Ignorance is bliss: Or seven reasons not to use uncertainty analysis

F. Pappenberger[1] and K. J. Beven[1]

Received 20 December 2005; revised 19 March 2006; accepted 23 March 2006; published 16 May 2006.

[1] Uncertainty analysis of models has received increasing attention over the last two decades in water resources research. However, a significant part of the community is still reluctant to embrace the estimation of uncertainty in hydrological and hydraulic modeling. In this paper, we summarize and explore seven common arguments: uncertainty analysis is not necessary given physically realistic models; uncertainty analysis cannot be used in hydrological and hydraulic hypothesis testing; uncertainty (probability) distributions cannot be understood by policy makers and the public; uncertainty analysis cannot be incorporated into the decision-making process; uncertainty analysis is too subjective; uncertainty analysis is too difficult to perform; uncertainty does not really matter in making the final decision. We will argue that none of the arguments against uncertainty analysis rehearsed are, in the end, tenable. Moreover, we suggest that one reason why the application of uncertainty analysis is not normal and expected part of modeling practice is that mature guidance on methods and applications does not exist. The paper concludes with suggesting that a Code of Practice is needed as a way of formalizing such guidance.

Citation: Pappenberger, F., and K. J. Beven (2006), Ignorance is bliss: Or seven reasons not to use uncertainty analysis, *Water Resour. Res.*, *42*, W05302, doi:10.1029/2005WR004820.

1. Introduction

[2] Uncertainty analysis of models has received increasing attention over the last two decades in water resources research as computer power has increasingly allowed more extensive analysis of models and data. The issue is fundamental. As *Beven* [2001a] has noted, if the water balance equation is posed as a hypothesis in the study of any hydrological system, it cannot be proven without allowing significant uncertainty in every input and output term. There are many hydrology and hydraulic researchers who see uncertainty analysis as an important component of good scientific practice and a wide range of papers can be found on uncertainty estimation methods and applications in hydrology, hydraulics and water resources. However, a significant part of the community still seems very reluctant to embrace the concept of uncertainty in making predictions. Uncertainty analysis is still not standard practice in many modeling exercises and it remains common to show results without uncertainty bounds to decision makers, at scientific conferences, in refereed publications or in consultancy applications. This commentary does not aim to review different uncertainty estimation methods but rather explores the reasons for the resistance to the routine use of uncertainty analysis methods by hydrologists and hydraulic modelers, whether for reasons of expense, understanding of methods, or training in the requisite skills. Our arguments arise directly out of exchanges and discussions with modelers and users of model results about the uncertainty issue over the past two years, particularly within the context of the ongoing UK Flood Risk Management Research Consortium project. Our aim is to promote the use of uncertainty estimation as routine in hydrological and hydraulic science. As yet, despite all of the research on methods that has been done in hydrology, hydraulics and water resources, it is not. Seven of the reasons why not are as follows:

2. Uncertainty Analysis Is Not Necessary Given Physically Realistic Models

[3] There are fundamentally different philosophical positions within the hydrological and hydraulic modeling community, which influence particular views on uncertainty analysis and, indeed, whether an uncertainty analysis should be performed at all.

[4] There are some physically based modelers who believe that their models are (or at least will be in the future) physically correct and thus these models can be used in a deterministic framework (modeler type 0). This means that all parameters, structures and boundary conditions can be defined a priori and do not need to be adjusted under any circumstances. Such modelers would argue that parameter calibration or uncertainty analysis should not be necessary if predictions are based on a true understanding of the physics of the system simulated. Others take a less strongly realist position, but believe that model parameters should be only calibrated within a strictly known range (modeler type 1). This type of modeler would argue that any calibration beyond such ranges cannot be physically justified. There are also modelers who have a less firm belief in the correctness of the implementation of physical equations and laws within any modeling framework and who will happily adjust effective values of parameters even beyond their normally accepted ranges (modeler type 2); see *Wagener and Gupta* [2005] for a more detailed description

[1]Department of Environmental Sciences, Lancaster University, Lancaster, UK.

0043-1397/06/2005WR004820$09.00

of modeler type 2. Our simple classification of modelers is not meant to be impermeable or crisp, and we acknowledge the fuzziness which exists between the different categories. This is best illustrated by another group of modelers which has not yet been acknowledged in this section: data-based and data-based mechanistic modelers (modeler type 3) [e.g., *Young et al.*, 2004]. In many cases these types of modelers tend to feel close to modeler type 2 [*Seibert et al.*, 2000]. Another example was given by one of our anonymous reviewers: she/he wanted to be classed as modeler of type 2a, who agreed that mechanistic models of type 2 are empirical description of the behavior of a system, but argued that the investigator has to switch back to type 1 at least for estimating the model parameters under changing boundary conditions, despite the lack of publications in the literature that demonstrate that the prior estimation of parameter values provides satisfactory reproduction of responses where data are available to check performance. In fact, in the few cases where such studies have been reported in modeling catchment systems it has generally been demonstrated that the approach fails [e.g., *Parkin et al.*, 1996].

