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Uncertainty in the calibration of effective roughness parameters in HEC-RAS using inundation and downstream level observations

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Abstract

An uncertainty analysis of the unsteady flow component (UNET) of the one-dimensional model HEC-RAS within the generalised likelihood uncertainty estimation (GLUE) is presented. For this, the model performance of runs with different sets of Manning roughness coefficients, chosen from a range between 0.001 and 0.9, are compared to inundation data and an outflow hydrograph. The influence of variation in the weighting coefficient of the numerical scheme is also investigated. For the latter, the empirical results show no advantage of using values below 1 and suggest the use of a fully implicit scheme (weighting parameter equals 1). The results of varying the reach scale roughnesses shows that many parameter sets can perform equally well (problem of equifinality) even with extreme values. However, this depends on the model region and boundary conditions. The necessity to distinguish between effective parameters and real physical parameters is emphasised. The study demonstrates that this analysis can be used to produce dynamic probability maps of flooding during an event and can be linked to a stopping criterion for GLUE.

Keywords: GLUE; HEC-RAS; Uncertainty; Flood; Roughness; Inundation

1. Introduction

One-dimensional (1D) flow routing approaches such as Mike 11, ISIS or HEC, based on the St. Venant/Shallow Water Equations or variations, still form the majority of traditional numerical hydraulic models used in practical river engineering. The widespread usage in practice might be explained not only by the fact that 1D models are (in comparison to higher dimensional models) simpler to use and require a minimal amount of input data and computer power, but also because the basic concepts and programs have already been around for several decades (Stoker, 1957; US Army Corps of Hydraulic Engineers, 2001).

However, these models have been criticised not only because of the expectation that representation of floodplain flow as a two-dimensional (2D) flow interacting with the channel flow will give more accurate predictions of flood wave propagation (Anderson et al., 1996; Aronica et al., 1998; Bates et al., 1992; Bates et al., 1998;

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Nomenclature

θ	Weighting factor
Θ	Parameter set
$\mu_{obs/com}$	Observed and computed membership value of the cells
$\Delta\mu$	Absolute difference between observed and computed membership value of each cell
Δt	Time step
Δx	Space step
c	Speed of floodwave
D	Kuiper statistic distance
F	Coefficient of efficiency (inundation)
$L_o(\Theta)$	Prior likelihood weight of parameter set Θ
$L_y(\Theta\|z)$	Calculated likelihood weight of the parameter sets (with the set of new observations z)
$L_p(\Theta\|z)$	Posterior likelihood weight
n_{Sobs}	Number of flooded cells observed
$N_{1,2}$	Number of data points in the first and second distribution
R^2	Coefficient of efficiency (outflow)
$S_{obs/comp}$	Set of observed and computed flooded cells/pixels, respectively
S_N	Cumulative probability distribution
t	Time
V_k	Constant sum of the negative and positive Kuiper statistic D

Subscripts

c	Channel
f	Floodplain

Cunge, 1975; Dutta et al., 2000; Ervine and MacLeod, 1999; Gee et al., 1990; Hromadka et al., 1985), but also for the usage of the Manning equation (which can be also a criticism for higher dimensional models). This flow equation is computed:

(1) with an exponent of the wetted perimeter which Manning set to 2/3 despite the fact that his (and later) analysis of existing data showed that the value can vary (in his case between 0.6175 and 0.8395) (Laushey, 1989; Manning, 1891);
(2) is dimensionally inhomogeneous (Chow, 1959; Dooge, 1992; Manning, 1895);
(3) furthermore, was developed to represent uniform flow and not non-uniform conditions (see criticism of Laushey, 1989).

All model packages focus on the calibration of the roughness parameter which, together with the geometry, is considered to have the most important impact on predicting inundation extent and flow characteristics (Aronica et al., 1998; Bates et al., 1996; Hankin and Beven, 1998; Hardy et al., 1999; Rameshwaran and Willetts, 1999; Romanowicz et al., 1996).

Whether the model is more sensitive to either or both of the roughness and geometry uncertainty is in part a result of the dimensionality of the model structure, which represents geometry in different ways (Lane et al., 1999). Every model geometry is an approximation of the real geometry, with all its downstream variations, and therefore will have an implicit effect on the values of the effective roughness parameters. This also means that it should be possible to compensate to a certain degree for geometrical uncertainty, by varying the effective roughness values (Aronica et al., 1998; Marks and Bates, 2000). The extent to which this is possible varies with model dimensionality and discretisation.

Therefore, the focus of this study is an evaluation of the uncertainty of the roughness coefficients which is also driven by the fact that many modellers see the main problem in practical applications as a problem of choosing the 'correct' roughness (Barr and Das, 1986; Bathurst, 2002; Boss International, 2001; Dingman and Sharma, 1997; Graf, 1979; Rameshwaran and Willetts, 1999; Rice et al., 1998; Tinkler, 1997). Some studies (Trieste and Jarrett, 1987) have demonstrated discrepancies between calibrated effective model values and roughnesses which have been estimated based only on the nature of the channel and flood plain surfaces, despite many sources of guidance about how to choose a value, such as photographs (Arcement and Schneider, 1989; Chow et al., 1988), tables (Chadwick and Morfett, 1999; Chow, 1959; Chow et al., 1988; King, 1918), composite formulae (Barkau, 1997; Bathurst, 1994; Dingman and Sharma, 1997; Knight et al., 1989; Li and Zhang, 2001;

Rice et al., 1998; Riggs, 1976) or measurement programs (Ackers, 1991; Dingman and Sharma, 1997; Ervine and MacLeod, 1999; Harunurrashid, 1990).

These estimates have usually been based on velocities measured for local velocity profiles or across a single cross-section. A flood routing model requires ‘effective’ values of roughness at the scale of the distance increment of the model (Beven and Carling, 1992), including all the effects of variable cross-sections, heterogeneous slopes and vegetation cover at that scale, as it is impossible to quantify every source of energy loss separately (Ervine et al., 1993). These parameters also have to compensate for the effects of man made structures on the flood plain neglected in the specification of the reach geometry, the method used to combine the roughness of the floodplain and channels (Bousmar and Zech, 1998), and possibly the particular numerical algorithms used. Any attempts, for example, to split the Manning roughness according to each of these component losses (Arcement and Schneider, 1989) will experience difficulties. It is problematic to quantify each loss in respect of the approximation of the model structure.

Several studies have been conducted to investigate the uncertainty in the structure of flood inundation models. Horritt and Bates (2002) compared 1D and 2D model codes (HEC-RAS, LISFLOOD-FP and TELEMAC-2D) in an optimisation framework without consideration of parameter uncertainty. They found that all models performed equally well, although different responses to changes in the friction parameterisation.

One methodological approach to formalise the uncertainty in the roughness parameters is presented in this study with the generalised likelihood uncertainty estimation (GLUE) methodology (Beven and Binley, 1992), which is explained in more detail later. This method has been applied by various researchers with one, two and quasi-two dimensional inundation codes (Romanowicz and Beven, 2003; Romanowicz et al., 1996; Aronica et al., 2002; Aronica et al., 1998). It could be shown that several sets of model roughness parameters perform equally well.

The first objective of this study is to extend the previous research of parameter uncertainty to the 1D model code HEC-RAS (US Army Corps of Hydraulic Engineers), because this type of inundation model is still widely used. It further compares the findings of two different sites (the River Morava in the Czech Republic and the River Severn in Great Britain) and two different data sets: elevation and inundation measurements for cross-sections only for the River Morava; and a full distributed inundation map for the River Severn. A new methodology to quantify the global performance of flood inundation within fuzzy set theory (extending Aronica et al., 2002; Horritt and Bates, 2001b) is utilised.

The paper also investigates the role of the accuracy of the numerical solution and its impact on model predictions. The role of parameters which control properties of the numerical solution are very often neglected, although a considerable impact has been found (Claxton, 2002).

Finally, a method to investigate the number of runs necessary within the GLUE framework to achieve consistent predictions is presented. This is a contribution to the common question on how many simulations are necessary within this type of Monte Carlo framework.

This paper discusses initially the model which has been applied, together with uncertainties faced in flood inundation modelling. Then the GLUE methodology is presented and how it has been applied within this framework. This is followed by a brief presentation of the catchments. Subsequently, the results of this study are discussed and a final conclusion is drawn at the end.

2. Uncertainties in flood inundation modelling using the example of HEC-RAS

In this section we explore some sources of uncertainties of a 1D flood inundation model. These are: structure, implementation of the numerical scheme, topography, model input/output and parameters.

2.1. Structure

A large number of model structures have been developed to predict flood inundation. However, each structure only approximates nature and therefore has to make many simplifications. For example, the unsteady flow component UNET of HEC-RAS (Brunner, 2001) assumes:

- that the flow can be represented by a cross-section mean velocity and that the water surface is

horizontal across any channel section (Bladé et al., 1994);
- all flows are gradually varied with water of uniform density and hydrostatic pressure prevailing at all points in the flow so that vertical acceleration can be neglected (Barkau, 1997);
- the model in this form cannot represent any complex interactions between channel and floodplain (Knight and Shiono, 1996) and complex floodplain flows (Ervine and MacLeod, 1999; Sellin et al., 1993);
- the channel boundaries are fixed and therefore no erosion or deposition can occur;
- the resistance to flow under dynamic flow conditions can be approximated by empirical uniform flow formulae such as Manning's or Chezy's equation (Barkau, 1997).

(after Chow et al., 1988).

These assumptions may not always be fully valid which may also not be necessary in every case. Nevertheless, they will introduce uncertainty in the model results to some extent.

2.2. Numerical scheme

UNET uses the St. Venant equations which can be solved with an implicit finite difference scheme using a modified Newton–Raphson iteration technique (Barkau, 1982; Fread and Harbaugh, 1971). The choice of the type of the numerical solution can introduce additional uncertainty in some cases, although this is not always the case (Bates et al., 1995; Bates et al., 1997; van Looveren et al., 2000).

For this implicit numerical method, stability analyses have been performed by Fread (1974); Liggett and Cunge (1975) showing that theoretically the solution is unconditionally stable for $0.5 < \theta \leqslant 1.0$ (θ is the time weighting factor of the numerical scheme). Moreover, it is conditionally stable for $\theta = 0.5$. They also proved that numerical diffusion is indirectly correlated to the ratio of wavelength divided by the reach length. However, they state that convergence should not be problematic, because the spatial distances are short compared to the wavelength. Nevertheless the user must be aware of the fact that the solution must balance numerical accuracy and computational robustness. Barkau (1997) suggested that larger values of θ produce a more robust simulation at the cost of accuracy.

Another factor which has a great impact on the model robustness is the time step. One rule of the thumb, suggested by Barkau (1997), is to choose a step which is one 20th of the time of the rise of the inflow hydrograph (Barkau, 1997). Moreover, the user is advised in the HEC-RAS User Manual to ensure that the Courant condition (which indicates the limit for explicit numerical solutions) is met:

$$\Delta x \geq c \times \Delta t \tag{1}$$

Δx Space step
c Speed of floodwave
Δt Time step

However, it remains unclear how to choose an optimal time step, especially because it is reported that for implicit solutions the Courant condition does not need to be satisfied and large time steps should produce good results (Barkau, 1997).

