# Introduction to special section on Uncertainty Assessment in Surface and Subsurface Hydrology: An overview of issues and challenges

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[1] This paper introduces the *Water Resources Research* special section on Uncertainty Assessment in Surface and Subsurface Hydrology. Over the past years, hydrological literature has seen a large increase in the number of papers dealing with uncertainty. In this article, we present an overview of the different sources of uncertainty and the different types of problems associated with uncertainty assessment. It is argued here that clarity about which part of the large field of uncertainty research is addressed by a given research activity would already help guide discussions within the hydrological community. We present an introduction to the differences between the more classical frequentist approach to uncertainty and Bayesian approaches and between probabilistic and nonprobabilistic approaches. Bayesian approaches allow for inclusion of more subjective expert knowledge and would be more appropriate where less "hard" data are available. Any underlying assumptions need to be made very clear to the end user. Finally, a brief classification of the articles of the special section is presented.

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## 1. Introduction

[2] Uncertainty estimation in hydrological surface and subsurface modeling is receiving increasing attention from researchers and practitioners, according to the numerous contributions in recent scientific literature. Uncertainty assessment is also one of the main goals of the Prediction in Ungauged Basins (PUB) initiative promoted by the International Association of Hydrological Sciences. However, the transfer of knowledge about uncertainty assessment among scientists and from scientists to end users is still difficult, notwithstanding the extensive research invested in the topic.

[3] Intense scientific interest in uncertainty analysis has resulted in many different approaches and philosophies for quantifying the reliability of hydrological models. As a result, an active debate began about the relative advantages of each of the different approaches. On the one hand, such a debate stimulated additional developments and insights in itself; on the other hand it is still not clear which approach is most appropriate given the needs of a specific user. For this reason, the hydrologic scientific community calls for a more effective approach to uncertainty estimation.

[4] The great interest in uncertainty and the varied approaches being used led us to propose the present special section of *Water Resources Research*, which can serve as a reference for anyone dealing with uncertainty in hydrology. The purpose of this review is to provide an overview of the current issues about uncertainty assessment in our field.

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## 2. Issues and Terminology in Current Uncertainty Assessment

[5] Hydrology is a science that is highly uncertain. The main reason for this uncertainty is that we still do not know the intrinsic dynamics of many hydrological and water quality processes. Moreover, we cannot observe in detail and, consequently, cannot mathematically represent the geometry of hydrological control volumes (river beds, subsurface preferential flow paths, etc.), as well as most of the related initial and boundary conditions and biogeochemical processes. Finally, hydrologists are typically working under conditions of data scarcity, which limit the efficiency of an inductive approach for tackling the above problems.

[6] Uncertainties are caused by our lack of perfect understanding of hydrologic phenomena and processes involved. Uncertainties could arise from the following: (1) inherent randomness (e.g., weather), (2) model structural error that reflects the inability of a model to represent precisely the system's true behavior, (3) model parameter value error, and (4) data error. When using models to make engineering or management decisions about hydrologic systems we also have to deal with (5) operations uncertainties (associated with construction and maintenance) and (6) a weak ability to accurately quantify decision criteria including social objectives, aversion to risk, etc. [*Loucks and van Beek*, 2005]. Uncertainties can be grouped into two

major categories: (7) natural variability (also called structural uncertainty, aleatory, external, objective, inherent, random, or stochastic uncertainty) and (8) knowledge uncertainty (also called epistemic, functional, internal, or subjective uncertainty) [*National Research Council*, 2000, Table 3.1].

[7] The uncertain nature of hydrology has raised many questions related to uncertainty assessment. The most urgent ones are those related to quantifying the reliability of hydrological output forecasts by model simulations. Hydrological simulation is often used in real time prediction systems for natural hazards or for assessing longer-term effects of climate change or proposed water resource infrastructure. In these cases, quantifying the uncertainty of the hydrological model response is extremely important from a societal point of view. This is the reason for the strong interest of users in this application.

[8] The necessity to provide good descriptions of the uncertainty associated with simulated and predicted variables and efforts to increase reliability of hydrological models, induced hydrologists to address additional research issues. Among them, there is the call for assessing the uncertainty of observed hydrological variables, model parameters and model structure. These issues are also significant for gaining further insight into the dynamics of hydrological processes. Indeed, to identify the most appropriate model is a means to provide support to hydrological theory. Therefore, uncertainty assessment became strongly related to parameter estimation, multiobjective optimization, model identification, model building, model diagnostics, model averaging, data collection and information theory in general. All topics in this list have gained attention of researchers in recent years. Today, all these topics are often put under the one umbrella of uncertainty assessment in hydrology. We believe it would be very helpful for end users to formally identify such subtopics and the related research questions. As a matter of fact, uncertainty assessment in hydrology is becoming a very wide research field within which end users may have difficulty orienting themselves. In our opinion it is very important that each contribution clearly identifies the research question it is addressing as well as the type of approach that is used (see also section 3). This would definitely help communication between scientists and end users for a topic that is rapidly coming of age.

