  Journal of Hydroinformatics | 15.3 | 2013

Exploring the potential of SRTM topographic data for flood inundation modelling under uncertainty

Kun Yan, Giuliano Di Baldassarre and Dimitri P. Solomatine

ABSTRACT

The desirable data for model building and calibration to support the decision-making process in flood risk management are often not sufficient or unavailable. A potential opportunity is now offered by global remote sensing data, which can be freely (or at low cost) obtained from the internet, for example, Shuttle Radar Topography Mission (SRTM) topography. There is a general sense that inundation modelling performance will be degraded by using SRTM topography data. However, the actual effectiveness and usefulness of SRTM topography is still largely unexplored. To overcome this lack of knowledge, we have explored the value of SRTM topography to support flood inundation modelling under uncertainty. The study was performed on a 98 km reach of the River Po in northern Italy. The comparison between a hydraulic model based on high-quality topography and one based on SRTM topography was carried out by explicitly considering other sources of uncertainty (besides topography inaccuracy) that unavoidably affect hydraulic modelling, such as parameter and inflow uncertainties. The results of this study showed that the differences between the high-resolution topography-based model and the SRTM-based model are significant, but within the accuracy that is typically associated with large-scale flood studies.

Key words | floodplain monitoring, inundation modelling, light detecting and ranging (LiDAR) topography, shuttle radar topography mission (SRTM) topography, uncertainty analysis

Kun Yan (corresponding author)
Giuliano Di Baldassarre
Dimitri P. Solomatine
Department of Integrated Water System and Governance,
UNESCO-IHE,
Institute for Water Education,
Westvest 7,
2601 DA Delft,
The Netherlands
E-mail: *k.yan@unesco-ihe.org*

Dimitri P. Solomatine
Water Resources Section,
Delft University of Technology,
The Netherlands

INTRODUCTION

The growing availability of distributed remote sensing data has allowed for significant progress in building and testing flood inundation models over past decades (Bates 2004; Schumann *et al.* 2009). Among these data, digital elevation models (DEMs) are essential, as hydraulic modelling of floods (Chau *et al.* 2005) is highly dependent on accurate, high-resolution spatially distributed elevation data (Walker & Willgoose 1999; Yin & Wang 1999; Charlton *et al.* 2003; Ludwig & Schneider 2006).

Several DEM products (Hannah *et al.* 2011) with different accuracy levels are available for modellers and practitioners. Airborne light detecting and ranging (LiDAR) instruments provide high-precision topographic mapping tools via discrete surface height samples instead of a continuous coverage across small areas (Sun *et al.* 2003), while the Shuttle Radar Topography Mission (SRTM) provides the most complete and robust surface elevation data at the global scale. The mission was finished by the joint endeavour of the National Aeronautics and Space Administration (NASA), the National Geospatial-Intelligence Agency, and the German and Italian Space Agencies in February 2000 (Farr *et al.* 2007). LiDAR DEMs are often associated with high accuracy and high price, therefore, for the majority of rivers and floodplains, they are either not available or difficult to access, particularly in developing countries. SRTM DEMs are free products with lower resolution (90 m) and accuracy (with the elevation accuracy varying from 5 to 16 m; Schumann *et al.* 2008). However, their value in supporting flood inundation modelling remains largely unexplored.

The scientific literature has extensively shown that the results of hydraulic modelling are affected by many sources

doi: 10.2166/hydro.2013.137

of uncertainty: model structure, model parameters, topography data and boundary conditions (Aronica *et al.* 1998; Romanowicz & Beven 1998, 2003; Bates *et al.* 2004; Pappenberger *et al.* 2005; Solomatine & Shrestha 2009). To better estimate the overall uncertainty, the uncertainty assessment exercises should be carried out throughout the modelling process, starting from the very beginning, rather than be added after the completion of the modelling work (e.g. Refsgaard *et al.* 2007; Merwade 2008; Di Baldassarre *et al.* 2010). In particular, the inflow (i.e. design flood) and the model parameter uncertainties were found to often be the most significant sources of uncertainty in one-dimensional (1D) hydraulic modelling for predicting design flood profiles (flood elevations at cross-sections computed from design flood) (e.g. Pappenberger *et al.* 2008). Specifically, to construct inflow data for hydraulic models, the design flood estimation via flood frequency analysis is in turn affected by other sources of uncertainty, such as observation errors (e.g. rating curves), limited sample size and selection of the distribution model (Di Baldassarre *et al.* 2009a). In addition, more recently, Moya Quiroga *et al.* (2013) showed that topographic uncertainty has a considerable influence on flood extent by using a simplified sampling technique of changing the cell elevations independently.

Given that traditional topography data, based on ground surveys, are only seldom available, while many remote sensing technologies are often too expensive (e.g. LiDAR; Castellarin *et al.* 2009), testing the usefulness of freely and globally available data (such as SRTM topography) in supporting hydraulic modelling of floods is of extremely high interest from both a scientific and engineering point of view. In this context, Sander (2007) evaluated diverse public DEMs for flood inundation modelling, and found that SRTM topography yielded a 25% larger flood zone compared with the high-resolution topography in a steady-flow Santa Clara River application. Indeed, whether or not this is a useful prediction surely depends on the application itself. Whether the high-resolution topography will justify the cost also depends on the characteristics of the study area (such as scale, geographic importance) as well as the objective of the modelling exercise. In addition, SRTM topography may appear attractive while there are other larger sources of uncertainty. However, Sander (2007) did not account for the other sources of uncertainty (besides topography inaccuracy) that unavoidably affect hydraulic modelling. Hence, the novelty of our study is that the impact of different topographical input on the performance of flood inundation models is analysed by explicitly considering the other sources of uncertainty (such as parameters and inflow) that would unavoidably affect any hydraulic modelling exercise. The uncertainty introduced by topographic inaccuracy is therefore analysed in the following perspective: to what extent do the topographic errors affect the floodplain model results? And is this significant in view of the other sources of uncertainty (inflow, parameters) that are intrinsic to any modelling exercise?

