# Guidelines for good practice in flood risk mapping: The catchment change network

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**Abstract** The assessment and mapping of flood risk 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 uncertain flood risk maps are being prepared. It is suggested that 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 NERC, 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. The paper will set out the background to developing Guidelines for flood risk mapping and give an application to a site in Yorkshire, UK.

**Keywords** uncertainty; guidelines; good practice; flood risk mapping; catchment change network

## THE BACKGROUND TO PREDICTING CATCHMENT CHANGE

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 example in this paper) nor can we be sure that all the uncertainties are aleatory or can be treated as if they were aleatory. 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 what form guidelines for good practice should take.

## 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 aleatory 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 nonstationary 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. Such errors are what Frank Knight (1921) called the *real uncertainties* as opposed to those that could be assessed in terms of odds.

The case study introduced later is concerned with uncertain flood risk mapping, so let us consider which sources of uncertainty that influence the assessment of flood risk in space are aleatory in nature, and which are epistemic. 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 flood plain (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. 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.

The debate has not even started about how far such uncertainties can be represented as if they were aleatory probabilistic errors. 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 flood risk. But taking uncertainty into account might be important if it changes the types of planning or flood defence strategy decisions that are taken.

## THE CATCHMENT CHANGE NETWORK (CCN)

Developing Guideline-based decision-support systems is one of the aims of the Catchment Change Network, a NERC Knowledge Transfer project being led by Lancaster University in tandem with other Universities (Durham, Leeds and Newcastle), UK regulatory agencies and the business community. 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 dissemination gap –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 also supports implementation of greater transparency within the decision process and so enhances credibility and trust across catchment management activities.

To date, it has formalised a growing network of scientists and science users across catchment management with a broad interest in the implications and adaptation to future change. It has also developed and delivered a series of exploratory Workshops designed to develop the framework and content of our practical guidance and also held its first annual conference to encourage dissemination and actively identify future research requirements.

Ultimately, the key aim of the Network is to integrate modern uncertainty estimation methods to improve decision making for adaptive management across catchments. Workshop activities in each of the Network Focus Areas have recently explored the form, scope and content of such Guidance with debate centering on sources of uncertainty, the range and composition of audiences for the guidance produced and the communication and transparency of the underlying assumptions made.

Progressively updated Guides to Good Practice will be produced for each of the three Focus Areas with content defined and developed via Workshop activities and interactive web-based involvement across a range of stakeholders. The web site www.catchmentchange.net will act as both an information hub and knowledge exchange portal to communicate and interact across our project partners both in the UK and Europe. These documents will outline the current state of knowledge and science, provide guidance for tools that could be used for taking account of uncertainties in different types of applications and outline practical case studies of where tools have been applied successfully.

Our 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. One way of ensuring this is to structure the Guidelines in terms of a set of decisions about options that have to be agreed between analysts, stakeholders and users.

## 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 analyst 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.

A summary of the current list of high level decisions in the draft of the Guidelines for Good Practice for Flood Risk Mapping, under their highest level categories, is given in Table 1. The methodology allows for different types of decision trees at lower levels depending on the options chosen at higher levels.

## A CASE STUDY: MEXBOROUGH, YORKSHIRE

In summer 2007 in the UK there were 2 periods of extensive pluvial and fluvial flooding. The area around Mexborough was flooded during the event of 25th June when some 80 mm rainfall fell on already wetted catchments. This region has been modelled by JBA Consulting for a (deterministic) evaluation of flood risk using the JFLOW model (Bradbrook, 2006), in the version implemented on graphics processing units (GPUs) (see Lamb et al., 2009). This greatly speeds up the 2 dimensional calculations which then allows many runs of the model to be made in assessing the effects of different sources of uncertainty. There is no space here to address the responses to all the decisions required for this application outlined above but a summary is given in the text below and in Table 1.

Figure 1 shows the modelled depths of flood inundation predicted using the JFLOW-GPU model following model conditioning using the observed extents for the peak of the 2007 event. Effective roughness coefficients, here assumed uniform in space for channel and floodplain were sampled from prior uniform distributions. Some 500 model runs were made to span the range of the roughness distributions. Each run was then assigned a posterior likelihood value based on how well it simulated the observed wrack marks associated with maximum inundation extent. Due to the complex interaction between model parameters and the input uncertainty, this model performs acceptably well over a range of effective roughness values.