[5] Fundamentally, only modeler type 0 would reject any uncertainty analysis on the basis of physical correctness. This position seems difficult to justify considering published discussions of the modeling process in respect of the sources and impacts of uncertainties [see *Beven*, 1989, 2006; *Oreskes et al.*, 1994]. Such critical appraisals suggest that the type 0 position is untenable, and we would argue further that the type 1 position difficult to sustain. Both modelers of type 1 and 2 would not in principle oppose calibration (to improve predictive capability) or uncertainty analysis. However, the uncertainty analysis approach taken by the two types of modeler would differ in extent and magnitude. This is illustrated in the discussion between *Beven and Pappenberger* [2003] (type 2) and *Abbott et al.* [2003] (type 1). *Abbott et al.* [2003] have argued that uncertainty analysis should not be necessary given an adequate understanding of the system and its boundary conditions, whereas modelers of type 2 would argue that modelers of type 1 have too much faith in the model representation of physical laws or empirical equations. This line of argument could be also used by modelers of type 3, who inherently accept uncertainties in the modeling process, at least as a result of errors and natural variability in time series.

3. Uncertainty Analysis Is Not Useful in Understanding Hydrological and Hydraulic Processes

[6] There are still things to learn about how water flows through the landscape and a lot of research remains curiosity driven. In this setting, hypothesis testing with the help of models is a common instrument. Indeed, there have been many papers in the literature that explore hypotheses purely on the basis of hypothetical model predictions, without reference to observations. How far such a testing is possible or can be believed in, depends on your position within the modeling community (in terms of the classification of modelers outlined in point 1 in section 2). However, if, for example, the water balance equation cannot be validated using observations without allowing for uncertainty, it would seem that all hypothesis testing should explicitly consider the potential sources of uncertainty in applications to real systems [see *Beven*, 2002a, 2002b]. In such a framework the results will have to be stated in a probabilistic or possibilistic rather than a deterministic manner [*Hall et al.*, 2004]. Several methods have been proposed based on a probabilistic framework to choose for example between models as hypotheses [see *Congdon*, 2005, and references therein]. One example is given by *Cloke* [2005], who has illustrated how to evaluate the hypothesis of whether a till layer (on a hillslope) controls the flow direction and magnitude beneath a river in a probabilistic way. *Beven* [2006] has also suggested that hypothesis testing of models may be done in a nonstatistical way by the rejection of models that cannot provide acceptable results (noting that acceptability may depend on errors in the input data as well as model structure or parameter values). In all these approaches, attention is focused on the value of different types of data in constraining uncertainty and (hopefully) refining the hypotheses tested.

4. Uncertainty (Probability) Distributions Cannot Be Understood by Policy Makers and the Public

[7] Another goal of modeling, beside simple curiosity, is to provide knowledge in a form that is accessible and useful to decision makers and other stakeholders (here defined as all parties/persons with a direct interest (stake) in an issue). Many modelers argue that policy makers and the public are not capable of understanding uncertainty or even the simplest form of probability estimate. In a particular case quoted by *Patt and Dessai* [2005] (many others can be found), people were asked to estimate the chances that a person had a rare disease, given a positive result from a test that sometimes generates false positives. If the problem was framed for a single patient receiving the test result, and the probability of the disease (e.g., 0.001) together with the reliability of the test (e.g., 0.95), most people significantly overestimated the chance. However when the problem was framed in the form of a thousand patients, they resorted to counting the people and usually arrived at the correct result. Thus errors in logic as well as a misunderstanding of probabilities can lead to wrong conclusions [*Patt and Dessai*, 2005]. This example is comparable to misunderstood definitions of flood frequency and probability of exceedance, which is at the centre of debate in many articles [see *Sayers et al.*, 2002]. *Sayers et al.* [2002] suggest that it may be effective communication that is the major problem, rather than any real lack of understanding.

[8] The concepts of "uncertainty" and "risk" are perceived and understood in a variety of different ways by different communities and different people. However, it can be shown that when both scientists and public work together this gap may be bridged. For example, several studies have shown that probabilistic weather forecasts can be understood [e.g., *Luseno et al.*, 2003]. Moreover, argument 3 conveniently ignores the fact that policy makers derive decisions on a regular basis under severe uncertainties, because the scientific basis is not sufficient at the time. For example, the maximum pesticide level in surface waters in Switzerland was initially based on the detection limits of analytical methods and had to be redefined after new

toxicological evidence was forthcoming [*Chèvre and Escher*, 2005]. This uncertainty was known to the decision makers. Scientific studies suggest that decision makers actually want to get a feeling for the range of uncertainty and the risk of possible outcomes. This is demonstrated, for example, in the case of possible signal errors in the U.S. command and control system in the case of a nuclear attack in which the politicians wanted to have an understanding of the uncertainties involved [*Pate-Cornell*, 1995]. This point is also illustrated by the political demand of an analysis of "handling uncertainty in scientific advice" to the UK Parliament [*Ely*, 2004]; numerous other examples could also be cited.

[9] This is a very important point for the modeler since a misunderstanding of the certainty of modeling results can lead to a loss of credibility and trust in the model and the modeling process [*Demeritt*, 2001; *Lemos et al.*, 2002]. The example of the use of model results in the Public Inquiry into the Rock Characterisation Facility at Sellafield in the UK remains an example of this. The application to build this underground laboratory to study the suitability of the site for nuclear waste storage was rejected for "concerns about scientific uncertainty" [*U.K. Parliament*, 1997]. Evidence presented on both sides was based on completely different deterministic modeling exercises, with no attempt to reach agreement on sources of uncertainty. Another example is the prediction in the 1980s of a widespread forest dieback as a result of acid precipitation, which failed to occur to the extent predicted and which resulted in a loss of scientific credibility [*Eisner et al.*, 2003]. It will be extremely interesting to see how the IPCC consensus about the range of uncertainty in future climate predictions develops in this respect, in terms of both methods (as more computer power becomes available and some ensemble runs become possible with the different available model structures) and presentation.

