Flood modelling: parameterisation and inflow uncertainty

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This paper presents an analysis of uncertainty in hydraulic modelling of floods, focusing on the inaccuracy caused by inflow errors and parameter uncertainty. In particular, the study develops a method to propagate the uncertainty induced by, firstly, application of a stage–discharge rating curve and, secondly, parameterisation of a one-dimensional hydraulic model by way of the power function and the conditioning of Manning's roughness coefficients. The proposed methodology was applied to a 98 km reach of the River Po, Italy. Model performance was evaluated using two independent sets of observed water levels in the river reach within a generalised likelihood uncertainty estimation framework. The inflow uncertainty was found to have a greater contribution to the overall uncertainty of the 1D model than the roughness parameters. Independent parameter conditioning and validation, as well as the uncertainty analysis, showed satisfactory model performance. When conditioned on one flood event, the model adequately simulated flood levels and high water marks for another (independent) event, as the observations were within 90% confidence interval of the simulation ensemble.

Notation

A	area
H	water level
H_0	water level corresponding to zero discharge
h	water depth
n	Manning's roughness coefficient
Q	discharge
R	hydraulic radius
S_0	user-specified friction slope
Δt	computation time step
u	flood wave velocity
Δx	cross-section spacing

1. Introduction

Flood disasters pose an ever-present danger to people and the environment, as witnessed in the recent flood occurrences in Bangkok in 2011 and Jakarta in 2013. The response to flood hazard is generally based on the construction and reinforcement of structural defences, and the implementation of non-structural measures such as land use, urban planning and the provision of flood forecasting and warning (Kidson and Richards, 2005). To ensure safe habitation of floodplains and plan appropriate risk reduction measures, knowledge of the spatial distribution of the flood hazard is necessary (Loucks *et al.*, 2005).

The achievement of 'as accurate as possible' characteristics of the flood hazard is a research challenge that is widely addressed. Flood mitigation methodologies to deal with prior flood warning,

quantification of envisaged disasters, uncertainty in flood risk management tools and coping mechanisms are continuously being researched (e.g. McCarthy *et al.*, 2007; Montanari, 2007; Pappenberger and Beven, 2006). These initiatives are bolstered by the availability of ever-increasing computer power and new models developed to analyse hydro-meteorological inputs and generate flood warnings and estimates of flood extent and other specific hazard characteristics; new information sources such as spatial data derived from satellite imagery are also increasingly becoming available (Bates, 2012; Di Baldassarre *et al.*, 2009a, 2009b; Schumann *et al.*, 2009). These improvements in flood risk management tools and methodologies result in a reduction of flood risk.

One-dimensional (1D) hydraulic modelling is commonly used in computationally intensive applications such as Monte Carlo analysis and probabilistic mapping of outputs (e.g. Di Baldassarre *et al.*, 2009a; Pappenberger *et al.*, 2006; Quiroga *et al.*, 2013). Reduced-complexity two-dimensional (2D) hydraulic model codes are gaining popularity, given their computational efficiency when compared with fully physically based 2D model codes, and have even been applied in large-scale flood inundation case studies (e.g. Bates *et al.*, 2010; Dottori and Todini, 2011; Hunter *et al.*, 2005a, 2005b; Neal *et al.*, 2012). The selection of hydraulic models is typically based on a trade-off among the different factors of physical realism, computational efficiency, consistency with the quantity and quality of input and observation data, and objectives of the specific study.

The primary data requirements of 1D hydraulic models are the system boundary conditions (upstream and downstream) and terrain characteristics such as the topography and effective roughness values (Pappenberger *et al.*, 2005, 2006). Discharge hydrographs (often derived from measured water levels using rating curves) are typically used as the upstream boundary condition. Water level measurement accuracy is reported to be relatively high, with commonly used measurement instruments having an accuracy ranging from 2 to 15 mm (Boiten, 2008). However, indirectly observed river discharges are affected by significant uncertainty (Clarke, 1999; Di Baldassarre and Montanari, 2009).