The Courant condition and the analysis of the best weighting parameter are based on theoretical linear analyses and in practice many other factors influence the results, including, for example, changes in cross-section properties, hydraulic structures, a sudden increase/decrease of the channel slope or the Manning roughness. The choice of both can introduce numerical errors, which may be hard to distinguish from responses due to other sources and thus this choice introduces additional uncertainty.

2.3. Topography

Topography is also often derived by using remote sensing (Bowen and Waltermire, 2002; Burgmann et al., 2000; Eineder, 2003; Kervyn, 2001; Wilson, 2004) and although one of the main inputs into most models, topography is very often seen as the factor with the least uncertainty. Various studies have shown that small errors in the topography can have significant effects on model results (Aronica et al., 1998; Bates et al., 1997; Nicholas and Walling, 1998; Wilson, 2004). The issue is made even more complex when the representation of infrastructure is included or very often neglected. This study restricts investigations into uncertainty to the model evaluation process and addresses the issue of topography in the actual modelling process only to a lower degree.

2.4. Input/output

Another problem which is partially considered within this study is the impact of input and output uncertainty on the modelling process.

Model input is very often quantified by a discharge hydrograph, which is either derived by rating curves or is the output of another model. In both cases significant uncertainty has to be considered. Flood inundation models produce both hydrographs and inundation information as model output. The latter is to an increasing degree compared to data which are acquired by manual survey (Romanowicz and Beven, 2003) or remote sensing (see e.g. the SNAKE algorithm Horritt, 1999). Significant uncertainties can be introduced into this comparison data, e.g. vegetation or wind (Ramsey, 1995; Richards et al., 1987; Wang et al., 1995) or survey errors.

2.5. Parameters

Another factor is parameter uncertainty, in this case surface roughness, which has been discussed in the introduction and is the main focus of this study. It has to be emphasised that uncertainty in effective local surface roughness may influence inundation pattern at local scale significantly, but can have only a small impact on the overall inundation predictions. Furthermore, it will be significantly more difficult to identify parameter combinations in a high dimensional space.

The uncertainties mentioned above are evaluated within the GLUE.

3. The GLUE methodology

In this section the GLUE methodology is introduced, followed by the introduction of the measures used to evaluate model results. Finally, a stopping criteria, which indicates the number of runs necessary in performing such an analysis is presented.

3.1. Methodology

GLUE is a Bayesian Monte Carlo method which allows that different parameter sets within a model structure (here various roughness coefficients) might perform equally well in reproducing the limited field observations in any practical application (Beven and Binley, 1992; Freer et al., 1996). This can also be the case for different initial conditions, boundary conditions, model structures or topographies (Ambroise et al., 1996; Marks and Bates, 2000). In other words it may be difficult to distinguish between the performances of various simulations in fitting the data (the concept of *equifinality* Beven, 2002). In GLUE this is acknowledged by running the model with many different randomly chosen sets of parameters.

The choice of prior distributions of the effective parameter range is influenced, but not necessarily restricted, by the physical meaning. Uniform distributions are mainly used as they make no assumptions about prior parameter distribution other than specifying a feasible range and scale (Freer et al., 1996). In GLUE each parameter set is associated with a likelihood weight and uniform sampling can then be retained throughout any updating of likelihood (Beven and Binley, 1992):

$$L_p(\Theta|y) \propto L_y(\Theta|y)L_o(\Theta) \quad (2)$$

$L_o(\Theta)$ Prior likelihood weight of parameter set Θ
$L_y(\Theta|y)$ Calculated likelihood weight of the parameter sets (with the set of new observations y)
$L_p(\Theta|y)$ Posterior likelihood weight

The numbers of parameters varied and parameter ranges chosen will always also affect the minimum number of runs required to sample the parameter space adequately, which is not easy to determine a priori. If the parameters are sampled without restriction from a uniform distribution as suggested above, no clear guidelines exist concerning the number of minimal necessary runs. This depends on the number and range of the parameters and on the peakiness of the response surface which, unfortunately, is largely unknown in advance.

3.2. Model evaluation criteria

The shape of this response surface is strongly influenced by the kind of goodness-of-fit or objective function which is chosen to evaluate the results of the model runs. This in turn depends on the type of observations available for model calibration. Possibilities for likelihood measures include the sum of absolute errors or the R^2 coefficient of efficiency described by Nash and Sutcliffe (1970), which depends on the sum of squared errors (for a discussion on the suitability of this measure see Pappenberger and Beven, 2004; Pappenberger et al., 2004).

An interesting approach to evaluate the model performance is used by Aronica et al. (1998) and Romanowicz and Beven (2003) who applied fuzzy based measures in evaluating a flood inundation model to allow for measurements with high uncertainties. The latter can be used to evaluate distributed predictions. If the water level is interpolated from the cross-sections on a DTM the uncertainty of this interpolation algorithm and of the accuracy of the DTM can be taken into account. A simple method is to assume that a cell is fully flooded only when the interpolated water level is higher than some threshold and assume just a 'partial' flooding or membership value on values below this (Fig. 1) where the threshold reflects the approximate uncertainty in the DTM.

The difference between an interpolated picture and the observed one can then be determined, for example by the global inundation measure of Aronica et al. (Aronica et al., 2002; Horritt and Bates, 2001a)

$$F = \frac{\text{No. of correct predicted cells} - \text{No. of incorrect predicted cells}}{\text{Total number of observed flooded cells}} \quad (3)$$

which is modified in this application to the fuzzy classification to:

$$F = \frac{\sum(1 - \Delta\mu(S_{\mathrm{obs}} \cup S_{\mathrm{comp}})) - \sum \Delta\mu(S_{\mathrm{obs}} \cup S_{\mathrm{comp}})}{\sum \mu_{\mathrm{obs}}} \quad (4)$$

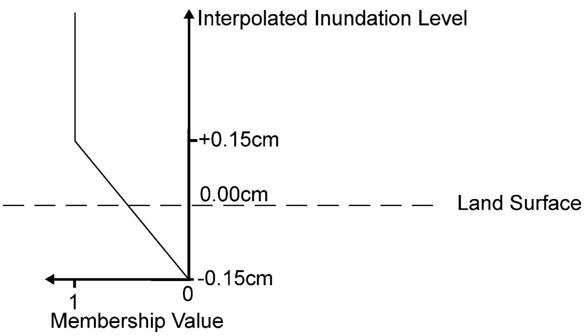

Fig. 1. Membership function of interpolated inundation.

$$\Delta\mu = |\mu_{\mathrm{obs}} - \mu_{\mathrm{comp}}| \quad (5)$$

where

F	Fuzzy goodness of fit
$S_{\mathrm{obs/comp}}$	Set of observed and computed flooded cells/pixels, respectively
$\mu_{\mathrm{obs/com}}$	Observed and computed membership value of the cells
$\Delta\mu$	Absolute difference between observed and computed membership value of each cell

This measure achieves a value of 1 for perfect fit and gets increasingly negative with non-fitting simulations.

The likelihood values computed with Eq. (4) can be used to reject certain parameter sets as 'non-behavioral'. The likelihoods of the remaining simulations are re-scaled to sum to unity (Aronica et al., 1998; Freer et al., 1996). The calculated likelihood weights can then be used to form a likelihood-weighted cumulative distribution of predictions from which uncertainty quantiles can be calculated.

3.3. Stopping criteria for GLUE

It must be stressed that the *combination* of parameter values is important and that within the GLUE methodology the calculated likelihood measure is always associated with a particular *set* of parameters conditioned on observed data variables. The GLUE procedure allows also the evaluation of sensitivity by analysing the cumulative distribution function (CDF) of parameter classified behavioural sets or marginal distributions for individual parameters classified behavioural by integrating across the parameter space (Beven and Binley, 1992; Romanowicz et al., 1994). Convergence of the CDF can be used as a measure to evaluate if the number of model runs done is sufficient to justify, e.g. the prediction of a 5 and 95% quantile. When additional model runs do not change the shape of the CDF these predictions can be made. One method to test this is the approach of Kuiper (1962), which has the advantage of being easy to apply and being sensitive towards changes in the tails of the distribution which are of high interest in the calculation of flood probabilities of sections or individual cells. The Kuiper statistic is defined in the Appendix.

To compare distributions with different numbers of runs a fixed number of increments can be interpolated on the abscissa. The size of each increment is determined by the accuracy wanted and the need to have sample realisations in each increment.

As is clear from the outline of the GLUE method above, parameter *sets* form the heart of this kind of uncertainty analysis.

4. Model case studies

This section briefly describes the two locations and the data available. It explains how the models have been set-up and explains in which way the river sections have been evaluated.

4.1. Catchment description

4.1.1. Morava

The first stream modelled is the River Morava, which flows in the eastern part of the Czech Republic. The region modelled has a length of approximately 25 km and an average slope of 0.5 m/km. This region was affected by large floods in 1938, 1966, 1981 and 1997 and for the 1997 event a comprehensive data set of inflow, outflow and maximum water levels at 77 cross-sections is available via the FRIEND network (for information on the FRIEND network see Centre for Ecology and Hydrology (2002)). An inflow hydrograph with 200 time steps (each 30 min) which is also part of this data set, was used as upstream boundary. At the downstream boundary a Manning equation approximation was chosen which needs an initial guess of the friction slope (average valley slope applied to a boundary reach further downstream (Singh et al., 1997)).

4.1.2. Severn

The second stream modelled is a 60 km long reach of the River Severn/UK (mean slope of 0.27 m/km). The reach is described by 19 ground surveyed cross-sections and airborne laser altimetry. The evaluation data are provided on a 10×10 m high accuracy ($\sim$15 cm) floodplain DEM (Mason et al., 1999). Validation data is provided by a SAR image of the 30th October 1998. In principle there would also be a second image of the 11th November 2000 available (Horritt and Bates, 2003), however, the magnitude of both events is very similar and therefore it was not additionally included in this analysis. A statistical active contour model (Horritt, 1999; Horritt et al., 2001) was used to delineate the shoreline of the 1998 flood. This algorithm was capable of locating the boundary to $\sim$2 pixels and could be used to derive an inundation map with a resolution of 25 m. As in the other reach, a dynamic discharge at the upstream end of the reach has been imposed. To make this study comparable to Horritt and Bates (2002) a downstream boundary with an imposed dynamic water surface elevation at the downstream end was used. However, in order to match the analysis of the Morava, additional runs have been done with the same Manning approximated boundary type.

4.2. Model set-up

4.2.1. Morava

For the River Morava initial Monte Carlo tests of 10,000 model runs with different numbers (8, 17, 35, 77) and location of cross-sections showed that with an increasing number of sections the number of numerically stable models decreased significantly. On the basis of these tests it was decided to use a model with eight cross-sections with two effective roughness values for the whole region (one for the floodplains and one for the river) and to perform additional tests with three roughnesses for each individual region (two for the floodplains and one for the channel).

4.2.2. Severn

The study of Horritt and Bates (2002) showed that this region can be approximated with the profiles of the 19 measured cross-sections. Therefore, the main analysis was done with these sections with roughnesses chosen as for the River Morava case. However, a small study with 38 and 72 sections indicated the same behaviour with respect to stability as previously mentioned.

Setting the cross-sections in both models to have on average the same spacing allows a reasonably direct comparison of the different types of evaluation data.

For both models it was decided to choose the parameters randomly from a uniform distribution for each section without any constraints. Therefore the edges of this distribution have been set between 0.001 and 0.900, which are the constraints given by the UNET program and represent extreme values to be expected physically for the Manning coefficient.

