an acronym of five categories to describe quantitative information including uncertainty: Numeral,
30 Unit, Spread, Assessment, Pedigree.

1 and diversifying assumptions (the plurality of models argument). Note that pedigree
2 assessment involves expert opinion itself.

3 **2.2 Formal use of expert opinion**

4 Table 2 synthesises an extensive body of literature describing the increasingly formal uses of
5 expert opinion in environmental models. Some disciplines, particularly ecology (e.g. Rykiel,
6 1989), have acknowledged explicitly that in many complex environmental systems the best
7 available information may be in the form of expert opinion as measured data and formal
8 theories are limited, inconsistent or lacking. More specifically, expert opinion has been
9 found to help assess which evidence is limited or inconclusive, to make explicit the
10 published and unpublished knowledge and the wisdom of experts, to provide a temporary
11 summary of the limited available knowledge, to inform policy before conclusive scientific
12 evidence becomes available, and to serve as a basis for action when problems are too
13 urgent or stakes too high to postpone measures until more complete knowledge is available
14 (Kangas and Leskinen, 2005; Knol *et al.*, 2010).

15 Formal expert opinion has limited applicability to issues that are extremely uncertain or
16 controversial as experts cannot “make up” knowledge when no expertise of one form or
17 another is available (Knol *et al.*, 2010). It should also be noted that the number and types of
18 experts consulted formally in environmental modelling studies varies (Table 1), and so does
19 the account taken of uncertainty (Table 1). In some cases (e.g. van der Werf and Zimmer,
20 1998; Arrignon *et al.*, 2007; Baerlund *et al.*, 2009; Calder *et al.*, 2009), the authors of the
21 study qualify as the experts without further justification, but this lack of methodological
22 documentation is rather unsatisfactory scientifically.

23 Different locations of formal expert opinion can be distinguished: the construction of
24 conceptual (or causal) models; the parameterisation of models; the provision of boundary
25 conditions (especially model input and response data); the evaluation of models; and the
26 development of scenarios. Table 2 provides detailed examples from different areas of
27 environmental modelling. The causal or conceptual modelling stage typically involves
28 experts in weighting the importance of model components, deriving rules, reviewing or
29 constructing graphs (often precursor to developing probabilistic networks), or selecting
30 statistical models and predictors.

1 At the data provision stages (parameters and boundary conditions), experts may provide
2 unique data sets or augment existing ones (with or without uncertainty estimates), or
3 further qualify or validate data derived from other sources. Typical is the specification of
4 prior parameter distributions in Bayesian inference or the provision of probability tables for
5 probabilistic networks. Experts may also provide response data for statistical regression.
6 Note that the 2nd order uncertainty of expert opinion may itself be analysed (e.g. Burgman
7 *et al.*, 2010).

8 The model evaluation stage typically uses expert-provided data, 2nd order uncertainty
9 estimates or post-hoc model modifications, but may also enlist experts in the process of
10 peer review, or extended peer review involving extra opinion from outside the scientific
11 community (Healy, 1997; Refsgaard *et al.*, 2007; Kloprogge *et al.*, 2009). Peer review usually
12 pertains to conceptual models and aims at assessing whether appropriate levels of detail
13 and aggregation, logic, and mathematical and causal relationships are used for a model's
14 intended purpose (Nguyen *et al.*, 2007).

15 The scenario development stage (e.g. Mahmoud *et al.*, 2009) goes towards using models in
16 the context of environmental management and is beyond the scope of this paper. Note that
17 (2nd order) expert opinion is also involved in selecting experts, and this can easily result in an
18 infinite recursion (Funtowicz and Ravetz, 1992), but may, in practice and in the same way as
19 informal expert opinion above, be countered by adhering to formal procedures and
20 including all stakeholders.

21 **3 Expert systems**

22 Table 2 demonstrates that expert opinion can enter formally into many types of
23 environmental models. One specific class of models are *expert systems* (sometimes called
24 “knowledge-based systems” or “knowledge-based models”), as these models are designed
25 specifically to perform expert-like reasoning. It is this reasoning process that distinguishes
26 them from mechanistic and statistical models, although expert systems can incorporate
27 elements of those. Here we do not deal with expert systems that are purely developed as
28 meta-models or data mining techniques.

1 By definition, an expert system consists of a knowledge base and an inference engine, i.e.
2 rules and a procedure for processing them (e.g. Rykiel, 1989; Cowell *et al.*, 2007). Typically,
3 both are encoded in a computer programme. For exceptions, see Girard and Hubert (1999)
4 and the state and transition models discussed by Bashari *et al.* (2009), for example. Here,
5 we focus on computer-based expert systems. The knowledge base can be a mixture of
6 measured data, scientific theory and expert opinion. Note that the term expert system
7 refers to expert-like reasoning and not expert opinion *per se*.

