Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-496, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 28 September 2016

Hydrology and Earth System Sciences
Open Access
Discussions

Reproducing an extreme flood with uncertain post–event information

Diana Fuentes–Andino[1,2], Keith Beven[1,3], Sven Halldin[1,2], Chong–Yu Xu[1,4], José Eduardo Reynolds[1,2] and Giuliano Di Baldassarre[1]

[1]{Department of Earth Sciences, Uppsala University, Villavägen 16, SE–752 36 Uppsala, Sweden}

[2]{Centre for Natural Disaster Science (CNDS), Uppsala University, Uppsala, Sweden}

[3]{Lancaster Environment Center, Lancaster University, Lancaster LA1 4YQ, UK}

[4]{Department of Geosciences, University of Oslo, P O Box 1047, Blindern, NO–0316, Oslo, Norway}

Correspondence to: D. Fuentes (diana.fuentes@geo.uu.se)

Abstract

Prevention and mitigation of floods require information on discharge and extent of inundation, commonly unavailable or uncertain, especially during extreme events. This study was initiated by the devastating flood in Tegucigalpa when Hurricane Mitch struck the city. In this study we hypothesised that it is possible to estimate, in a trustworthy way despite large data uncertainties, this extreme 1998 flood discharge and the extent of the inundations that followed, from a combination of models and post–event measured data. Post–event data collected in 2000 and 2001 were used to estimate discharge peaks, times of peaks and high water marks. These data were used in combination with rain data from two gauges to drive and constrain a combination of well–known models: TOPMODEL, Muskingum–Cunge–Todini routing, and the LISFLOOD–FP hydraulic model. Simulations were performed within the GLUE uncertainty–analysis framework. The model combination predicted peak discharge, times of peaks and more than 90% of the observed high–water marks within the uncertainty bounds of the evaluation data. This allowed an inundation likelihood map to be produced. Observed high–water marks could not be reproduced at a few locations on the floodplain. These locations are useful to improve model set–up, model structure or post–event data–estimation methods. Rainfall data were of central importance in simulating the times of peak

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-496, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 28 September 2016

and results would be improved by a better spatial assessment of rainfall, e.g. from satellite data or a denser rain–gauge network. Our study demonstrated that it was possible, considering the uncertainty in the post–event data, to reasonable reproduce the extreme Mitch flood in Tegucigalpa in spite of no hydrometric gauging during the event.

Keywords: post–event measured data, extreme floods, rainfall-runoff and hydraulic model combination, uncertainty analysis.

1 Introduction

The costs related to natural disasters have a significant impact on the world economy, floods account for around half of all disasters globally (UN/ISDR, 2016). Prevention and mitigation of floods require information on discharge and extent of inundation. Such information is commonly unavailable or uncertain, especially during extreme events when gauging equipment becomes insufficient or is lacking. Data scarcity is further aggravated in developing countries with weak infrastructure.

Nearly 11 000 people were killed in Central America during Hurricane Mitch because of extreme flooding, about 2.7 million lost their homes and flood damages were estimated to more than 6 billion USD (McCown et al., 1999). This study was initiated by the flood in Tegucigalpa, the capital city of Honduras, on 30–31 October 1998 when Mitch struck the city. The estimated 500–year return period rainfall produced by Mitch (JICA, 2002) caused significant damage to Tegucigalpa, where one thousand casualties were reported and approximately 40% of its capital stock was damaged (Angel et al., 2004; JICA, 2002). In addition to these calamities, much of Honduras' hydrological archives were swept away from their premises at SANAA (Servicio Autónomo Nacional de Acueductos y Alcantarillados) which was sited close to the main channel of the upper Choluteca River.

Simulations of water–level dynamics caused by disastrous events are needed for preparedness, to produce flood–inundation maps useful for urban planning and to prioritise investments (Pappenberger et al., 2006; Schanze, 2006). Such simulations are also relevant to better comprehend the hydraulic mechanism of large flood events in order to improve model structure (Beven et al., 2011; Jarrett, 1990). However, given that simulations of extreme floods are generally associated with limited data availability and large uncertainties, the

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-496, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 28 September 2016

Hydrology and Earth System Sciences
Open Access
Discussions

question arises as to whether it is possible to achieve simulations that can be truly useful for contingency planning and prevention?

When hydrometric measurements of discharge and water levels during an event are lacking or highly inaccurate, such information may be inferred from post–event surveys. These can be done through eye–witness accounts and field campaigns (Brandimarte and Di Baldassarre, 2012; Gaume and Borga, 2008; Horritt et al., 2010; JICA, 2002; Smith et al., 2002), sometimes in combination with additional methods such as search into historical documentation and paleo–flood techniques (Mård Karlsson et al., 2009; Smith et al., 2012; Valyrakis et al., 2015). Such surveys have been useful to estimate hydrometric data of the floods. Pictures and movies can be used to identify locations, flow type, depth, flow velocity and discharge at the time they were taken (Le Boursicaud et al., 2016). Post–event information of channel topography and maximum water level can be used to estimate maximum peak discharge (Dalrymple and Benson, 1968; Matthai, 1968).

Post–event–estimated maximum peak discharges can also be used to produce probabilistic regional envelope curves (PREC) (Castellarin, 2007; Gaume et al., 2009) and discharge series for flood–frequency analysis (FFA) (Cœur and Lang, 2008). PREC and FFA can provide design–flood estimates to be used for inundation mapping (Brandimarte and Di Baldassarre, 2012). However, an assessment of flood development in time is required for early–warning systems (Schanze, 2006). The development of a flood in time can be obtained through a strategically planned post–event survey of peak discharge and the associated time of the peak (e.g. Delrieu et al., 2005). Detailed hydrographs can also be obtained from rainfall time series in conjunction with post–event hydrometric data, by the use of a rainfall–runoff model (RRM). A RRM in turn can be coupled with a hydraulic model to estimate the water–level development along a floodplain (Bonnifait et al., 2009; Montanari et al., 2009; Pappenberger et al., 2005a). Results from hydraulic models can be validated against post–event–estimated peak discharge, time of the peak, maximum water–level and flood extent data (Bonnifait et al., 2009; Brandimarte and Di Baldassarre, 2012; Horritt et al., 2010).

Post–event data have been used to calibrate hydraulic models using deterministic calibration (e.g. Horritt et al., 2010; JICA, 2002). Borga et al. (2008) and Pappenberger et al. (2006) suggest that post–event data should be used within an uncertainty–analysis set–up given their large uncertainties. The Generalised Likelihood Uncertainty Estimation (GLUE) framework (Beven and Binley, 1992) has been used to account for uncertainty in hydraulic models

(Aronica et al., 1998; Brandimarte and Di Baldassarre, 2012; Pappenberger et al., 2005a, 2007) and for the coupling of a RRM with a hydraulic model (Montanari et al., 2009; Pappenberger et al., 2005a) using during–event measured data. Using post–event data, Bonnifait et al. (2009) present a multi–variable assessment to find a group of best parameter sets for the TOPMODEL RRM and a 1D hydraulic model.

In this study we hypothesise that it is possible to reasonable estimate, despite the large uncertainties, the extreme 1998 flood discharge in Tegucigalpa and the extent of the inundations that followed, from a combination of models and post–event data. We are aware of works that use the combination of hydraulic models and RRMs to assess flood dynamics or others that use post–event data to calibrate RRMs and hydraulic models, both deterministic and through uncertainty analyses. We are not aware of any previous study combining a RRM, a hydraulic model, and post–event data within an uncertainty analysis framework to prove that reasonable estimation of an extreme flood is possible when hydrometric data are lacking. The methodology suggested in this paper integrates TOPMODEL (Beven and Kirkby, 1979; Kirkby, 1997), Muskingum–Cunge–Todini (MCT) (Todini, 2007) routing, and the LISFLOOD–FP (Neal et al., 2012) hydraulic model in a GLUE framework.