The rating curve is an empirical relation between the measured water level and the discharge in an open channel. Parameterisation of the rating curve is dependent on the accuracy of measurement of the discharge and water levels. However, these measurements are affected by uncertainty, broadly classified either as random natural occurring errors or due to lack of knowledge of the behaviour of the natural system (Braca, 2008). Some of the main sources of rating curve error Neal *et al.* show an example of a practical case in which the rating curve for a gauging station had to be revised using a hydraulic model due to significant inconsistency in the measured rating curve and the actual flood event. Sources of rating curve error include those induced by

- geometrical changes in the cross-section configuration due to sediment transport
- vegetation growth and depletion and the resulting effect on bed roughness
- the time interval with which rating curves are updated
- the presence of unsteady flow and backwater effects (Boiten, 2008; Di Baldassarre and Montanari, 2009; Pappenberger *et al.*, 2006)

A rating curve is a cross-section-specific relationship between the water stage and the corresponding flow discharge and is often represented by a piecewise power law or polynomial functions to fit observed water levels and discharge data (Braca, 2008; Fenton, 2001). In this study, rating curves were derived by fitting a power-law function with two parameters (Di Baldassarre and Montanari, 2009; Herschy, 1999) to contemporaneous observations of river flow and water stage. The power function is widely used for stage–discharge rating curves because of its parsimony and hydraulic justifications (Fenton, 2001; Petersen-Øverleir, 2005). Functions that are more complex have been developed to better capture transitions to overbank flow. For instance, Reitan and Petersen-Øverleir (2009) proposed the use of multiple power-law segments. However, the use of these complex functions is often complicated by a limited number of direct measurements of water levels and discharge during floods, which are needed to parameterise the power-law segments related to high flow conditions. Thus, a single power-law curve is often considered a reasonable compromise and is used for many rivers (Di Baldassarre and Montanari, 2009). Additionally, in the river reach

considered in this study, the direct measurements of discharge and water levels do not significantly deviate from a power-law curve (Franchini *et al.*, 1999).

Operational river flow measurements and monitoring should be carried out to a high quality (ISO, 1996; ISO, 2010). During the actual water level measurements, components of uncertainty and changing channel properties result in errors and, consequently, the rating curve uncertainty has a significant effect on hydraulic model output (Hunter *et al.*, 2007; Schmidt, 2002). Fuzzy-based approaches (e.g. Pappenberger *et al.*, 2006; Westerberg *et al.*, 2011) and analysis of errors (e.g. Di Baldassarre and Montanari, 2009; Domeneghetti *et al.*, 2012) have been applied to characterise the uncertainty.

This study looks at the estimation of uncertainty in flood modelling, considering both inflow inaccuracy and model parameter uncertainty. The discharge uncertainty was derived through the rating curve by sampling from the distributions of the parameters of the power law. Parameter distributions were based on prior knowledge of possible ranges for the river gauging stations in the reach. An ensemble of input hydrographs was generated from the distributions of the parameters and was used to define the input inaccuracy in the hydraulic modelling.

2. Study area and model set-up

The study was carried out on a 98 km river reach (Cremona–Borgoforte) of the River Po, Italy (Figure 1). It was anticipated that the use of a 1D model would be viable given the predominant 1D flow in a heavily embanked river, especially during high (and flood) flows. In total, 68 cross-sections were used; these were derived from a 2 m digital elevation model (DEM). The DEM was prepared in 2005 by augmenting floodplain data derived from laser scanners mounted on aircraft and, for the river bathymetry, multi-beam sonar was used. In addition, cross-sections from a field survey were acquired from the Interregional Authority of the River Po in 2005 (Di Baldassarre *et al.*, 2009a).

The 1D hydraulic model HEC-RAS (Brunner, 2010a) was used to carry out the simulations. A time step of 1 min was used to fulfil the Courant condition and ensure stability of the model runs (Brunner, 2010a)

$$1. \quad \Delta t \leq \frac{\Delta x}{u}$$

where Δt is the computation time step, Δx is the cross-section spacing and u is the flood wave velocity (Brunner, 2010b).