4.3. Model evaluation

4.3.1. Morava

For each of these simulations the sum of the absolute error in the predicted maximum water surface elevation height at each cross-section was calculated and normalised for all behavioural simulations. A model was classified as non-behavioural if the water level at one single cross-section had an error of more than 2 m or if the sum of errors over left and right floodplain inundation levels for all sections was higher than 20 m. These values have been chosen based on field observations. The method can be combined with additional rejection criteria (e.g. velocity) if data are available. For these behavioral runs the efficiency of the outflow level hydrograph was calculated by using the R^2 coefficient and the outcome was also normalised.

These two measures (hydrograph and inundation error) are combined using a weighted average to give a combined likelihood weight and again all simulations are normalised. The cross-sections have been given the weight of 8 (No. evaluation data for cross-sections) to reflect the information content and model aim priority (to predict flood inundation extent). However, in order to build individual CDFs for each section it must be borne in mind that the order of good performing models for all sections does not necessarily reflect the order in single sections, which can lead to inconsistency in individual CDFs. Therefore, the stopping criterion is demonstrated by comparing the CDF for the water elevation at each single section.

4.3.2. Severn

The inundation extent on the River Severn was predicted by using a linear interpolation algorithm given the predicted local water levels at the cross-sections projected onto the high resolution DEM. This map was then compared to the inundation map using the measure of Eq. (4), and all maps which predicted less than 95% of the flooded cells correctly have been classified as non-behavioural. Similarly to the River Morava case study, the behavioural runs have been used for an evaluation of the outflow hydrograph. The two normalised performance values have been combined as previously (this time a weight of 19 for the result of the inundation). For the test of the stopping criteria 19 individual cells at the location of the cross-sections have been chosen and evaluated against the overall inundation performances.

The CDFs for water elevation can then be used to calculate a flood risk map. The flood risk map for the distributed case of the River Severn could be calculated for each individual cell of the high resolution DEM, whereas at the River Morava only a computation at each cross-section was possible. Strictly speaking any outcome in the form of a risk map of flooding is only valid for this particular case, at this particular time of year, with this particular vegetation cover, with this particular stream geometry (no additional flood defences) and this particular size of flood event (as in Romanowicz et al., 1996).

As mentioned above UNET showed that a surprising number of runs failed because of stability problems despite using a weighting parameter θ of the implicit scheme in the 'unconditionally stable' range. Consequently a preliminary study of the model with different randomly chosen values ranging from 0.6 to 1.0 was performed for both regions.

5. Results and discussion

5.1. Stability

Many simulations, which have not been rejected as unstable by UNET itself, have been identified as physically impossible by visual inspection. The current version of UNET appears to have significant numerical problems that could not be associated with any particular cross-section, roughness combination or weighting parameter.

It must be pointed out that the user community is aware of some of these problems and avoids them by, e.g. cutting pilot channels in the original geometry and avoiding 'low flow' periods, as part of the calibration procedure. Sometimes the geometry is changed completely by, e.g. including additional cross-sections. However, the stability is also affected by the choice of other parameters in the model environment. For example UNET requires the limits and accuracy of the look-up tables for the hydraulic properties (area and conveyance vs. elevation) to be specified. This relationship has to be carefully balanced between necessary accuracy (small steps) and range (large steps), because if a too small range is chosen one might have a higher accuracy but the model classifies more runs as unstable. This might be due to the fact that the model run is classified as unstable when the program has to interpolate above the range of the look-up tables for several time steps. Of course, one further reason for instability is the unconditional random sampling of Manning's n values, used in this study, which can produce combinations of roughness values that result in unstable solutions. However, no definite patterns of roughness leading to instability could be found.

The time step is another parameter which influences the stability and accuracy of the model outcomes to a large extent. In this study a smaller time step (the minimum allowed in UNET of 1 min) than the chosen one (5 min for all models) did not change the findings and did not lead to more stable model results. However, the number of stable model outputs decreases significantly with larger steps (maximum allowed is 24 h) which is common to most flood inundation models. If we had followed the guidelines in Section 2 and used a time step of one 20th of the time of the rise of the inflow hydrograph, a value of 2.3 (for the Morava) and 2.1 h (for the Severn) would have been suitable. In addition, a time step of lower than 4.6 (Morava) or 9.6 h (Severn) (Eq. (1)) would satisfy the Courant condition. It is somewhat surprising that all of these suggested time steps would have significantly decreased the model stability to the point of having no useful model results. Other experience suggests that similar issues apply to other 1D implementations of the St. Venant equations.

These findings show that the user of this program has to evaluate the simulation results very carefully and should compute basic properties like slope or minimum elevation to verify any inference from model predictions (such as flood risk zones).

5.2. Tests with different weighting parameters (θ)

The other parameter, which has an important effect on stability and numerical accuracy is the difference weighting parameter, θ. The results of the River Morava and the River Severn show similar behavior and therefore this section only presents example results for the River Morava.

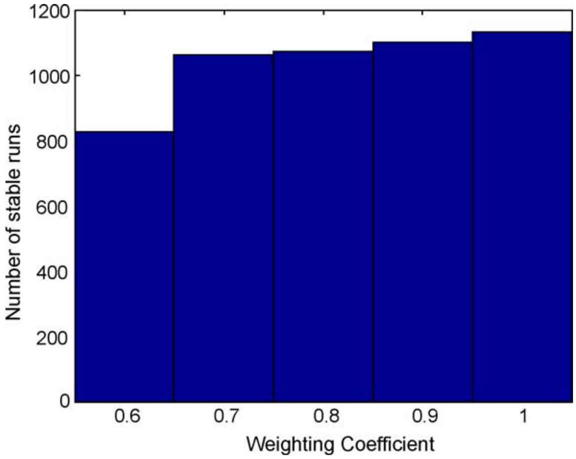

Fig. 2. Histogram of stable model runs against the weighting parameter of the numerical scheme.

Out of a total of approximately 1,600,000 model runs with θ between 0.6 and 1.0, only 52,000 were stable. These are shown in Fig. 2. Tests showed that any θ of 0.5 or below is rejected by UNET. The numerical stability problem is apparently hardcoded into UNET and a more detailed investigation is beyond the bounds of the investigation.

For the same reason it cannot be verified why instability or rejection of model runs occurs at higher values of θ, between 0.6 and 1.0, where any quasi-linear solution should be unconditionally stable (Fread, 1974; Liggett and Cunge, 1975). The analysis shows the difficulty in separating errors in the numerical scheme from variations due to parameters. Fig. 3 shows that

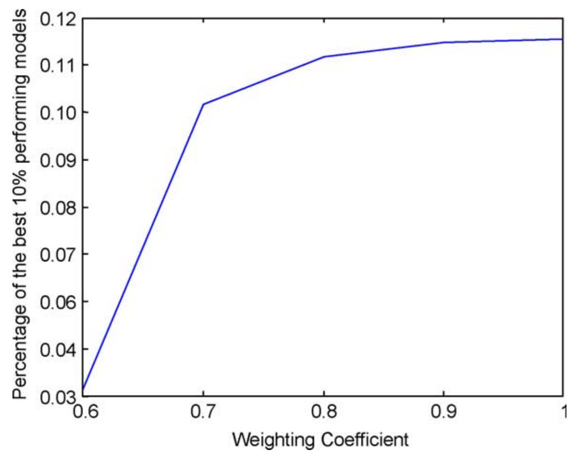

Fig. 3. Weighting coefficient against the number of the best 10% of the model runs divided by the total number of stable model runs.

when the number of the best 10% of the results divided by the number of all working results (out of Fig. 2) is plotted, the chance of getting a good model result is much higher with a θ of 0.9 or 1.0 than with 0.6. This implies that choosing a θ of 0.6 introduces difficulties in this particular case.

5.3. Variation of Manning roughness parameters: using 2 parameters for the full region (1 floodplain + 1 channel roughness)

Fig. 4 shows on the *x* axis the effective roughness of the floodplain of the River Severn and on the *y* axis the likelihood measure of the performance of the outflow (evaluated with the Nash–Sutcliffe efficiency measure) with an imposed stage boundary at the lower end.

Each dot represents one run of the model with randomly chosen *sets* of Manning roughness coefficients. The figure shows a maximum around 0.08 and a double peak, which is due to a change in the flow regime (Singh et al., 1997). The better performing lower roughness values of the floodplain are associated with high channel Manning values and then the floodplain acts as the main flow path in order to maintain the downstream boundary condition. Consequently, the plot of the channel roughness (Fig. 5) shows a double peak and sensitivity, too. This figure also illustrates the small range of stable and behavioral channel Manning values (initial sampling range was much wider) together with a clear rejection of models at the edges of the distribution.

This compares well to the results of Horritt and Bates (2003) which achieved an optimum in the range 0.08–0.10 for floodplain roughness and 0.04–0.05 for channel against hydrometric data (using a measure based on floodwave travel times rather than Nash–Sutcliffe efficiency).

An evaluation of the performance of the predicted inundation shows the same pattern (therefore it is not shown here). However, when inundation performance is plotted (Fig. 6) against the results of the floodplain roughness, it becomes apparent that the double maximum exists for this parameter as well, but these are non-behavioral models across the range of roughnesses considered so that a clear equifinality of floodplain roughness can be seen.

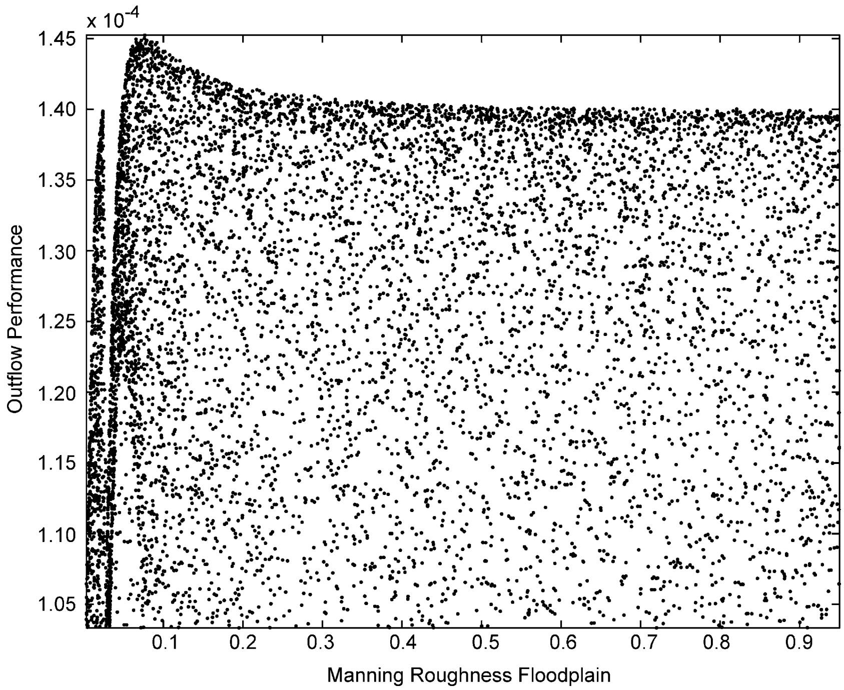

Fig. 4. Performance of the outflow hydrograph with different floodplain roughnesses for the River Severn (two roughness values for full reach) with a fixed downstream boundary.