2 Study area and data

2.1 Area description

The study area was the floodplain at Tegucigalpa City, approximately 13 km of river length located downstream of the upper part of the Choluteca River catchment. The area draining to the floodplain is around 811 km^2 and is composed of five sub–catchments: Grande River (448 km^2), Guacerique River (243 km^2), Chiquito River (71 km^2), Salada creek (25 km^2) and Las Lomas creek (12 km^2) (Fig. 1). The catchment characteristics such as land use and geology are approximately uniform in all sub–catchments. The land use is mainly composed of sparse coniferous forest at higher elevation land; fallow, pastures and urbanised area in the low land (CIAT, 2007). The geology at the surface is mainly composed of tuff and limestone to a minor degree; the superficial aquifer is classified as poor to moderately productive (ING, 1996). The average basin slope in the Grande River, Guacerique River, Chiquito River, Salada creek and Las Lomas creek sub–catchments is 2.3, 2.8, 4.1, 6.0 and 5.2 % respectively. Two reservoirs operated by SANAA are established within the Tegucigalpa floodplain upstream sub–

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-496, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 28 September 2016

Hydrology and Earth System Sciences
Open Access
Discussions

catchments: the Concepción reservoir, located at Grande River sub–catchment, and Los Laureles reservoir, located at Guacerique River sub–catchment.

2.2 Data

2.2.1 Topography

An airborne light–detection and ranging (LIDAR) survey in Tegucigalpa was conducted in 2000 by the University of Texas in cooperation with the U.S. Geological Survey (USGS) during their survey in Honduras in response to Hurricane Mitch (Mastin, 2002). They generated a 1.5 m cell–resolution digital–terrain model (DTM) with an estimated vertical accuracy of 0.14 m (Fig. 2). In 2001 JICA (2002) also conducted a topographic field survey as part of a flood/landslide–mitigation master plan and a total of 99 cross–sections along the rivers in the floodplain at Tegucigalpa surveyed at intervals of approximately 100 m were used in this study (Fig. 2). In addition, orthographic pictures were taken at Tegucigalpa city by JICA (2002).

The topography of the Tegucigalpa floodplain upstream sub–catchments was available from the 90–m spatial resolution Shuttle Radar Topography Mission (SRTM) data described by Reuter et al. (2007) (Fig. 1).

2.2.2 Precipitation

Upstream the Tegucigalpa floodplain, two stations measured hourly rainfall during the Mitch event (Fig. 1 and 3). One of the stations is operated by Servicio Meteorológico Nacional (SMN, national weather service) and the other by the Universidad Nacional Autónoma de Honduras (UNAH).

2.2.3 Discharge

Peak discharge at different locations was estimated post–event by JICA (2002) and Smith et al. (2002) (Table 1). Discharge at three locations was estimated post–event by Smith et al. (2002) using the standard USGS techniques in Benson and Dalrymple (1967). The peaks at Chiquito River and Grande River (points 1 and 2 in Table 1) were estimated using the width–contraction analysis that uses the continuity and energy equations between a cross–section approaching the contraction section under a bridge (Matthai, 1968). The peak at Choluteca (point 3) was estimated using the slope–area analysis, in which discharge is computed on the basis of the uniform–flow equation involving channel geometry, high water marks, and roughness coefficients (Dalrymple and Benson, 1968). In JICA (2002), three additional discharge estimates (points 4, 5 and 7) were made by setting a rainfall–runoff analysis using the linear reservoir model with a design rainfall pattern constructed using hourly rainfall data from the SMN station.

Controlled flow release through the spillway at the Concepción reservoir was conducted and recorded by SANAA during the Mitch event (Fig. 3). The outflow over Los Laureles dam was not recorded. However, SANAA reported that its gate was overtopped at 22:30 on 30 October, reaching a maximum of approximately 1 200 m^3s^{-1} (JICA, 2002; Smith et al., 2002). Peak times in Table 1, except at point 5, were obtained by interviewing witnesses. The time of the peak at point 5 was estimated by propagating the peak reported at los Laureles reservoir.

2.2.4 Maximum water levels

High water marks during the Mitch flood were surveyed post–event by JICA (2002); the data were obtained by interviewing residents who experienced the event. The survey was carried out at the same locations where the topographic cross–sections were made (Fig. 2).

3 Method

3.1 Modelling framework

The dynamic of the water level along the river channel and floodplain was reproduced with the sub–grid channel formulation of the LISFLOOD–FP hydrodynamic model (Neal et al., 2012). The model requires flow hydrograph as upstream boundary condition. Since discharge hydrographs were not measured, the RRM TOPMODEL (Beven and Kirkby, 1979; Kirkby, 1997) as in Fuentes Andino et al. (2016) together with the Muskingum–Cunge–Todini (MCT) flood–routing approach (Todini, 2007) were used to generate the hydrographs at the outlets of the Chiquito River, Grande River, Guacerique River, Salada Creek and Las Lomas Creek sub–catchments (points 1, 2, 5, 8 and 9 in Fig. 1 and 2 and Table1).

Model evaluation

To quantify the propagation of uncertainty from input data, model parameters and model structure, the Generalised Likelihood Uncertainty Estimation (GLUE) method was used.

Within the GLUE methodology, parameter sets were generated using a Monte Carlo technique, assuming a prior distribution of the parameters. Behavioural parameter sets were selected by using a likelihood measure that reflected the performance of individual simulations with respect to one or more evaluation variables.

Comparison of simulations and evaluation (o_{i}) was done by using a membership function of a fuzzy set to obtain a grade or degree of belief (d_i). Here, a fuzzy membership function was chosen to account for uncertainties in the post–event estimated values, thus the degree of belief for a difference smaller than a between the simulated and post–event estimated values is equal to one and it declines linearly until a value of zero for differences larger than b (Fig. 4).

Behavioural parameter sets were those for which all evaluation variables (o) fell within the support of a fuzzy set defined by the uncertainty range associated with the post-event estimated evaluation data. Differences between prior and posterior parameter distributions were analysed as an indication of the sensitivity of the model parameters.

For every parameter set, a global score (*GS*) was calculated based on a weighted average of the degrees of belief obtained for each evaluation. Subsequently, likelihood values were obtained by scaling the global scores by a constant *C*, so they will sum to unity over all behavioural sets (Beven, 2009).

3.2 Rainfall–runoff modelling within an uncertainty analysis

Hydrographs were reproduced by combining the rainfall–runoff TOPMODEL as in Fuentes Andino et al. (2016) with MCT routing. Topographic information is a fundament for our TOPMODEL set–up, which was one reason to select it for our mountainous catchment. The MCT routing was incorporated to consider the sudden release of water from the Concepción reservoir. The effect of Los Laureles dam on simulating the hydrograph of the Guacerique River sub–catchment was assumed to be negligible since the dam was overtopped much before the most intensive period of the storm.

The length of the main channel for the MCT was estimated having a minimum drainage area equal to 65 km^2. For each sub–catchment, the channel was sub–divided in reaches of approximately 2.5 km to execute the MCT routing. For the MCT routing at Grande River, the inflow for the most upstream reach was set equal to the outflow hydrograph from the reservoir, and for other sub–catchments, to be equal to the hydrograph draining to that reach

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-496, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 28 September 2016

routed using TOPMODEL. For the subsequent reaches, this inflow was estimated as the sum of the outflow from the MCT routing at the immediate upstream reach and the hydrograph produced by TOPMODEL on the draining area to that reach (excluding the draining area to the upstream reaches). The modelling time step was equal to five minutes, smaller than the estimated travel time of the flood wave along the reach, as required by the MCT routing.

For the TOPMODEL, a network width function for each reach was created using topography from the SRTM raster. Rainfall was assumed spatially uniform and estimated as the average of the rainfall registered at the two gauging stations. Uncertainty in rainfall input was taken into account by a multiplier (R). In addition to the rainfall multiplier, uncertainty of six model parameters was considered: the rate of decline of transmissivity (m), horizontal transmissivity (T_{o}), time constant (t_{d}), land use coefficient (l_{u}), flood wave celerity (v_{c}) and soil maximum infiltration rate (i_{max}). The MCT method required information about the river slope and the geometry of the cross–sections. The former was approximated from SRTM data, while the latter was inferred as a function of discharge using the Manning equation for a wide parabolic channel as in Tewolde and Smithers (2007), with channel roughness coefficient (n_{cu}) assumed uniform along all the reaches.

All parameters were sampled from uniform distributions with ranges considered large but possible in the literature (Table 2) and each generated parameter set was used to simulate Chiquito, Grande and Guacerique River sub–catchments. A stopping criteria as in Pappenberger et al. (2005b) was used to decide the number of simulations required. For every 500 behavioural simulations added, a cumulative distribution function (CDF) of the predicted peak discharge and one of the time of the peak were estimated. These estimated CDFs were compared with the previous one and the number of runs was considered sufficient when the addition of behavioural simulations did not change the CDF significantly (i.e. $P < 0.05$) using the Kuiper (1960) statistic test.