To this end, design flood profiles are estimated by using hydraulic models built based on SRTM topography. These design flood profiles are then compared with the ones provided by a hydraulic model based on accurate and precise topography (i.e. combination of LiDAR survey, multi-beam bathymetry and cross-sections). This comparison is made in view of the associated uncertainty, which is estimated by following a simple and pragmatic approach proposed by Brandimarte & Di Baldassarre (2012). They estimated the uncertainty in predicting design flood profiles via hydraulic modelling based on high-quality DEMs, while we developed a SRTM-based model and compared it with the LiDAR-based model and used a similar Monte Carlo-based approach to estimate uncertainty. Another related study in this area is that of Schumann *et al.* (2010), who compared the water surface gradient generated by intersecting Synthetic Aperture Radar (SAR) flood images and SRTM DEMs to that derived from intersecting SAR flood image with a high-resolution and quality LiDAR DEM. It was found that they are remarkably close to each other in this portion of the River Po. The SRTM-derived water profiles were also compared with the ones obtained from the LiDAR-based hydraulic model. However, the main focus of the Schumann *et al.* (2010) study was the potential of orbital SAR to estimate the magnitude of a flood wave, rather than uncertainties in hydraulic modelling as proposed in this study. Prestininzi *et al.* (2011) investigated the ability of timely low-resolution satellite imagery to assist the selection of the most appropriate hydraulic model structure in this portion of River Po. It has been proved that the two-dimensional (2D) model performs better than the 1D model in the validation (low-magnitude event) phase. Di Baldassarre *et al.* (2009b) calibrated the LiDAR-based hydraulic model in the same portion of the River Po by using the 2000 flood event and validated the model against the 2008 flood event. It was found that the hydraulic models that are able to reproduce the high-magnitude event (2000 flood) failed to reproduce the low-magnitude event (2008 flood) in the same study area.

TEST SITE

The study was performed on a 98 km reach of River Po from Cremona to Borgoforte (Figure 1). The Po River is the largest and longest river in Italy, when considering the drainage area of about 71,000 km^2 and its 650 km reach length. For the river reach studied, the main channel width varies from ~200 to ~300 m, while the river banks are confined by two lateral artificial levees with a width from 400 m to 4 km. A high-resolution 2 m DEM of this portion of the River Po was constructed by the River Po Basin Authority. The DEM was constructed on the basis of data collected in 2005 during numerous flights from altitudes of approximately 1,500 m, using two different laser scanners (3033 Optech ALTM and Toposys Falcon II). Below the water surface, channel bathymetry of the navigable portion was acquired during the same year by a boat survey using a multi-beam sonar (Kongsberg EM 3000D). Moreover, these data were complemented by the ground survey for 200 cross-sections developed by the Interregional Authority of the River Po in 2005 (Castellarin *et al.* 2011). For convenience, and also because the major part of the DEM was constructed using the LiDAR technique, this DEM will be called the LiDAR DEM in this study. A relatively coarse-resolution DEM of this portion of the River Po based on the SRTM was also used for this study (Figure 1).

Figure 1 | Po River between Cremona and Borgoforte: LiDAR DEM (left panel, grey scale), SRTM DEM (right panel, grey scale).

HYDRAULIC MODELLING

This study uses HEC-RAS (US Army Corps of Engineers 2001), a 1D hydraulic model that solves the De Saint-Venant equations with an algorithm based on the Preissmann implicit four-point finite scheme (Preissmann 1961). The model was used to simulate the flood profiles for the 98 km reach between Cremona and Borgoforte. In particular, two hydraulic models were built based on 88 cross-sections including both the floodplain and the main channel. It is worth mentioning that the in-channel bathymetries of the LiDAR-based model come from the boat survey, while the in-channel bathymetries of the SRTM-based model were extracted from the raw SRTM DEM without artificial manipulation. The locations of the cross-sections for both LiDAR- and SRTM-based models are identical, while the cross-section bathymetries are significantly different, particularly in the main channel (Figure 2). Indeed, the use of SRTM topography for inundation modelling should be carefully justified because radar waves cannot penetrate the water surface. Therefore, the in-channel bathymetries are very poorly represented by SRTM topography in general. Conveniently, the SRTM topography data were obtained during an 11 day mission in February, which is winter time in the River Po basin, meaning that the river water levels were relatively low and the floodplain was not inundated. The vegetation height and density during this winter time are also lower than in the summer. These give the opportunity to capture most of the in-channel bathymetries and provide relatively accurate floodplain topography.

HEC-RAS has been widely used for hydraulic modelling (e.g. Pappenberger *et al.* 2005, 2006; Schumann *et al.* 2007; Brandimarte *et al.* 2009), and a number of studies have proven its reliability in simulating floods in natural rivers (e.g. Horritt & Bates 2002; Castellarin *et al.* 2009) compared with 2D models (LISFLOOD-FP, TELEMAC-2D). However, it should be noted that HEC-RAS cannot reproduce the interaction process between the main channel and floodplain, the 2D process on the floodplain, as well as minor hydraulic effects such as secondary circulations and high-order turbulence. Often, these minor effects can be neglected considering the accuracy requirements in large-scale problems and modelling purposes. In addition, previous studies

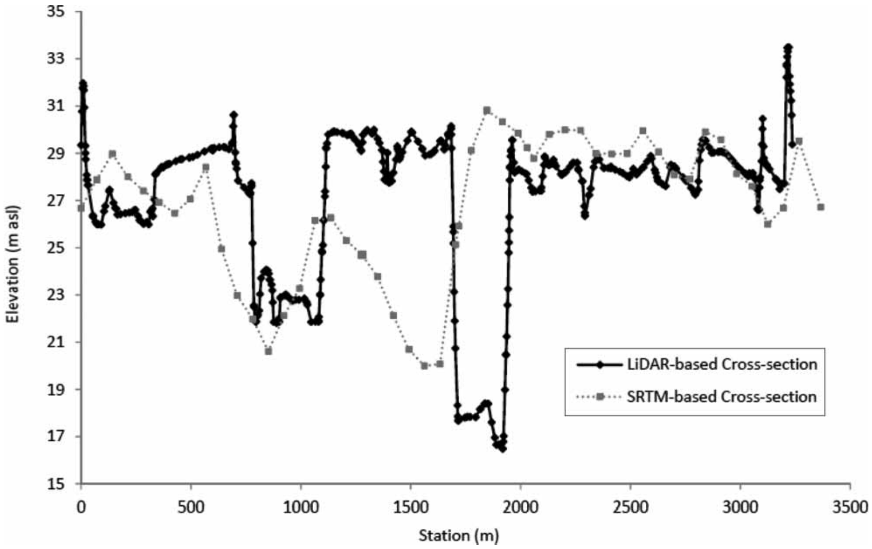

Figure 2 | Cross-sectional comparisons for LiDAR-based model (solid line) and SRTM-based model (dashed line).

have shown that the unprotected floodplain, together with the main channel of this portion of the River Po between the artificial levees, can be treated as a compound 1D channel for a high-magnitude flood event (e.g. Castellarin *et al.* 2009; Di Baldassarre *et al.* 2009b; Brandimarte & Di Baldassarre 2012). Moreover, a 1D model is more efficient than a 2D model in terms of computational time, especially for large areas. It has been shown (Brandimarte & Di Baldassarre 2012) that for this test site, the computation of flood profiles via steady-state simulations provided results as accurate as the ones obtained via unsteady simulation because of the broad and flat hydrographs of this alluvial river, which leads to relatively little transient behaviour. Thus, a dynamic model was not needed here, as the modelling purpose is to derive the maximum water stage levels, i.e. flood profiles. Moreover, it should be noted that Bates & De Roo (2000) demonstrate that, for example, for a particular 1-in-63 year flood event in River Meuse, the dynamic simulations are marginally less good predictors of inundation extent than the steady-state models. In addition, steady-flow routines are commonly adopted by regulatory agencies for floodplain mapping studies (Di Baldassarre *et al.* 2010).