The model was set up with the upstream boundary condition hydrograph and a normal depth for the downstream boundary condition. This depth was calculated using Manning's formula

Figure 1. Study area, processed from data obtained from Lehner *et al.* (2006)

$$2. \quad Q = \frac{1}{n} A(h) R(h)^{2/3} S_0^{1/2}$$

(Brunner, 2010a) where A is the area and R is the hydraulic radius, which are a function of the water depth (h), S_0 is the user-specified friction slope, Q is the discharge and n is Manning's roughness coefficient.

The choice of the normal-depth downstream boundary condition, as opposed to using the observed water levels, was made to reduce backwater effects of using the observed water levels on the simulated water levels at the gauging stations. Water levels from two gauging stations (Cassalmaggiore and Boretto) were used in the evaluation of the model performance using the root mean square error (RMSE) (Hall, 2001)

$$3. \quad \text{RMSE} = \left(\frac{1}{N} \sum_{t=1}^N [h(t) - \hat{h}(t|\theta)]^2 \right)^{1/2}$$

where N is the number of simulations, $h(t)$ represents the observation at an instantaneous time t and $\hat{h}$ is the simulated water level given the parameter set θ at the same time.

The uncertainty analysis was carried out using the generalised likelihood uncertainty estimation (Glue) approach, given its ease of understanding and implementation (Beven, 2006; Beven and Binley, 1992). The interested reader is referred to Beven (2006) and Stedinger *et al.* (2008) for further reading about alternative

likelihood measures and approaches to implementing the Glue methodology. Behavioural model sets were selected where the RMSE values were found to be less than 1.0 m. The choice of the rejection threshold for the RMSE is comparable to the policy of the Po River basin authority whereby a freeboard of 1 m is applied to the designed dyke levels (Brandimarte and Di Baldassarre, 2012)

$$4. \quad w_i = \frac{\max(\text{RMSE}_i) - \text{RMSE}_i}{\max(\text{RMSE}_i) - \min(\text{RMSE}_i)}$$

where w_i is the weight assigned to objective function values for each behavioural simulation. The likelihood weights were then rescaled to a cumulative sum of 1.

The Monte Carlo analysis toolbox was used for the uncertainty analysis (Wagener and Kollat, 2007). Identifiability plots were used to show the marginal distributions of the behavioural parameter sets (based on the likelihood). The plots consisted of a bar chart and a superimposed cumulative distribution (Wagener *et al.*, 2002). A total of 10 000 model simulations were run for each configuration of input parameters for the uncertainty analysis. This number was chosen based on two considerations – relative stabilisation of the mean and standard deviation of the output variable (water level).

3. Input inaccuracy

The inaccuracy of the upstream boundary condition was attributed to the rating curve uncertainty. For this study, a single-segment power function was chosen for the conversion of water levels to generate the discharge hydrograph. Inflow inaccuracy

was attributed to the function parameters α and β . The water level corresponding to zero discharge H_0 was taken from the cross-section geometry (Boiten, 2008)

$$5. \quad Q = \alpha(H - H_0)^\beta$$

(Hersch, 1999). Figures 2 and 3 show the resulting ensembles of the rating curve and upstream boundary condition (Cremona gauging station, October 2000 flood event) achieved by varying the values of the rating curve parameters.

4. Model conditioning

Two prominent high-magnitude flood events were experienced in the river reach in November 1994 and October 2000 (Arpa, 1994, 2000). A statistical analysis of the historical discharge at Pontelagoscuro (a station downstream of the reach) approximated

Figure 2. Rating curve uncertainty (Cremona station, October 2000)

Figure 3. Resulting hydrograph ensemble for October 2000 flood event (at Cremona station)

discharges of 12 000 m³/s and 8000 m³/s as having return periods of 100 years and 10 years respectively (Marchi *et al.*, 1995, 1996). Consequently, the November 1994 and the October 2000 flood events, with estimated peak discharges of 10 800 and 11 800 m³/s respectively were categorised as high-magnitude events (see Di Baldassarre *et al.*, 2011).