Las Lomas creek and Salada creek did not have data to constrain the simulations and, by proximity, the behavioural parameters found at both Grande and Chiquito were used to simulate them. As the areas for Salada creek and Las Lomas creek were smaller than the threshold drainage area for applying MCT, only parameters from TOPMODEL were transferred to those sub–catchments.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-496, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 28 September 2016

Rainfall–runoff model evaluation

To decide on behavioural hydrographs for Chiquito, Guacerique and Grande River sub–catchments the simulated maximum peak and time of the peak post–event observations were used. The assumed uncertainty range for the peak discharge, assuming all predictions within the fuzzy set equally good, was $b = a = \pm 50\%$ of the peak flow and for the time of peak $b = a = \pm 2.5$ hours (Fig. 4). Considering the unavoidable fuzziness associated with this sort of data, a large uncertainty was allowed in post–event estimated maximum peaks and time of the peaks. For example, the uncertainty in post–event estimated discharge was assumed to be about 50%. This value is larger than the 25%, which is the minimum uncertainty expected in less than ideal conditions given steep slopes and large roughness (Benson and Dalrymple, 1967; Cook, 1987), but smaller than 100% possible overestimation for slopes greater than 0.002 (Jarrett, 1987).

To reduce computational costs and avoid redundancy, 100 representative hydrographs (class hydrographs) were obtained for each sub–catchment by clustering the full behavioural ensemble. Clustering was done using a hierarchical divisive clustering technique with the K–means flat algorithm (Madhulatha, 2012). The mean absolute error was used as a metric and the maximum distance as linkage criteria.

3.3 Hydraulic model within an uncertainty analysis

The LISFLOOD–FP was used to propagate the flood waves along the channels and across the flood plain. Here the sub–grid channel formulation after Neal et al. (2012) was used, where the floodplain and the channel have a 2D square grid representation and flood waves are propagated using the local inertia formulation (de Almeida et al., 2012). Thus, the convective acceleration term is assumed to be negligible making the model computationally more efficient than a full 2D dynamic model and therefore suitable for uncertainty analysis. The model outputs are the discharge and water–level time series at any grid along the channel or floodplain.

The basic input data for the LISFLOOD–FP are topography, hydrographs at the upstream boundary conditions, a downstream boundary condition and Manning roughness coefficients. The LIDAR data aggregated to 21 meter cell resolution was used as topographic input to the model, the surveyed cross–sections and orthographic pictures from JICA (2002) were used to define channel depth and width respectively. Test simulations of this event were performed

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-496, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 28 September 2016

within the HEC–RAS one-dimensional hydraulic model considering the topography of the bridges, results showed that bridges had a negligible effect on the overall flood profile. Thus, the geometry of bridges was neglected by assuming a limited and localised impact on flood levels as in e.g. Castellarin et al. (2009).

From the results of a trial test, errors in the channel depth had only a small effect on the simulated water levels. However, uncertainty in the channel width was considered by multiplying the estimated channel width by a factor (w_{f}). By assuming normal flow, the overall downstream valley slope, b_{c}, was used as downstream boundary condition. Besides b_{c}, the channel roughness coefficient, assumed uniform along all the channel length, n_{c}, and the floodplain roughness coefficient uniform along all the floodplain, n_{f}, were also considered to be uncertain parameters. Uncertainty of the input hydrographs at each of the upstream boundary conditions was considered by sampling from 100 class hydrographs.

For this model, a total of 130 000 parameter sets were sampled from a uniform distribution with ranges considered large but possible in the literature (Table 3) in the same way as for the RRM.

Model evaluation for hydraulic model

A grade or degree of belief (d_i) (Fig. 4) was obtained for the values simulated for the following evaluation data:

– One degree of belief value, d_1, as performance in predicting the maximum peak discharge value of point 3 (Table 1).
– Two degree of belief values, d_{2-3}, as performance in predicting time of the maximum peak discharge of points 3 and 6 (Table 1).
– Ninety-nine degree of belief values, d_{4-102}, as performance in predicting maximum water levels along the main river and two tributaries (Fig. 2).

The fuzzy set values of *a* and *b* for evaluating the simulated peak, time of the peak and water levels were set to 20 and 50% of observed peak discharge, 0.5 and 2.5 hours and 0.5 and 1.8 metres respectively. A parameter set was considered behavioural if the degree of belief was larger than zero for each of the 102 evaluation points. For prediction, the likelihood of a parameter set was inferred by normalising the global score (*GS*) estimated by weighted average of the different degrees of belief.

$$GS = \sum_{i=1}^{i=102} w_{\mathrm{i}} d_{\mathrm{i}} \quad (1)$$

Where w_{i} are the weights associated to degree of belief correspondent to the observations. The weight associated to the peak discharge and the two times of the peak data (d_{1-3}) were set equal to 0.1 each, thus 0.7 was the compounded weight correspondent to the degree of belief associated to all the observed maximum water level (d_{4-102}). Finally, the behavioural parameter sets were used to generate a fuzzy likelihood water level profile and map of the maximum flood extension during the Mitch event.

4 Results

4.1 Hydrographs for the upstream boundary condition

Behavioural hydrographs to use as the upstream boundary conditions of the hydraulic model were obtained for the sub–catchments of the Grande, Guacerique and Chiquito Rivers. The TOPMODEL behavioural parameter sets at Grande and Chiquito River sub–catchments were used to simulate hydrographs at Salada creek and Las Lomas creek sub–catchments (Fig. 5).

The cumulative distribution function (CDF) of the predicted peak discharge and of the time of the peak of 2 000, 8 000 and 9 000 behavioural simulation for sub–catchments of the Chiquito, Guacerique and Grande Rivers respectively did not change significantly by adding 500 behavioural simulations more. Thus a total of 3 000, 9 000 and 10 000 behavioural simulations were considered enough to infer 100 class hydrographs for each sub–catchment respectively. When comparing the prior and posterior distribution of the rainfall–runoff model parameters, five out of eight parameters were sensitive (Fig. 6).

4.2 Hydraulic model floodwave propagation

There were no simulations for which all degrees of belief were larger than zero. Criteria d_{1-3} were fulfilled by a total of 47 894 out of 130 000, but some observed water marks were constantly and largely under– or over–predicted. To allow for special cases, i.e. larger error in the observations or in the hydraulic simulations, the constraints were relaxed by allowing 10 % of observed water marks (10 out of 99 observations) to be outside the fuzzy bounds i.e. the degree of belief was allowed to be equal to zero. By relaxing the constraints a total of 6 357 parameter sets were found, the degree of belief for those parameters varied between 0.001–1, 0.04–0.96, 0.29–0.79 and 0.46–0.75 (for d_1, d_2, d_3 and average of d_{4-102} respectively) and between 0.40–0.78 for the global score (GS).

Change in the posterior distributions of the parameters showed that the channel roughness coefficient and floodplain roughness coefficient were more sensitive than the channel width factor and the slope for the downstream boundary condition (Fig. 7). Changes in the posterior distribution of the peak and time of the peak showed that the model was more sensitive to input hydrographs from large catchments than from small catchments (Fig. 8). Flood–wave propagation of different input hydrograph combinations led to prediction of two markedly different time of the peak at the floodplain resulting in under– (over–) prediction when the earliest (latest) peak of input hydrograph combinations prevailed (Fig. 9).

Particularly, there were three observed high water marks in the Chiquito sub–catchment that were constantly under–predicted and outside the uncertainty bounds of the observations (Fig. 10). Expectedly, propagation of the water level uncertainty in the flood extent was more evident at highly dense urban areas (Fig. 11). From behavioural simulations, the 90% confidence interval for prediction of the discharge at the floodplain outlet was 2 708 to 4 619m^3s^{-1} encompassing the 3 880 m^3s^{-1} value estimated in JICA, (2002) (reference point 7). For reference point 4, at Chiquito River, the 90% confidence interval was 247 to 482 m^3s^{-1} also encompassing the 436 m^3s^{-1} value estimated in JICA, (2002).

5 Discussion

A field campaign after a large flood event is a possibility to collect information useful for flood forecasting and subsequent contingency planning in places where hydrometric measurements are lacking because of non–existing or broken gauges.

Our study demonstrated that it was possible, considering the uncertainties associated with the data, to reasonably reproduce an extreme flood event in a data–scarce situation. Our results support those of Bonnifait et al. (2009) about the possibility to reproduce an extreme flood event by a suitable model combination when event–based data are lacking. Here we additionally incorporated the GLUE methodology to account for various sources of uncertainties and their interaction. This allowed us to obtain predictive ranges that accounted for expert knowledge of uncertainties in model parameters, rainfall input and evaluation data. We could drive and constrain a combination of RRM and hydraulic models with only event–

based rainfall data and post–event hydrometric data while accounting for these uncertainties. Behavioural parameter sets were identified that could be used to obtain a realistic probabilistic reproduction of the flood water level (Fig. 10) and flood extension (fig. 11).