Model calibration

In October 2000, the River Po experienced a significant flood event, with a peak discharge of about 11,850 $m^3 s^{-1}$. The return period was estimated at ~60 years (Maione *et al.* 2003). The two hydraulic models were calibrated by varying the Manning coefficients and comparing the numerical results to the high-water marks recorded after the October 2000 flood event (Coratza 2005). Given the homogeneous characteristics of the river reach, the potentially distributed Manning n value were limited to one value for the channel and one for the floodplain (Di Baldassarre *et al.* 2009b). The high-water marks are appropriate to calibrate the model for the purpose of reproducing the flood profile. The sensitivity analysis is carried out by varying the Manning channel coefficient from 0.01 to 0.06 $m^{1/3}$ s and the Manning floodplain coefficient from 0.03 to 0.13 $m^{1/3}$ s, for both the LiDAR-based model and the SRTM-based model. The model performances are evaluated by using the mean absolute error, ε.

There is a clear tendency that the Manning channel coefficients are increasing, while the Manning floodplain coefficients are decreasing within areas with similar mean absolute errors for both LiDAR- and SRTM-based models (Figure 3). This is because the increasing roughness on the channel is compensated by the decreasing roughness on the floodplain. The shapes of the hyperbolic that contain the optimal values are similar between the two models. In addition, both models clearly show more sensitivity on Manning channel coefficients than Manning floodplain coefficients. The model sensitivity of the LiDAR-based

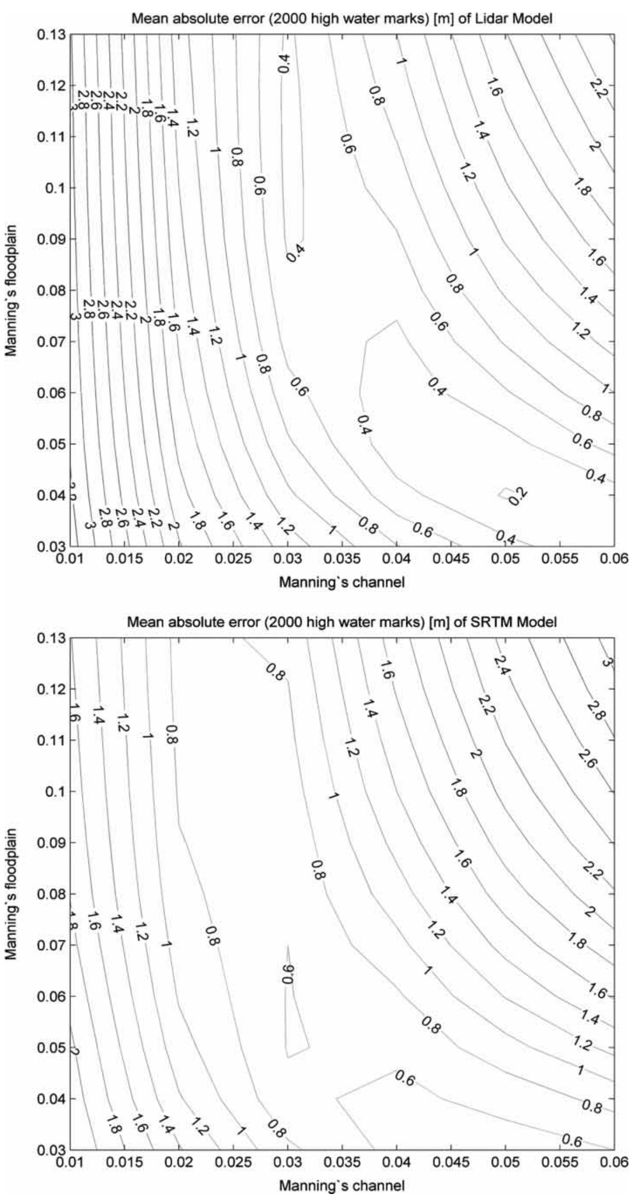

Figure 3 | Model responses to changes in Manning coefficients: LiDAR-based model (upper panel) and SRTM-based model (lower panel).

model is higher than the SRTM-based model for small Manning channel coefficients. Figure 4 represents flood profiles of the best-fit model for both the LiDAR-based model and the SRTM-based model, which were selected by minimizing the mean absolute error and rejecting the simulations where the Manning floodplain coefficients were smaller than the Manning channel coefficients. The rejection criterion was based on the fact that there is a consensus that the channel roughness is typically smaller than that of the floodplain since water flows in the riverbed almost all the time and makes it smoother (Chow 1959). The mean absolute errors between the observed and simulated water levels seem to indicate that both models can simulate the October 2000 flood profile reasonably well (Table 1), although the optimal Manning coefficients lie in different locations of the parameter space (Figure 3).

Model evaluation

The River Po experienced a low-magnitude flood event (return period around 3 years) in June 2008. For this event, a coarse-resolution (~100 m) SAR flood image was acquired and processed by Schumann *et al.* (2010). This SAR flood image was used in this study to evaluate the two models. In particular, the inundation widths were derived to validate the best-fit LiDAR- and SRTM-based models. The two models were used to simulate the June 2008 flood, and the simulated inundation widths were compared with the ones derived by the SAR images. The validation of the two models (Figure 5) shows that they provide similar results. In particular, the mean absolute errors of the two models in reproducing the SAR inundations were found equal to 945 m for the LiDAR-based model and 862 m for the SRTM-based model. The difference between the two models is within the accuracy of the inundation width derived from the SAR image (around 150 m; e.g. Prestininzi *et al.* 2011).

DESIGN FLOOD PROFILE PREDICTION WITH UNCERTAINTY

The traditional approach to estimate design flood profiles is to feed the design flood into a calibrated model. In this case, the 1-in-200 year design flood ($Q_{200} \sim 13{,}700\ m^3\ s^{-1}$, estimated using Gumbel distribution) is simulated using the model calibrated against the October 2000 flood event ($11{,}850\ m^3\ s^{-1}$). The similar flood peaks magnitudes of the 1-in-200 year flood and the October 2000 flood indicate the profile predictions might be reliable, given that the high-magnitude floods are restricted by the two lateral banks of the River Po, which means the flood propagation processes remain mainly 1D for this test site (e.g. Castellarin *et al.* 2009; Di Baldassarre *et al.* 2009b).