## 3. How to Deal With Uncertainty in Hydrology

[9] The traditional way of dealing with uncertainty in science is through statistics and probability. The classical "frequentist" view of probability defines the probability of an event occurring in a particular trial as the frequency with which it occurs in a long sequence of similar trials. In a Bayesian or "subjectivist" view, the probability of an event is dependent upon the state of information available and this information can include expert opinion. Probability theory forms the basis of classical statistics, which has estimators based on a likelihood function that represents how likely an observed data sample is for a given model and parameter set. Bayesian methods can also be used in a probabilistic framework [e.g., see *Bliznyuk et al.*, 2008].

[10] There are both probabilistic and nonprobabilistic approaches to uncertainty analysis. For instance, the generalized likelihood uncertainty estimation (GLUE) [e.g., *Beven*, 2006a] is widely used in hydrology, even though it does not have a likelihood function that is consistent with probability theory. GLUE instead has a "likelihood measure" that is defined by the user without satisfying probabilistic conditions, so we will refer to GLUE and other methods that do not have probability-based likelihood as "nonprobabilistic" methods.

[11] There are also other nonprobabilistic methods for uncertainty including random set theory, evidence theory, fuzzy set theory and possibility theory [*Montanari*, 2007; *Jacquin and Shamseldin*, 2007]. In particular, fuzzy set theory and possibility theory are interesting concepts for hydrologists because much expert reasoning about hydrological systems is possibilistic rather than strictly probabilistic. We reason about whether a given scenario could happen, without necessarily attempting to attach probabilities to the likelihood of it happening, particularly in situations of very scarce information. There are also many variants of GLUE; for example, *Tolson and Shoemaker* [2008] and *Mugunthan and Shoemaker* [2006] combine optimization methods with a nonprobabilistic GLUE-like approach to increase computational efficiency of nonprobabilistic uncertainty analysis.

[12] The decision to use probabilistic or nonprobabilistic methods is currently the most controversial issue in hydrologic uncertainty analysis. This debate has raised the very relevant question about the capability of probabilistic and nonprobabilistic methods to correctly infer the frequency properties of hydrological simulations and predictions [see, e.g., *Beven*, 2006b; *Montanari*, 2005, 2007; *Mantovan and Todini*, 2006; *Beven et al.*, 2007, 2008]. Criticism about probabilistic methods is focused on the concern that for many data sets it is not clear that the assumptions of classical statistics (e.g., stationarity) can be justified. The main reason for criticism of nonprobabilistic methods is that they are subjective and not necessarily "coherent" from a statistical point of view (see, for instance, the criticism of *Mantovan and Todini* [2006] with respect to GLUE). Moreover, on known problems for which the data do support the necessary probabilistic assumptions, probabilistic and nonprobabilistic methods provide different answers [e.g., *Stedinger et al.*, 2008].

[13] In our opinion, when sufficient information is available to support statistical hypotheses with appropriate statistical tests, a probabilistic statistical approach is preferable as a way to efficiently summarize the information content of the data. Conversely, data scarcity calls for expert knowledge to support uncertainty assessment. Above all, data scarcity calls for the integration of different types of information, within a framework that is unavoidably subjective, given that the information itself is often "soft."

[14] Whatever approach is chosen, the end user should be made fully aware of the drawbacks of the method that is being used. The presence of subjectivity should be clearly stated and the limitations of the underlying assumptions, both in the probabilistic and nonprobabilistic approaches, clearly described and discussed. In our opinion an appropriate terminology should be also used to make the meaning of the provided confidence bands clear. Whenever a subjective method is adopted, the user should be made aware that the uncertainty bands reflect user perception instead of

providing a frequentist assessment of the probability of the true value to fall between them. Appropriate use of the methods being proposed by the scientific community, depending on the user needs and data availability, would allow us to successfully reach a better communication between scientists and end users.

## 4. Overview of the Papers Published in the Special Section

[15] The set of articles presented here shows that there is a clear need for exchange of opinions about fundamental concepts, main achievements gained in the past, and future avenues of research. The articles all present recent research and bring together perspectives from groundwater modelers and surface water hydrologists. Different sources of uncertainty are recognized and tools have been developed to describe and quantify each source, or to control and reduce uncertainty. As can be expected, there is not yet a single framework that covers all methods. Still, this special section provides the reader with a very good starting point to obtain a relatively complete overview of the different approaches that exist in the hydrological community today.

[16] A set of eight papers deals with uncertainty assessment for hydrological simulation and forecasting, parameter optimization and parameter uncertainty [*Blazkova and Beven*, 2009; *Götzinger and Bárdossy*, 2008; *Montanari and Grossi*, 2008; *Solomatine and Shrestha*, 2009; *Thyer et al.*, 2009; *Tonkin and Doherty*, 2009; *Zhang et al.*, 2008]. *Stedinger et al.* [2008] compare probabilistic with nonprobabilistic methods for parameter estimation. Five contributions are also presented dealing with hydrological model identification, model selection and model structural uncertainty [*Bulygina and Gupta*, 2009; *Chiu et al.*, 2009; *Clark et al.*, 2008; *Hsu et al.*, 2009; *Schoups et al.*, 2008]. Finally, four papers deal with hydrological modeling in the presence of uncertainty [*Fienen et al.*, 2008; *Ross et al.*, 2009; *Smith and Marshall*, 2008; *Vrugt et al.*, 2008].

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