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UNCERTAINTY AND GOOD PRACTICE IN HYDROLOGICAL PREDICTION

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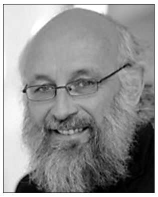

Abstract

All forms of hydrological prediction involve many different sources of uncertainty. Many of these sources of uncertainty involve knowledge (epistemic) uncertainties that are not necessarily easy to represent statistically. This can create problems for communication and interpretation between modeller and users when uncertain predictions are presented. One way of dealing with this problem is to define Guidelines for Good Practice in the form of a set of decisions that must be agreed and recorded for later evaluation and review. The Catchment Change Network (CCN) is a knowledge transfer project, funded by the UK Natural Environment Research Council, that aims to bring academic research and practitioners together to produce guidelines for good practice for uncertainty estimation in predicting the future in the areas of flood risk, water quality and water scarcity all of which involve important epistemic uncertainties.

Key words – flood risk mapping; communication of uncertainty; epistemic error; hydraulic models; risk-based decisions

Sources of Uncertainty in Hydrological Prediction

The current legislative framework for management of water in Europe, including the Water Framework Directive and Floods Directive requires some hard decisions about future investments to achieve the requirements of good ecological and chemical status for sustainable use and good flood risk management. Such decisions require predictions about the nature of future hydrological responses, predictions that must be inherently uncertain. The degree to which the predictions are uncertain, and the possibility of constraining the uncertainty by the collection of (cost-effective) observations, might change the investment decisions taken. So, it follows that as well as needing good models to make such predictions, we also need robust ways of estimating the associated uncertainties in a way that can inform a risk-based decision making framework. This is currently a difficulty because we cannot be sure that our models or knowledge of the relevant boundary conditions are adequate (particularly in water quality, ecohydrology and the flood risk models). We cannot be sure that these knowledge or epistemic uncertainties can be treated as if they are statistical in nature (i.e. a result of random variability). Thus, good practice is not necessarily to invoke statistical uncertainty estimation, which does not deal well with complex epistemic uncertainties (see Beven, 2002, 2006, 2009). This then raises some interesting issues about how to communicate the assumptions used to describe the different sources of uncertainty in hydrological prediction.

The nature of errors in environmental modelling

It has been traditional to deal with uncertainty in risk-based decision making in terms of probabilities. Indeed some statisticians suggest that probability is the only coherent framework with which to deal with uncertainty (e.g. O'Hagan and Oakley, 2004). This implies however that the uncertainties can be assumed to be aleatory (i.e. at base due to random variability) in nature, or, at least, can be treated *as if* they were probabilistic in nature. But this is often difficult to justify given the nature of errors in environmental modelling. We can recognise, all too easily, sources of epistemic uncertainty in representing environmental systems. Epistemic uncertainty arises from lack of knowledge and may be difficult to characterise due to changing characteristics in time and space. Epistemic uncertainty arises in the meaning of observations, in the representation of relevant processes in a model structure, and in the representation of the boundary conditions and states of that model. Very often, we also understand that the nature of such errors will be non-stationary in time and space; variability that will ultimately control the complex structure of any residual series between model prediction and observation. This recognition is not new. In the past such errors have been called the *real uncertainties* as opposed to those that could be assessed in terms of probabilities.

Consider the sources of uncertainty that influence the assessment of flood risk. In flood risk mapping, a distributed hydraulic model (generally formulated in either 1 or 2 dimensions) is provided with upstream, downstream and lateral boundary conditions. To make predictions it will require a representation of the geometry of the flood plain, and a representation of the conveyance of the channel and floodplain (including the representation of geometry and any effects of vegetation, structures, hydraulic jumps, internal shear on effective momentum losses etc). Uncertainty in such flood inundation predictions has been considered in the past using a variety of different models and methods (e.g. Romanowicz et al., 1996; Romanowicz and Beven, 1998, 2003; Aronica et al. 1998; Bates et al., 2004; Pappenberger et al; 2005, 2007a,b; Werner et al.,2005; Mason et al., 2009). All of these papers have included only some of the relevant uncertainties, though in many cases this was justified by conditioning on observed inundation data to give a likelihood to each of an ensemble of simulations such that any sources of uncertainty not treated explicitly can be assumed to have an implicit effect. It does not then follow that predictions under different (possibly more extreme) conditions will be equally well represented (see, for example, the three events considered in Romanowicz and Beven, 2003). For a full risk analysis, estimates of the potential damages for different levels of inundation will be required. This will be a further source of uncertainty.