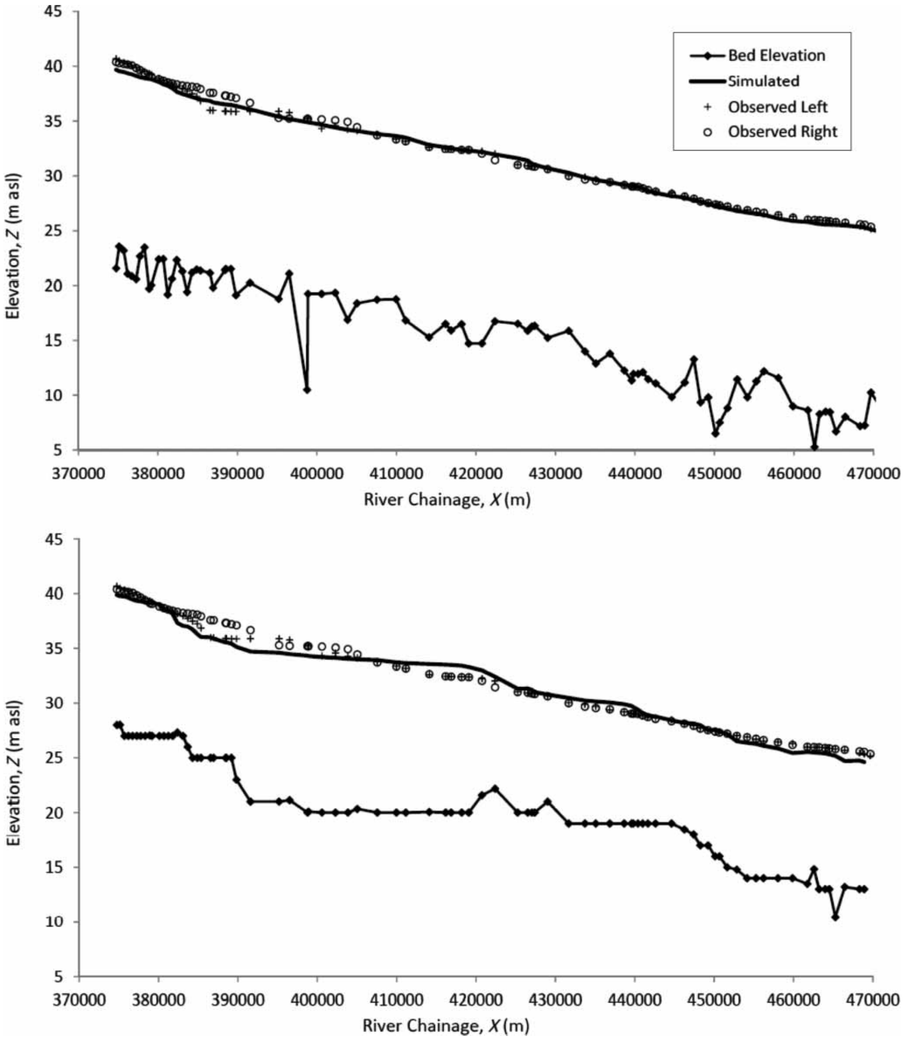

Figure 4 | Model calibration: observed left and right bank high-water marks and results of the best-fit model: LiDAR-based model (upper panel) and SRTM-based model (lower panel).

Table 1 | Mean absolute error for LiDAR-based model and SRTM-based model

	Mean absolute error (m)
LiDAR-based model	0.27
SRTM-based model	0.56

Recent literature has pointed out that single (deterministic) predictions of flood profiles, which use the 'best-fit' model and a single design flood estimation, might misrepresent the existence of uncertainties intrinsic to any hydraulic modelling exercise (Beven & Freer 2001; Bates *et al.* 2004; Beven 2006; Di Baldassarre *et al.* 2010). Therefore, the use of the probabilistic approach is increasingly recommended.

A rigorous approach for the estimation of all sources of uncertainty might be computationally heavy and requires strong assumptions of the nature of the errors. Hence, a simple pragmatic approach, based on generalized likelihood uncertainty estimation (GLUE) (Beven & Binley 1992), is used here to estimate the design flood profile uncertainty. It is worth mentioning that GLUE is criticized by some researchers as it requires a number of subjective decisions and uses a non-standard notion of likelihood (Hunter *et al.* 2005; Mantovan & Todini 2006; Montanari 2007; Stedinger *et al.* 2008). At the same time, it is still a widely used approach to estimate uncertainty in hydrological modelling (e.g. Montanari 2005; Winsemius *et al.* 2009; Krueger

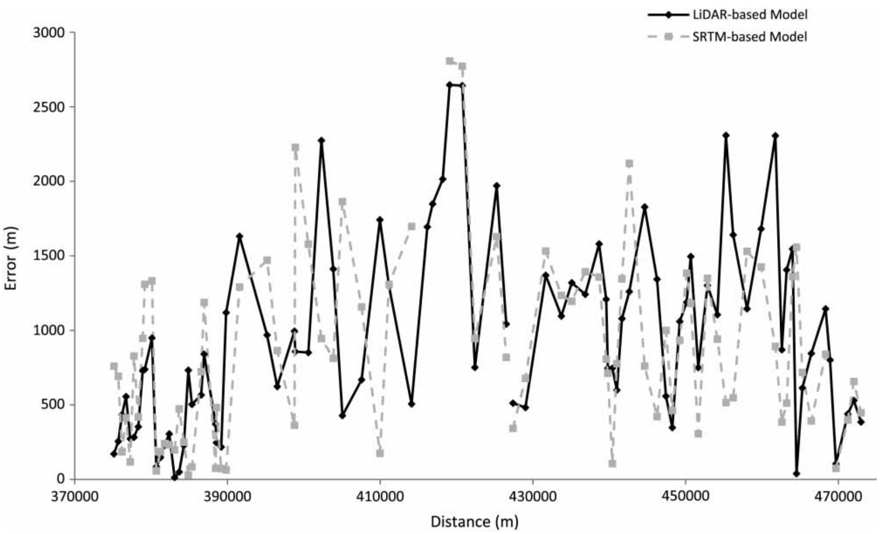

Figure 5 | Error of simulated and observed inundation widths of 2008 flood, LiDAR-based model (solid line) and SRTM-based model (dashed line).

et al. 2010). One aspect that, as we discovered, has an influence on many Monte Carlo-related methods (such as GLUE) is the sampling strategy used (Kayastha *et al.* 2010), but such an analysis is left for future studies.