**Table 1**. Shows condensed responses to the Guidelines for Good Practice in flood risk mapping high level questions applied to the Mexborough (Yorkshire UK) case study.

| | **High level decision description** | **Mexborough case study** |
|---|---|---|
| **D1** | Uncertainty in design flood magnitude | Use WinFAP to calculate AEP using the single gauge site at Adwick. The 2007 event data was included as this had a significant effect on the analysis results. |
| **D2** | Uncertainty in conveyance estimates | A DTM, cross-section geometry, and wrack mark data base were used to calibrate roughness/channel capacity parameters |
| **D3** | Uncertainty in rating curve extrapolation | The stage to flow relationship is thought to be valid for events of ~0.01AEP. A calibrated regression equation was used to generate flow estimates for 0.01AEP of between 73.5 and $71.1 m^3 s^{-1}$ |
| **D4** | Uncertainty in flood plain topography | A 2m resolution LiDAR topography map was used. This resolution exceeds the JFLOW model resolution |
| **D5** | Uncertainty in model structure | The JFLOW model scheme was limited to 3 variables: a uniformly distributed Manning's N value, channel capacity, and upstream inflow. |
| **D6** | Uncertainty in effects of flood plain infrastructure | No consideration of infrastructure is included beyond that represented by the DTM |
| **D7** | Uncertainty in observations used in model calibration/conditioning | Estimates of +/-95% confidence intervals are available for stage measurement, no uncertainty is considered for DTM |
| **D8** | Uncertainty in assessing effects of future catchment change | None considered for this application |
| **D9** | Uncertainty in assessing effects of future climate change | None considered for this application |
| **D10** | Uncertainty in fragility of defences | None considered for this application |
| **D11** | Uncertainty in consequences/vulnerability | Results not extended to vulnerability for this application |
| **D12** | Assessing interaction between sources of uncertainty | Assumed to be handled by weights associated to MC simulation results |
| **D13** | Defining an uncertainty propagation process | Use MC simulation. The chosen sampling strategy is a 500 member ensemble using independent random sampling across the three parameters chosen to represent model uncertainty: Upstream inflow, channel capacity, and floodplain roughness |
| **D14** | Defining a model calibration/conditioning process | A posterior likelihood function was formed for the model parameter space conditioned on the fit of the inundation outline of a single large flood event (June 2007) |
| **D15** | Defining a presentation method | GIS and Google map with interactive querying using DHTML |
| **D16** | Managing and reducing uncertainty | No new data is available that could be used to reduce uncertainty at time of writing |

**Fig 1.** Mexborough 2007 - JFLOW predicted peak inundation depths and point flood extent observations made after the 2007 event.

An important uncertainty, both for the historical event and for any design event subsequently used for flood risk mapping is in the input discharge. In this case an annual maximum flood series from the local gauging station were available for analysis. The procedures of the UK Flood Estimation Handbook (FEH, Institute of Hydrology, 1999) were used to estimate the AEP0.01 (100 year return period) peak discharge using the FEH WinFAP software to fit the Generalised Logistic Distribution. This is the distribution of choice in the FEH recommendations, but is fitted without any account taken of the potential uncertainties in the historical flood peak estimates. It does however allow an estimate of the distribution of the desired return period to be made, under the statistical assumptions of the distribution fitting. In this case the best estimate of the AEP0.01 flood was estimated to have a mean of 86.6 $m^3s^{-1}$ with standard error 2.5 $m^3s^{-1}$. In this case, the input discharge from upstream was thought to dominate any lateral inflows and there were no significant tributaries so it was not necessary to simulate covarying inputs. This input discharge distribution was run, using Monte Carlo sampling, with the uncertain flood inundation model to produce uncertain flood extent maps that can then be used in further risk analysis.

As part of this work, a visualisation tool for uncertain risk maps has been developed with a view to developing Guidelines for how to present the results to users. The latest version of the tool makes use of Google Maps to overlay the results of the uncertain design flood simulations. Figure 2 shows the outputs from the likelihood weighted ensemble of model runs interpreted as risks of inundation. Here, the database generated by the modelling exercise is tied to the base Google map in such a way as to allow the user to perform interactive attribute selection using a slider tool. The attributes of the database include probability of inundation exceedance and probability of depth exceedance (for a given depth). The user can also interact with the map by clicking at a point to select from the database the probability of the flood exceeding a range of depths at the chosen location. Further work using open source GRASS and Quantum GIS software that allows these risk maps to be registered to properties for damage calculations is currently in progress.

From Figure 2 it can be seen that some areas at risk of flooding are relatively insensitive to the uncertainties considered, where a relatively flat floodplain is bounded by rather steep topography at its margin. In such locations, variations in predicted depth of inundation have little effect on predicted extent. Other areas are much more sensitive. There is a sewage treatment works on the southern edge of the town, close to the river, that is protected by flood embankments. For a purely deterministic flood risk map, this is shown as not being at risk at flooding, but if the uncertainties are taken into account it is at potential risk of flooding. The probability of flooding by the AEP0.01 event can be evaluated, consistent with the assumptions that have been defined by the set of decisions for this application.

**Fig 2** Uncertain AEP0.01 flood extent map at Mexborough overlain onto Google Maps.

## CONCLUSIONS

The assessment and mapping of flood risk 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 uncertain flood risk maps are being prepared. It has been suggested in this paper that one way of facilitating this communication is to use framework of Guidelines for Good Practice within which sets of decisions form the basis for interaction (the translationary discourse) between analyst and users. An example application of the approach to flood risk mapping at Mexborough, Yorkshire, conditioned on observations for the 2007 flood is given. An essential feature of the approach is that the decisions must be recorded so that they are available for later evaluation and revision. The Catchment Change Network (see www.catchmentchange.net) is intending to develop this approach in the flood risk and other water management areas.

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