8 Expert systems can be described in terms of their structure and their treatment of
9 uncertainty. Table 2 gives examples from the environmental modelling literature. The
10 structure of an expert system is often a *graph*, i.e. a collection of *vertices* connected by
11 *edges*, with the *tree*, i.e. a graph where any two vertices are connected by exactly one
12 simple path, as a special case. For a detailed treatment of graph theory, see Diestel (2010).
13 The uncertainty treatment is typically either qualitative, fuzzy (possibilistic) or probabilistic,
14 though see Sikder *et al.* (2006) for an expert system based on rough set theory. See Walley
15 (1996) for a unifying theory of imprecise probabilities.

16 Qualitative reasoning is the basis of *qualitative expert systems* where processes are
17 characterised in terms of directions of change and orders of magnitude instead of real
18 values. Those models often employ (semi-) quantitative calculations, in which case
19 uncertainties around results are typically assumed implicitly (qualitatively) rather than
20 explicitly, hence we subsume them under qualitative expert systems here. Probabilistic
21 reasoning is the underpinning of *probabilistic networks*, often restrictively called “Bayesian
22 networks” (Cowell *et al.*, 2007). Reviews of probabilistic networks in environmental
23 modelling can be found in Marcot *et al.* (2006) and Uusitalo (2007), with focus on ecological
24 applications, and Varis and Kuikka (1999), with focus on management applications. Fuzzy
25 logic gives rise to *fuzzy expert systems* (Siler and Buckley, 2005), sometimes called “fuzzy
26 rule-based systems” or “fuzzy rule-based models”, and *possibilistic networks* (e.g. Benferhat
27 *et al.*, 2002). For a review of fuzzy expert systems in the context of ecological modelling, see
28 Adriaenssens *et al.* (2004). The extension of probabilistic networks to imprecise probabilities
29 has been realised through *credal networks* (see review by Cozman, 2000), but without any
30 application in environmental modelling that we know of.

4 Eliciting expert opinion and modelling uncertainty

Expert elicitation is defined as a formal heuristic process of acquiring an expression of the opinion of one or more experts in the form of words, numbers, language, pictures or figures (Ayyub, 2001). A comprehensive review of elicitation techniques is beyond the scope of this paper. Our aim here is to highlight the main concepts and issues, and we refer the reader to standard texts (Cooke, 1991; Ayyub, 2001; Meyer and Booker, 2001; O'Hagan *et al.*, 2006) for in-depth treatments. The single expert case is clearly limited for estimating the true state of knowledge and corresponding ignorance about a topic, even when the subject's uncertainty is explicitly elicited, so we focus on the multiple expert case here. With multiple experts, too, as with any type of data, there remain the issues of sample size, representativeness of experts and bias, which we will discuss briefly in sections 4.4. and 4.5.

Different methods of elicitation can lead to different results (illustrated by O'Leary *et al.*, 2009; Kuhnert *et al.*, 2010, for example, for the case of expert-based prior parameter distributions in Bayesian inference). This sensitivity of results to the 2nd order expert opinion of the analyst discussed in section 2.2 makes the need for explicit justification and documentation of the chosen methods even more important. We will now summarise the prevalent elicitation techniques briefly under the following headings: type of information elicited; direct or indirect elicitation; individual or group elicitation; elicitation medium; elicitation with or without subject uncertainty; opinion aggregation; uncertainty model.

4.1 Information type, direct versus indirect elicitation, individual versus group elicitation, medium

Fundamentally important in designing an elicitation procedure is the type of information that is sought (quantitative, qualitative or conceptual/causal) as this largely dictates either direct or indirect elicitation and limits the choice of appropriate techniques (e.g. O'Leary *et al.*, 2009; Kuhnert *et al.*, 2010, Tab. 1, p. 4). The next important design choice is that between individual or group elicitation, which is closely linked to the elicitation media that can be used. Resource constraints aside, there are benefits associated with both types of elicitation. Individual interviews may allow for more targeted questionings and explanation (Knol *et al.*, 2010), but might be compromised by preconceived ideas of the interviewer

1 (Ayyub, 2001), who might of course also bias group processes. Group discussions may make
2 disciplinary biases more explicit and discount redundant information through sharing of
3 knowledge, but might be dominated by single individuals and might over-emphasise
4 consensus (Knol *et al.*, 2010). Individual elicitation may also be carried out remotely using
5 questionnaires or software tools, with the benefits of lower cost, standardisation and
6 freedom for the interviewees to respond in their own time (Knol *et al.*, 2010). Face-to-face
7 interviews, however, leave more room for explanation and may increase the motivation and
8 responsibility of experts (Knol *et al.*, 2010). A special elicitation medium is the map which
9 has obvious benefits for eliciting location-based information (Denham and Mengersen,
10 2007; James *et al.*, 2010).