[10] Work has already been carried out elsewhere on the communication of uncertainty to decision makers, the public and other stakeholders [e.g., *Brashers*, 2001; *Fox and Irwin*, 1998; *Patt and Dessai*, 2005; *Porter*, 2005]. A hydrological related application is the guidance for uncertainty assessment and communication published by RIVM/MNP, the Netherlands Environmental Assessment Agency [*Janssen et al.*, 2004; *van der Sluijs et al.*, 2003]. It provides a detailed questionnaire, which makes the modeler aware of potential problems in the modeling process (though the responses will undoubtedly be conditioned by the modeler's philosophical position, as set out in point 1 in section 2). There is an extensive literature on the settings and processes of developing uncertainty dialogues with stakeholders. Yet the suggestion that scientific uncertainty cannot be understood by stakeholders and decision makers persists (on both sides). There would seem to be little reason why this argument should continue to be made in the future in terms of understanding, but there is still a lack of guidance on successful methodologies.

5. Uncertainty Analysis Cannot Be Incorporated Into the Decision-Making Process

[11] This statement is often supported by two arguments: first that many decisions are binary in nature and second that uncertainty bounds can be so large that it is impossible to make a decision between various scenarios.

5.1. Decisions Are Binary

[12] Many decisions involve deciding between a finite number of alternative scenarios. Such categorical systems require a specific decision about whether to invoke a certain threshold and take the consequent actions or not (for example, in a flood warning system (M. Werner, personal communication on the National Flood Forecasting System (NFFS) of the UK, 2005)). Such a decision can still be embedded in an uncertainty analysis. The literature on decision support systems and decision analysis provides a wealth of methods for decision making under uncertainty based on assessments of the risk and costs of possible outcomes (though generally under certain specific assumptions with their own uncertainty). Examples include: aquifer management [*Orr and Meystel*, 2005], decisions on water pollution policy [*Schultz et al.*, 2005], decision on flood defense alternatives on the Red River [*de Kort and Booij*, 2006], control of lake level for flood protection [*Todini*, 1999] and decisions under uncertainty of flood frequency [*Wood and Rodriguez-Iturbe*, 1975a, 1975b]. What is needed, however, is a sociopolitical discussion on how this decision process is implemented in different situations (e.g., "risk averse," "risk neutral," or "risk accepting").

5.2. Uncertainty Bounds Are Too Wide to Be Useful in Decision Making

[13] There is no question that, for many environmental systems, a rigorous estimate of uncertainty leads to wide ranges of predictions. This leads to the perception that decisions are difficult to make. There are certainly cases in which the predictive uncertainty for outcomes of different scenarios is significantly larger than the differences between the expected values of those scenarios, while the probabilities of the future scenarios themselves may be unknown. The cascade of uncertainty through multiple model components will in most cases increase the uncertainty, unless the addition of a model component allows more observations to be used to condition the uncertainty in predictions. A typical and topical example of this type of uncertainty cascade is the use of different scenarios of climate change with rainfall-runoff models to assess impacts for water resource and flood defense purposes [*Intergovernmental Panel on Climate Change*, 2000]. There have been many published applications where these predictions have been made without any consideration of the sources of uncertainty, perhaps because of an expectation that the bounds would be too wide to be useful. *Cameron et al.* [2000] have shown that the differences between the uncertainty bounds of flood peak magnitudes under three climate change scenarios (without taking account of the uncertainty on the scenarios itself) are small in comparison to the uncertainty in flood frequency under current conditions, but that the risk of exceeding critical thresholds (such as overtopping a particular flood embankment) still changes significantly (this work was recently updated with new climate scenarios by *Cameron* [2006]). In the future, ensemble predictions of future climate will further increase the range of possible outcomes, but this is not a reason to ignore the uncertainties in predicting the impacts of change.

[14] Another example is given by *Reichert and Borsuk* [2005]. In this paper the uncertainty bounds for different scenarios of a phosphorus model were significantly larger than a choice between these scenarios. Thus in the first instance it looked like that it did not make any difference which policy scenario was implemented. It is an interesting notion not to report the uncertainty bandwidth or exclude it from further scientific analysis, when faced with such a situation. Rather than an approach based on ignorance, we instead suggest the problem should be tackled proactively. *Reichert and Borsuk* [2005] offer a solution to this dilemma by finding that the knowledge about the difference of the uncertainty of single scenarios can be included in the decision process. In both examples, additional information or information content beyond the classical uncertainty bounds is necessary in decision making.