Combining an RRM with a hydraulic model within an uncertainty framework as in Montanari et al. (2009) and Pappenberger et al. (2005a) was proven to be useful also in the case of only having post–event–estimated hydrometric data. If real–time discharge measurements are available to calculate the initial saturation of a catchment, behavioural parameter sets updated from a range of events can be used for forecasting as shown by Romanowicz and Beven (2003) and Montanari et al. (2009). In the absence of such measurements, a guess of the initial discharge may also work since it will not significantly affect the prediction for the intense period of the event. Furthermore, for that period, our methodology can give a better performance since calibration is done against discharge, time and water level at the peak.

The combination of TOPMODEL and MCT allowed us to estimate behavioural hydrographs at Chiquito, Guacerique and Grande sub–catchments. The RRM simulations could be constrained (Fig. 5) in spite of the wide uncertainty ranges in the data. The mean rainfall multiplier of the posterior distribution varied across sub–catchments (0.93, 1.5 and 1.3 for Chiquito, Guacerique and Grande respectively) (Fig. 6), suggesting that spatial average rainfall estimated from gauges was overestimated at Chiquito and underestimated at Guacerique and Grande sub–catchments. The posterior distribution of the rainfall multiplier at Chiquito and Guacerique sub–catchments showed a RRM model sensitivity to this parameter in the same way as in Fuentes Andino et al. (2016). The sensitivity was different in the case of the Grande sub–catchment, which also showed a different posterior distribution shape for the rate of depletion and time constant. Different shapes of posterior parameter distributions at Grande River sub–catchment relative to Guacerique and Chiquito River sub–catchments could be caused by parameter adjustment to fit the observations or by different hydrological processes going on in the sub–catchment. The sudden release of water from the dam could also be a reason for these differences. The posterior distributions for the Grande River sub–catchment suggest it has shallower effective soil depth (low m) and a faster channel response in the MCT routing (low n_{cu}) than the other two sub–catchments.

The transfer of behavioural parameter sets from the Grande and Chiquito River sub–catchments to the Salada creek and Las Lomas creek sub–catchments allowed us to simulate hydrographs for these as well. These catchments have a small contributing area relative to the

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-496, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 28 September 2016

three sub–catchments where post–event data were available and thus did not affect the system very much (Fig. 8). It still allowed us to use hydrographs from a total of five sub–catchments (Fig. 5) as upstream boundary conditions for the hydraulic simulations.

From the hydraulic simulations, behavioural simulations were selected for which the degree of belief for the peak discharge, time of the peak and at least 90% of predicted high–water marks (89 out of 99 observations) were above zero. The prediction of high–water marks was quite acceptable with average degrees of belief for the criteria d_{4-102} varying from 0.46 to 0.75 for behavioural simulations even when the criterion was relaxed. Larger weights were given to predict the observed water marks in comparison to the peak discharge and times of the peaks because the focus was on predicting flood extent. The weights could be changed according to the purpose of the study which might also result in different ensembles being behavioural for different purposes (Pappenberger et al., 2007).

The channel and floodplain roughness coefficients and the hydrograph input from Grande River and Guacerique River sub–catchments (Fig. 7 and 8) were the most important factors for the hydraulic model. Two peaks in the input rainfall (Fig. 3) led to two large peaks in the hydrographs as input boundary conditions (Fig. 5). The propagation of input hydrographs along the floodplain led to under– or over–prediction of the times of peak (Fig. 9). Since rainfall data played an important role in predicting the times of peak, this was an indication that an improved spatial characterisation of rainfall by using e.g. satellite data or a denser rain–gauge network would be beneficial for this methodology.

The LISFLOOD–FP model predicted the observed high–water marks, peaks and times of peaks well. In comparison to the estimates made by JICA (2002), water levels produced here encompassed observations better because a range, instead of a value, was estimated. But some observed high–water marks were constantly under predicted in the estimates by JICA (2002) and outside the predicted bounds made herein even accounting for the uncertainty in the evaluation data (Fig. 10). The problem of predicting at some locations could be caused by large errors in the post–event data, or by the inability of the hydraulic model to simulate the system under complex conditions such as strong river bends (e.g. three constantly under–predicted observations at Fig. 10), or special topographic details in a highly populated area with man–made structures, that could not be captured by the DEM. A general under–prediction of the water level at the Chiquito River reach could be due to the under–estimation of the post–event–estimated peak discharge, as in comparison to the Grande and Guacerique sub–catchments, most of the hydrograph simulations for Chiquito River sub–catchment were rejected because the simulated peaks were larger than the observations (even considering the uncertainty) (Fig. 5). A detailed inspection of model structure, model set–up and data at specific points where the model did not perform well even after considering possible uncertainties in the parameters, input and evaluation data, could reveal areas for improvement. In general, the simulated water levels were satisfactory, but post–event observations of flood extent might do better than water levels in constraining the LISFLOOD–FP (Horritt and Bates, 2002).

This study was set up to demonstrate the use of post–event data and a combination of suitable RRM and hydraulic models within an uncertainty analysis to reproduce an extreme flood in a data–scarce area. The post–event data in this case came from airborne topographic surveys, field surveys of channel geometry and witnesses account of high–water marks and time of peaks. Post–event estimates in the future could likely also come from social–media information which is becoming gradually more available. It is also tempting to consider the possibility to use the model combination in this study as a starting point to develop a real–time early–warning system fed both by an improved rain–gauge network and water–level information from social media.

6 Conclusions

In this study we tested the possibility to reproduce an extreme flood disaster in a data–scarce area, in this case the devastating flood in Tegucigalpa triggered by Hurricane Mitch in 1998. It was possible to realistically reproduce this large ungauged flood event by using post–event data, demonstrating the value of post–event field campaigns to estimate hydrometric data from the event for which such data were unavailable. A methodology has been proposed where post–event–estimated data are used to drive and constrain a combination of well–established rainfall–runoff and hydraulic models to estimate floods within a GLUE uncertainty–analysis framework. The propagation of hydrographs, estimated by integrating TOPMODEL with the MCT routing scheme, through the hydraulic LISFLOOD–FP 2D model resulted in successful predictions of observed high–water marks, discharge peaks and times of peaks within the uncertainty bounds for most of the evaluation variables. A few critical locations in the floodplain were identified where the model set–up could not reproduce the maximum water level. These locations can provide information useful to improve model structure or post–event data–estimation methods. Rainfall data were of central importance in simulating the times of peaks and results would be improved by a better spatial assessment of rainfall e.g. from satellite data or a denser rain–gauge network. In the future, the post–event part of the methodology could take advantage of pictures and videos as well as other soft information of floods that are becoming increasingly available in social media.

Author contribution

The experiment was designed by D. Fuentes, K. Beven, S. Halldin, C–Y Xu and G. Di Baldassarre. D. Fuentes carried out the experiment and performed the simulations. D. Fuentes prepared the manuscript with contribution from all co-authors.

Acknowledgements

This research was carried out within the Universidad Nacional Autónoma de Honduras (UNAH) through agreement number 75000511–01 and the CNDS research school, supported by the Swedish International Development Cooperation Agency (Sida) through their contract with the International Science Programme (ISP) at Uppsala University (contract number: 54100006). The computations were performed on resources provided by SNIC through Uppsala Multidisciplinary Center for Advanced Computational Science (UPPMAX) under Project p2011010 and the High Performance Computing Center North (HPC2N) under Project SNIC 2015/1–448. Thanks to the School of Geographical Sciences at the University of Bristol for useful support regarding the LISFLOOD-FP model.

References

de Almeida, G. A. M., Bates, P., Freer, J. E. and Souvignet, M.: Improving the stability of a simple formulation of the shallow water equations for 2-D flood modeling, Water Resour. Res., 48(5), W05528, doi:10.1029/2011WR011570, 2012.

Angel, S., Bartley, K., Derr, M., Malur, A., Mejía, J., Nuka, P., Perlin, M., Sahai, S., Torrens, M. and Vargas, M.: Rapid urbanization in Tegucigalpa, Honduras. Preparing for the doubling of the city´s population in the next twenty-five years, Woodrow Wilson School of Public and International Affairs, Princenton. [online] Available from: http://wws.princeton.edu/research/final_reports/wws591g_f03.pdf, 2004.