The sources of uncertainties estimated here are the inflow (i.e. design flood) and the model parameters. Topography uncertainty is also taken into account by simulating flood profiles using two models based on two different topographies. As mentioned above, the quality of the LiDAR DEM is high in terms of both resolution and accuracy. The usefulness of SRTM topography is estimated by comparing the design flood profiles predicted by the SRTM-based model with the design flood profiles predicted by the LiDAR-based model, which is considered a reference model. These profiles are compared by including an explicit representation of inflow uncertainty and model parameter uncertainty. It is assumed here that these sources of uncertainty prevail over the uncertainty induced by imprecise model structure, and this can be justified by the (aforementioned) satisfactory results obtained by previous studies in simulating high-magnitude events in this test site via HEC-RAS modelling (e.g. Castellarin *et al.* 2009; Di Baldassarre *et al.* 2009b).

Experiment 1

The first modelling exercise is carried out by considering parameter uncertainty only, varying the Manning channel coefficient in the range 0.01–0.06 $m^{1/3}\ s^{-1}$ (with an interval of 0.01) and the Manning floodplain coefficient in the range 0.03–0.13 $m^{1/3}\ s^{-1}$ (with an interval of 0.01). A set of simulations satisfying a threshold criteria is selected from the sensitivity analysis (the same as the model calibration). In this case, all the simulations (66 in total) associated with a mean absolute error that is larger than 1 m are rejected. This (subjective) assumption was by considering the fact that the current policy in the Po River basin requires that levees should have at least 1 m of freeboard above the 200 year flood profile elevations (see Brandimarte & Di Baldassarre 2012). In addition, the simulations when the Manning coefficients on the floodplain are smaller than those on the channel are rejected (see above). The models passing these filters are termed (following the GLUE method) 'behavioural', and are used to simulate the 1-in-200 flood event.

In GLUE, each behavioural simulation is associated with a rescaled likelihood weight, W_i, ranging from 0 to 1 within the framework of GLUE (Beven & Binley 1992). Many studies (e.g. Mantovan & Todini 2006; Beven *et al.* 2007, 2008; Stedinger *et al.* 2008) have pointed out that the likelihood function used in GLUE should be able to correctly represent the statistical sampling distribution of the data to make the prediction coherent and consistent. However, it should be noted that the choice of likelihood measure might greatly influence the resulting uncertainty intervals, and this choice must be made explicit so they can be the 'subject of discussion and justification' (Beven & Freer 2001). Here, we followed previous studies in hydraulic modelling of floods (Bates *et al.* 2004; Hunter *et al.* 2005; Pappenberger *et al.* 2006). The likelihood weight, L_i, is expressed as a function of the measure of fit, ε_i, of the behavioural models:

$$L_i = \frac{\varepsilon_{\max} - \varepsilon_i}{\varepsilon_{\max} - \varepsilon_{\min}} \tag{1}$$

where $\varepsilon_{\max}$ and $\varepsilon_{\min}$ are the maximum and minimum values of the mean absolute error of the behavioural models. Then, the likelihood weights are rescaled to a cumulative sum of 1. Rescaled likelihood weights were calculated using:

$$W_i = \frac{L_i}{\sum_{i=1}^{n} L_i} \tag{2}$$

This uncertainty analysis was implemented for both the LiDAR-based model and the SRTM-based model. Thus, Figure 6(a) shows the 5, 50 and 95th weighted percentiles, which represent the likelihood weighted uncertainty bounds, for both the LiDAR-based model and the SRTM-based model.

Experiment 2

The second modelling exercise also considers the important source of uncertainty in hydraulic modelling, i.e. the estimation of the design flood. To this end, the 1-in-200 year flood was estimated by statistically inferring the time series of 42 annual maximum flows, recorded at the Cremona gauge station, which is the upstream end of the river reach under study.

In particular, five distribution functions commonly used in extreme value analysis in hydrology (i.e. lognormal (LN), three-parameter lognormal (LN3), exponential (E), Gumbel (EV1) and generalized Pareto (GP)) were fitted to the annual maximum flows using the method of moments. Five 1-in-200 year design floods were then obtained from these fitted distributions (Table 2). The shapes of the design hydrographs were not estimated because of the steady-state assumption already discussed. Thus, the additional uncertainties that might have been caused by the estimation of hydrograph shapes were avoided here. Hence, five simulations of the best-fit models were run for both the LiDAR- and the SRTM-based models. The 5, 50 and 95th percentiles were computed. Comparisons are made between profiles for each percentile of the LiDAR-based model and the SRTM-based model (Figure 6(b)).

Experiment 3

The third modelling practice is carried out by combining model parameter and inflow uncertainties. Therefore, we run a total of 115 simulations by feeding 23 behavioural models using five design flood values generated from five distribution functions for the LiDAR-based model. For the SRTM-based model, we run a total of 120 simulations by feeding 24 behavioural models using the same five design flood values. The 5, 50 and 95th weighted percentiles of the 1-in-200 year flood, which take into account the parameter and inflow uncertainties, were calculated for both the LiDAR-based model and the SRTM-based model. The comparisons of profiles from two models (LiDAR and SRTM) of the same percentile are also made (Figure 6(c)).

For the three experiments mentioned above, the chosen Manning coefficient parameter space is sufficiently large to cover the possible coefficient combinations for hydraulic modelling (Chow 1959). The sampling interval of 0.01 is reasonably small given by a sensitivity analysis, which increases the sampling interval of floodplain Manning coefficients to 0.02. The results show that the uncertainty bounds for all three experiments have very minor variations. This means the uncertain model performance will not be affected much if the number of simulations is increased.

DISCUSSION

The bed elevations in the SRTM and LiDAR models were significantly different to each other (Figure 4). We also conducted a two-sample Kolmogorov–Smirnov test to quantitatively evaluate these differences. We test the hypothesis H_0: $P_1 = P_2$ that two samples come from the same distribution. The results show that it rejects the null hypothesis as the p-value 2.78×10^{-6} is much smaller than 0.05,