6. Uncertainty Analysis Is Too Subjective

[15] In any application of uncertainty estimation methodologies, certain subjective decisions must be made, from the choice of prior parameter distributions to be considered to assumptions about observational errors or residual error structures. In principle, many of these assumptions can be checked as part of the analysis but usually at the risk of finding that they are not fully justified (this may be one reason why the inclusion of posterior analysis of such assumptions is rarely reported, even in research publications). The implication of this statement, however, is that any analysis which does not considering uncertainties in the modeling can be objective. This view is based on a misplaced faith in deterministic modeling in the light of the inevitable uncertainty in the modeling process. Even a fully deterministic model run requires assumptions about what to use as model inputs and boundary conditions [see, e.g., *Cloke et al.*, 2003], and about how to evaluate model performance [see *Beven*, 2006], that will also be necessarily subjective. The important issue is that the nature of the assumptions should be made explicit so that they can be assessed and discussed (for an example, see the discussion of *Thiemann et al.*'s [2001] work by *Beven and Young* [2003] and the uncertainty estimation comparison experiment, HUGE, suggested by the International Working-Group on Uncertainty Analysis in Hydrologic Modeling (Uncertainty Analysis in Environmental Modeling Workshop, see http://www.es.lancs.ac.uk/hfdg/uncertainty_workshop/uncert_intro.htm, hereinafter referred to as International Working Group on Uncertainty Analysis in Hydrologic Modeling, 2004)). Such discussion can, for example, be embedded into an expert elicitation process [*Arnell et al.*, 2005], although it maybe hindered by philosophical disagreements about the nature and value of the modeling process (for a list of pitfalls and problems with expert elicitation see, for example, *Morgan and Keith* [1995] and *Otway and Vonwinterfeldt* [1992]).

7. Uncertainty Analysis Is Too Difficult to Perform

[16] This is a common attitude amongst practitioners. It seems to be a consequence of the need to spend more time and money on assessing the different potential sources of uncertainty in any particular application, coupled with a lack of clear guidance about which methods might be useful in different circumstances. In general, uncertainty analysis is not too difficult to perform but is often made more opaque by a difficult mathematical notation. Example applications and programs (if their basics are well explained to the user) can help to perform most types of uncertainty analysis. Several software packages exist to undertake various types of uncertainty analysis such as the GLUE toolbox (http://www.es.lancs.ac.uk/hfdg/hfdg_freeware.htm), the Captain toolbox (http://www.es.lancs.ac.uk/cres/captain/), @RISK for Excel (http://www.palisade.com/) or PEST (http://www.sspa.com/pest/) and many others. Unfortunately, these software packages rarely list and demonstrate pitfalls of each implementation. Summaries of methods have been assembled by third parties in reports or on Web pages [e.g., *Sayers et al.*, 2002; *Pappenberger et al.*, 2005; *van der Sluijs et al.*, 2003; International Working Group on Uncertainty Analysis in Hydrologic Modeling, 2004], but there is little guidance available to the user about which methods are most appropriate to different types of problem.

[17] *Yoe and Skaggs* [1997] suggest that there cannot be a one-size-fits-all uncertainty analysis. Although, their argument has been restricted to ecosystem restoration projects it can be applied to modeling exercises in general. They propose, an "eight step framework for uncertainty analysis" which is similar to suggestions by *van der Sluijs et al.* [2003]. Beside the benefits of such guidelines, the criticism implied by argument 6 highlights key areas which need further research. Existing software or programs will increasingly need to interact with uncertainty tools and this poses a large number of research questions on software implementation (for an in-depth discussion, see *Harvey et al.* [2005]). Moreover, existing guides are limited in the way that they link available uncertainty methods to critical assumptions, limitations, application areas and software packages (see discussion in section 6). This is perhaps the most important current constraint on the more widespread application of uncertainty estimation methods. The potential user is always faced with a difficult decision about which of the available methods to choose (especially given that there will be a learning curve associated with each method). Similarly the potential users of predictions will find it difficult to know which type of methods to require in commissioning new projects. Until there is some Code of Practice for uncertainty estimation, agreed between practitioners and users (clients and decision maker), this is unlikely to change. Some progress in this direction can already be seen, for example, in the Working Group on Uncertainty and Parameter Estimation of the U.S. Federal Interagency Steering Committee on Multimedia Environmental Modeling (see http://www.iscmem.org/WorkGroup_02.htm [*Beven*, 2004]) and the IAHS PUB Working Group on Uncertainty Analyses and Model Diagnostics (see http://cee.uiuc.edu/research/pub/htmlStorage/WorkingGroups/Uncertainty_PUB_WG7.pdf).

8. Uncertainty Does Not Really Matter in Making the Final Decision

[18] In many past modeling and decision-making processes, uncertainty analysis has been ignored and it can be argued that under many circumstances it simply would not have mattered to the eventual outcome. *Morgan* [1994]

stated that uncertainty analysis is currently a fashionable discipline but that it cannot be denied that civilization has advanced by simply muddling along and not explicitly acknowledging uncertainty. However, his arguments for uncertainty analysis are compelling as he stresses that (1) it makes one think about the processes involved and the decisions based on our model results, (2) it makes predictions of different experts more comparable and leads to a transparent science, (3) it allows a more fundamental retrospective analysis and allows new or revised decisions to be based on the full understanding of the problem and not only a partial snapshot, and (4) decision makers and the public have the right to know all limitations in order to make up their own minds and lobby for their individual causes [after *Morgan*, 1994].

[19] It cannot be ignored that an open scientific discourse on uncertainty would have important implications for the environmental decision process. Uncertainty clearly does matter in the current debate over the significance of future predictions of climate change and its implications for future global policies (and consequent impacts on future water resources management and capital investment). This is a an area where neither side in the debate has been open in the communication of the uncertainties involved, leading to disputed results rather than an evaluation of risk.