Aronica, G., Hankin, B. and Beven, K.: Uncertainty and equifinality in calibrating distributed roughness coefficients in a flood propagation model with limited data, Adv. Water Resour., 22(4), 349–365, doi:10.1016/S0309-1708(98)00017-7, 1998.

Benson, M. A. and Dalrymple, T.: General field and office procedures for indirect discharge measurements, in Techniques of Water- Resources Investigations of the United States Geological Survey. [online] Available from: http://pubs.usgs.gov/twri/twri3-a1/html/pdf.html, 1967.

Beven, K., Leedal, D., McCarthy, S., Hunter, N. M., Keef, C., Bates, P. D., Neal, J. and Wicks, J.: Framework for Assessing Uncertainty in Fluvial Flood Risk Mapping., 2011.

Beven, K. J.: Environmental Modelling: An Uncertain Future? An introduction to techniques for uncertainty estimation in environmental prediction, Routledge: London., 2009.

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

Beven, K. J. and Kirkby, M. J.: A physically based, variable contributing area model of basin hydrology / Un modèle à base physique de zone d'appel variable de l'hydrologie du bassin versant, Hydrol. Sci. Bull., 24(1), 43–69, doi:10.1080/02626667909491834, 1979.

Bonnifait, L., Delrieu, G., Lay, M. L., Boudevillain, B., Masson, A., Belleudy, P., Gaume, E. and Saulnier, G.-M.: Distributed hydrologic and hydraulic modelling with radar rainfall input: Reconstruction of the 8–9 September 2002 catastrophic flood event in the Gard region, France, Adv. Water Resour., 32(7), 1077–1089, doi:10.1016/j.advwatres.2009.03.007, 2009.

Borga, M., Gaume, E., Creutin, J. D. and Marchi, L.: Surveying flash floods: gauging the ungauged extremes, Hydrol. Process., 22(18), 3883–3885, doi:10.1002/hyp.7111, 2008.

Brandimarte, L. and Di Baldassarre, G.: Uncertainty in design flood profiles derived by hydraulic modelling, Hydrol. Res., 43(6), 753–761, doi:10.2166/nh.2011.086, 2012.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-496, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 28 September 2016

Hydrology and Earth System Sciences Open Access
Discussions

Castellarin, A.: Probabilistic envelope curves for design flood estimation at ungauged sites, Water Resour. Res., 43(4), W04406, doi:10.1029/2005WR004384, 2007.

Castellarin, A., Baldassarre, G. D., Bates, P. D. and Brath, A.: Optimal Cross-Sectional Spacing in Preissmann Scheme 1D Hydrodynamic Models, J. Hydraul. Eng., 135(2), 96–105, doi:10.1061/(ASCE)0733-9429(2009)135:2(96), 2009.

CIAT: Land Use in Honduras, International Center for tropical agriculture., 2007.

Cœur, D. and Lang, M.: Use of documentary sources on past flood events for flood risk management and land planning, Comptes Rendus Geosci., 340(9–10), 644–650, doi:10.1016/j.crte.2008.03.001, 2008.

Cook, J.: Quantifying peak discharges for historical floods, J. Hydrol., 96(1–4), 29–40, doi:10.1016/0022-1694(87)90141-7, 1987.

Dalrymple, T. and Benson, M. A.: Measurement of peak discharge by the slope-area method, in Techniques of Water- Resources Investigations of the United States Geological Survey. [online] Available from: http://pubs.usgs.gov/twri/twri3-a2/pdf/twri_3-A2_a.pdf, 1968.

Delrieu, G., Nicol, J., Yates, E., Kirstetter, P.-E., Creutin, J.-D., Anquetin, S., Obled, C., Saulnier, G.-M., Ducrocq, V., Gaume, E., Payrastre, O., Andrieu, H., Ayral, P.-A., Bouvier, C., Neppel, L., Livet, M., Lang, M., du-Châtelet, J. P., Walpersdorf, A. and Wobrock, W.: The Catastrophic Flash-Flood Event of 8–9 September 2002 in the Gard Region, France: A First Case Study for the Cévennes–Vivarais Mediterranean Hydrometeorological Observatory, J. Hydrometeorol., 6(1), 34–52, doi:10.1175/JHM-400.1, 2005.

Fuentes Andino, D., Beven, K., Kauffeldt, A., Xu, C.-Y., Halldin, S. and Baldassarre, G. D.: Event and model dependent rainfall adjustments to improve discharge predictions, Hydrol. Sci. J., 0(ja), null, doi:10.1080/02626667.2016.1183775, 2016.

Gaume, E. and Borga, M.: Post-flood field investigations in upland catchments after major flash floods: proposal of a methodology and illustrations, J. Flood Risk Manag., 1(4), 175–189, doi:10.1111/j.1753-318X.2008.00023.x, 2008.

Gaume, E., Bain, V., Bernardara, P., Newinger, O., Barbuc, M., Bateman, A., Blaškovičová, L., Blöschl, G., Borga, M., Dumitrescu, A., Daliakopoulos, I., Garcia, J., Irimescu, A., Kohnova, S., Koutroulis, A., Marchi, L., Matreata, S., Medina, V., Preciso, E., Sempere-Torres, D., Stancalie, G., Szolgay, J., Tsanis, I., Velasco, D. and Viglione, A.: A compilation of data on European flash floods, J. Hydrol., 367(1–2), 70–78, doi:10.1016/j.jhydrol.2008.12.028, 2009.

Horritt, M. S. and Bates, P. D.: Evaluation of 1D and 2D numerical models for predicting river flood inundation, J. Hydrol., 268(1–4), 87–99, doi:10.1016/S0022-1694(02)00121-X, 2002.

Horritt, M. S., Bates, P. D., Fewtrell, T. J., Mason, D. C. and Wilson, M. D.: Modelling the hydraulics of the Carlisle 2005 flood event, Proc. Inst. Civ. Eng. - Water Manag., 163(6), 273–281, doi:10.1680/wama.2010.163.6.273, 2010.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-496, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 28 September 2016

Hydrology and Earth System Sciences
Discussions
Open Access

ING: Mapa hydrogeológico de la zona Central de Honduras (The hydrogeological map of the center zone of Honduras), 1996.

Jarrett, R.: Hydrologie and hydraulic research in mountain rivers, Water Resour. Bull., 190, 1990.

Jarrett, R. D.: Errors in slope-area computations of peak discharges in mountain streams, J. Hydrol., 96(1–4), 53–67, doi:10.1016/0022-1694(87)90143-0, 1987.

JICA: On flood control and landslide prevention in Tegucigalpa metropolitan area of the republic of Honduras, Pacific consultants International and Nikken consultants, Tegucigalpa, Honduras., 2002.

Kirkby, M. J.: TOPMODEL: A personal view, Hydrol. Process., 11(9), 1087–1097, doi:10.1002/(SICI)1099-1085(199707)11:9<1087::AID-HYP546>3.0.CO;2-P, 1997.

Kuiper, N. H.: Tests concerning random points on a circle, Indag. Math. Proc., 63, 38–47, doi:10.1016/S1385-7258(60)50006-0, 1960.

Le Boursicaud, R., Pénard, L., Hauet, A., Thollet, F. and Le Coz, J.: Gauging extreme floods on YouTube: application of LSPIV to home movies for the post-event determination of stream discharges, Hydrol. Process., 30(1), 90–105, doi:10.1002/hyp.10532, 2016.

Madhulatha, T. S.: An Overview on Clustering Methods, ArXiv12051117 Cs [online] Available from: http://arxiv.org/abs/1205.1117 (Accessed 18 July 2016), 2012.

Mård Karlsson, J., Skelton, A., Sandén, M., Ioualalen, M., Kaewbanjak, N., Pophet, N., Asavanant, J. and von Matern, A.: Reconstructions of the coastal impact of the 2004 Indian Ocean tsunami in the Khao Lak area, Thailand, J. Geophys. Res. Oceans, 114(C10), C10023, doi:10.1029/2009JC005516, 2009.

Mastin, M.: Flood-hazard mapping in Honduras in response to hurricane Mitch, U.S. Geological Survey, Tacoma, Washington. [online] Available from: http://pubs.usgs.gov/wri/wri014277/pdf/WRIR01-4277.pdf, 2002.