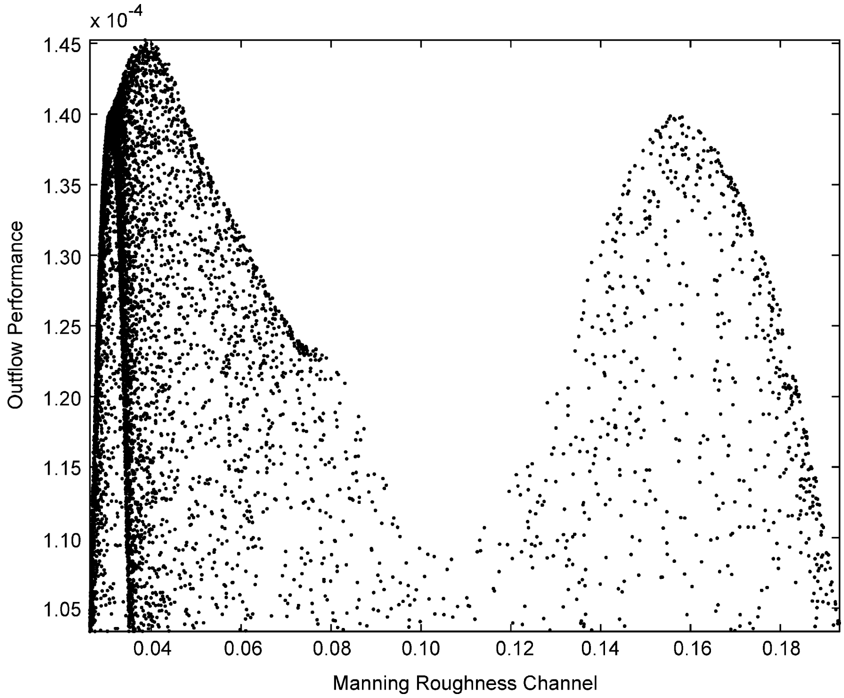

Fig. 5. Performance of the outflow hydrograph with different channel roughnesses for the River Severn (two roughness values for full reach) with a fixed downstream boundary.

Fig. 6 also indicates the existence of a lower performance boundary at higher floodplain Manning values. This might be simply a restriction given by the geometry in a way that a high enough roughness value will always leads to a certain level of inundation and cannot under perform (e.g. a complete filling of the floodplain). In comparison with the previous figures the best performing models are at different locations and they are not at similar roughness values any more, which supports the thesis of partial independence between good flow and inundation predictions. Moreover, this can give us further insight into the hydraulics of this area: as long as the floodplain fills, pretty good extent results can be achieved, and because of the steep bounding slopes over prediction is unlikely to occur.

It can be argued that the double peak only exists, because, in one way or another, enough water has to be delivered downstream to satisfy the lower boundary condition. In fact when a different boundary condition is assumed (Manning type with an initial guess for the slope) the roughness of the floodplain becomes entirely equifinal and the channel roughness shows only one single peak in terms of the performance of the model in predicting inundation or outflow (Fig. 7). This might give us the hindsight to reject further simulations as non-behavioural, because they are physically unreasonable.

Fig. 7 shows a very distinctive peak which has a lower boundary in performances at roughnesses lower than about 0.05. The origin of this threshold in behaviour could not be ascertained, but may be due to some characteristics of the solution scheme, the effect of which is only made apparent by these multiple runs. The other obvious feature in this plot is that the roughness range that is considered as behavioural is much larger than with the previous boundary condition. In other words, the new boundary condition allows more flexibility in respect of the effective roughnesses by not restricting the outflow. In contrast the River Morava, which was set-up with the same boundary condition, does not show any identifiability of floodplain or channel roughness with any performance measure (inundation and outflow), and shows an equifinality over a large range (Fig. 8 shows the combined measure). This plot also shows a non-existence of lower performance boundaries due to a smoother geometry.

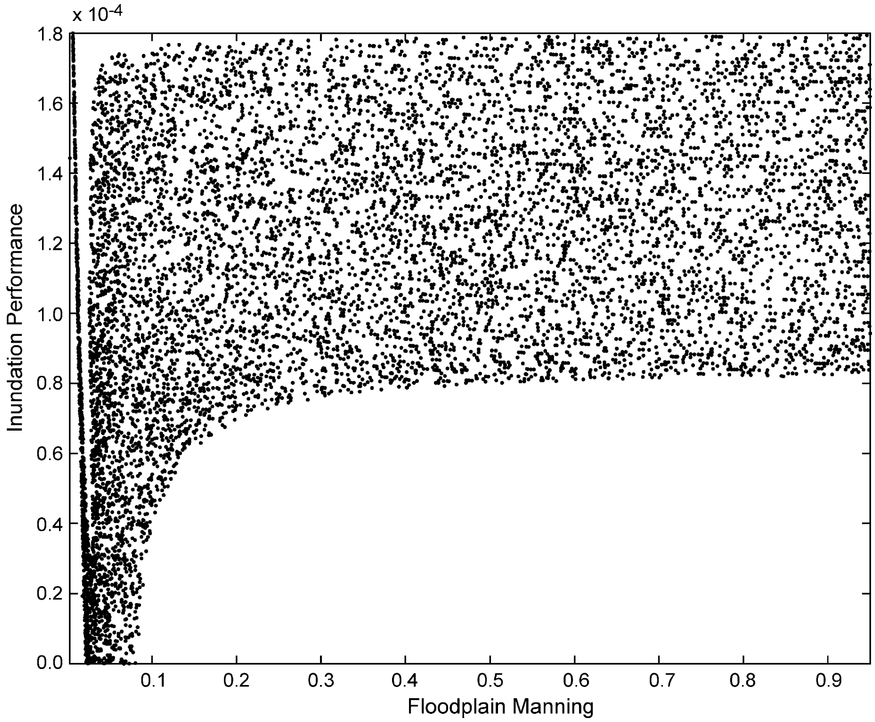

Fig. 6. Performance of the inundation with different floodplain roughnesses for the River Severn (two roughness values for full reach) with a fixed downstream boundary.

The roughness range of optimum values for the River Morava and the floodplain of the River Severn (Manning-type lower boundary) is larger than any table or similar in a textbook would suggest as 'reasonable' values. Furthermore, the roughness of the channel for the River Severn cannot be identified uniquely and depends on the boundary condition. However, the values for the channel are in the range of typical engineering estimates, if the 20% error margin of Trieste and Jarrett (1987) is considered.

The figures showing the combined likelihood look very similar to the plots of the performance of the floodplains, which is not surprising considering that the inundation has the most weight in the combined measure (River Severn see Fig. 9 for the floodplain).

5.4. Spatial variation of manning roughness parameters: results using 8 (Morava) or 19 (Severn) cross-sections with individual parameters for the full region

It can be reasonably argued that the use of just two roughnesses does not represent the heterogeneity of the region. If multiple roughnesses are used the equifinality problem for the River Morava does not change (see for example cross-section 2, Fig. 10), indeed it gets worse because with this set-up 8×3 parameters have to be considered. Also a change in a single cross-section parameter gives only a small change in global performance—to get big changes you need to change the parameters together (i.e. get back to a uniform parameterisation). It was not possible to compute enough stable model results for the River Severn to present an analysis in this paper. This instability may be due to the higher number of cross-sections (see above) such that it is very difficult to find a stable combination of Manning roughness values.

In summary, it can be stated that the simulated River Morava and Severn show different behaviours especially in the sensitivity of the channel friction. The Severn shows some sensitivity, whereas the Morava does not. Both regions show the same insensitivity of the roughness of the floodplain. The differences between these results may be explained by the different data quality. Whereas the Morava has to rely on very

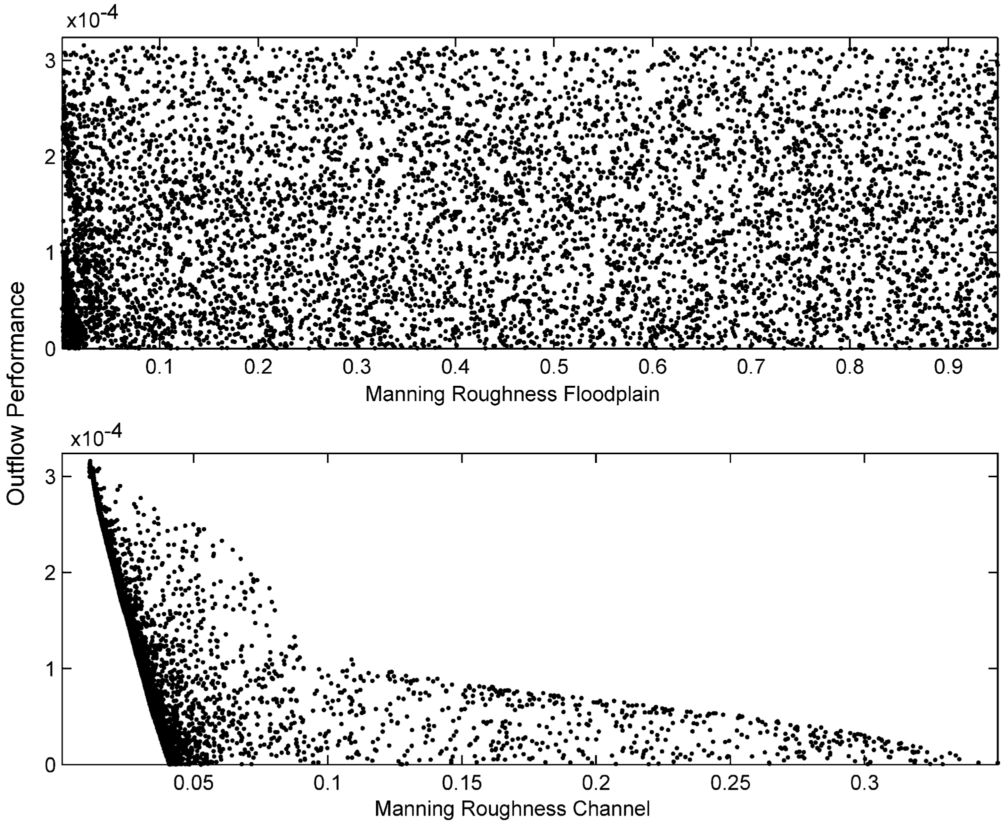

Fig. 7. Performance of the outflow hydrograph with different roughnesses for the River Severn (two roughness values for full reach) with a flexible downstream boundary.

uncertain point measurements, the data set of the Severn allows a fully distributed model evaluation. However, the difference is also partly due to the different scale and geometry of the reaches, otherwise the plots of the outflow hydrographs would have a similar shape.

Many modellers assume that a good prediction of an outflow hydrograph always leads to a good inundation map. Fig. 11 shows again the dotty plot of the roughness of the floodplain and the likelihood measure of the inundation of the River Morava of the best 10% (as example) performing outflow models. If the performances would have been linked directly this plot should show only dots in the upper part of the figure and no simulations in the lower part. A similar picture can be shown for the River Severn and therefore it is misleading to use only a hydrograph analysis for the prediction of the inundation extent. This is not contradictory to the results found by Horritt and Bates (2002), which did find a connection between performance of outflow hydrograph and inundation predictions because it may be on the one hand model dependent and on the other hand a result of this more comprehensive analysis of the parameter uncertainties.