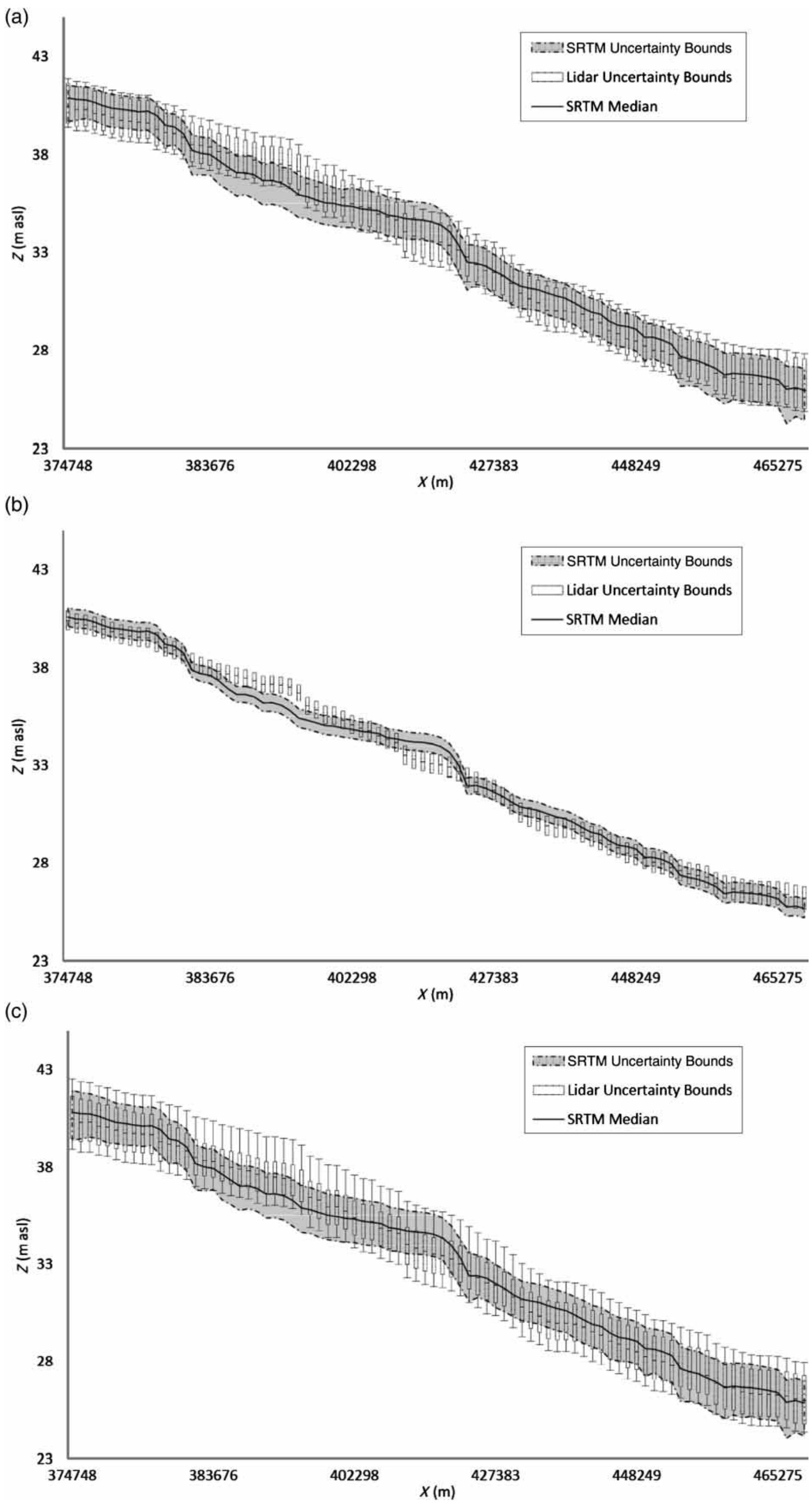

Figure 6 | Uncertainty design flood profiles by considering: (a) model parameter uncertainty only; (b) design flood uncertainty only; and (c) model parameter and design flood uncertainty. LiDAR-based model uncertainty bounds are shown in the boxplots (lower and upper quantiles are 5th and 95th percentiles). SRTM-based model uncertainty bounds are shown in the grey areas (dashed lines show 5th and 95th percentiles).

Table 2 | 1-in-200 year design flood estimation using five probabilistic models

Distribution	LN	LN3	E	EV1	GP
Discharge (m^3/s)	13,743	13,254	15,037	13,695	12,449

which is the default value of the level of significance. Therefore, the difference between two samples is significant enough, as they have different distributions. Figure 2 shows that the bed elevations differ by around 4 m, which definitely affects the main channel conveyance. Given that the cross-sectional profile of the main channel is a very important factor for 1D hydraulic modelling, the following question may arise. Why were the modelling results very close in terms of water level? In fact, the topography of the floodplain areas (Figure 2) of the two models is not as different as those in the main channel. Therefore, as the main channel and floodplain within the lateral embankments are treated as a whole cross-section in this 1D HEC-RAS model, the total conveyance in flood conditions is not significantly different. In addition, the topographic uncertainties in the SRTM geometry are partly compensated for by the Manning coefficient during model calibration. All these factors result in similar simulated flood profiles for the LiDAR- and SRTM-based models, despite the fact that the 'conveyances' in the main channel are different.

Figure 6 shows the uncertainty bounds vary according to the source of uncertainty under consideration. For the SRTM-based model, the difference between the 95% percentile and the median is 0.4–0.5 m if only inflow uncertainty is considered. This value increases to 0.6–1.0 m if only parameter uncertainty is considered. It continues to rise to 0.9–1.2 m if both parameter and inflow uncertainty are taken into account (Figure 6). Therefore, both sources of uncertainty contribute to the overall uncertainty. Moreover, the bounds of inflow uncertainties are relatively small. This is due to the fact that the differences of design flood estimations generated from five distributions are small (within ±10% of the 1-in-200 year flood estimated by the Gumbel distribution (EV1)).

The hydraulic model performance based on SRTM topography are evaluated when the LiDAR-based model results are taken as the 'truth', by comparing the flood profiles obtained from the LiDAR- and SRTM-based models for the three experiments (Table 3). The mean absolute error

Table 3 | Comparison of flood profiles obtained from LiDAR-based model and SRTM-based model by considering uncertainties

Source of uncertainty	Percentile	Mean absolute error (m)
Parameter uncertainty	5th percentile	0.46
	50th percentile	0.47
	95th percentile	0.32
Inflow uncertainty	5th percentile	0.41
	50th percentile	0.40
	95th percentile	0.39
Combined uncertainty	5th percentile	0.47
	50th percentile	0.43
	95th percentile	0.36
Mean		0.41

of LiDAR- and SRTM-based model profiles, taking the major sources of uncertainties into account, is around 0.41 m, which is the same order of magnitude as the accuracy of the high-water marks (around 0.5 m; e.g. Neal *et al.* 2009; Horritt *et al.* 2010). In addition, the current policy in the Po River basin requires that levees should have at least 1 m of freeboard above the 200 year flood profile elevations.

In this study, model performance evaluation was always based on water levels, as the calibration data of the October 2000 flood event are high-water marks. In addition, the estimation of the 1-in-200 flood profile is usually performed for dyke or levee design, which requires estimation of the flood water levels. In fact, the water depth differences for the LiDAR-based model and the SRTM-based model have up to 30% relative error for all the modelling practices because the SRTM DEM overestimates the topography elevation, particularly in parts of the main channel.