9. Need for a Code of Practice

[20] None of the arguments against uncertainty analysis rehearsed above are, in the end, tenable. However, neither is there any readily available guidance about how to do uncertainty analysis in hydrologic and hydraulic modeling (nor about whether a particular problem is amenable to being addressed by modeling at all [see *Klemeš and Sellars*, 2000]). There are, instead, a number of competing methods, within different philosophical frameworks, that might be more or less appropriate in different situations with different model dimensionalities and sources of uncertainty. This makes it difficult for a modeler to choose a method, and for the end user of modeling results to interpret the resulting uncertainties. This discussion deliberately does not list one key point of uncertainty analysis: cost and resources. Uncertainty estimation is currently considered to be an added component to an analysis, at extra cost. It should, however, be an intrinsic and expected part of any modeling exercise.

[21] Undoubtedly, mature guidance on the use of different methods will develop over time, but it is not too early to suggest that modeling studies might follow a Code of Practice that makes uncertainty analysis an integral part of the modeling process. From the modeler's point of view, a Code of Practice would (mostly) represent an extension of normal practices for the quality assurance and version tracking of computer codes, with similar documentation requirements. Such a Code of Practice would need to address the following issues.

9.1. Taking Account of Model Context

[22] Any model is usually applied for a particular purpose and this purpose has to be recorded at the onset of the modeling exercise. This is important as, for example, a catchment model could be used for catchment management purposes or for understanding runoff generation mechanisms. In the first instance, one would need to look at the variables which are important for the management, in the second, one may be interested only in variables influencing specific runoff generation processes. This would result in a different treatment of uncertainty in both cases. This includes the necessity of representing the mechanisms by the model for those aspects for which predictions under modified driving forces have to be made.

9.2. Taking Account of Uncertainty in Model Choice (and Implementation Details)

[23] A model is an abstract construct to represent a system for the purposes of reproducing, simplifying, analyzing, or understanding it. Any model used is based on a perceptual model (summary of our (personal) perceptions on how a system responds), which gets translated into a conceptual model (mathematical description) and implemented as a procedural model (computer code) [see *Beven*, 2001b]. Uncertainties in this process should be documented as part of the model development quality assurance process and made available to users, including an archive of test cases.

9.3. Taking Account of Uncertainty in Model Drivers (Inputs and Boundary Conditions)

[24] The uncertainty of all model inputs and boundary conditions should be quantified, listed and recorded. For example, most hydrological and hydraulic models have at least rain and/or a flow/stage hydrograph as input boundary conditions. Influence of boundary conditions on model results have been documented [e.g., *Pappenberger et al.*, 2006] and can interact with model structural errors in affecting uncertainty in model parameter values [*Beven*, 2006].

9.4. Taking Account of Prior Uncertainty in Model Factors

[25] The choices made in effecting the procedural model will normally involve the choice of scale and resolution at which the calculations will be made. For the nonlinear equations common in environmental modeling problems, the sensitivity of solutions to space and time resolution can generally only be estimated locally, but it can be expected that there will be an interaction between scale and resolution and the effective values of the factors required by a model (see discussion by *Beven* [2000]). This issue has to our opinion not been properly addressed in the literature, but more experience and archiving of modeling applications will be needed to allow estimates of prior distributions of effective values of parameters of different types to be made.

9.5. Taking Account of Dependency in Model Factors

[26] This is an important issue in the application of uncertainty estimation methods in that a variety of dependencies will have an effect on the resulting prediction bounds. There will be dependencies between different model components and different model parameters in producing good model performance. There will be dependencies between errors in boundary condition data, model structural error and observations that will have an effect on calibrated values of model parameters. There will be spatial and temporal dependencies in model residuals that may be difficult to represent by some simple error structure (but which if ignored are known to lead to bias in proba-

bilistic inference of parameter values, even for linear systems). It may be very difficult, even with experience of the application of a particular model, to specify the expected dependencies for a new application. It may be possible to elucidate some of these dependencies a posteriori as part of the calibration process; others may be difficult such as the interaction between input error, model structural error and effective parameter values when the true nature of the errors in inputs or model structure cannot be fully known given the information available. It is clearly also an issue in trying to provide prior estimates of effective parameters in applications (like the prediction of future change) where no conditioning data is available to allow evaluation of a posteriori distributions and dependencies. What is important is that all model applications should be aware of the potential effects of such dependencies.

9.6. Choice of Uncertainty Estimation Methodology

[27] A general guideline for choosing an uncertainty method is given by *Pappenberger et al.* [2005], which is part of an experiment in which a decision tree for uncertainty analysis is published as a wiki publication and can be edited by anybody interested in contributing their experience or adding to the discussion (at http://www.floodrisk.net). Many applications will involve only a forward uncertainty analysis, reflecting the identified uncertainties in model structures, drivers and prior estimates of parameter values expressed either in terms of prior probabilities or fuzzy measures. No real philosophical issues arise in forward uncertainty analysis. The main Code of Practice requirement here will be to demonstrate an adequate approximation to integrating over the sources of uncertainty (e.g., by testing convergence of output quantiles to different numbers of samples under similar prior assumptions).