5.5. Stopping criteria for GLUE

From the behavioural runs with eight cross-sections of the River Morava 50,000 stable simulations were taken and split in a way such that the first set contained 5000, the next set the 5000 of the first set and additional 5000 and so on. This simulates the addition of more and more runs. For each of the resulting sets a CDF of the sum of error was calculated for each cross-section and compared to the previous CDFs. Tables 1 and 2 show the results of the test with the Null hypothesis that

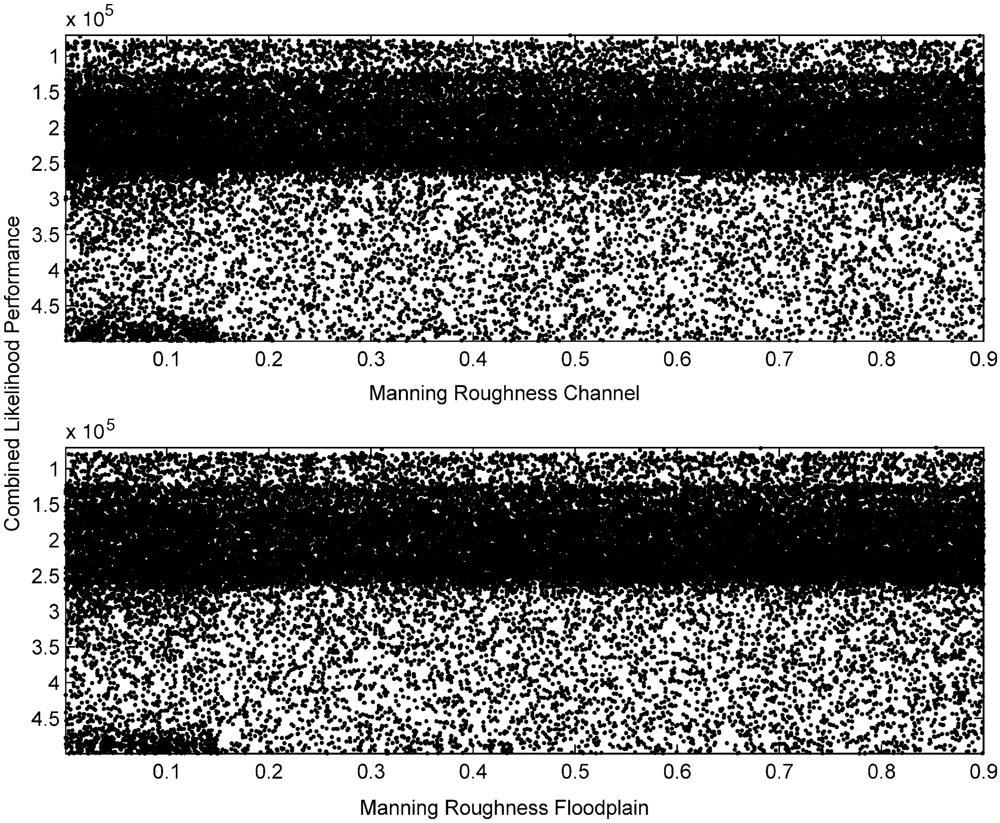

Fig. 8. Combined performance of the outflow hydrograph and inundation with different roughnesses for the River Morava (two roughness values for full reach) with a flexible downstream boundary.

the distributions are equal. A 0 means the Null hypothesis can be accepted with a significance level of 0.05 and 1 means it is rejected. It can be seen that for this case 25,000 simulations would have been enough for convergence at all cross-sections and the analysis could have been stopped.

The same analysis has been performed on 19 points at the cross-sections of the River Severn (with fixed downstream boundary) with the overall performance of the inundation. Tables 3 and 4 shows the results indicating that 8000 runs would be sufficient to calculate risk maps of inundation.

Both evaluations have been done in the post-model run stage to explore different settings of significance level and step sizes. Therefore, the overall number of runs is much larger than the adequate number for convergence. Furthermore, a smaller sufficient number of runs results in a dotty plot of the performances against model parameters which is much less convincing than the one shown.

This comparison illustrates very clearly the possibility of using different numbers of run-number-steps to test for stopping criteria. It also becomes apparent that the criterion for stopping does not solely correspond to the upper surface of the dotty plots of the parameters (otherwise it would have been expected that more simulations would be necessary for the River Severn), but depends on the contributions of all behavioural runs. Further, the tables show the possibility of a behaviour change in different sections, or in other words: although the Null hypothesis has been accepted at one stage it gets rejected at the next one. This is due to a small step size and the sensitivity of this test towards the tails. Therefore, it is advisable always to exceed the number of runs and allow for this error.

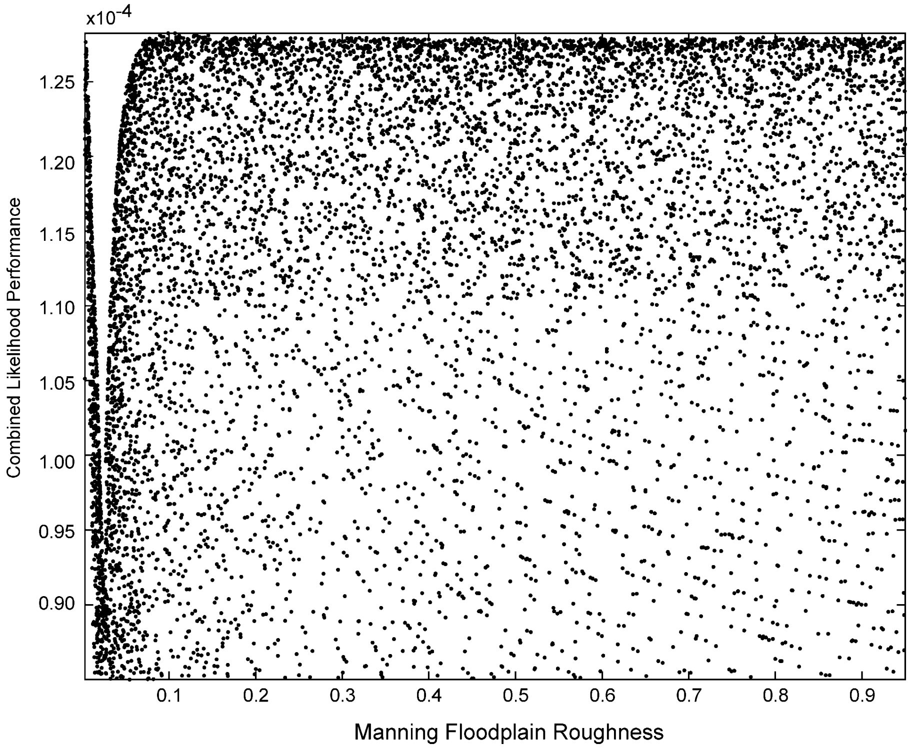

Fig. 9. Combined performance of the outflow hydrograph and inundation with different roughnesses for the River Severn (two roughness values for full reach) with a fixed downstream boundary.

Another effect which seems apparent from these tables is the faster stabilisation of D_- compared to D_+. A closer look at the position of the distance D_+ shows it occurs mainly at the lower end of the CDF (at lower Manning values). This suggests a smoother response surface towards high flood levels which filled the floodplains fully for higher roughness values.

5.6. Map of flood probabilities

As soon as the stopping criterion indicates a sufficient number of behavioral model runs to define the CDF of predictive variables, flood probability maps can be drawn. The flood maps are direct estimates of these CDFs. Fig. 12 is such an example of a maximum flood inundation map for the River Morava, which shows an example sub-reach (for better illustration) of the river with probability estimations of 5 and 95%. It can be seen that the risk of flooding differs largely between these two quantiles. The range of this uncertainty may be narrowed, by the collection, evaluation and combination of additional information, although this will be not necessarily the case (Blazkova et al., 2002; Kuczera and Mroczkowski, 1998). The difference between the quantiles behaves as we might expect: they are widely separated over flat areas of the floodplain (top of the reach) and are closer where floodplain slopes are higher (bottom of the reach).

A similar picture can be drawn for part of the region of the River Severn (Fig. 13), in which the inundation calculations are based on a cell by cell evaluation for the DEM. In this figure the probability for each cell to get flooded in an event of this size is demonstrated rather than drawing quantiles. The range of the quantiles proves to be very small which is reasonable considering that the flood filled up the floodplains totally. Again variation in the spread of flood probabilities can be seen, with the most uncertainty

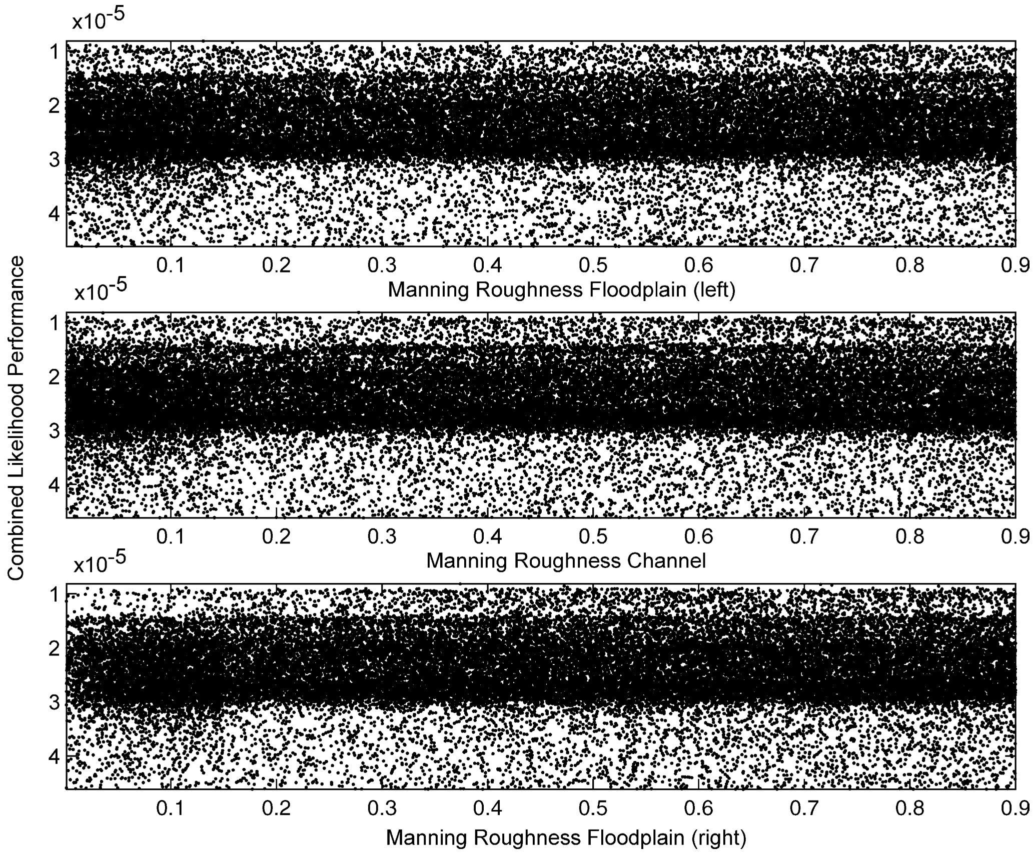

Fig. 10. Combined performance of the outflow hydrograph and inundation with different roughnesses for the River Morava (three roughness values for each section) with a flexible downstream boundary. Example cross-section 2.

