Inundation probability mapping using Generalised Likelihood Uncertainty Estimation - Paul Bates, Matt Horritt, Giuseppe Aronica, Keith Beven

PUB-IAHS Workshop
Uncertainty Analysis in Environmental Modelling
6th – 8th July 2004

a) Introduction:

Many of the predicted quantities required by users of hydrological models are distributed in space e.g. runoff, nutrient loadings or floodplain inundation. As a consequence methods are required to unearth the spatial uncertainty in distributed model predictions.

The method is based on the GLUE technique and uses Monte Carlo analysis of a distributed hydraulic model. For each realisation *j* in the ensemble we evaluate a single global likelihood function *L* for parameter set Θ. The key problem is then to use these global likelihoods to map uncertainty in flood inundation in space for a given event. To do this we first eliminate non-behavioural simulations. Then for an observed event *E*, we then take the flood state predicted by the model for pixel *i* in simulation *j* for each parameter set Θ_j and weight it according to the measure of fit $L(\Theta_j)$ evaluated against data set *Y* to give a flood risk for each pixel, P_i^{flood} . Hence, for observed event E_1 with data set Y_1 we evaluate:

$$P_i^{flood}(E_1)=\frac{\sum_j f_i(\Theta_j,E_1)L(\Theta_j \mid E_1,Y_1)}{\sum_j L(\Theta_j \mid E_1,Y_1)}$$

$f_i(\Theta_j,E_1)$ represents the numerical model result at a pixel *i* for each parameter set, and takes a value of 1 for a flooded pixel and is zero otherwise. The results of each simulation for each pixel are thus weighted according to how well the model reproduces the flood extent in a global sense, $L(\Theta_j \mid E_1,Y_1)$ acting as a generalised relative risk measure for each simulation. P_i^{flood} will assume a value of 1 for pixels that are predicted as flooded in all simulations and 0 for pixels always predicted as dry. Model uncertainty (here defined by the interaction of the global performance measure and spatially distributed probabilities of the event being modelled) will manifest itself as a region of pixels with intermediate values, maximum uncertainty being indicated by pixels with $P_i^{flood} \approx 0.5$. When events different from the conditioning event are to be modelled, the same values of $L(\Theta_j \mid E_1,Y_1)$ can be used (these are associated with each parameterisation), but the predicted values of f_i will differ. Hence, for a second event the flood probabilities for each pixel can be calculated using the parameter sets conditioned on the first event:

$$P_i^{flood}(E_2)=\frac{\sum_j f_i(\Theta_j,E_2)L(\Theta_j \mid E_1,Y_1)}{\sum_j L(\Theta_j \mid E_1,Y_1)}$$

Observations of the second event can also be used to evaluate new sets of $L(\Theta_j)$ that can then be combined using Bayes' equation. The result is a map of uncertainty in predicted inundation across the model domain.

b) Advantages

- Maps likelihoods calculated in a parameter space back into real space to give an indication of spatial structure in uncertainty
- Can unearth spatial uncertainty for design events for which no validation are available
- Likelihoods can be updated using Bayes equation as new data becomes available
- Presents information on model uncertainty in a form which is complementary with, but gives different information to more the traditional dotty plots or mappings of likelihoods over a parameter space.

c) Disadvantages

- Only applies to binary quantities.
- P_i^{flood} Is not a true probability and is difficult to interpret except when where it takes a value of 0 or 1. Rather it is a generalised relative risk measure that we assume approximates the true risk given sufficient sample of realisations.
- What constitutes a behavioural simulation remains subjective.
- Choice of objective function is also subjective.
- A priori we make no assumptions about the probability density function for each model parameter.
- Use of Bayesian updating in the method has only received limited testing

d) Assumptions

The assumptions of the GLUE method plus we assume that:

- P_i^{flood} Approximates the true risk given sufficient sample of realisations
- Only tried thus far for uncertainty in model parameters, but should apply well for data uncertainty and perhaps even model structural uncertainty

e) Most appropriate application areas

Applications involving the prediction of the presence/absence of a particular artefact e.g. flooded/not flooded, snow/no snow, saturated/unsaturated.

f) Reading list

Aronica, G., Bates, P.D. and Horritt, M.S., (2002). Assessing the uncertainty in distributed model predictions using observed binary pattern information within GLUE. Hydrological Processes, 16, 2001-2016.

Bates, P.D., Horritt, M.S., Aronica, G. and Beven, K., (in press). Bayesian updating of flood inundation likelihoods conditioned on flood extent data. Hydrological Processes.

g) Software availability

Not yet.

h) Web links or other information

http://www.ggy.bris.ac.uk/research/hydrology/paul_research.htm

i) Figures

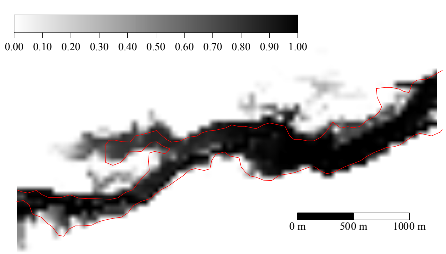

Figure 1: Probability map of predicted inundation, P_i^{flood}, for a 1 in 5 year flood event in December 1992 event for a 3 km reach of the River Thames, UK calculated with the LISFLOOD-FP 2D hydraulic model (Bates and De Roo, 2000). The probability map was calculated from an ensemble of 500 realisations of the model using randomly selected parameters for floodplain and channel friction. Each realisation was evaluated by comparing model predicted inundation to an observed flood extent map derived from the ERS-1 satellite Synthetic Aperture Radar.

j) Delegates Comments (please add !!)