CONCLUSIONS

This paper described a first scientific study to quantitatively evaluate the value of the SRTM topography to support hydraulic modelling with the purpose of predicting design flood profiles when taking into account the main sources of uncertainty unavoidably associated with any modelling exercise. The outcomes of this study show that the prediction of 1-in-200 year flood profiles in the study area of River Po, using the HEC-RAS model based on SRTM

DEM topography data, are within the accuracy that is typically associated with large-scale flood studies, as long as the other sources of uncertainty are explicitly considered, despite the fact that some differences in water-level predictions (compared with the LiDAR-based model) are not negligible. Thus, the results indicate the added value of SRTM topography in supporting the prediction of design flood profiles in medium- to large-scale rivers, even though detailed studies for the ultimate design of hydraulic structures (e.g. bridges) do require more accurate modelling based on the best available topography. This study also investigated the uncertainty in hydraulic modelling due to model parameters and design flood estimation. It was shown that both sources of uncertainty have a strong influence on the uncertainty of the model output.

The outcomes of this study are unavoidably associated with the particular nature of the case study. 1D modelling can, for example, be inappropriate in different instances, especially when the floodplain is not confined by two lateral artificial levees. Thus, future research will focus on the potential value of the SRTM-based hydraulic model tested on case studies with significant 2D inundation patterns. This study is also limited by the particular scale of the river. In smaller rivers, SRTM-based models are not expected to have this performance. Hence, the usefulness of the globally and freely available SRTM topography data to support hydraulic modelling will be further tested by considering different scales and flood scenarios. In addition, in order to have a comprehensive evaluation of hydraulic models based on SRTM topographic data, different model calibration and validation approaches should be implemented according to the hydraulic model used, the available data and the source of uncertainty considered. Lastly, it should be noted that subjective assumptions were made in estimating uncertainty via the GLUE framework. This is a common issue in estimating uncertainty, which requires that all these (subjective) decisions are made transparent to the end-users.

ACKNOWLEDGEMENTS

The authors are extremely grateful to the Interregional Agency for the River Po (Agenzia Interregionale per il Fiume Po, AIPO, Italy) and the River Po Basin Authority (Autorità di Bacino del Fiume Po, Italy) for providing useful input data. We also acknowledge the EC research project KULTURisk and Chinese Scholarship Council (CSC) that provided partial funding that made the preparation of this paper possible.

REFERENCES

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

Bates, P. D. 2004 Remote sensing and flood inundation modelling. *Hydrol. Process.* **18**, 2593–2597.

Bates, P. D. & De Roo, A. P. J. 2000 A simple raster-based model for flood inundation simulation. *J. Hydrol.* **236** (1–2), 54–77.

Bates, P. D., Horritt, M. S., Aronica, G. & Beven, K. 2004 Bayesian updating of flood inundation likelihoods conditioned on flood extent data. *Hydrol. Process.* **18** (17), 3347–3370.

Beven, K. 2006 A manifesto for the equifinality thesis. *J. Hydrol.* **320** (1–2), 18–36.

Beven, K. & Binley, A. 1992 The future of distributed models: model calibration and uncertainty prediction. *Hydrol. Process.* **6**, 279–298.

Beven, K. & Freer, J. 2001 Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology. *J. Hydrol.* **249** (1–4), 11–29.

Beven, K., Smith, P. & Freer, J. 2007 Comment on 'Hydrological forecasting uncertainty assessment: incoherence of the GLUE methodology', by Mantovan, P. & Todini, E. *J. Hydrol.* **338**, 315–318.

Beven, K., Smith, P. & Freer, J. 2008 So just why would a modeler choose to be incoherent? *J. Hydrol.* **354**, 15–32.

Brandimarte, L. & Di Baldassarre, G. 2012 Uncertainty in design flood profiles derived by hydraulic modelling. *Hydrol. Res.* **43** (6), 753–761.

Brandimarte, L., Brath, A., Castellarin, A. & Baldassarre, G. D. 2009 Isla Hispaniola: a trans-boundary flood risk mitigation plan. *Phys. Chem. Earth, Parts A/B/C* **34** (4–5), 209–218.

Castellarin, A., Di Baldassarre, G., Bates, P. & Brath, A. 2009 Optimal cross-sectional spacing in Preissmann Scheme 1D hydrodynamic models. *J. Hydraul. Eng.* **135** (2), 96–105.

Castellarin, A., Di Baldassarre, G. & Brath, A. 2011 Floodplain management strategies for flood attenuation in the River Po. *River Res. Appl.* **27** (8), 1037–1047.

Charlton, M. E., Large, A. R. G. & Fuller, I. C. 2003 Application of airborne LiDAR in river environments: the River Coquet, Northumberland, UK. *Earth Surf. Proc. Land.* **28** (3), 299–306.

Chau, K. W., Wu, C. L. & Li, Y. S. 2005 Comparison of several flood forecasting models in Yangtze River. *J. Hydrol. Eng.* **10** (6), 485–491.

Chow, V. T. 1959 *Open Channel Hydraulics.* McGraw-Hill Book Co, New York.

Coratza, L. 2005 *Aggiornamento del Catasto delle Arginature Maestre di Po.* River Po Basin Authority, Parma.

Di Baldassarre, G., Laio, F. & Montanari, A. 2009a Design flood estimation using model selection criteria. *Phys. Chem. Earth, Parts A/B/C* **34** (10–12), 606–611.

Di Baldassarre, G., Schumann, G. & Bates, P. 2009b Near real time satellite imagery to support and verify timely flood modelling. *Hydrol. Process.* **23** (5), 799–803.

Di Baldassarre, G., Schumann, G., Bates, P. D., Freer, J. E. & Beven, K. J. 2010 Flood-plain mapping: a critical discussion of deterministic and probabilistic approaches. *Hydrolog. Sci. J.* **55** (3), 364–376.

Farr, T. G., Rosen, P. A., Caro, E., Crippen, R., Duren, R., Hensley, S., Kobrick, M., Paller, M., Rodriguez, E., Roth, L., Seal, D., Shaffer, S., Shimada, J., Umland, J., Werner, M., Oskin, M., Burbank, D. & Alsdorf, D. 2007 The Shuttle Radar Topography Mission. *Rev. Geophys.* **45** (2), RG2004.

Hannah, D. M., Demuth, S., van Lanen, H. A. J., Looser, U., Prudhomme, C., Rees, G., Stahl, K. & Tallaksen, L. M. 2011 Large-scale river flow archives: importance, current status and future needs. *Hydrol. Process.* **25** (7), 1191–1200.

Horritt, M. & Bates, P. 2002 Evaluation of 1-D and 2-D models for predicting river flood inundation. *J. Hydrol.* **268**, 87–99.

Horritt, M. S., Bates, P. D., Fewtrell, T. J., Mason, D. C. & Wilson, M. D. 2010 Modelling the hydraulics of the Carlisle 2005 flood event. *Proc. ICE Water Manage.* **163** (6), 273–281.