(probabilities $\sim$0.5) concentrated in small regions of the floodplain. In other areas, there is a sharp transition between $P=0$ and $P=1$, indicating a low level of uncertainty in model predictions.

This methodology, while computationally intensive, allows areas which are at risk of flooding and the uncertainty in predicting future events to be defined and communicated in a simple manner. In this way it can be used for flood risk mapping. For example, some areas of the floodplain (within the 5% quantile boundary for the Morava, and in the $P=0.8$ category for the Severn) are inundated in nearly all simulations. These areas can be classified as extremely likely to flood, despite the uncertainty in the model. These maps may thus be used to prioritise actions to reduce flood risk in a way of which would be impossible with single deterministic predictions. However, the parameterisation and hence predictions may require updating as soon as new event data are available (Romanowicz and Beven, 2003) which also has to be considered when design flood risks are evaluated.

6. Conclusions

In this study a 1D unsteady flow model (UNET, part of HEC-RAS 3.0) is analysed within a GLUE framework. In this Monte Carlo type analysis the weighting parameter of the numerical scheme (θ) and the Manning roughness parameters are varied using the model for cross-sections of the River Morava (Czech Republic) and the River Severn (United Kingdom). The results are evaluated with an absolute error criterion

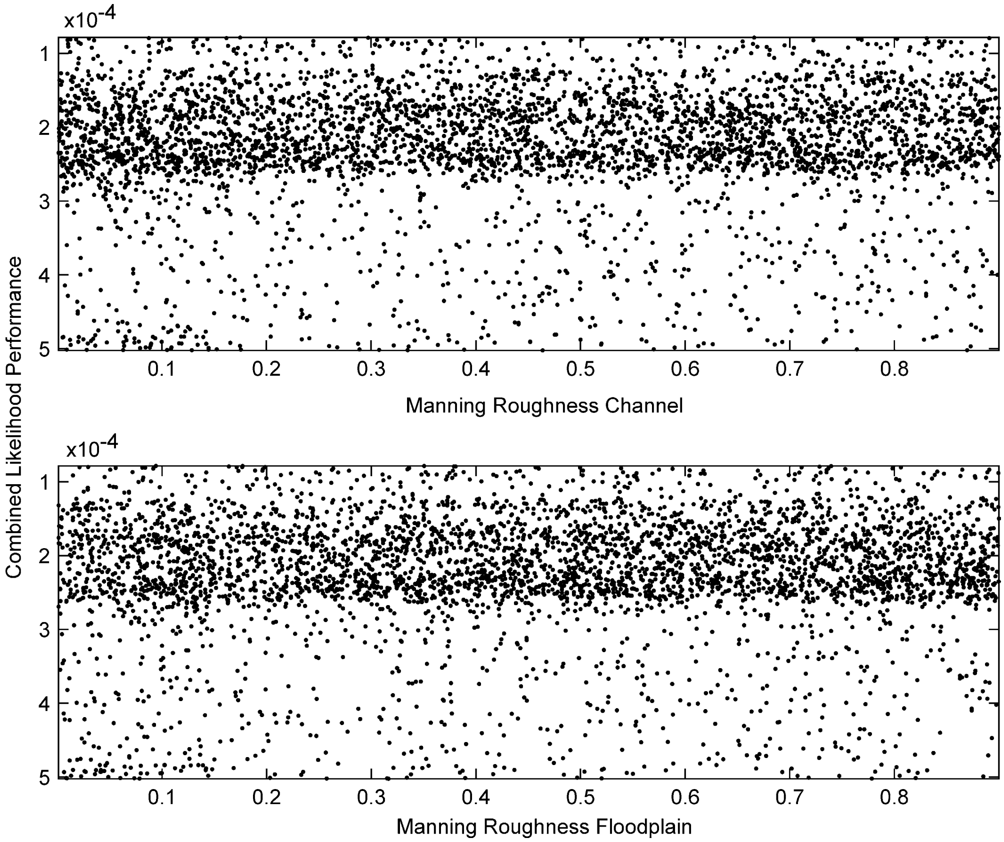

Fig. 11. Combined likelihood measure against Manning roughness for the best 10% performing models for the predicted outflow of the River Morava.

against maximum inundation level at cross-sections for a 25 km long stretch of the Morava and with a performance measure which is based on the full pattern of the inundation in a 60 km section of the Severn. These likelihood measures have then been combined using a weighted sum of the different measures with the Nash–Sutcliffe efficiency measure of fit to the outflow hydrographs.

Table 1
Test with significance level of 0.05 of D_+. Null hypothesis: distributions (with previous number of runs and current number of runs) are equivalent. 0 means Null hypothesis is accepted and 1 that it is rejected. (River Morava)

Cross-section No. of runs	1	2	3	4	5	6	7
10,000	0	1	1	1	1	1	0
15,000	0	1	1	1	1	1	0
20,000	0	1	1	1	1	1	0
25,000	0	0	0	0	0	0	0
30,000	0	0	0	0	0	0	0
35,000	0	0	0	0	0	0	0
40,000	0	0	0	0	0	0	0
45,000	0	0	0	0	0	0	0
50,000	0	0	0	0	0	0	0

Table 2
Test with significance level of 0.05 of D_{-}. Null hypothesis: distributions (with previous number of runs and current number of runs) are equivalent. 0 means Null hypothesis is accepted and 1 that it is rejected. (River Morava)

Cross-section No. of runs	1	2	3	4	5	6	7
10,000	0	1	1	1	1	1	0
15,000	0	0	0	0	0	0	1
20,000	0	0	0	0	0	0	0
25,000	0	0	0	0	0	0	0
30,000	0	0	0	0	0	0	0
35,000	0	0	0	0	0	0	0
40,000	0	0	0	0	0	0	0
45,000	0	0	0	0	0	0	0
50,000	0	0	0	0	0	0	0

The models showed a high number of failed runs, either detected by the model itself or by later analysis of the outputs. This clearly indicates problems in the numerical model algorithm for these geometries. It was possible to carry out a detailed analysis using effective roughness parameter values in eight reaches for the Morava and 19 for the Severn.

These instabilities occurred despite using weighting parameters of the numerical scheme which are in the 'unconditionally stable' range. It can be shown that the choice of weighting parameter (θ) for the implicit scheme does not have any effect on the quality of the model results. However, it does affect the percentage of stable model runs, which decreases as θ is changed from 1.0 to 0.6. The difficulty of distinguishing between numerical accuracy and variations due to different parameter sets is demonstrated.

Further findings demonstrate the importance of the boundary conditions applied in the model. At the River Severn for example, the boundaries of which impose a level at the downstream end result in a double peak of the performance measure. In this case, the main flow pattern changes from channel dominated flow to floodplain dominated flow in order to deliver enough water to satisfy this downstream boundary. As soon as this condition is relaxed and a flexible boundary condition is assumed (in this case a Manning equation type) this double peak disappears and the roughness of the floodplain becomes unidentifiable. However, the channel roughness still shows a peak in performance. This is also the main difference to the River Morava case study in which not only the floodplain roughness is equifinal, but also the channel roughness. This difference is due to the different evaluation data available and illustrates the importance of these. However, the different geometry and magnitude of the two events compared must also have an influence.

Table 3
Test with significance level of 0.05 of D_{+}. Null hypothesis: distributions (with previous number of runs and current number of runs) are equivalent. 0 means Null hypothesis is accepted and 1 that it is rejected. (River Severn)

Cross-section No. of runs	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
2000	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3000	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
4000	1	1	0	0	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0
5000	1	1	0	0	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0
6000	1	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0
7000	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
8000	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9000	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10,000	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11,000	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 4
Test with significance level of 0.05 of D_{-}. Null hypothesis: distributions (with previous number of runs and current number of runs) are equivalent. 0 means Null hypothesis is accepted and 1 that it is rejected. (River Severn)

Cross-section No. of runs	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
2000	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3000	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4000	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5000	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6000	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7000	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8000	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9000	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10,000	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11,000	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

The equifinality becomes more apparent when the modeller tries to represent the heterogeneity of different reaches by the application of multiple roughnesses. Neither the channel nor the floodplain roughnesses are then identifiable and a large range of model results has to be considered as equally good. These findings can be extended to the estimation of effective distributed roughnesses. In principle it may be possible to get better results by reflecting local effective values, in practice it may be very difficult to find combinations in high dimensional space (especially since interactions must be expected).

This study is novel that it demonstrated the use of a stopping criterion for the GLUE by analysing the change of the CDFs of each section. As soon as these distributions do not change any more a probability map of inundation risk can be drawn. Such a map is fundamentally different from more traditional approaches where just one line is used for, e.g. a 100 year flood event, because it shows the distributed

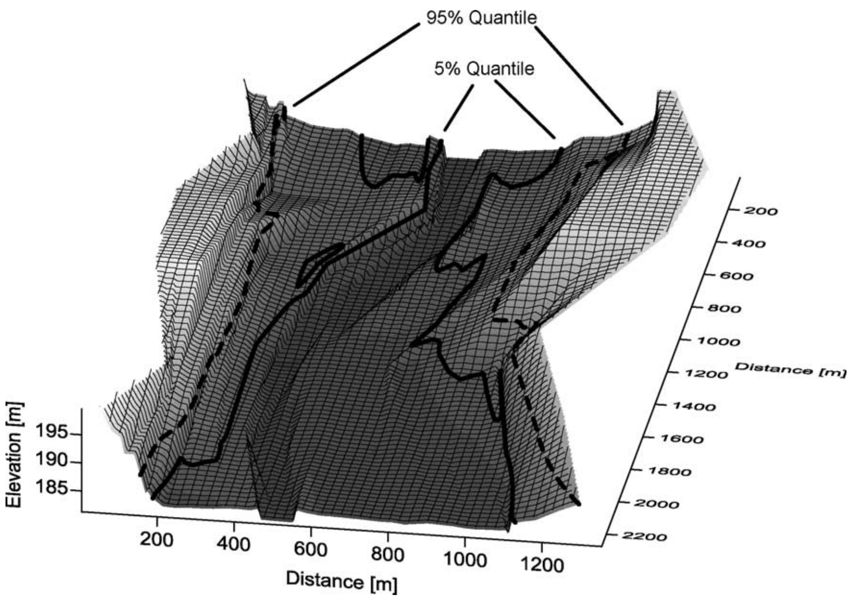

Fig. 12. Predicted uncertainty bounds for an exemplary stretch of the channel of the River Morava.