In fact, it is difficult to see any of the sources of uncertainty listed above as free from epistemic uncertainty. Consider the representation of the boundary conditions. One dimensional hydraulic models require two boundary conditions (for sub-critical flow) at both upstream and downstream boundaries because there are two unknowns, depth and velocity. This is normally achieved by setting a water level and then inferring a mean velocity or discharge from a rating curve or uniform flow equation (assuming a water surface parallel to the bed slope). Two-dimensional models are more complex in requiring water levels and velocities in every element at the upstream and downstream boundaries, though usually similar simplifying assumptions are made. However, it is rare that rating curve observations extend to flood stages, even at gauging stations. Thus there is a certain lack of knowledge about what the true mean velocity (or equivalent roughness) would be when a hydraulic model is used to predict extreme flood events. The boundary conditions will be subject to epistemic error.

Similarly, lateral inflows (or transmission losses) are often neglected as negligible or estimated from rather poor information, unless there is a major tributary (which will be subject to similar or greater uncertainty to upstream and downstream boundary discharges). Over short reaches this may be acceptable; over long reaches it will be a source of error and uncertainty, but because we have little knowledge of how to estimate the magnitude of lateral inflows, this will be epistemic in nature.

Channel geometry can be another source of epistemic error. Surveys of the in-bank channel are expensive and are only made at a restricted number of cross-sections. Representation of flood plain geometry and infrastructure has improved with the more widespread availability of high resolution LIDAR and SAR digital elevation data, but there may still be features such as field boundaries, walls and flow pathways under bridges that affect the effective roughness, water storage and flow velocities on flood plains but which do not appear in the digital elevation model. Estimates of the nature of the vegetation on flood plains from LIDAR surveys have also been used to estimate roughness coefficient (e.g. Mason et al., 2003) but LIDAR surveys are rarely repeated and vegetation is not a stationary characteristic. There will be epistemic uncertainties in inferring values of an effective roughness coefficient at different times and flood magnitudes from the limited data available.

An example of a flood risk map produced for the town of Carlisle in Cumbria, UK is shown in Figure 1 (see Leedal et al., 2010). To make a proper interpretation and assessment of the probabilistic representation of the uncertainties in this case it would be necessary to know something about how the various sources of uncertainty discussed above have been treated. Experience suggests that treating uncertainties as if they were simple aleatory probabilistic errors tends to lead to overconfi-

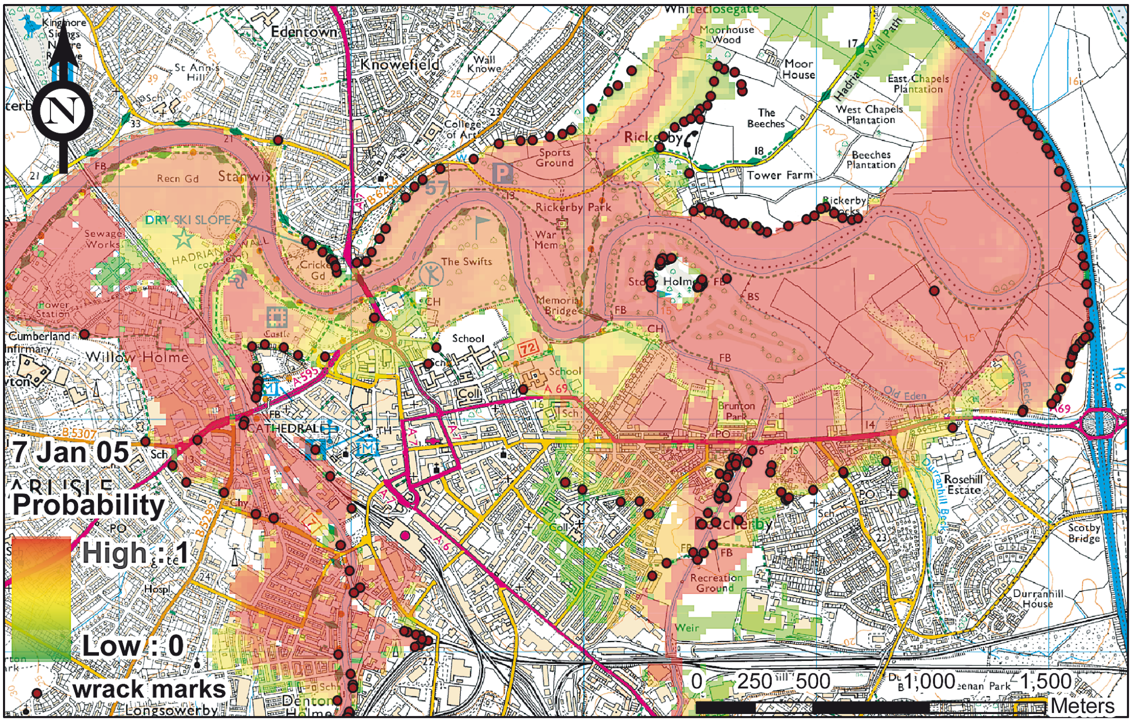

Figure 1. *A colour coded map of the predicted probability of inundation of the maximum extent of inundation for the January 2005 flood event at Carlisle, Cumbria, UK. The red dots represent post-event surveys of maximum inundation extent.*