9.7. Taking Account of Uncertainty in Observations Used in Model Calibration/Conditioning

[28] Philosophical issues do arise when there is an opportunity to constrain the uncertainty in predicted variables by calibrating or conditioning on observed data. This requires a decision about how to evaluate and treat the error between observed and predicted variables, as discussed at length by *Beven* [2006]. A Code of Practice should only require, however, that whatever choice of approach that is made is justified by an examination of whether the assumptions of that approach are valid for a particular application.

9.8. Taking Account of Uncertainty in Predicting the Future

[29] The future is, of course, inherently uncertain, but in most practical applications it is prediction of the future that is required [*Hall and Anderson*, 2002]. There is then no possibility of constraining uncertainty with respect to future observables, and uncertainty estimation is necessarily a forward estimation process, albeit that the models used may have been conditioned on past data and performance. However, as shown by the classic postaudit analyses of groundwater models of *Konikow and Bredehoeft* [1992] and *Anderson and Woessner* [1992], future boundary conditions may be difficult to predict even if model parameters can be constrained on past data. Thus assumptions about the choice of boundary conditions should be justified and the uncertainty associated with that choice assessed by forward propagation, taking account of the uncertainty in model choice and parameters.

9.9. Communicating Results to Users

[30] This last step is probably the most critical and important in the entire code of practice as without it our scientific analysis will not be used by anyone else beside ourselves. The discussions above have been concerned more with the meaning of quantitative estimates of uncertainty, but it is important to recognize that in all model applications, those quantitative estimates are necessarily based on qualitative choices and assumptions at earlier steps in the modeling process. A Code of Practice would need to provide a framework for the justification and testing of those assumptions, but most users will not wish to delve into that background material, in the same way as they do not normally wish to query the numerical methods and coding methods used in, say, a flood inundation model. Users require model predictions to make decisions that are based on an assessment of potential future outcomes and the risk (or impacts) associated with those outcomes. This is a natural product of uncertainty estimation.

[31] If our science is to be meaningful, we should aim to communicate the limitations of the predictions we make in ways that are useful to the wider community. This, in itself, cannot be divorced from the wider socio-political context, as has been demonstrated by the IPCC presentations of uncertainty in future climate predictions, but if the community can start to discuss just what form a Code of Practice should take, these issues should at least begin to be addressed. We suggest that this is now timely. As computer power continues to increase, and remote sensing and the networking of pervasive environmental sensors start to make it easier to obtain conditioning information for new sites, some consensus about good practice in uncertainty estimation and constraint, as routine practice in hydrological science, would undoubtedly be a good thing!

[32] **Acknowledgments.** Florian Pappenberger has been funded by the Flood Risk Management Research Consortium (http://www.floodrisk.org.uk). Development of extensions to the generalized likelihood uncertainty estimation (GLUE) methodology has been supported by the NERC grant NER/L/S/2001/00658 awarded to Keith J. Beven. Many thanks to Hannah Cloke (King's College London), Dave Leydall, Paul Smith, Tobias Krueger (all Lancaster University), Andrew Wood (JBA Consulting/Lancaster University), and Michael Schaerer (Bundesamt fuer Umwelt, Wald und Landschaft, Switzerland) for their valuable comments. We further would like to thank two anonymous reviewers, Peter Reichert (EAWAG–Zürich, Switzerland), and Marc Parlange (EPFL, Lausanne, Switzerland) for their very helpful reviews.

References

Abbott, M. B., V. M. Babovic, and J. A. Cunge (2003), Towards the hydraulics of the hydroinformatics era by M. B. Abbott, V. M. Babovic and J. A. Cunge, *J. Hydraul. Res.*, Volume *39* 2001, Issue 4, pp. 339–349—Response to Beven and Pappenberger, *J. Hydraul. Res.*, *41*(3), 331–333.

Anderson, M. P., and W. W. Woessner (1992), The role of the postaudit in model validation, *Adv. Water Resour.*, *15*(3), 167–173.

Arnell, N. W., E. L. Tompkins, and W. N. Adger (2005), Eliciting information from experts on the likelihood of rapid climate change, *Risk Anal.*, *25*(6), 1419–1431.

Beven, K. J. (1989), Changing ideas in hydrology—The case of physically-based models, *J. Hydrol.*, *105*(1–2), 157–172.

Beven, K. J. (2000), Uniqueness of place and process representations in hydrological modelling, *Hydrol. Earth Syst. Sci.*, *4*, 203–213.

Beven, K. J. (2001a), On hypothesis testing in hydrology, *Hydrol. Processes*, *15*(9), 1655–1657.

Beven, K. J. (2001b), *Rainfall-Runoff Modelling: The Primer*, John Wiley, Hoboken, N. J.

Beven, K. J. (2002a), Towards a coherent philosophy for modelling the environment, *Proc. R. Soc. London, Ser. A*, *458*(2026), 2465–2484.

Beven, K. J. (2002b), Towards an alternative blueprint for a physically based digitally simulated hydrologic response modelling system, *Hydrol. Processes*, *16*(2), 189–206.

Beven, K. J. (2004), Does an interagency meeting near Washington imply uncertainty?, *Hydrol. Processes*, *18*(9), 1747–1750.

Beven, K. J. (2006), A manifesto for the equifinality thesis, *J. Hydrol.*, *320*(1–2), 18–36.