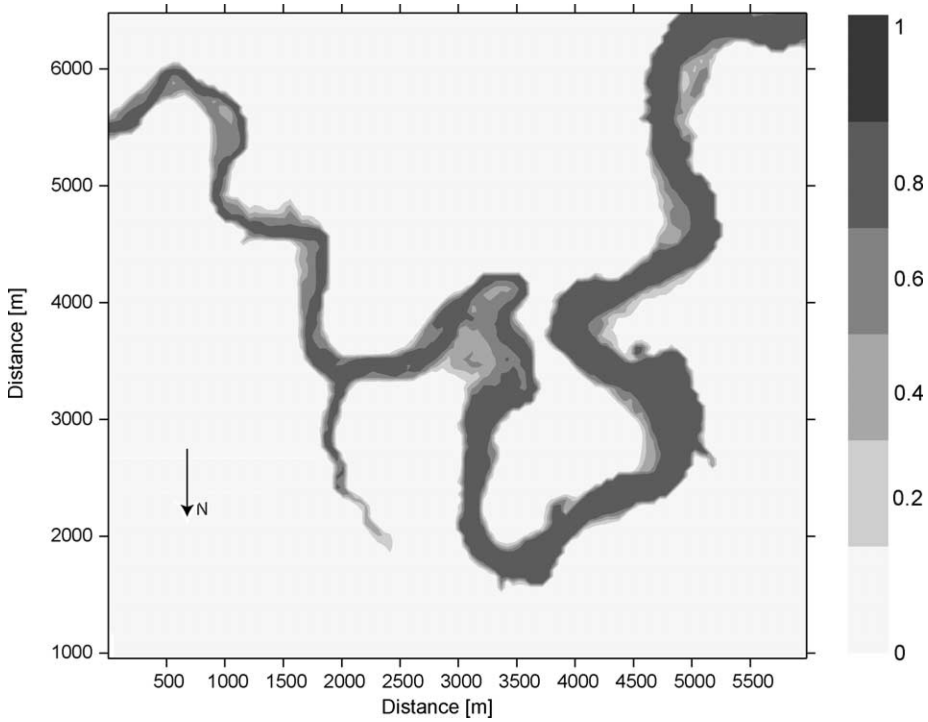

Fig. 13. Predicted uncertainties for an exemplary stretch of the channel of the River Severn.

probabilities of inundation for a given flow event and provides an easy way to evaluate the risk of inundation in future events.

This methodology is general and the visualisation can be done with any flood inundation model (subject only to computational limitations). However, it can be expected that the findings of the parameter uncertainty are valid for other 1D flood models like ISIS and Mike 11, because studies comparing 1D model types show the equifinality of different implementations (Pappenberger et al., 2003; van Looveren et al., 2000). This uncertainty analysis is far from being complete and future testing on other model parameter and data sets should be done, particularly concerning how geometry structural parameters and uncertainties in the upstream and lateral hydrograph influence these results, or the importance of validation with further internal validation data, e.g. multiple continuous depth measurements.

This study demonstrates the use of distributed data compared to cross-section or point variables. Moreover, recent developments show the increasing availability of remote sensing data and the possibility to use these for a wide variety of applications (Halounova, 2002; Horritt et al., 2001; Yamada, 2001). If the possibility exists to use distributed data, then of course one might ask why the 2D flow pattern of the flood plains should be approximated by a 1D model, especially if/when for such cases 'ready to use' models become available and do not require much more work than a 1D approach. The answer is simple and straightforward: The more complex model will have similar uncertainty problems to the simpler one, but on a larger scale, because it will normally require more parameter values, which will be again effective parameters at the model element scale compensating for the remaining model errors. Experience suggests that there will still be significant uncertainty in reproducing both pattern information and discharge hydrographs with higher dimensional models (Aronica et al., 1998; Hankin et al., 2002), particularly when predictions for design or warning purposes outside of the discharge range of the available calibration data are required.

All operational flood inundation predictions are made in situations when the data available to define and evaluate model representations are limited (see discussion of Beven, 2002). Thus, regardless of which model is actually chosen as most suitable, the modeller must also have in mind that there might be an equifinality of the model structures and that the parameters required by a model will always take effective rather than 'physically real' values. A better understanding of the interaction between these two might ultimately allow the uncertainty of the predictions to be constrained and to model, or assess the risk of, flood inundation in ungauged catchments within reasonable uncertainty limits.

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Appendix A. Kuiper statistic

The Kuiper's statistic V is defined as:

$$V = D_+ + D_- = \max_{-\infty<x<\infty}[S_{N1}(x) - S_{N2}(x)] + \max_{-\infty<x<\infty}[S_{N2}(x) - S_{N1}(x)]$$

S_N Cumulative probability distribution, 1 and 2, respectively

D Kuiper statistic distances

The function to calculate the significance is given by the following sum:

$$Q_{KP}(\lambda) = 2\sum_{j=1}^{\infty}(4j^2\lambda^2 - 1)e^{-2j^2\lambda^2}$$

The significance level is then computed as:

$$\text{Probability}(V > \text{Observed}) = Q_{\mathrm{KP}}\left(\left[\sqrt{N_\mathrm{e}} + 0.155 + 0.24/\sqrt{N_\mathrm{e}}\right]D\right)$$

N_e Effective number, defined as $N_\mathrm{e} = N_1 N_2 / N_1 + N_2$

N Number of data points in the first and second distribution (Kuiper, 1962; Press et al., 2002).

References

Ackers, P., 1991. The Hydraulic Design of Straight Compound Channels. SR 281, Hydraulics Research, Wallingford.

Ambroise, B., Beven, K.J., Freer, J., 1996. Toward a generalization of the TOPMODEL concepts: topographic indices of hydrological similarity. Water Resources Research 32 (7), 2135–2145.

Anderson, M.G., Bates, P.D., Walling, D.E., 1996. The general context for floodplain process research, in: Anderson, M.G., Walling, D.E., Bates, P.D. (Eds.), Floodplain Processes. Wiley, New York.

Arcement, G., Schneider, V., 1989. Guide for Selecting Manning's Roughness Coefficient for Natural Channels and Flood Plains US Geological Survey Water-Supply Paper 2339.

Aronica, G., Hankin, B., Beven, K.J., 1998. Uncertainty and equifinality in calibrating distributed roughness coefficients in a flood propagation model with limited data. Advances in Water Resources 22 (4), 349–365.

Aronica, G., Bates, P.D., Horritt, M.S., 2002. Assessing the uncertainty in distributed model predictions using observed binary pattern information within GLUE. Hydrological Processes 16 (10), 2001–2016.

Barkau, R.L., 1982. Simulation of the July 1981 Flood Along the Salt River, CE695BV. Department of Civil Engineering, Colorado State University, Ft. Collins.

Barkau, R.L., 1997. UNET One-Dimensional Unsteady Flow Through a Full Network of Open Channels User's Manual. US Army Corps of Engineers, Hydrologic Engineering Center, Davis.

Barr, D.I.H., Das, M.M., 1986. Direct Solutions for Normal Depth Using the Manning Equation Proceedings of the Institution of Civil Engineers Part 2—Research and Theory, 81 pp. 315–333.

Bates, P.D., Anderson, M.G., Baird, L., Walling, D.E., Simm, D., 1992. Modeling floodplain flows using a 2-dimensional finite-element model. Earth Surface Processes and Landforms 17 (6), 575–588.

Bates, P.D., Anderson, M.G., Hervouet, J.M., 1995. Initial comparison of 2 2-dimensional finite-element codes for river flood simulation. Proceedings of the Institution of Civil Engineers-Water Maritime and Energy 112 (3), 238–248.

Bates, P., Anderson, M., Price, D., Hardy, R., Smith, C., 1996. Analysis and development of hydraulic models for floodplain flows, in: Anderson, M.G., Walling, D.E., Bates, P.D. (Eds.), Floodplain Processes. Wiley, New York.

Bates, P.D., Anderson, M.G., Hervouet, J.M., Hawkes, J.C., 1997. Investigating the behaviour of two-dimensional finite element models of compound channel flow. Earth Surface Processes and Landforms 22 (1), 3–17.

Bates, P.D., Anderson, M.G., Horritt, M., 1998. Terrain information in geomorphological models: stability, resolution and sensitivity, in: Lane, S.N., Richards, K.S., Chandler, J.H. (Eds.), Landform Monitoring, Modelling and Analysis. Wiley, New York.

Bathurst, J.C., 1994. Flow resistance estimation in mountain rivers. Journal of Hydraulic Engineering (ASCE) 111 (4), 625–643.

Bathurst, J.C., 2002. At-a-site variation and minimum flow resistance for mountain rivers. Journal of Hydrology 269 (1–2), 11–26.

Beven, K.J., 2002. Towards a coherent philosophy for modelling the environment. Proceedings of the Royal Society of London Series A—Mathematical Physical and Engineering Sciences 458 (2026), 2465–2484.

Beven, K.J., Binley, A., 1992. The future of distributed models: model calibration and uncertainty prediction. Hydrological Processes 6, 279–298.

Beven, K.J., Carling, P., 1992. Velocities, roughness and dispersion in the lowland River Severn, in: Carling, P., Petts, G. (Eds.), Lowland Floodplain Rivers. Wiley, New York.

Bladé, E., Gómez, M., Dolz, J., 1994. Quasi-two dimensional modelling of flood routing in rivers and flood plains by means of storage cells, in: Molinaro, P., Natal, L. (Eds.), Modelling of Flood Propagation Over Initially Dry Areas. American Society of Engineers, Milan.

Blazkova, S., Beven, K.J., Kulasova, A., 2002. On constraining TOPMODEL hydrograph simulations using partial saturated area information. Hydrological Processes 16 (2), 441–458.

Boss International, 2001. HEC-RAS support forum.http://www.bossintl.com/forums/forumdisplay/forumid/7.html, 12.03.2001.

Bousmar, D., Zech, Y., 1998. Water Profile computation in compound channels, in: Blain, W.R. (Ed.), Hydraulic Engineering Software VII, Computational Mechanics Publications Proceedings of the Hydrosoft'98 Conference. Witpress, Boston, Como, Italy, pp. 217–224.

Bowen, Z.H., Waltermire, R.G., 2002. Evaluation of light detection and ranging (LIDAR) for measuring river corridor topography. Journal of the American Water Resources Association 38 (1), 33–41.

Brunner, G.W., 2001. HEC-RAS, River Analysis Ssytem Users'-Manual. US Army Corps of Engineers, Hydrologic Engineering Center, Davis p. 320.

Burgmann, R., Rosen, P.A., Fielding, E.J., 2000. Synthetic aperture radar interferometry to measure Earth's surface topography and its deformation. Annual Review of Earth and Planetary Sciences 28, 169–209.

Centre for Ecology and Hydrology, 2002. FRIEND—Flow Regimes From International Experimental and Network Data.http://www.nwl.ac.uk/ih/www/research/bfriend.html, 11.04.2002.

Chadwick, A., Morfett, J., 1999. Hydraulics in Civil and Environmental Engineering. Spon, London.

Chow, V.T., 1959. Open Channel Hydraulics. MacGraw-Hill, New York.

Chow, V.T., Maidment, D.R., Mays, C.W., 1988. Applied Hydrology. McGraw-Hill, New York.

Claxton, A., 2002. Modelling Subsurface Water and Chemical Transport through Floodplain Systems. Bristol University, Bristol.

Cunge, J.A., 1975. Two dimensional modeling of flood plain flows, in: Mahmood, K., Yevjevich, V. (Eds.), Unsteady Flow in Open Channels. Water Resources Publication, Fort Collins.

Dingman, S.L., Sharma, K.P., 1997. Statistical development and validation of discharge equations for natural channels. Journal of Hydrology 199, 13–35.

Dooge, J.C., 1992. The Manning formula in context, in: Yen, B.C. (Ed.), Channel Flow Resistance: Centennial of Manning's Formula. Water Resources Publications, Littelton, pp. 136–185.

Dutta, D., Herath, S., Musiake, K., 2000. Flood inundation simulation in a river basin using a physically based distributed hydrologic model. Hydrological Processes 14 (3), 497–519.