The model was run in a Monte Carlo based framework to assess the parameter uncertainty using Glue. A prior uniform distribution for the rating curve parameters was used. The November 1994 event was taken as the dataset to condition the model and the October 2000 event was used for validation and uncertainty analysis. Parameter distributions were taken as $\alpha \sim U(4, 12)$ and $\beta \sim U(2.3, 3.0)$; these ranges were based on previous estimates of the parameters for the gauging stations along the reach (Arpa, 1994, 2000). The roughness coefficients that were used in this study were chosen from the documented ranges roughness parameters (Chow, 1959), with the main channel roughness ranging from 0.01 to 0.05 m^{1/3}/s and floodplain roughness values ranging from 0.04 to 0.11 m^{1/3}/s.

From Figure 4, the power-function parameter β and the main channel roughness coefficient show central tendencies in the posterior distribution.

5. Model validation

The roughness and rating parameter (effective) values, for use in the validation of the model using the October 2000 flood event, were sampled from the empirical distributions of the parameters derived from the model conditioning (Figure 4).

The model ensemble was able to simulate the peak of the flood event within a 90% confidence interval (CI). However, the model was not able to simulate the kink in the observed data (see Figure 5). This was attributed to the floodwater flowing out of bank, similar to the findings reported by Di Baldassarre and Montanari (2009). Given the availability of the high water marks of the October 2000 flood event, the model was also tested in simulating this observation.

Figure 6 shows that the model ensemble performed well in the simulation of the high water marks within a confidence interval of 90%. Thus, the parameter uncertainty analysis was based on the available water levels at the internal gauging stations.

6. Uncertainty analysis

The uncertainty analysis was based on the October 2000 flood event and the water levels at the two internal gauging stations. The analysis was carried out in three cases corresponding to the following uncertainty sources

- input inaccuracy (case 1) Figure 7
- roughness coefficient uncertainty (case 2) Figure 8
- combined inflow inaccuracy and roughness uncertainty (case 3) Figure 9.

Figure 4. Identifiability plots for the November 1994 flood event

Figure 5. Model validation: observed water level in October 2000 at the internal gauging stations: (a) Cassalmaggiore; (b) Boretto

Figure 6. Model validation: high water marks October 2000 flood event

Figure 7. Identifiability plots: case 1, rating curve parameters

Figure 8. Identifiability plots: case 2, roughness parameters

Figure 8 shows the results of the case 2 ensemble. The ensemble resulted in a large number of non-behavioural models and an exception was made to use a threshold of 1.5m for the RMSE to show results for the case.

7. Discussion

The results of the uncertainty analysis showed that the main channel roughness was more sensitive than the floodplain roughness, which is similar to results reported in other studies (e.g. Pappenberger *et al.*, 2006; Werner *et al.*, 2005). The sensitivity of the main channel roughness (see Figures 4, 8 and 9) is attributed to the high conveyance capacity of the main channel section, most especially for the predominant 1D flow (e.g. Werner *et al.*, 2005). However, for the combined analysis (case 3) the power-function parameter β (therefore the inflow uncertainty) is the most sensitive. This is evident from the distinct identifiability plot

Figure 9. Identifiability plots: case 3, combined parameters

of parameter β (Figures 4, 7 and 9), especially Figure 4, whereby the posterior distribution shows a strong central tendency in contrast to the prior uniform distribution. Additionally, the results of cases 1 and 3 (Figures 7 and 9) show that the power-function parameters are more dominant in achieving a higher likelihood value when compared with case 2 (Figure 8), whereby the roughness parameters were unable to adequately produce behavioural models.

Figures 8 and 9 (cases 2 and 3) show that the optimal main channel roughness values were $0.0365 \text{ m}^{1/3}/\text{s}$ and $0.02 \text{ m}^{1/3}/\text{s}$ respectively; this implies that the power-function and the roughness parameters compensate for each other (e.g. Romanowicz and Beven, 2003). Consequently, the discussion and deductions were carried out with reference to a set of parameters rather than single values.