Matthai, H. F.: Measurement of peak discharge at width contractions by indirect methods, in Techniques of Water- Resources Investigations of the United States Geological Survey. [online] Available from: http://pubs.usgs.gov/twri/twri3-a4/pdf/twri_3-A4_a.pdf, 1968.

McCown, S., Ross, T. and Lott, N.: Mitch: The Deadliest Atlantic Hurricane Since 1780, Natl. Ocean. Atmospheric Adm. NOAA [online] Available from: http://www.ncdc.noaa.gov/oa/reports/mitch/mitch.html (Accessed 2 September 2016), 1999.

Montanari, M., Hostache, R., Matgen, P., Schumann, G., Pfister, L. and Hoffmann, L.: Calibration and sequential updating of a coupled hydrologic-hydraulic model using remote sensing-derived water stages, Hydrol Earth Syst Sci, 13(3), 367–380, doi:10.5194/hess-13-367-2009, 2009.

Neal, J., Schumann, G. and Bates, P.: A subgrid channel model for simulating river hydraulics and floodplain inundation over large and data sparse areas, Water Resour. Res., 48(11), W11506, doi:10.1029/2012WR012514, 2012.

Pappenberger, F., Beven, K. J., Hunter, N. M., Bates, P. D., Gouweleeuw, B. T., Thielen, J. and de Roo, A. P. J.: Cascading model uncertainty from medium range weather forecasts (10 days) through a rainfall-runoff model to flood inundation predictions within the European Flood Forecasting System (EFFS), Hydrol Earth Syst Sci, 9(4), 381–393, doi:10.5194/hess-9-381-2005, 2005a.

Pappenberger, F., Beven, K., Horritt, M. and Blazkova, S.: Uncertainty in the calibration of effective roughness parameters in HEC-RAS using inundation and downstream level observations, J. Hydrol., 302(1–4), 46–69, doi:10.1016/j.jhydrol.2004.06.036, 2005b.

Pappenberger, F., Matgen, P., Beven, K. J., Henry, J.-B., Pfister, L. and Fraipont de, P.: Influence of uncertain boundary conditions and model structure on flood inundation predictions, Adv. Water Resour., 29(10), 1430–1449, doi:10.1016/j.advwatres.2005.11.012, 2006.

Pappenberger, F., Beven, K., Frodsham, K., Romanowicz, R. and Matgen, P.: Grasping the unavoidable subjectivity in calibration of flood inundation models: A vulnerability weighted approach, J. Hydrol., 333(2–4), 275–287, doi:10.1016/j.jhydrol.2006.08.017, 2007.

Reuter, H. I., Nelson, A. and Jarvis, A.: An evaluation of void-filling interpolation methods for SRTM data, Int. J. Geogr. Inf. Sci., 21(9), 983–1008, doi:10.1080/13658810601169899, 2007.

Romanowicz, R. and Beven, K.: Estimation of flood inundation probabilities as conditioned on event inundation maps, Water Resour. Res., 39, 12 PP., doi:200310.1029/2001WR001056, 2003.

Schanze, J.: Flood risk management - A basic framework, in Flood Risk Management: Hazards, Vulnerability and Mitigation Measures, Springer Netherlands. [online] Available from: http://www.springerlink.com/content/u27867381875884l/references/, 2006.

Smith, M., Phillips, J. and Spahr, N.: Hurricane Mitch: peak discharge for selected river reaches in Honduras, U.S. Geological Survey. [online] Available from: http://pdf.usaid.gov/pdf_docs/Pnacp984.pdf, 2002.

Smith, R. A. E., Bates, P. D. and Hayes, C.: Evaluation of a coastal flood inundation model using hard and soft data, Environ. Model. Softw., 30, 35–46, doi:10.1016/j.envsoft.2011.11.008, 2012.

Tewolde, M. H. and Smithers, J. C.: Flood routing in ungauged catchments using Muskingum methods, Water SA, 32(3), 379–388, doi:10.4314/wsa.v32i3.5263, 2007.

Todini, E.: A mass conservative and water storage consistent variable parameter Muskingum-Cunge approach, Hydrol Earth Syst Sci, 11(5), 1645–1659, doi:10.5194/hess-11-1645-2007, 2007.

UN/ISDR: Disaster Statistics - UNISDR, [online] Available from: https://www.unisdr.org/we/inform/disaster-statistics (Accessed 7 September 2016), 2016.

Valyrakis, M., Solley, M. and Koursari, E.: Flood Risk Modeling of Urbanized Estuarine Areas under Uncertainty: A Case Study for Whitesands, UK, Br. J. Environ. Clim. Change, 5(2), 147–161, doi:10.9734/BJECC/2015/12915, 2015.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-496, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 28 September 2016

Hydrology and Earth System Sciences
Open Access
Discussions

Table 1 Post–event estimated peak discharge and time of peaks.

Location	Discharge (m^3s^{-1})	Time of peak (day h:min)	Source	Reference number (Figures 1 and 2)
Chiquito River	167	31 Oct 00:00	(Smith et al., 2002)	1
Grande River	2 340	31 Oct 00:00–02:00	(Smith et al., 2002)	2
Choluteca River	4 360	31 Oct 00:30	(Smith et al., 2002)	3
Chiquito River	436	–	(JICA, 2002)	4
Guacerique River	1 177	30 Oct 23:00	(JICA, 2002)	5
Choluteca River	–	31 Oct 01:00	(JICA, 2002)	6
Choluteca River	3 880	–	(JICA, 2002)	7

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-496, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 28 September 2016

Hydrology and Earth System Sciences
Open Access
Discussions

Table 2 Sampling parameter ranges to run the rainfall–runoff model

Parameter	Abbreviation	Unit	Sampling range
Rainfall multiplier	R	(–)	0.4–2.0
Rate of decline of transmissivity	m	(m)	0.005–0.035
Horizontal transmissivity	T_o	(m^2 h^{-1})	0.001–20
Time constant	t_d	(m h^{-1})	1–60
Land–use coefficient	l_u	(m s^{-1})	0.04–0.2
Flood–wave celerity	v_c	(m s^{-1})	1.0–3.5
Maximum soil infiltration rate	i_{max}	(m h^{-1})	0.005–0.03
Main channel roughness coefficient	n_{cu}	(s $m^{-1/3}$)	0.001–0.08

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-496, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 28 September 2016

Hydrology and Earth System Sciences
Open Access
Discussions

Table 3 Sampling range of parameters to run the hydraulic model.

Quantity	Parameter	Abbreviation	Unit	Sampling range
1	Channel width factor	w_f	–	0.5–2.0
1	Slope for downstream boundary condition	b_c	%	0.005–0.03
1	Channel roughness coefficient	n_c	$s\ m^{-1/3}$	0.005–0.3
1	Floodplain roughness coefficient	n_f	$s\ m^{-1/3}$	0.005–0.3
5	Hydrograph for the upstream boundary condition (100 class hydrographs)	–	units	1–100

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-496, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 28 September 2016

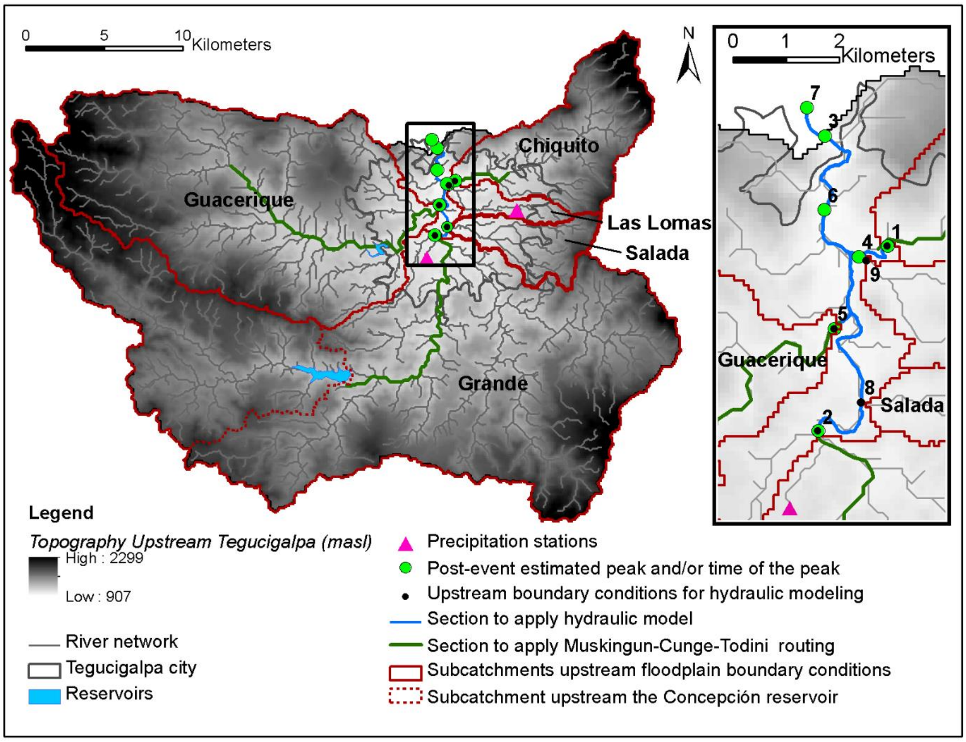

Figure 1 Study area and data location, Topography data from the Shuttle Radar Topography Mission (SRTM).