dence in estimating the prediction uncertainties. This is because the probabilistic model derived in any calibration or conditioning exercise might not hold if the effect of epistemic errors is different in prediction. Certainly we need to make some assumptions about the nature of such errors even in making plausible scenario simulations (or continue to treat them implicitly when calibration data are available). The question is how to agree what assumptions to use.

Developing Guidelines for Good Practice in incorporating risk and uncertainty in environmental models

This recognition of complexity in uncertainty estimation underlies the concept of using Guidelines for Good Practice as a way of sharing experience in this type of environmental modelling problem. Such Guidelines can serve as a repository for experience in dealing with different types of uncertainty in different types of application. There are many existing guidelines or standards used for assessing flood risk and resulting planning decisions in different countries. The Floods Directive itself is a framework for setting standards in assessing flood risk. Few such standards to date have, however, taken any account of the different sources of uncertainty in assessing the predictions of hydrological models for different purposes. But taking uncertainty into account might be important if it changes the types of planning or investment decisions that are taken. In some types of application it might then be appropriate to be more precautionary; in others more risk accepting.

Guidelines as a translationary discourse between modeller and stakeholders

One barrier to the uptake of uncertainty estimation for these types of environmental problems involving epistemic uncertainty, is the communication of information between modeller and client, decision maker, policy maker or other stakeholder. Our experience from workshops run to discuss the incorporation of risk and uncertainty into decision making is that decision makers are not reluctant to deal with uncertainty (though they would like to see it managed and reduced as far as possible) but they want to be quite clear about what is being presented. Faulkner et al. (2007) discuss this issue in applications to flood risk management and suggest that a *translationary discourse* between modeller and stakeholder is necessary. This requires that not only the results of an analysis be communicated but also the assumptions on which the analysis is based. Thus, a framework is required that allows this communication to start at an early stage.

One way of trying to achieve this is being tried in terms of defining the Guidelines for Good Practice as a set of decisions to be agreed between the modeller and user. The decisions will cover uncertainties in data and modelling, together with choices for the presentation and visualisation of the results. Response to those decisions can be agreed and recorded as part of the audit trail for a particular application. Such a decision structure allows such evolution over time (including, for example, making the Guidelines available as a wiki document to which anyone can contribute, see also Pappenberger et al., 2006), while making the assumptions of any analysis to be defined explicitly and therefore open to later evaluation and review.

The Catchment Change network (CCN)

Developing Guideline-based decision-support systems is one of the aims of the Catchment Change Network, a project of the UK Natural Environment Research Council (see www.catchmentchange.net). The Network – made up of three discrete but interlinked Focus Areas covering flood risk, water quality and water scarcity – will exchange knowledge across a wide range of project partners about how best to handle uncertainties in integrated catchment management. It recognises a need to reduce the disparity between the largely academic knowledge base and its implementation across a range of user groups and the need for a supportive professional framework to ensure consistency and the sharing of knowledge and best practice. It proposes to do this by means of Guides of Good Practice, structured as a set of decisions to be made in any application by agreement between modellers and users. This framework is intended to support greater transparency within the decision process and enhance credibility and trust across catchment management activities. Future evaluation of the decisions that were made and recorded should lead to improvements in future practice.

The intention is that these Guides will ultimately become embedded across a wide range of catchment management professionals with the aim of encapsulating a convenient decision-support framework for practitioners and decision makers by focussing on key variables whilst clarifying the strength of available evidence. These will be living documents that, with broad user input will be refined as experience of "good practice" increases.

Conclusions

Hydrological prediction involves many different sources of uncertainty. Many of these sources of uncertainty involve epistemic uncertainties that are not necessarily easy to represent statistically. This can create problems for communication between analyst and users when prediction uncertainties are being presented and interpreted. It has been suggested in this paper that one way of facilitating this communication is to use a framework of Guidelines for Good Practice within which sets of decisions form the basis for interaction (the translationary discourse) between analyst and users. An essential feature of the approach is that the decisions must be recorded so that they are available for later evaluation and revision. In the UK the Catchment Change Network is intending to develop this approach in the flood risk and other water management areas.

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