In the case of the power-function parameters, parameter β is more sensitive than α ; in Figures 4, 7 and 9, β shows a distinct distribution with a central tendency. Given that the parameter is an exponent (Equation 5), the contribution to the magnitude of the discharge is high.

The results of this study show that the 1D HEC-RAS model

effectively simulates the peak discharge within the 90% CI of the model simulation ensembles, which is evident in Figure 5. However, in the same figure, the observation data show a kink in the observed data, which was not simulated by the model. Considering the fact that the River Po is heavily embanked, with primary and secondary dykes (Marchi *et al.*, 1995, 1996), this inability of the model to adequately simulate this observed kink shows that the lateral (2D) flow effects of out-of-bank flow could not be effectively simulated. In addition, the HEC-RAS model uses the vertically divided channel method (VDCM) to calculate the discharge conveyance. The VDCM does not account for the turbulent momentum exchanges between the main channel flow and the floodplain flow, thus resulting in errors in the simulated discharge (Lambert and Sellin, 1996; Myers *et al.*, 2001; Werner and Lambert, 2007); the discrepancy thus may be attributed to the model structure error. In the 1D model, the only parameters that can be adjusted are the roughness coefficients to compensate for this additional energy loss, which may be inadequate, especially for river channels with varying local conditions (see Figure 8). The use of higher order models or hybrid models (1D–2D) could overcome the inability of the 1D model to simulate lateral flows (e.g. Prestininzi *et al.*, 2011). Essentially, such a decision would be taken by considering the nature of the channel

geometry and local conditions, and available computation capacity.

Figure 9 shows that, for the best performing models, the value of the floodplain roughness was high. This is attributed to the fact that, during the October 2000 event, the channel experienced a peak flow (estimated as a 1:100 year flood). As the water depth increases, the main channel and the floodplain sections of the river behave as one channel with predominant 1D flow (Figure 10), and the shear stress between the flow in the main channel and the floodplain decreases; this means that the sensitivity of the floodplain roughness increases.

A comparison of the parameters in Figures 4, 7 and 8 shows that the power-function parameters are more significant in matching the discharge of the October 2000 flood event (Figure 7) as compared with the roughness parameters (Figure 8). Thus, inclusion of the power-function parameters as well as the roughness parameters (Figure 9) shows the ability of the model ensemble to achieve a better fit of the observed and simulated water levels. Moreover, given the disparity of local and global performance measures (see Pappenberger *et al.*, 2007), the inclusion of variable power-function parameters gives the model greater flexibility to simulate the water levels and high water marks (along the length of the reach) when conditioned on water level data (see Figures 5 and 6). The choice of the rejection threshold, while conditioning the model, and the resulting model ensemble validation in Figures 5 and 6 indicate that the rejection criteria may have been lowered to get a narrower CI band. The subjective choice of the rejection criteria may thus be guided by the accuracy of the simulated water levels.

8. Conclusions

A methodology for the inclusion of input uncertainty (resulting from rating curve inaccuracy) and roughness conditions propagated through a 1D hydraulic model has been presented. Four coefficients were parameterised (two for the rating curve and two for the roughness specification in the model) and analysed within the Glue framework. Model performance was based on the two internal gauging stations using the RMSE as the objective function, whereby the rejection criterion for non-behavioural models was an RMSE value of 1 m.

Figure 10. Example cross-section at the chainage 39 239-45 m showing the dyke system during peak flow

The model was conditioned and validated using two independent flood events. The resulting model was able to simulate observed water levels and the high water marks of the October 2000 flood event, when conditioned on the observed November 1994 flood event water levels, due to significance of inflow inaccuracy.

The inclusion of the uncertainty of the rating curve parameters allows for an ensemble of input hydrographs to be sampled to represent uncertainties resulting from local effects at the gauging station; more specifically, for 1D hydraulic models where the model structure is predominantly governed by 1D flow with all energy losses due to friction and turbulence lumped on to the roughness parameters. Increasing the parameterisation by including the rating curve parameters gives the model more flexibility to represent uncertainties in the channel roughness and inputs. However, when inflow inaccuracy is considered, there is a possibility for the inadequacy of the model structure to be compensated by the roughness values.