Hunter, N. M., Bates, P. D., Horritt, M. S., De Roo, A. P. J. & Werner, M. G. F. 2005 Utility of different data types for calibrating flood inundation models within a GLUE framework. *Hydrol. Earth Syst. Sci.* **9** (4), 412–430.

Kayastha, N., Shrestha, D. L. & Solomatine, D. P. 2010 Experiments with several methods of parameter uncertainty estimation in hydrological modeling. In: *Proc. 9th International Conference on Hydroinformatics*, September, Tianjin, China.

Krueger, T., Freer, J., Quinton, J. N., Macleod, C. J. A., Bilotta, G. S., Brazier, R. E., Butler, P. & Haygarth, P. M. 2010 Ensemble evaluation of hydrological model hypotheses. *Water Resour. Res.* **46** (7), W07516.

Ludwig, R. & Schneider, P. 2006 Validation of digital elevation models from SRTM X-SAR for applications in hydrologic modeling. *ISPRS J. Photogramm.* **60** (5), 339–358.

Maione, U., Mignosa, P. & Tomirotti, M. 2003 Regional estimation model of synthetic design hydrographs. *Int. J. River Basin Manage.* **12**, 151–163.

Mantovan, P. & Todini, E. 2006 Hydrological forecasting uncertainty assessment: incoherence of the GLUE methodology. *J. Hydrol.* **330** (1–2), 368–381.

Merwade, V. 2008 Uncertainty in flood inundation mapping: current issues and future directions. *J. Hydrol. Eng.* **13** (7), 608–620.

Montanari, A. 2005 Large sample behaviors of the generalized likelihood uncertainty estimation (GLUE) in assessing the uncertainty of rainfall-runoff simulations. *Water Resour. Res.* **41** (8), W08406.

Montanari, A. 2007 What do we mean by 'uncertainty'? The need for a consistent wording about uncertainty assessment in hydrology. *Hydrol. Process.* **21** (6), 841–845.

Moya Quiroga, V., Popescu, I., Solomatine, D. P. & Bociort, L. 2013 Cloud and cluster computing in uncertainty analysis of integrated flood models. *J. Hydroinf.* **15** (1), 55–70.

Neal, J. C., Bates, P. D., Fewtrell, T. J., Hunter, N. M., Wilson, M. D. & Horritt, M. S. 2009 Distributed whole city water level measurements from the Carlisle 2005 urban flood event and comparison with hydraulic model simulations. *J. Hydrol.* **368** (1–4), 42–55.

Pappenberger, F., Beven, K., Horritt, M. & Blazkova, S. 2005 Uncertainty in the calibration of effective roughness parameters in HEC-RAS using inundation and downstream level observations. *J. Hydrol.* **302** (1–4), 46–69.

Pappenberger, F., Beven, K. J., Ratto, M. & Matgen, P. 2008 Multi-method global sensitivity analysis of flood inundation models. *Adv. Water Resour.* **31**, 1–14.

Pappenberger, F., Matgen, P., Beven, K. J., Henry, J.-B., Pfister, L. & de Fraipont, P. 2006 Influence of uncertain boundary conditions and model structure on flood inundation predictions. *Adv. Water Resour.* **29** (10), 1430–1449.

Preissmann, A. 1961 Propagation of translatory waves in channels and rivers. In: *Proc. First Congress of French Association for Computation*, Grenoble, France.

Prestininzi, P., Di Baldassarre, G., Schumann, G. & Bates, P. D. 2011 Selecting the appropriate hydraulic model structure using low-resolution satellite imagery. *Adv. Water Resour.* **34**, 38–46.

Refsgaard, J. C., van der Sluijs, J. P., Højberg, A. L. & Vanrolleghem, P. A. 2007 Uncertainty in the environmental modelling process – a framework and guidance. *Environ. Modell. Softw.* **22** (11), 1543–1556.

Romanowicz, R. & Beven, K. 1998 Dynamic real-time prediction of flood inundation probabilities. *Hydrolog. Sci. J.* **43** (2), 181–196.

Romanowicz, R. & Beven, K. 2003 Estimation of flood inundation probabilities as conditioned on event inundation maps. *Water Resour. Res.* **39** (3), 1073.

Sander, B. F. 2007 Evaluation of on-line DEMs for flood inundation modeling. *Adv. Water Resour.* **30**, 1831–1843.

Schumann, G., Bates, P. D., Horritt, M. S., Matgen, P. & Pappenberger, F. 2009 Progress in integration of remote sensing-derived flood extent and stage data and hydraulic models. *Rev. Geophys.* **47** (4), RG4001.

Schumann, G., Di Baldassarre, G., Alsdorf, D. & Bates, P. D. 2010 Near real-time flood wave approximation on large rivers from space: application to the River Po, Italy. *Water Resour. Res.* **46**, W05601.

Schumann, G., Matgen, P., Cutler, M. E. J., Black, A., Hoffmann, L. & Pfister, L. 2008 Comparison of remotely sensed water stages from LiDAR, topographic contours and SRTM. *ISPRS J. Photogramm.* **63** (3), 283–296.

Schumann, G., Matgen, P., Hoffmann, L., Hostache, R., Pappenberger, F. & Pfister, L. 2007 Deriving distributed roughness values from satellite radar data for flood inundation modelling. *J. Hydrol.* **344** (1–2), 96–111.

Solomatine, D. P. & Shrestha, D. L. 2009 A novel method to estimate model uncertainty using machine learning techniques. *Water Resour. Res.* **45**, W00B11.

Stedinger, J. R., Vogel, R. M., Lee, S. U. & Batchelder, R. 2008 Appraisal of the generalized likelihood uncertainty estimation (GLUE) method. *Water Resour. Res.* **44**, W00B06.

Sun, G., Ranson, K. J., Kharuk, V. I. & Kovacs, K. 2003 Validation of surface height from shuttle radar topography mission using shuttle laser altimeter. *Remote Sens. Environ.* **88** (4), 401–411.

US Army Corps of Engineers 2001 *Hydraulic Reference Manual.* US Army Corps of Engineers, Hydrologic Engineering Center, Davis, CA, USA.

Walker, J. P. & Willgoose, G. R. 1999 On the effect of digital elevation model accuracy on hydrology and geomorphology. *Water Resour. Res.* **35** (7), 2259–2268.

Winsemius, H. C., Schaefli, B., Montanari, A. & Savenije, H. H. G. 2009 On the calibration of hydrological models in ungauged basins: a framework for integrating hard and soft hydrological information. *Water Resour. Res.* **45** (12), W12422.

Yin, Z. Y. & Wang, X. 1999 A cross-scale comparison of drainage basin characteristics derived from digital elevation models. *Earth Surf. Proc. Land.* **24** (6), 557–562.

First received 21 August 2012; accepted in revised form 14 December 2012. Available online 29 January 2013