IAJ The Integrated Assessment Journal
Bridging Sciences & Policy
Vol. 6, Iss. 1 (2006), Pp. 83–88

To what extent, and how, might uncertainty be defined?
Comments engendered by "Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support": Walker et al., Integrated Assessment 4: 1, 2003

John P. Norton
Department of Electronic, Electrical and Computer Engineering
The University of Birmingham
Edgbaston, Birmingham B15 2TT, United Kingdom
and
Department of Mathematics and
Integrated Catchment Assessment & Management Centre
The Australian National University
ACT 0200, Australia *

James D. Brown
Institute for Biodiversity and Ecosystem Dynamics
Universiteit van Amsterdam
Niewe Achtergracht 166, 1018 WV Amsterdam, The Netherlands †

Jaroslav Mysiak
UFZ Centre for Environmental Research
Leipzig-Halle, Permoserstraße 15D-04318, Leipzig, Germany ‡

Decisions about the exploitation and management of social and natural resources are frequently informed by predictions from models. In order to manage the contribution of models to decision making, it is important to understand the uncertainties associated with these predictions. In practice, this is not straightforward, for several reasons: models are structurally diverse, they are

*E-mail: j.p.norton@bham.ac.uk
†E-mail:brown@science.uva.nl
‡Corresponding Author; E-mail:jaroslav.mysiak@ufz.de, Phone: ++49 +341 2353199, Fax: ++49 +341 2352825

used in a wide range of contexts and for many different reasons (Beck, 2002), and the quality of a model's predictions may be highly case-dependent. Central to coping with this complexity is the need for new concepts that link classes of uncertainty to the types of situation in which models are used and the methods available for evaluating uncertainty. Walker et al. (2003) propose a scheme for classifying uncertainties in models intended for decision support. The purpose of this note is to examine 1) the extent to which the aims of Walker et al. are achievable and 2) whether the proposed classification meets these aims.

Walker et al. aim to provide an interdisciplinary framework for assessing uncertainties in models used for decision support. We agree that such a framework is needed and should be developed from a classification of types of uncertainty and situations in which they arise. Numerous taxonomies of imperfect knowledge have been proposed in recent years, including schemes that focus on general types of imperfect knowledge (Suter et al., 1987; Smithson, 1989; Faber et al., 1992, 1996; Wynne, 1992; Dovers et al., 2001) and taxonomies that focus on specific sources of imperfect knowledge (Wätzold, 2000). However, an important barrier to achieving a common understanding or interdisciplinary framework is the diversity of meanings associated with terms such as 'uncertainty' and 'ignorance', both within and between disciplines. A further impediment is the depth with which different meanings are embedded in particular disciplines; common understanding is not simply a matter of clarity. For example, some authors equate uncertainty with 'doubt' or 'unsureness' (Brown, In Press), while others include in their definitions sources of uncertainty, such as imprecision and randomness, or even view ignorance as an extreme form of scientific uncertainty (Walker et al., 2003; Smithson, 1989).

Also, uncertainties may be framed by the presentation, sources, and social construction of information (a social science perspective), as well as the degrees and perceived quality of information available (a Bayesian, physical science perspective). Indeed, from a social science perspective, the apparently uncontroversial assertion of Walker et al. that "completely deterministic knowledge of the relevant system" is "ideal" can be viewed as deeply problematic, because the pursuit of this "ideal" would discourage consideration of the disposition of people to exaggerate, suppress or complicate expressions of uncertainty, intentionally or unintentionally. Thus, while classification is an important source of meaning, some discussion on the scope of uncertainty is a prerequisite to understanding terms such as 'location', 'level' and 'nature' of uncertainty, as used by Walker et al.. In the absence of a discussion about the different meanings of uncertainty and the situations in which they arise, a classification cannot be expected to provide a common understanding or interdisciplinary framework for assessing uncertainties in models used for decision support.