11 **4.2 Subject uncertainty and opinion aggregation**

12 Expert opinion may be elicited with or without each subject's individual uncertainty,
13 although uncertainty is easier represented for quantitative rather than qualitative or
14 conceptual/causal information. Representing subject uncertainty is arguably the more
15 realistic option when assessing the true state of knowledge about a topic, but its influence
16 should decrease as the number of experts whose opinions are combined increases. The
17 aggregation of opinions is, therefore, an important step in expert elicitation. Note that both
18 subject uncertainty elicitation and opinion aggregation rely on the choice of uncertainty
19 model (discussed in section 4.3) because different models require different elicitation and
20 aggregation techniques. The means of aggregation can be divided into behavioural and
21 mathematical methods (e.g. O'Leary *et al.*, 2009), although practice might involve aspects of
22 both (Clemen and Winkler, 1999). Note that the conditions that warrant aggregation and its
23 means remain controversial (Knol *et al.*, 2010).

24 *Behavioural aggregation* aims for consensus, which may mean an agreement on
25 uncertainty. For different types of consensus see, for example, Ayyub (2001, Fig. 6.1, p.
26 239). A prominent technique is the Delphi method (e.g. Ayyub, 2001; Kuhnert *et al.*, 2010),
27 which involves several iterations of individual expert elicitation, feedback and adjustment of
28 opinions remotely, e.g. by questionnaire. For a recent critique, see Landeta (2006). The
29 Nominal Group technique (e.g. Clemen and Winkler, 1999, who also cite further techniques)
30 is an equivalent of Delphi where the feedback step takes place during a face-to-face meeting

1 of experts. For such group settings, Ayyub (2001) note the following potential shortcomings:
2 socially reinforced irrelevance or conformity within the group; dominance of strong-minded
3 or strident individuals; group motive of quickly reaching agreement; group-reinforced bias
4 due to common background of group members. There is also evidence that groups are more
5 confident than individuals, with a tendency to overconfidence (e.g. Janis, 1971; Janis, 1972;
6 Esser, 1998). It thus becomes clear that the success of group (but also remote) consensus
7 techniques hinges on the skill of the facilitator (Clemen and Winkler, 1999; Hubacek and
8 Reed, 2009; Kuhnert *et al.*, 2010).

9 In many situations, the disagreement among experts itself may be important information
10 that should be retained (Knol *et al.*, 2010). In these cases, *mathematical aggregation* allows
11 representing expert disagreement as uncertainty by combining individual opinions through
12 statistical or other means. The actual techniques are a continuing research topic (Booker
13 and McNamara, 2004) and range from simple and weighted averaging to various Bayesian
14 updating models (Clemen and Winkler, 1999). See Stiber *et al.* (2004) for an example of
15 Bayesian averaging of multiple probabilistic networks constructed by different experts.
16 Important issues are the weighting of experts and the accounting for expert correlation,
17 which we discuss further in section 4.4.

18 **4.3 Uncertainty model**

19 The inevitable uncertainty of expert opinion should be accounted for as it enters models. In
20 principle, this requirement is similar to that of other measured data (e.g. Krueger *et al.*,
21 2009; Krueger *et al.*, 2010), despite differences in the acquisition processes and associated
22 sources of bias and imprecision between both types of data. Yet, this similarity is rarely
23 recognised explicitly (though see Booker and McNamara, 2004; Knol *et al.*, 2010, for
24 exceptions), which has arguably hampered possible synergies resulting from applying the
25 same techniques to both data types. A particular issue with expert opinion, however, is that
26 without proper consultation with the experts it is often unclear what their uncertainty
27 actually reflects (Kuhnert *et al.*, 2010). Kuhnert *et al.* suggest that it might be epistemic
28 rather than aleatory uncertainty, i.e. ignorance rather than inherent stochasticity in
29 environmental systems.