Eineder, M., 2003. Efficient simulation of SAR interferograms of large areas and of rugged terrain. IEEE Transactions on Geoscience and Remote Sensing 41 (6), 1415–1427.

Ervine, D.A., MacLeod, A.B., 1999. Modelling a river channel with distant floodbanks. Proceedings of the Institution of Civil Engineers—Water, Maritime & Energy 136, 21–33.

Ervine, D.A., Willetts, B.B., Sellin, R.H.J., Lorena, M., 1993. Factors affecting conveyance in meandering compound flows. Journal of Hydraulic Engineering (ASCE) 119 (12), 1383–1399.

Fread, D.L., 1974. Numerical properties of the implicit four point finite difference equations, NWS Hydro-18. US Department of Commerce, NOAA, Silver Spring.

Fread, D.L., Harbaugh, T.E., 1971. Open channel profiles by Newton's iteration technique. Journal of Hydrology 13 (1), 70–80.

Freer, J., Beven, K.J., Ambroise, B., 1996. Bayesian estimation of uncertainty in runoff prediction and the value of data: an application of the GLUE approach. Water Resources Research 32 (7), 2161–2173.

Gee, D.M., Anderson, M.G., Baird, L., 1990. Large-scale floodplain modelling. Earth Surface Processes and Landforms 15 (6), 513–523.

Graf, W.L., 1979. Rapids in canyon rivers. Journal of Geology 87 (5), 533–551.

Halounova, L., 2002. Use of remote sensing in monitoring river floods and their effects on the landscape. Special Publication—International Association of Sedimentologists 32, 269–282.

Hankin, B.C., Beven, K.J., 1998. Modelling dispersion in complex open channel flows: Equifinality of model structure (1). Stochastic Hydrology and Hydraulics 12 (6), 377–396.

Hankin, B.G., Holland, M.J., Beven, K.J., Carling, P., 2002. Computational fluid dynamics modelling of flow and energy fluxes for a natural fluvial dead zone. Journal of Hydraulic Research 40 (4), 389–401.

Hardy, R.J., Bates, P.D., Anderson, M.G., 1999. The importance of spatial resolution in hydraulic models for floodplain environments. Journal of Hydrology 216 (1–2), 124–136.

Harunurrashid, M., 1990. Estimation of Manning roughness coefficient for basin and border irrigation. Agricultural Water Management 18 (1), 29–33.

Horritt, M., 1999. A statistical active contour model for SAR image segmentation. Image and Vision Computing 17, 213–224.

Horritt, M.S., Bates, P.D., 2001a. Effects of spatial resolution on a raster based model of flood flow. Journal of Hydrology 253 (1–4), 239–249.

Horritt, M.S., Bates, P.D., 2001b. Predicting floodplain inundation: raster-based modelling versus the finite-element approach. Hydrological Processes 15 (5), 825–842.

Horritt, M.S., Bates, P.D., 2002. Evaluation of 1D and 2D numerical models for predicting river flood inundation. Journal of Hydrology 268 (1–4), 87–99.

Horritt, M.S., Bates, P.D., 2003. Evaluation of 1D and 2D numerical models for predicting river flood inundation. Journal of Hydrology 268 (1–4), 87–99.

Horritt, M.S., Mason, D.C., Luckman, A.J., 2001. Flood boundary delineation from synthetic aperture radar imagery using a statistical active contour model. International Journal of Remote Sensing 22 (13), 2489–2507.

Hromadka, T.V., Berenbrock, C.E., Freckleton, J.R., 1985. A two-dimensional dam-break flood plain model. Advances in Water Resources 8, 7–15.

Kervyn, F., 2001. Modelling topography with SAR interferometry: illustrations of a favourable and less favourable environment. Computers and Geosciences 27 (9), 1039–1050.

King, H.W., 1918. Handbook of Hydraulics for the Solution of Hydraulic Problems. McGraw-Hill, New York.

Knight, D.W., Shiono, K., 1996. Channel and floodplain hydraulics, in: Anderson, M.G., Walling, D.E., Bates, P.D. (Eds.), Floodplain Processes. Wiley, New York.

Knight, D.W., Shiono, K., Pirt, J., 1989. Prediction of depth mean velocity and discharge in natural rivers with overbank flow, in: Falconer, R.A., Goodwin, P., Matthew, R.G.S. (Eds.), Proceedings of International Conference on Hydraulic and Environmental Modelling of Coastal, Estuarine and River Waters. Gower Technical, University of Bradford, pp. 419–428.

Kuczera, G., Mroczkowski, M., 1998. Assessment of hydrologic parameter uncertainty and the worth of multiresponse data. Water Resources Research 34 (6), 1481–1489.

Kuiper, N.H., 1962. Tests concerning random points on a circle. Proceedings of the Koninklijke Nederlandse Akademie Van Wetenschappen, Series A 63, 38–47.

Lane, S.N., Biron, P.A., Roy, A.G., Bradbrook, K.F., Richards, K.S., 1999. The application of computational fluid dynamics to natural river channels: three-dimensional versus two-dimensional approaches. Geomorphology 29 (1–2), 1–20.

Laushey, L.M., 1989, 1989. A dimensionless Manning-type equation, in: Yen, B.C. (Ed.), International Conference on Channel Flow and Catchment Runoff: Centennial of Manning's Formula and Kuichling's Rational Formula. American Society of Civil Engineers, Charlottesville, pp. 453–461.

Li, Z., Zhang, J.T., 2001. Calculation of field Manning's roughness coefficient. Agricultural Water Management 49 (2), 153–161.

Liggett, J.A., Cunge, J.A., 1975. Numerical methods of solution of the unsteady flow equation, in: Mahmood, K., Yevjevich, V. (Eds.), Unsteady Flow in Open Channels. Water Resources Publications, Ft. Collins.

Manning, R., 1891. On the flow of water in open channel and pipes. Transactions of the Institution of Civil Engineers of Ireland 20, 161–207.

Manning, R., 1895. On the flow of open channels and pipes-supplement to 1889 paper. Transactions of the Institution of Civil Engineers of Ireland 24, 179–207.

Marks, K., Bates, P., 2000. Integration of high-resolution topographic data with floodplain flow models. Hydrological Processes 14 (11–12), 2109.

Mason, D.C., Cobby, D.M., Davenport, I.J., 1999. Image processing of airborne scanning laser altimetry for some environmental applications, Image and Signal Processing for Remote Sensing V. International Society for Optical Engineering, Bellingham pp. 55–62.

Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models, part I—a discussion of principles. Journal of Hydrology 10, 282–290.

Nicholas, A.P., Walling, D.E., 1998. Numerical modelling of floodplain hydraulics and suspended sediment transport and deposition. Hydrological Processes 12 (8), 1339–1355.

Pappenberger, F., Beven, K., Horritt, M., Bates, P., 2003. Comparison of the Uncertainty in ISIS and HEC-RAS within the Generalized Likelihood Uncertainty Estimation Framework Conditioned on Historical Data. EGS XXVII General Assembly, Nice, France.

Pappenberger, F., Beven, K., 2004. Functional classification and evaluation of hydrographs based on multicomponent mapping. International Journal of River Basin Management 2004; in press.

Pappenberger, F., Matgen, P., Beven, K.J., Henry, J.B.F., Pfister, L., de Fraipont, P., 2004. The influence of rating curve uncertainty on flood inundation predictions. Conference on Flood Risk Assessment, Bath 7/8 September 2004.

Press, W.H., Teukolsky, S.A., Vetterling, W.T., Flannery, B.P., 2002. Numerical Recipies in C++. Cambridge University Press, Cambridge.

Rameshwaran, P., Willetts, B.B., 1999. Conveyance prediction for meandering two-stage channel flows. Proceedings of the Institution of Civil Engineers—Water, Maritime and Energy 136, 153–166.

Ramsey, E.W., 1995. Monitoring flooding in coastal wetlands by using radar imagery and ground-based measurements. International Journal of Remote Sensing 16 (13), 2495–2502.

Rice, C.E., Kadavy, K.C., Robinson, K.M., 1998. Roughness of loose rock riprap on steep slopes. Journal of Hydraulic Engineering 124 (2), 179–185.

Richards, J.A., Woodgate, P.W., Skidmore, A.K., 1987. An explanation of enhanced radar backscattering from flooded forests. International Journal of Remote Sensing 8 (7), 1093–1100.

Riggs, H.C., 1976. A simplified slope area method for estimating flood discharge in natural channels. US Geological Survey Journal of Research 4, 285–291.

Romanowicz, R., Beven, K.J., 2003. Estimation of flood inundation probabilities as conditioned on event inundation maps. Water Resources Research 39 (3), 1073.

Romanowicz, R., Beven, K.J., Tawn, J.A., 1994. Evaluation of predictive uncertainty in nonlinear hydraulic models using a Bayesian approach, in: Barnett, V., Turkman, K.F. (Eds.), Statistics for the Environment 2, Water Related Issues. Wiley, New York.

Romanowicz, R., Beven, K.J., Tawn, J., 1996. Bayesian calibration of flood inundation models, in: Anderson, M.G., Walling, D.E., Bates, P.D. (Eds.), Floodplain Processes. Wiley, New York.

Schmidt, A.R., 2002. Analysis of Stage-Discharge Relations for Open-Channel Flow and their Associated Uncertainties. Universitz of Ollinois, Urbana p. 328.

Sellin, R.H.J., Ervine, D.A., Willetts, B.B., 1993. Behaviour of meandering two-stage channels. Proceedings of the Institution of Civil Engineers—Water, Maritime and Energy 101, 99–111.

Singh, A.K., Porey, P.D., Raju, K.G.R., 1997. Criterion for location of downstream control for dynamic flood routing. Journal of Hydrology 196 (1–4), 66–75.

Stoker, J., 1957. Water Waves. Interscience, New York.

Tinkler, K.J., 1997. Critical flow in rockbed streams with estimated values for Manning's n. Geomorphology 20, 147–164.

Trieste, D., Jarrett, R., 1987. Roughness coefficients of large floods, in: James, L., English, M. (Eds.), Proceedings of a Conference sponsored by the Irrigation and Drainage Division of the American Society of Civil Engineers and the Oregon Section. ASCE, Portland, Oregon, pp. 32–40.

US Army Corps of Hydraulic Engineers, HEC-RAS. http://www.hec.usace.army.mi

US Army Corps of Hydraulic Engineers, 2001. HEC-2 User's Manual. http://www.hec.usace.army.mil/publications/pubs_distrib/hec-2/hec2.html

van Looveren, R., Willems, P., Sas, M., Bogliotti, C., Berlamont, J., 2000. in: Blain, W.R., Brebrian, C.A. (Eds.), Hydraulic Engineering Software. WITPress, Southampton, pp. 3–14.

Wang, Y., Hess, L.L., Filoso, S., Melack, J.M., 1995. Understanding the radar backscattering from flooded and nonflooded Amazonian forests: results from canopy backscatter modeling. Remote Sensing of Environment 54 (3), 324–332.

Wilson, M.D., 2004. Evaluating the Effect of Data and Data Uncertainty on Predictions of Flood Inundation. University of Southampton, Southampton p.276.

Yamada, Y., 2001. Detection of flood-inundated area and relation between the area and micro-geomorphology using SAR and GIS. International Geoscience and Remote Sensing Symposium 7, 3282–3284.