Although a common framework is difficult to envisage in practice (and impossible without very careful treatment of definitions), a systematic treatment of uncertainty might nevertheless be possible. The Walker et al.. scheme specifically aims "to provide a systematic treatment of uncertainty in decision support in order to improve the management of uncertainty in decision making processes". Given the applied nature of this aim, it follows that the scheme for classifying uncertainty should (eventually) link to the application of models as decision-support tools, and to the methods available for assessing their uncertainties. In this context, the scheme of Walker et al.. is limited in two important ways. First, by adopting a modellers' view of uncertainty rather than a decision makers' perspective, the classification scheme omits some relevant sources of uncertainty (perhaps even the most important ones) that arise before and after scientific models are applied. For example, it fails to consider the different ways in which goals (concepts) are translated into decision criteria (entities) and then into observable quantities (data and models), or how decision maker's preferences based on model predictions are aggregated by decision-support tools such as cost-benefit analysis or multi-criteria analysis. Secondly, by not relating classes of uncertainty to the types of situation in which models are used or the methods available for estimating uncertainty, Walker et al. do not achieve their central aim of providing an operational scheme. If, having identified a specific class of uncertainty, the classification is not accompanied by some means, however crude, to follow up its implications for model-based decision support, it is inherently limited as an operational tool. Of course, it may lead to a deeper understanding of the fundamental components of uncertainty, but many classifications have been proposed for this purpose (see above), and the current scheme is no more successful in this respect than the previous attempts, because 1) it does not address the diversity of meanings associated with terms such as 'uncertainty' and 'ignorance' in the context of model-based decision support, and 2) it does not explore how these concepts are assessed and used by different groups of modellers, including model developers and model users (e.g. 'academics' versus 'practitioners').

In the scheme proposed by Walker et al., uncertainty is classified according to its location, level and nature, each with a small number of classes. This resembles a taxonomy. Taxonomies usually have one or more orderings, often hierarchical. Examples are the periodic table and the standard zoological classification scheme. The attribute "location" has classes (context, model, inputs, parameters, outputs) and subclasses, and "nature" includes a binary split between epistemic uncertainty and ontological uncertainty (ignoring linguistic imprecision). While these do not impose any natural ordering, the attribute "level" introduces an order from 'certainty' through 'statistical uncertainty' and 'scenario uncertainty' to 'recognised ignorance' and 'unrecognised ignorance'. This ordering is problematic if uncertainty is viewed as a state of confidence, because certainty does not imply that a judgement is correct; rather, ignorance or 'unrecognised ignorance' in the Walker et al. scheme is fundamentally different from a state of confidence. Furthermore, if 'statistical uncertainty' is assumed to refer to quantifiable uncertainty, Walker et al. fail to acknowledge the distinct spectrum of well-established methods, not all statistical, for characterising degrees of credibility, ranging from bounds (binary classification as possible/impossible) through rough sets (ternary classification as possible/doubtful/impossible), fuzzy sets (graded from possible to impossible) and histograms (graded in relative frequency with a probabilistic interpretation available) to probability density functions (taking a Bayesian view). However, this one-dimensional spectrum does not cover all ways of describing uncertainty. For example, the characterisation of a group of uncertain items by their vector mean and covariance matrix has a non-probabilistic parallel in the specification of ellipsoid bounds, characterised by the center and defining matrix. The latter is algebraically identical to the former, quite different in its interpretation and implications, yet asymmetrically linked: the describing matrix of an ellipsoidal bound on a vector is an upper bound on its covariance, but a given covariance does not, of course, imply bounds on the vector. Similarly, pdfs are superficially complete descriptors of uncertainty, well suited to assessing uncertainty propagation through a model, whereas qualitative expressions of uncertainty are more difficult to define unequivocally and to use in an uncertainty propagation analysis, but are potentially more informative than pdfs, as they can contain an arbitrarily large number of types of attributes. As another example, information about the number of samples is typically lost in fitting a pdf to a probability test sample, but may be highly relevant if the number is small.

Although the scheme of Walker et al. is insufficiently precise about the attribute "level" and does not consider sufficiently the relationship between states of knowledge and methods for describing uncertainty, it has the advantage of being specific about the location of uncertainty in models. For example, it distinguishes between model-structure uncertainty and input uncertainty, and within the latter between uncertainty in external forcing and in measured data. Uncertainties in calibrated parameters and model solution (numerical approximation) might be included here. However, in non-linear systems the effects of inputs and parameters on outputs, or even stability, may be inextricably linked, so that the contribution of input uncertainty to the overall uncertainty in model prediction cannot be separated from those of uncertain model parameters, structure and solution. Thus, an uncertainty-propagation analysis should be performed for specific cases, and the roles of specific sources of uncertainty may be highly case-dependent. Walker et al. also distinguish between controllable and uncontrollable inputs, but if the aim is to explore the effects of uncertainty on model predictions it is necessary to consider controllability (of the state of a model, and thence of its outputs, from its inputs) as a property of the model and its inputs jointly, rather than its forcing inputs alone. Here the complementary properties of observability and identifiability should be considered alongside controllability, and the possibility acknowledged that over-parameterisation could accentuate uncertainties in model predictions. Of course, amplification of uncertainty by ill-posedness may originate from a poor choice of origin, scaling of variables or order of computation, as well as from over-parameterisation.