1 Two uncertainty models dominate in the expert elicitation literature: probability theory and
2 fuzzy set theory (equivalent to possibility theory (Hall, 2003)). The probabilistic approach
3 usually follows a Bayesian interpretation (DeGroot, 1988). There remains strong
4 disagreement as to which theory may be superior philosophically for describing expert
5 opinion. Zadeh (1983), for example, asserts that probability theory does not provide a
6 systematic basis for dealing with the inherent fuzziness of knowledge in the same way as
7 fuzzy logic. More specifically, Walley (1996) criticises probability theory for not adequately
8 modelling ignorance, partial information, imprecise or qualitative judgements of
9 uncertainty, vague predicates in natural language, and conflict between expert opinions.
10 Ross *et al.* (2008) see possibility theory as more flexible and intuitive for framing expert
11 opinion than probability theory. DeGroot (1988), in contrast, claims that fuzzy logic does not
12 provide a coherent operational meaning in all decision problems in the same way as
13 probability theory. See O’Hagan (this issue) for additional details of the coherence
14 argument. Walley (1996) criticises possibility theory for a lack of definite interpretation of
15 possibility measures and, partly as a result, a lack of justification of the combination rules.

16 Recently, theories of imprecise probability have been proposed to unify probability and
17 possibility theory (e.g. Walley, 1996; Hall, 2003; Ross *et al.*, 2009), with each complementing
18 the other by describing different types of ignorance (Ayyub, 2001, Tab. 2.10, p. 86). See
19 Rinderknecht *et al.* (this issue) for a derivation of imprecise probabilities of this kind. Walley
20 (1996) extends the coherence argument of the Bayesian interpretation of probability to
21 imprecise probabilities. From a practical perspective, the experience of Booker and
22 McNamara (2004, p. 332) suggests that “no one theory is universally applicable for
23 characterizing all uncertainties in all problems”, and they advocate “extracting the
24 knowledge in as raw (or perhaps pure) and unbiased a form as possible, according to the
25 way experts think and problem solve”. Choosing the uncertainty model based on the
26 reasoning behaviour of experts seems to be a pragmatic way around philosophical
27 differences, especially as technically one model can be translated into any other one.
28 Booker and McNamara advise that “most experts find it easier to express their initial
29 uncertainty in natural language terms” (Booker and McNamara, 2004, p. 333), while some
30 technical experts might think in ways consistent with probability theory and others in terms
31 of intervals or ranges when estimating uncertainty.

4.4 Expert bias, calibration and weighting

An issue warranting further discussion is that of expert bias (illustrated, for example, by Kuhnert *et al.*, 2010), particularly *motivational bias* (e.g. group thinking, misinterpretation, wishful thinking, impression management) and *cognitive bias* (e.g. anchoring, inconsistency, underestimation of uncertainty, availability) (Booker and McNamara, 2004). These biases are fundamentally conditioned by human heuristics, judgements and mental operations (e.g. Kuhnert *et al.*, 2010, Tab. 3, p. 7), but also the process of expert elicitation itself (e.g. question phrasing, information provision) (Booker and McNamara, 2004; Knol *et al.*, 2010) as well as “expert fatigue” affecting memory recall and accuracy (James *et al.*, 2010). A large body of psychological literature exists on these topics and we refer to standard texts (Kahneman *et al.*, 1982; Gilovich *et al.*, 2002) for further reading.

Expert bias may be countered by expert calibration (e.g. Ayyub, 2001; Knol *et al.*, 2010), e.g. giving experts feedback on training questions, evaluating their estimation of variables with known value (seed variables), or having them judge the same variable in two or more different ways. The latter two options allow numerical scores to be derived for the experts, which may be used as weights when aggregating opinions. Experts may also be asked to score themselves or each other (in absolute or relative terms). While this option can easily suffer from bias and overconfidence itself (Knol *et al.*, 2010), it has the advantage of simplicity which can be viewed as commensurate to the very nature of expert elicitation (Ayyub, 2001).

4.5 Expert selection and representativeness

Another important issue is that of selecting experts to ensure a representative sample, a process which frequently lacks justification (Cornelissen *et al.*, 2003). The selection process should: follow a formal nomination and selection process; ensure diversity of opinion, credibility and result reliability; minimise redundancy of information; and have a balanced and broad spectrum of viewpoints, expertise, technical points of view and organisational representation (Clemen and Winkler, 1999; Ayyub, 2001; Knol *et al.*, 2010). In order to achieve these objectives, sample sizes in the order of 3-5 (Clemen and Winkler, 1999) and 6-

1 12 (Ayyub, 2001; Knol *et al.*, 2010) have been reported (see also Table 1). Beyond these
2 numbers, marginal returns may be limited (Clemen and Winkler, 1999; Knol *et al.*, 2010).