Beven, K. J., and F. Pappenberger (2003), Towards the hydraulics of the hydroinformatics era by M. B. Abbott, V. M. Babovic and J. A. Cunge, *Journal of Hydraulic Research*, Volume *39* 2001, Issue 4, pp. 339–349—Discussion, *J. Hydraul. Res.*, *41*(3), 331–333.

Beven, K. J., and P. Young (2003), Comment on ‘‘Bayesian recursive parameter estimation for hydrologic models’’ by M. Thiemann, M. Trosset, H. Gupta, and S. Sorooshian, *Water Resour. Res.*, *39*(5), 1116, doi:10.1029/2001WR001183.

Brashers, D. E. (2001), Communication and uncertainty management, *J. Commun.*, *51*(3), 477–497.

Cameron, D. (2006), An application of the UKCIP02 climate change scenarios to flood estimation by continuous simulation for a gauged catchment in the northeast of Scotland, UK (with uncertainty), *J. Hydrol.*, in press.

Cameron, D., K. J. Beven, and P. Naden (2000), Flood frequency estimation by continuous simulation under climate change (with uncertainty), *Hydrol. Earth Syst. Sci.*, *4*(3), 393–405.

Chèvre, N., and B. Escher (2005), Pesticides, quel risque pour les eaux?, *EAWAG News*, *59*, 20–23.

Cloke, H. L. (2005), Process-based, distributed and terribly uncertain? Using the ESTEL model for hypothesis testing and the investigation of hydrological processes, paper presented at General Assembly, Eur. Geosci. Union, Vienna, 24–29 April.

Cloke, H. L., J. P. Renaud, A. J. Claxton, J. McDonnell, M. G. Anderson, J. R. Blake, and P. D. Bates (2003), The effect of model configuration on modelled hillslope-riparian interactions, *J. Hydrol.*, *279*(1–4), 167–181.

Congdon, P. (2005), Bayesian predictive model comparison via parallel sampling, *Comput. Stat. Data Anal.*, *48*(4), 735–753.

de Kort, I. A. T., and M. J. Booij (2006), Decision making under uncertainty in a decision support system for the Red River, *Environ. Modell. Software*, in press.

Demeritt, D. (2001), The construction of global warming and the politics of science, *Ann. Assoc. Am. Geogr.*, *91*(2), 307–337.

Eisner, M., N. Graf, and P. Moser (2003), *Risikodiskurse. Die Dynamik öffentlicher Debatten über Umwelt- und Risikoprobleme in der Schweiz*, Seismo, Zurich, Switzerland.

Ely, A. (2004), Handling uncertainty in scientific advice, report, 4 pp., Parliamentary Off. of Sci. and Technol., London.

Fox, C. R., and J. R. Irwin (1998), The role of context in the communication of uncertain beliefs, *Basic Appl. Soc. Psychol.*, *20*(1), 57–70.

Hall, J. W., and M. G. Anderson (2002), Handling uncertainty in extreme or unrepeatable hydrological processes—The need for an alternative paradigm, *Hydrol. Processes*, *16*(9), 1867–1870.

Hall, J. W., E. Rubio, and M. G. Anderson (2004), Random sets of probability measures in slope hydrology and stability analysis, *Z. Angew. Math. Mech.*, *84*(10–11), 710–720.

Harvey, H., J. Hall, P. D. Bates, G. Pender, N. G. Wright, and D. Mason (2005), Next generation computer modelling for the prediction of flood level and inundation extent: Part 3, modelling framework, technical report, Flood Risk Manage. Res. Consortium, Manchester, U. K.

Intergovernmental Panel on Climate Change (2000), *Special Report on Emissions Scenarios: A Special Report of Working Group III of the Intergovernmental Panel on Climate Change*, edited by N. Nakicenovic and R. Swart, Cambridge Univ. Press, New York. (Available at http://www.grida.no/climate/ipcc/emission/)

Janssen, P. H. M., A. C. Petersen, J. P. van der Sluijs, J. S. Risbeyc, and J. R. Ravetzd (2004), Towards guidance in assessing and communicating uncertainties, in *Sensitivity Analysis of Model Output*, edited by K. M. Hanson and F. M. Hemez, pp. 201–210, Los Alamos Natl. Lab., Los Alamos, N. M. (Available at http://library.lanl.gov/ccw/samo2004/)

Klemeš, V., and C. D. Sellars (2000), *Common Sense and Other Heresies: Selected Papers on Hydrology and Water Resources Engineering*, 378 pp., Can. Water Resour. Assoc., Cambridge, Ont.

Konikow, L. F., and J. D. Bredehoeft (1992), Groundwater models cannot be validated, *Adv. Water Resour.*, *15*(1), 75–83.

Lemos, M. C., T. J. Finan, R. W. Fox, D. R. Nelson, and J. Tucker (2002), The use of seasonal climate forecasting in policymaking: Lessons from northeast Brazil, *Clim. Change*, *55*(4), 479–507.

Luseno, W. K., J. G. McPeak, C. B. Barrett, P. D. Little, and G. Gebru (2003), Assessing the value of climate forecast information for pastoralists: Evidence from southern Ethiopia and northern Kenya, *World Dev.*, *31*, 1477–1494.

Morgan, M. G., and D. W. Keith (1995), Climate-change—Subjective judgments by climate experts, *Environ. Sci. Technol.*, *29*(10), A468–A476.