A further potentially important source of uncertainty in models originates from the extrapolation of model predictions into regions of behaviour that are poorly covered, or not covered at all, during model calibration. Thus, it is useful to distinguish between the quality of a model in approximating some aspects of 'reality' and the uncertainties associated with extrapolation of model predictions. The former may depend on a combination of insufficiently detailed knowledge about the system or its inputs, and deliberate reduction of model complexity for reasons of comprehensibility, computational load or analytical convenience. Approximation errors may be complex even in linear models. For example, aliasing or rounding errors, caused by an unsuitable sampling rate or quantisation interval for a variable in a model, may be entirely predictable from the characteristics of the variable being approximated, but may be very difficult to describe in an uncertainty analysis. The uncertainties associated with extrapolation are essentially case-dependent, and their evaluation is impossible without either extending experiments into a larger region of state space or making untested assumptions about regularity of behaviour over that space. Extended experimentation may be impossible in practice when resources are limited or the state space is difficult to observe (e.g., in groundwater hydrology), or if the model has to predict in scenarios that are not currently realisable (e.g., in changed climate).

Finally, in evaluating 'structural uncertainty' it is important to distinguish between the predictive performance of a model and its ability to explain real patterns and processes. The former is fully reflected in the quantifiable difference between model predictions and independent observations, whereas the latter depends also on collateral knowledge (e.g., recognising the possible contribution of snowmelt in calibrating a hydrological model relating rainfall to runoff). In this context, observations are not inherently more certain than models (although such an assumption is often implicit, especially for measured inputs) and their uncertainties may be poorly reflected in stationary statistics.

Underlying the classification of uncertainty in general, and undermining the classification of Walker et al. specifically, is the possibility that interactions between different sources of uncertainty are obscured or overlooked. Crucially, therefore, classifications of uncertainty should not sustain the generally unwarranted assumption, often made unconsciously, that the effects of different uncertainties are additive. Rather, once these uncertainties are identified (classified) they must be analysed and their implications for decision-making evaluated as a whole. For the same reason, an uncertainty analysis is always required in specific cases, and the quality of a classification should be judged by its ability to guide the application of an uncertainty analysis in specific cases. Since Walker et al. do not relate classes of uncertainty to methods of analysis or propagation, they cannot provide an operational scheme for addressing uncertainties and do not fulfil their central aim of providing "a systematic treatment of uncertainty in decision support in order to improve the management of uncertainty in decision making processes".

To summarise, the scheme proposed by Walker et al. is valuable in stimulating further thought about the role of uncertainty in model-aided decision-making, but incomplete in its discussion of concepts (e.g., the meaning of uncertainty) and hence difficult to apply within an interdisciplinary framework, and insufficiently grounded in methodology and thus difficult to apply in an operational content. Furthermore, it overlooks interactions between uncertainties that can severely limit a simple classification from both a modellers' and a decision makers' perspective.

1 Bibliography

Beck, M. B. (2002), *Environmental Foresight and Models: A Manifesto*, Elsevier, Oxford. 84

Brown, J. (In Press), 'Knowledge, uncertainty and physical geography: Towards the development of methodologies for questioning belief', *Transactions of the Institute of British Geographers*. 84

Dovers, S., Norton, T. & Handmer, J. (2001), Ignorance, uncertainty and ecology: Key themes, *in* J. Handmer, T. Norton & S. Dovers, eds, 'Ecology, Uncertainty, and Policy: Managing Ecosystems for Sustainability', Pearson Education Limited, Harlow, pp. 1–25. 84

Faber, M., Manstetten, R. & Proops, J. (1992), Towards an open future: Ignorance, novelty and evolution, *in* R. Costanza, B. Norton & B. Haskell, eds, 'Ecosystem Health: New Goals for Environmental Management', Island Press, Washington, D.C., pp. 72–96. 84

Faber, M., Manstetten, R. & Proops, J. (1996), *Ecological Economics*, Edward Elgar, Cheltenham. 84

Smithson, M. (1989), *Ignorance and Uncertainty: Emerging Paradigms*, Springer-Verlag, New York. 84

Suter, G., Barnthouse, L. & O'Neill, R. (1987), 'Treatment of risk in environmental impact assessment', *Environmental Management* **11**, 295–303. 84

Walker, W., Harremoës, P., Rotmans, J., van der Sluijs, J., van Asselt, M., Janssen, P. & Krayer von Krauss, M. (2003), 'Defining uncertainty: A conceptual basis for uncertainty management in model-based decision support', *Integrated Assessment* **4**(1), 5–18. 84, 85, 86, 87

Wätzold, F. (2000), 'Efficiency and applicability of economic concepts dealing with environmental risk and ignorance', *Ecological Economics* **2**(33), 299–311. 84

Wynne, B. (1992), 'Uncertainty and environmental learning: Reconceiving science and policy in the preventative paradigm', *Global Environmental Change* **2**, 111–127. 84