3 Different types of experts can be distinguished which all have specific roles in the elicitation
4 process (Ayyub, 2001, Tab. 6.1, p. 235; Knol *et al.*, 2010, p. 7). Briefing experts prior to
5 elicitation is an important step that establishes relevance and thus increases experts'
6 attention and sincerity levels. In this context, Ayyub (2001) speaks of experts becoming
7 stakeholders of the outcome of the elicitation and its further use. We come back to the
8 relationship between experts and stakeholders in section 5.2.

9 **4.6 Design and documentation**

10 In conclusion, there are pitfalls to avoid when eliciting expert opinion, but it has been
11 argued that design and documentation can overcome, or at least make explicit, most of the
12 existing limitations (Knol *et al.*, 2010). Knol *et al.* argue this point against the background of
13 the implicit expert judgement which is also inherent in many measured data. Ayyub (2001)
14 advises that, in order to conform to a rational consensus process, expert elicitation be:
15 reproducible (documented so as to enable peer review); accountable (anonymity, in
16 contrast, might degrade outcomes); empirically controllable (cross-checked against other
17 information/experts); neutral (in relation to the conduct of the elicitation process); and fair
18 (equal treatment of experts). To pre-empt expert contestation, all stakeholders in the
19 outcome of the elicitation and its use should co-design or at least review the expert
20 selection and elicitation process.

21 **5 Wider perspective on expert opinion and future opportunities**

22 We have demonstrated based on a literature review that expert opinion is a fundamental,
23 albeit often informal, element of environmental modelling owing to the evolutionary nature
24 of knowledge, the formal abstraction of models and the levels of subjectivity and value in
25 knowledge claims. This basis and the increasingly formal use of expert opinions from a
26 diverse range of expert backgrounds in environmental models has led us to adopt a
27 definition of "expert" as anyone with the *right kind of experience* in a topic of interest. This
28 broad perspective on expert opinion opens up knowledge production and peer review to a
29 wide range of stakeholders, which sits comfortably with the notions of post-normal science

1 (Funtowicz and Ravetz, 1993) and collaborative rationality (Innes and Booher, 2010) for
2 environmental decision making. Note that we are concerned with the co-production of facts
3 (much as these are influenced by values *implicitly*), while collaborative decision making
4 extends *explicitly* to values and requires a wider range of actors still. In practice, though,
5 both processes are linked and can be exercised synergistically, as discussed briefly next.

6 **5.1 Opportunities for participatory modelling**

7 New opportunities arise from tapping into previously neglected knowledge from non-
8 professional as well as professional domains. First of all, information becomes accessible for
9 which there is no measured data equivalent. This source allows building, parameterising and
10 driving models in situations that are notoriously data scarce, yet of acute policy relevance,
11 such as many areas of ecology and diffuse pollution. Expert data also allow the evaluation of
12 model predictions as these are becoming increasingly local. We see expert data as one of
13 many data sources, all with specific uncertainties that should be accounted for in modelling
14 and decision making. The result is a broadening of the knowledge base which we expect will
15 enhance the scientific enquiry and models, not least through creative conflict between
16 scientific and non-scientific knowledge (Funtowicz and Ravetz, 1993).

17 This argument resonates with the *substantive* benefits (e.g. van der Sluijs, 2002) of
18 stakeholder participation, particularly participatory modelling (illustrated by Brown Gaddis
19 *et al.*, 2010, for example). However, the incorporation of stakeholder expert data into
20 models is but one element of participatory modelling, which considers a much broader role
21 of models ranging from problem framing to decision making (Voinov and Bousquet, 2010).
22 At the same time, the level of incorporation of expert opinion into models as reported and
23 encouraged in this paper may be deeper and more formal than that of many participatory
24 modelling studies reviewed by Voinov and Bousquet, which were often limited to the
25 perceptual modelling stage.

26 Issues of confidentiality emerge if those providing data (experts) are also affected by
27 policies informed by these data through models (stakeholders). This conflict of interest can
28 be met if the provision of information is rewarded by an influence on decisions, which
29 requires an overarching collaborative framework of managing natural resources including all
30 stakeholders. Further societal benefits should accrue from the increased engagement of the

1 public in science, both through data provision as experts as well as through deliberation as
2 stakeholders. On the one hand, individuals may come to see themselves as part of
3 environmental problems as well as the process of understanding and resolving them. On the
4 other hand, public trust in science may increase as controversies are overcome in the
5 process of evaluating models. It can be expected that these *instrumental* benefits of
6 stakeholder participation will emerge alongside *normative* benefits, i.e. adherence to
7 democratic ideals (e.g. van der Sluijs, 2002). Ultimately, the opportunities for individual and
8 collective learning can help make communities more adaptive and resilient (Innes and
9 Booher, 2010).