Morgan, R. P. (1994), A predictive model for the assessment of soil erosion risk, *J. Agric. Eng. Res.*, *30*, 245–253.

Oreskes, N., K. Shrader-Frechette, and K. Belitz (1994), Verification, validation, and confirmation of numerical-models in the Earth-sciences, *Science*, *263*(5147), 641–646.

Orr, S., and A. M. Meystel (2005), Approaches to optimal aquifer management and intelligent control in a multiresolutional decision support system, *Hydrogeol. J.*, *31*(1), 223–246.

Otway, H., and D. Vonwinterfeldt (1992), Expert judgment in risk analysis and management—Process, context, and pitfalls, *Risk Anal.*, *12*(1), 83–93.

Pappenberger, F., H. Harvey, K. J. Beven, J. Hall, R. Romanovicz, and P. Smith (2005), Risk & uncertainty: Tools and implementation, report, Flood Risk Manage. Res. Consortium, Manchester, U. K. (Available at http://www.floodrisk.org.uk/images/stories/docs/Implementation_report_risk_uncertainty.pdf)

Pappenberger, F., P. Matgen, K. J. Beven, J.-B. Henry, L. Pfister, and P. de Fraipont (2006), Influence of uncertain boundary conditions and model structure on flood inundation predictions, *Adv. Water Resour.*, in press.

Parkin, G., G. O'Donnell, J. Ewen, J. C. Bathurst, P. E. O'Connell, and J. Lavabre (1996), Validation of catchment models for predicting land-use and climate change impacts. 2. Case study for a Mediterranean catchment, *J. Hydrol.*, *175*(1–4), 595–613.

Pate-Cornell, M. E. (1995), Pobabilistic interpretation of command and control signals: Bayesian updating of the probability of nuclear attack, *Reliab. Eng. Syst. Safety*, *47*(1), 27–36.

Patt, A., and S. Dessai (2005), Communicating uncertainty: lessons learned and suggestions for climate change assessment, *C. R. Geosci.*, *337*(4), 425–441.

Porter, J. (2005), Communicating uncertainty or uncertainty in communication? Public response to flood risk mapping and warning systems, a case study of Bostcastle and Lynmouth, M.Sc. thesis, King's Coll. London, London.

Reichert, P., and M. E. Borsuk (2005), Does high forecast uncertainty preclude effective decision support?, *Environ. Modell. Software*, *20*(8), 991–1001.

Sayers, P. B., B. P. Gouldby, J. D. Simm, I. Meadowcroft, and J. Hall (2002), Risk, performance and uncertainty in flood and coastal defence: A review, *DEFRA/EA R&D Tech. Rep. FD2302/TR1*, Flood and Coastal Defence R&D Programme, Wallingford, U. K.

Schultz, M. T., M. J. Small, and R. S. Farrow (2005), State water pollution control policy insights from a reduced-form model, *J. Water Resour. Plann. Manage.*, *130*(2), 150–159.

Seibert, J., S. Uhlenbrook, C. Leibundgut, and S. Halldin (2000), Multiscale calibration and validation of a conceptual rainfall-runoff model, *Phys. Chem. Earth, Part B*, *25*(1), 59–64.

Thiemann, M., M. Trosset, H. Gupta, and S. Sorooshian (2001), Bayesian recursive parameter estimation for hydrologic models, *Water Resour. Res.*, *37*(10), 2521–2535.

Todini, E. (1999), Using phase-space modelling for inferring forecasting uncertainty in non-linear stochastic decision schemes, *J. Hydroinf.*, *1*(2), 75–82.

U.K. Parliament (1997), Radioactive waste—Where next?, report, Parliamentary Off. of Sci. and Technol., London.

van der Sluijs, J., et al. (2003), RIVM/MNP guidance for uncertainty assessment and communication, report, Univ. of Utrecht, Utrecht, Netherlands.

Wagener, T., and H. V. Gupta (2005), Model identification for hydrological forecasting under uncertainty, *Stochastic Environ. Res. Risk Assess.*, *19*, 378–387, doi:10.1007/s00477-005-0006-5.

Wood, E. F., and I. Rodriguez-Iturbe (1975a), Bayesian approach to analyzing uncertainty among flood frequency models, *Water Resour. Res.*, *11*(6), 839–843.

Wood, E. F., and I. Rodriguez-Iturbe (1975b), Bayesian inference and decision-making for extreme hydrologic events, *Water Resour. Res.*, *11*(4), 533–542.

Yoe, C. E., and L. Skaggs (1997), Risk and uncertainty analysis procedures for the evaluation of environmental outputs, *IWR Rep. 97-R-7*, Inst. for Water Resour., U.S. Army Corps of Eng., Alexandria, Va. (Available at http://www.iwr.usace.army.mil/iwr/pdf/97r07.pdf)

Young, P. C., A. Chotai, and K. J. Beven (2004), Data-based mechanistic modelling and the simplification of environmental systems, in *Environmental Modelling: Finding Simplicity in Complexity*, edited by J. Wainwright and M. Mulligan, pp. 371–388, John Wiley, Hoboken, N. J.

K. J. Beven and F. Pappenberger, Department of Environmental Sciences, Lancaster University, Lancaster LA1 4YQ, UK. (f.pappenberger@lancaster.ac.uk)