Analysis of the parameters showed a complex relationship whereby the parameters compensate each other. Evaluation and subsequent deductions using the model should then be done by analysing the parameters as a combined set. The increase in parameterisation increased the ability of the model to simulate the input inaccuracy and the effective roughness. It is proposed that the increased hydraulic model parameterisation (to account for input uncertainty) and information on parameter behaviour may be included in probabilistic outputs to end users. Thus, the probabilistic output would give users information on the level of certitude of the model output when compared with the different sources of uncertainty.

Acknowledgements

This paper is the result of MSc thesis work done by Micah M. Mukolwe at Unesco-IHE Institute for Water Education, parts of which was presented at the European Geosciences Union 2011 Leonardo Conference in Bratislava, Slovakia, on 23–25 November 2011. The authors are grateful to the Netherlands Fellowship Programme and the European Commission for funding this study, which is part of the FP7 KultuRisk project (no. 265280).

REFERENCES

- Arpa (Regional Agency for Prevention and Environment) (1994) *Hydrological Records: Area Hydrology – Part 2. Meteorological and Hydrological service*. Emilia-Romagna, Italy (in Italian).
- Arpa (2000) *Hydrological Records: Area Hydrology – Part 2. Meteorological and Hydrological Service*. Emilia-Romagna, Italy (in Italian).
- Bates PD (2012) Integrating remote sensing data with flood inundation models: how far have we got? *Hydrological Processes* **26(16)**: 2515–2521.
- Bates PD, Horritt MS and Fewtrell TJ (2010) A simple inertial formulation of the shallow water equations for efficient two-