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-496, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 28 September 2016

Hydrology and Earth System Sciences
Discussions
Open Access

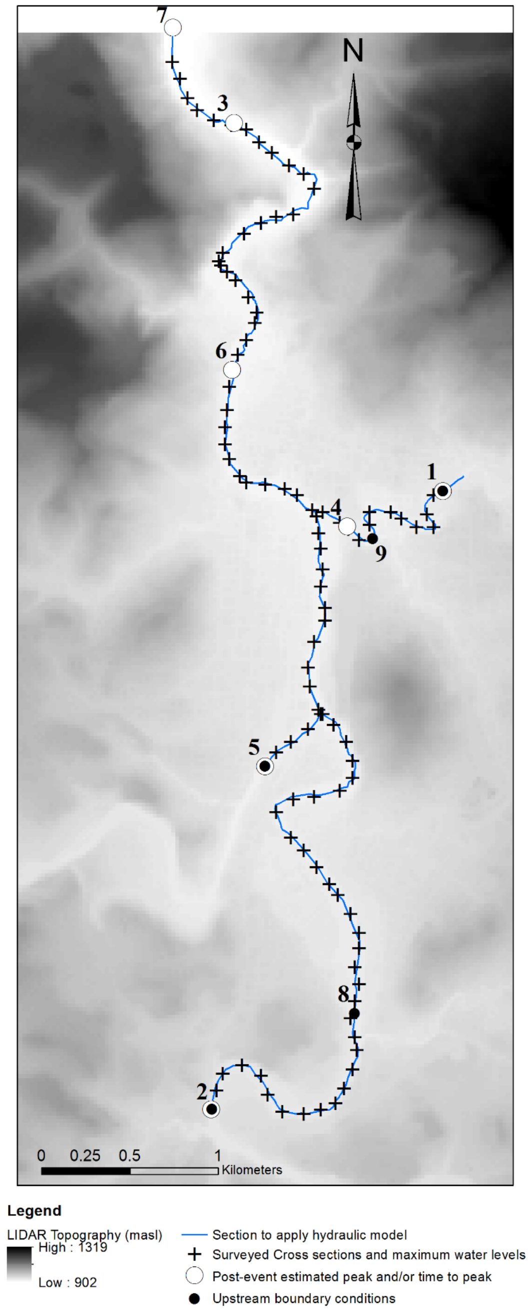

Figure 2 Geometry set–up for hydraulic simulation at the Tegucigalpa floodplain. Lidar data from Mastin (2002)

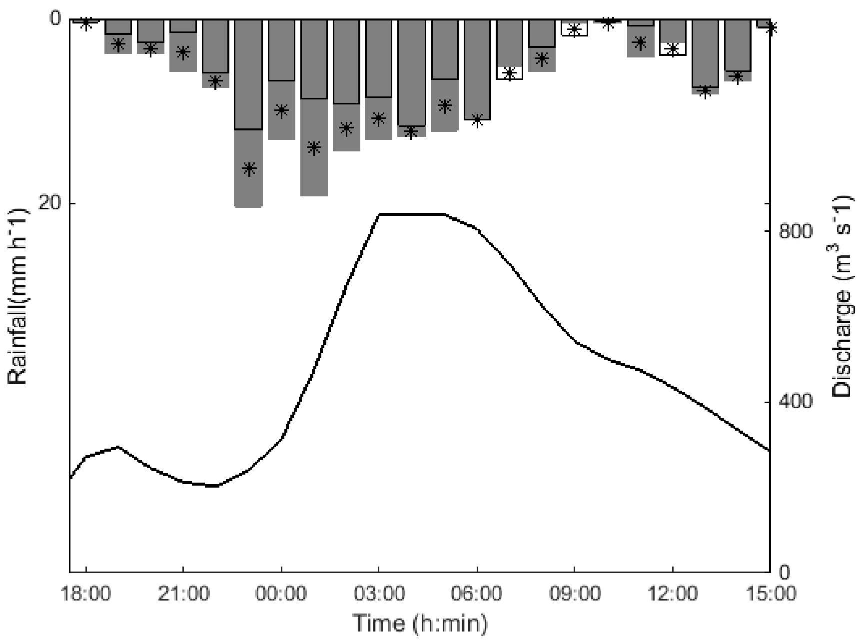

Figure 3 Hourly rainfall on 30–31 October 1998 at SMN station (grey bars), UNAH station (black outlined bars), average of the two stations (asterisks), and measured outflow at Concepción reservoir (continuous line).

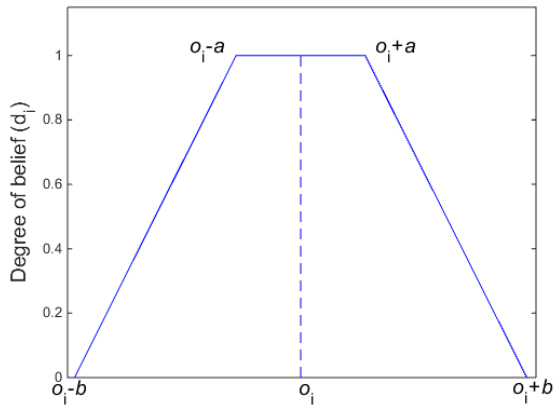

Figure 4 Fuzzy membership function for evaluation of model performance, a and b depend on the uncertainty associated with the evaluation (o_i).

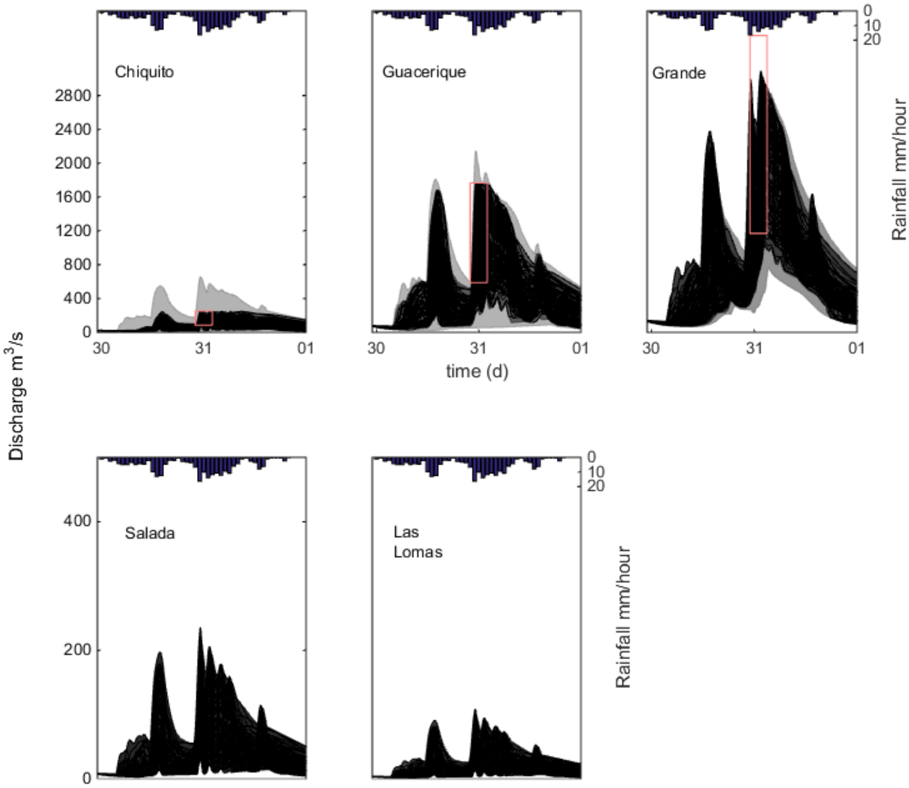

Figure 5 Precipitation (bars) and 100 class hydrographs chosen from the behavioural ones (black plots) for five floodplain–upstream sub–catchments. Predictive range of the 100% probability limits for all hydrographs simulations (grey shaded area) and rectangles representing the fuzzy set to allow for uncertainty for peak discharge and time of the peak for the sub–catchments of the Chiquito, Guacerique and Grande Rivers.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-496, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 28 September 2016