10 **5.2 Experts and stakeholders**

11 At this point it is helpful to reassess the distinction between experts and stakeholders in the
12 context of environmental modelling. We see experts and stakeholders being related in at
13 least three different ways: Not all stakeholders will classify as experts, but it can be argued
14 that all experts are stakeholders in the sense that they can *affect* the outcomes of models
15 and thus the outcomes of using models (such as policy and management decisions). There
16 may also be experts that have a more tangible stake in that they are *affected* by the
17 outcomes of using models (as in Ticehurst *et al.*, 2007, for example). It follows that no
18 expert will give a strictly impartial opinion, which is apparent already from the social
19 involvement of scientists with their objects of study and the intertwining of facts and values
20 discussed in section 1.1. It is also worth noting that *perceptions* of impartiality can change
21 depending on an expert's posture, but this can be pre-empted through transparency about
22 expert hypotheses, stakes and objectives (Lagabrielle *et al.*, 2010, for the case of perceived
23 scientist impartiality). However, adherence to the rational consensus argument for expert
24 accountability and against expert anonymity (Ayyub, 2001, see section 4.5) will further
25 increase the expert's stake in the use of their opinion (as envisaged explicitly by Ayyub,
26 2001) and bias the elicitation process. We thus suggest that expert accountability
27 necessitates a process in which expert critics are equally accountable, that is open and
28 transparent, and that embraces the evolutionary nature of knowledge.

5.3 Enhanced function of expert opinion and future research programme

The conclusion of this paper is not a discrediting of scientific expert opinion, but an enhanced awareness and function of expert opinion in science. We encourage a move away from the traditional ideal of unbiased and impartial experts towards an unbiased process of expert contestation (Munnichs, 2004) and a plurality of expertise. The focus should be on the quality of the enquiry rather than universal truth (Ravetz and Funtowicz, 1999). Where multiple legitimate perspectives on the behaviour of environmental systems exist, these should be reflected in a plurality of models. In the same way that knowledge is continuously tested and used, so should models. However, as our literature review demonstrates, there is the danger of informal use of expert opinion in models which undermines scientific legitimacy. It is important, therefore, as argued by many authors involved in expert elicitation and expert systems, that expert opinion enters models in an explicit, structured and documented way, i.e. formally, to allow scientific and extended peer review. Due to the complexity of models which cannot be laid out fully in scientific articles, effective peer review can only be achieved if source codes are in the public domain (e.g. Harvey and Han, 2002; Voinov *et al.*, 2008).

The formalisation of expert opinion itself presents future research challenges, including: the selection of representative experts and the demonstration that they have the right kind of experience for the task at hand; the calibration of experts and the weighting of their responses; the quantification of different types of individual and collective uncertainty; and cost effective and robust means of expert elicitation. It should be clear from our discussion that the processes as well as the outcomes of this research programme hold rewards for scientists, stakeholders and society at large.

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Table 1: Examples of experts found in the environmental modelling literature, number of experts consulted formally in each study, and account for uncertainty.

Types of experts	Number of experts	Uncertainty accounting	References
Scientists	1-12	yes	Borsuk <i>et al.</i> (2006)
Ecologist	1	no	Seoane <i>et al.</i> (2005)
Scientist	1	yes	Borsuk <i>et al.</i> (2001); Kampichler <i>et al.</i> (2010); Kuhnert <i>et al.</i> (2010)
Professional	1	yes	Cain <i>et al.</i> (1999)
Scientists	2	yes	Borsuk <i>et al.</i> (2003); Borsuk (2004); Borsuk <i>et al.</i> (2004); Lele and Allen (2006); Mathon <i>et al.</i> (2010)
Professionals	2	yes	O'Leary <i>et al.</i> (2009)
Ecologists	3	no	Pearce <i>et al.</i> (2001)
Ecologists	3	yes	Woolridge <i>et al.</i> (2005); Smith <i>et al.</i> (2007)
Farmer; agronomists; extension advisor	>3	no	Girard and Hubert (1999)
Professionals	4	yes	Montangero and Belevi (2007)
Mycologists	4	yes	Marcot (2006)
Governmental and non-governmental specialists in boating and marine biology	5-10	yes	Acosta <i>et al.</i> (2010)
Geomorphologists	5	yes	Besaw <i>et al.</i> (2009)
Scientists; engineering consultants	5	yes	Brouwer and De Blois (2008)
Biologists; field technicians	6	yes	Ahmadi-Nedushan <i>et al.</i> (2008)
Scientists	6	yes	Ferraro (2009)
Scientists; engineering consultants; government officials	6	yes	Taheriyoun <i>et al.</i> (2010)
National park managers; local researchers; deer hunters; photographers; park visitors	9	no	Yamada <i>et al.</i> (2003)
Conservation managers	9	yes	Murray <i>et al.</i> (2009)
Biologists; foresters and forest managers; local lichen specialist; biometrician	11	yes	Nyberg <i>et al.</i> (2006)
Climate change scientists	13	yes	Varis and Kuikka (1999)
Professionals	15	yes	Marcot <i>et al.</i> (2006)
Microbiologists; soil and contaminant scientists; manure management specialists; policy makers; geographers	16	yes	Fish <i>et al.</i> (2009), Oliver <i>et al.</i> (2010)
Professionals	18	yes	Cornelissen <i>et al.</i> (2003)
Experts with experience in response of birds to disturbance and field experience in grazed landscapes	20	yes	Martin <i>et al.</i> (2005); Kuhnert <i>et al.</i> (2010)
Representatives of stakeholder groups with expertise in deer populations and their impacts	21	no	Austin <i>et al.</i> (2009)
Government officials; scientists; fishermen; non-governmental specialists; tourism operators	21	no	Bello-Pineda <i>et al.</i> (2006)
Professional of varied educational/experiential backgrounds (academia, consultancy, government, industry)	22	yes	Stiber <i>et al.</i> (1999); Stiber <i>et al.</i> (2004)
Rice farmers	22	no	Naivinit <i>et al.</i> (2010)
Experts in management and research of species from state, Federal, tribal and private entities	25	no	Holthausen <i>et al.</i> (1994)
Farmers and technical specialists from the region; scientists; grazing industry representatives	32	yes	McDowell <i>et al.</i> (2009)