- dimensional flood inundation modelling. *Journal of Hydrology* **387**(1–2): 33–45.
- Beven K (2006) A manifesto for the equifinality thesis. *Journal of Hydrology* **302**(1–2): 18–36.
- Beven K and Binley A (1992) The future of distributed models: model calibration and uncertainty prediction. *Hydrological Processes* **6**(3): 279–298.
- Boiten W (2008) *Hydrometry: A Comprehensive Introduction to the Measurement of Flow in Open Channels*. CRC Press/Balkema, Rotterdam, the Netherlands.
- Braca G (2008) *Stage–discharge Relationships in Open Channels: Practices and Problems*. Università degli Studi di Trento, Dipartimento di Ingegneria Civile e Ambientale, Trento, Italy, Foralps technical report 11.
- Brandimarte L and Di Baldassarre G (2012) Uncertainty in design flood profiles derived by hydraulic modelling. *Hydrology Research* **43**(6): 753–761.
- Brunner G (2010a) *HEC-RAS, River Analysis System – Hydraulic Reference Manual*. Hydrologic Engineering Center, US Army Corps of Engineers, Davis, CA, USA.
- Brunner GW (2010b) *HEC-RAS River Analysis System: User's Manual*. US Army Corps of Engineers, Institute for Water Resources, Hydrologic Engineering Center, Davis, CA, USA.
- Chow VT (1959) *Open-channel Hydraulics*, International student edn. McGraw-Hill, Kogakusha, Tokyo, Japan.
- Clarke RT (1999) Uncertainty in the estimation of mean annual flood due to rating-curve indefiniteness. *Journal of Hydrology* **222**(1–4): 185–190.
- Di Baldassarre G and Montanari A (2009) Uncertainty in river discharge observations: a quantitative analysis. *Hydrology and Earth System Sciences* **13**(6): 913–921.
- Di Baldassarre G, Schumann G and Bates PD (2009b) A technique for the calibration of hydraulic models using uncertain satellite observations of flood extent. *Journal of Hydrology* **367**(3–4): 276–282.
- Di Baldassarre G, Schumann G and Bates P (2009a) Near real time satellite imagery to support and verify timely flood modelling. *Hydrological Processes* **23**(5): 799–803.
- Di Baldassarre G, Laio F and Montanari A (2011) Effect of observation errors on the uncertainty of design floods. *Physics and Chemistry of the Earth, Parts A/B/C* **42–44**: 85–90.
- Domeneghetti A, Vorogushyn S, Castellarin A, Merz B and Brath A (2012) Effects of rating-curve uncertainty on probabilistic flood mapping. *Hydrology and Earth System Sciences Discussions* **9**(8): 9809–9845.
- Dottori F and Todini E (2011) Developments of a flood inundation model based on the cellular automata approach: testing different methods to improve model performance. *Physics and Chemistry of the Earth, Parts A/B/C* **36**(7–8): 266–280.
- Fenton JD (2001) Rating curves: Part 1 – correction for surface slope. *Proceedings of 6th Conference on Hydraulics in Civil Engineering: The State of Hydraulics, Australia*. pp. 309–317.
- Franchini M, Lamberti P and Di Giammarco P (1999) Rating curve estimation using local stages, upstream discharge data and a simplified hydraulic model. *Hydrology and Earth System Sciences* **3**(4): 541–548.
- Hall M (2001) How well does your model fit the data? *Journal of Hydroinformatics* **3**(1): 49–55.
- Herschey RW (1999) *Hydrometry: Principles and Practices*. Wiley, Chichester, UK.
- Hunter NM, Bates PD, Horritt MS, De Roo PJ and Werner MGF (2005a) Utility of different data types for calibrating flood inundation models within a Glue framework. *Hydrology and Earth System Sciences* **9**(4): 412–430.
- Hunter NM, Horritt MS, Bates PD, Wilson MD and Werner MGF (2005b) An adaptive time step solution for raster-based storage cell modelling of floodplain inundation. *Advances in Water Resources* **28**(9): 975–991.
- Hunter NM, Bates PD, Horritt MS and Wilson MD (2007) Simple spatially-distributed models for predicting flood inundation: a review. *Geomorphology* **90**(3–4): 208–225.
- ISO (1996) ISO 1100-1: 1996 Measurement of liquid flow in open channels – Part 1: Establishment and operation of a gauging station. ISO, Geneva, Switzerland.
- ISO (2010) ISO 1100-2: 2010 Hydrometry – Measurement of liquid flow in open channels – Part 2: determination of the stage–discharge relationship. ISO, Geneva, Switzerland.
- Kidson R and Richards K (2005) Flood frequency analysis: assumptions and alternatives. *Progress in Physical Geography* **29**(3): 392–410.
- Lambert MF and Sellin R (1996) Discharge prediction in straight compound channels using the mixing length concept. *Journal of Hydraulic Research* **34**(3): 381–394.
- Lehner B, Verdin K and Jarvis A (2006) *HydroSHEDS Technical Documentation*. World Wildlife Fund US, Washington, DC, USA. See <http://hydrosheds.cr.usgs.gov> (accessed 21/02/2012).
- Loucks DP, Beek EV, Stedinger JR, Dijkman JPM and Villars MT (2005) *Water Resources Systems Planning and Management: An Introduction to Methods, Models and Applications*. Unesco, Paris, France.
- Marchi E, Roth G and Siccardi F (1995) The November 1994 flood event on the Po River: structural and non-structural measures against inundations. *Proceedings of US–Italy Research Workshop on the Hydrometeorology, Impact, and Management of Extreme Floods, Perugia, Italy*.
- Marchi E, Roth G and Siccardi F (1996) The Po: centuries of river training. *Physics and Chemistry of The Earth* **20**(5–6): 475–478.
- McCarthy S, Tunstall S, Parker D, Faulkner H and Howe J (2007) Risk communication in emergency response to a simulated extreme flood. *Environmental Hazards* **7**(3): 179–192.
- Montanari A (2007) What do we mean by ‘uncertainty’? The need for a consistent wording about uncertainty assessment in hydrology. *Hydrological Processes* **21**(6): 841–845.
- Myers W, Lyness J and Cassells J (2001) Influence of boundary roughness on velocity and discharge in compound river channels. *Journal of Hydraulic Research* **39**(3): 311–319.
- Neal JC, Bates PD, Fewtrell TJ et al. (2009) Distributed whole city