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Table 2: Examples of models and locations where expert opinion is found in the environmental modelling literature.

Location	Use of expert opinion	Type of model	Discipline, topic (references)
Construction of conceptual model	Weighting importance of model components	Expert system	<u>Biogeochemistry</u> , Faecal Indicator Organisms risk (Fish <i>et al.</i> , 2009; Oliver <i>et al.</i> , 2010)
	Rule derivation	Qualitative expert system	<u>Agronomy</u> , farming practices (Girard and Hubert, 1999); <u>agronomy</u> , land management (van Lanen and Wopereis, 1992; Wandahwa and van Ranst, 1996); <u>environmental management</u> , resource utility (Bello-Pineda <i>et al.</i> , 2006); <u>geomorphology</u> , soil erosion (de la Rosa <i>et al.</i> , 1999)
	Selection of statistical model & predictors	Statistical model	<u>Ecology</u> , species distribution (Pearce <i>et al.</i> , 2001; Seoane <i>et al.</i> , 2005)
Construction of conceptual model / parameterisation	Rule derivation / quantification	Fuzzy expert system	<u>Agronomy</u> , animal welfare (Cornelissen <i>et al.</i> , 2003); <u>climatology</u> , climate change impact (Eierdanz <i>et al.</i> , 2008); <u>ecology</u> , ecological quality (Kampichler <i>et al.</i> , 2010); <u>ecology</u> , species distribution (Ahmadi-Nedushan <i>et al.</i> , 2008; Acosta <i>et al.</i> , 2010); <u>ecology</u> , eutrophication (Taheriyoun <i>et al.</i> , 2010); <u>environmental management</u> , land management (Joss <i>et al.</i> , 2008); <u>geomorphology</u> , sediment transfer (Nguyen <i>et al.</i> , 2007); <u>hydrogeology</u> , groundwater contamination (Uricchio <i>et al.</i> , 2004); <u>soil science</u> , salinisation & alkalisation (Metternicht, 2001); <u>soil science</u> , soil condition (Ferraro, 2009)
	Graph / probability tables	Probabilistic network	<u>Biogeochemistry</u> , phosphorous transfer (McDowell <i>et al.</i> , 2009); <u>ecology</u> , population dynamic (Marcot <i>et al.</i> , 2001; Borsuk <i>et al.</i> , 2006; Marcot <i>et al.</i> , 2006; Nyberg <i>et al.</i> , 2006; Pollino <i>et al.</i> , 2007; Pollino <i>et al.</i> , 2007; Bashari <i>et al.</i> , 2009; Drescher and Perera, 2010); <u>ecology</u> , estuarine response to nutrient loads (Borsuk <i>et al.</i> , 2001); <u>ecology</u> , eutrophication (Borsuk <i>et al.</i> , 2003; Borsuk <i>et al.</i> , 2004); <u>ecology</u> , marine algal blooms (Hamilton <i>et al.</i> , 2007); <u>ecology</u> , species distribution (Marcot, 2006; Smith <i>et al.</i> , 2007); <u>environmental engineering</u> , drinking water treatment (Pike, 2004); <u>environmental management</u> , resource management (Cain <i>et al.</i> , 1999); <u>agronomy</u> , irrigation (Batchelor and Cain, 1999); <u>hydrogeology</u> , groundwater contamination (Stiber <i>et al.</i> , 1999; Stiber <i>et al.</i> , 2004; Henriksen <i>et al.</i> , 2007)
	Rule derivation / quantification	Mechanistic model	<u>Agronomy</u> , farming practices (Naivinit <i>et al.</i> , 2010)
Parameterisation	Parameterisation (incl. uncertainty)	Semi-qualitative expert system	<u>Ecology</u> , food web interactions (Rochette <i>et al.</i> , 2009)
	Rule modification	Fuzzy expert system	<u>Ecology</u> , species distribution (Mouton <i>et al.</i> , 2007)
	Probability tables	Probabilistic network	<u>Ecology</u> , population dynamics (Borsuk, 2004; Newton <i>et al.</i> , 2007; Burgman <i>et al.</i> , 2010); <u>climatology</u> , climate change impact (Varis and Kuikka, 1999); <u>hydrogeology</u> , salinisation (Ghabayen <i>et al.</i> , 2006)
	Prior parameter distributions	Statistical model	<u>Ecology</u> , species distribution (Martin <i>et al.</i> , 2005; Denham and Mengersen, 2007; Griffiths <i>et al.</i> , 2007; Low Choy <i>et al.</i> , 2009; Murray <i>et al.</i> , 2009; O'Leary <i>et al.</i> , 2009; James <i>et al.</i> , 2010; Kuhnert <i>et al.</i> , 2010); <u>geomorphology</u> , landslide occurrence (Milheiro-Oliveira, 2007)
	Prior parameter distributions	Mechanistic model	<u>Environmental engineering</u> , septic tanks (Montangero and Belevi, 2007)
	Parameterisation (incl. uncertainty)	Mechanistic model	<u>Hydrogeology</u> , groundwater flow (Ross <i>et al.</i> , 2008); <u>oceanography</u> , estuarine stratification (Borsuk <i>et al.</i> , 2001)
	Uncertainty assessment (parameter distributions)	Mechanistic model	<u>Biogeochemistry</u> , nitrogen/phosphorous transfer (Bijlsma <i>et al.</i> , 2007); <u>environmental modelling</u> , general (Refsgaard <i>et al.</i> , 2007)