- water level measurements from the Carlisle 2005 urban flood event and comparison with hydraulic model simulations. *Journal of Hydrology* **368**(1–4): 42–55.
- Neal JC, Schumann G and Bates P (2012) A sub-grid channel model for simulating river hydraulics and floodplain inundation over large and data sparse areas. *Water Resources Research* **48**(11): 1–16, W11506.
- Pappenberger F and Beven K (2006) Ignorance is bliss: or seven reasons not to use uncertainty analysis. *Water Resources Research* **42**: 1–8, W05302.
- Pappenberger F, Beven K, Horritt M and Blazkova S (2005) Uncertainty in the calibration of effective roughness parameters in HEC-RAS using inundation and downstream level observations. *Journal of Hydrology* **302**(1–4): 46–69.
- Pappenberger F, Matgen P, Beven KJ *et al.* (2006) Influence of uncertain boundary conditions and model structure on flood inundation predictions. *Advances in Water Resources* **29**(10): 1430–1449.
- Pappenberger F, Beven K, Frodsham K, Romanowicz R and Matgen P (2007) Grasping the unavoidable subjectivity in calibration of flood inundation models: a vulnerability weighted approach. *Journal of Hydrology* **333**(2–4): 275–287.
- Petersen-Overleir A (2005) *A Hydraulics Perspective on the Power-law Stage–discharge Rating Curve*. Norwegian Water Resources and Energy Directorate, Oslo, Norway, NVE report 05–05.
- Prestininzi P, Di Baldassarre G, Schumann G and Bates PD (2011) Selecting the appropriate hydraulic model structure using low-resolution satellite imagery. *Advances in Water Resources* **34**(1): 38–46.
- Quiroga VM, Popescu I, Solomatine DP and Bociort L (2013) Cloud and cluster computing in uncertainty analysis of integrated flood models. *Journal of Hydroinformatics* **15**(1): 55–70.
- Reitan T and Petersen-Overleir A (2009) Bayesian methods for estimating multi-segment discharge rating curves. *Stochastic Environmental Research and Risk Assessment* **23**(5): 627–642.
- Romanowicz R and Beven K (2003) Estimation of flood inundation probabilities as conditioned on event inundation maps. *Water Resources Research* **39**(3): 1073.
- Schmidt AR (2002) *Analysis of Stage–discharge Relations for Open-channel Flows and Their Associated Uncertainties*. PhD thesis, University of Illinois at Urbana, Champaign, IL, USA.
- Schumann G, Bates P, Horritt M, Matgen P and Pappenberger F (2009) Progress in integration of remote sensing-derived flood extent and stage data and hydraulic models. *Reviews of Geophysics* **47**(4): 1–20, RG4001.
- Stedinger JR, Vogel RM, Lee SU and Batchelder R (2008) Appraisal of the generalized likelihood uncertainty estimation (GLUE) method. *Water Resources Research* **44**(12): 1–17, W00B06.
- Wagener T and Kollat J (2007) Numerical and visual evaluation of hydrological and environmental models using the Monte Carlo analysis toolbox. *Environmental Modelling and Software* **22**(7): 1021–1033.
- Wagener T, Lees M and Wheater H (2002) A toolkit for the development and application of parsimonious hydrological models. In Singh VP and Frevert DK *Mathematical Models of Large Watershed Hydrology*. Water Resources Publications, pp. 91–140.
- Werner M and Lambert MF (2007) Comparison of modelling approaches used in practical flood extent modelling. *Journal of Hydraulic Research* **45**(2): 202–215.
- Werner M, Hunter N and Bates P (2005) Identifiability of distributed roughness data in flood extent estimation. *Journal of Hydrology* **314**(1–4): 139–157.
- Westerberg I, Guerrero JL, Seibert J, Beven KJ and Halldin S (2011) Stage–discharge uncertainty derived with a non-stationary rating curve in the Choluteca River, Honduras. *Hydrological Processes* **25**(4): 603–613.

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