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Location	Use of expert opinion	Type of model	Discipline, topic (references)
Construction of conceptual model / provision of boundary conditions	Predictor selection / provision of response data	Statistical model	<u>Ecology</u> , species distribution (Yamada <i>et al.</i> , 2003)
Provision of boundary conditions	Response data for learning fuzzy expert system	Fuzzy expert system	<u>Biogeochemistry</u> , water quality (Kawano <i>et al.</i> , 2005)
	Response data for regression	Statistical model	<u>Ecology</u> , population dynamics (Wooldridge <i>et al.</i> , 2005) ; <u>geomorphology</u> , soil erosion (Sonneveld and Albersen, 1999)
	Response data for regression tree	Statistical model	<u>Ecology</u> , ecological quality (Kampichler <i>et al.</i> , 2010)
	Augmentation of presence / absence data	Statistical model	<u>Ecology</u> , species distribution (Lele and Allen, 2006)
	Habitat value indices	Statistical model	<u>Ecology</u> , species distribution (Pearce <i>et al.</i> , 2001)
Evaluation	Geomorphic indices as training data for Artificial Neural Network	Statistical model	<u>Geomorphology</u> , stream-morphological change (Besaw <i>et al.</i> , 2009)
	Results comparison	Statistical model	<u>Ecology</u> , species distribution (Holthausen <i>et al.</i> , 1994; Austin <i>et al.</i> , 2009; Painsi <i>et al.</i> , 2010)
	Modification of model predictions	Statistical model	<u>Ecology</u> , species distribution (Pearce <i>et al.</i> , 2001)
	Post-hoc uncertainty assessment	Mechanistic model	<u>Biogeochemistry</u> , water quality (Brouwer and De Blois, 2008)
	Expert scoring of expert opinion	Mechanistic model	<u>Atmospheric chemistry</u> , tropospheric ozone impact (Kloprogge <i>et al.</i> , 2009)
	2nd order uncertainty about spatial parameter variation	Mechanistic model	<u>Hydrogeology</u> , groundwater flow (Ross <i>et al.</i> , 2009; Mathon <i>et al.</i> , 2010)