Hydrology and Earth System Sciences
Open Access
Discussions

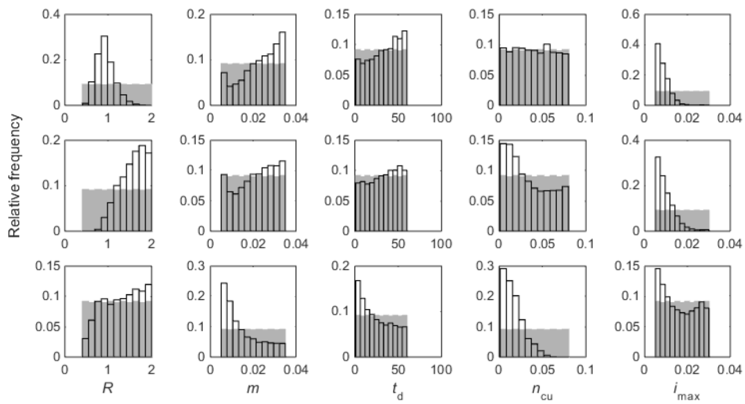

Figure 6 Prior (grey) and posterior (black outlined) relative frequency distribution for the most sensitive rainfall–runoff model parameters: rainfall multiplier (R), rate of depletion (m), time constant (t_d), the main channel roughness coefficient (n_{cu}) and maximum soil infiltration rate ($i_{\max}$) for the Chiquito, Guacerique and Grande catchments (first, second and third row respectively).

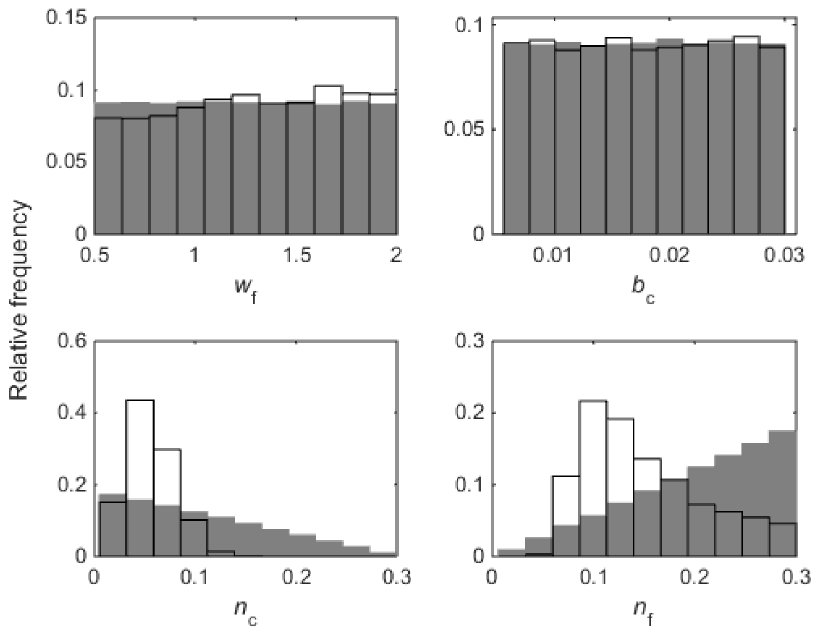

Figure 7 Prior and posterior relative frequency distribution (grey and black outlined bars respectively) of model parameters (width factor, slope for the downstream boundary condition, channel roughness coefficient and floodplain roughness coefficient, w_f, b_c, n_c and n_f respectively).

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-496, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 28 September 2016

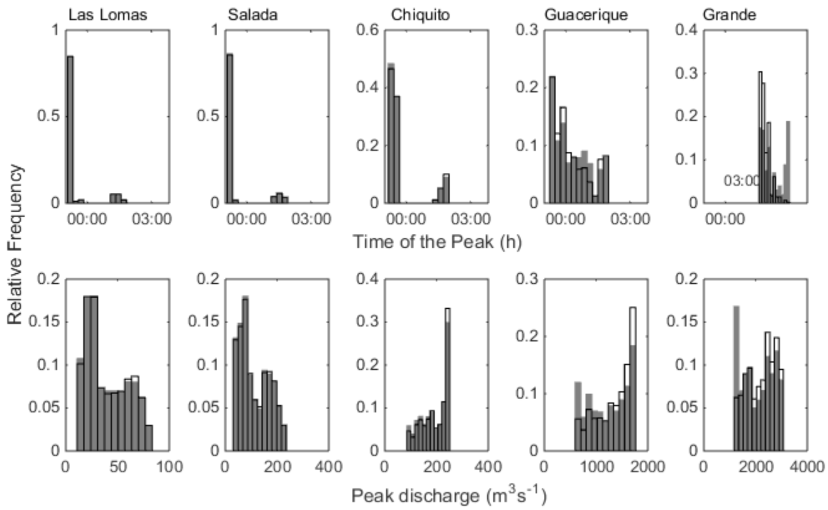

Figure 8 Prior and posterior relative frequency distribution (grey and black outlined bars respectively) of model maximum peak and time of the peak of input hydrographs for boundary conditions.

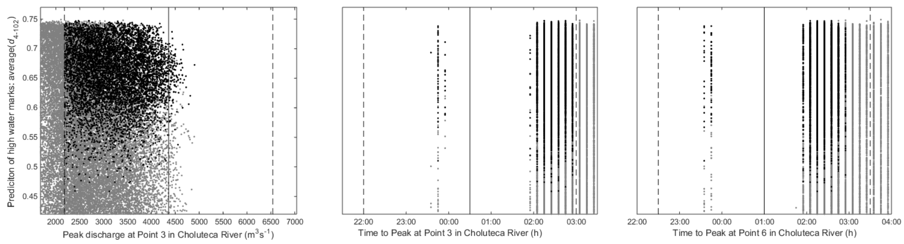

Figure 9 Performance of the model in predicting high water marks, average (d_{4-102}), against predicted maximum peak discharge and two times of peak at Choluteca River (reference points 3 and 6 at Table 1) for non–behavioural simulations (grey dots), behavioural ones (black dots). Observed values and their limits of acceptability are plotted in continues and dotted vertical lines respectively.

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-496, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 28 September 2016

Hydrology and Earth System Sciences
Open Access
Discussions

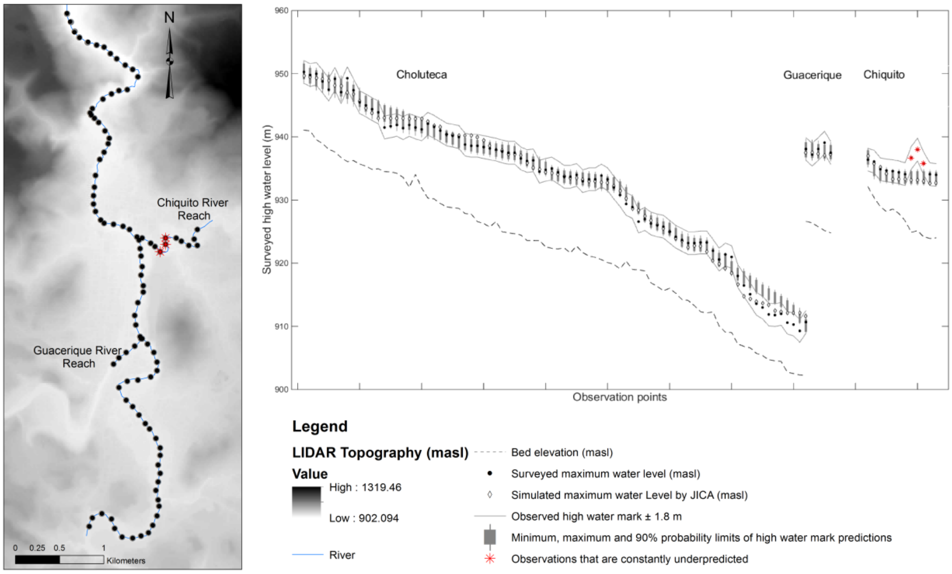

Figure 10 Likelihood of high–water–mark during the Mitch event, considering uncertainty in model parameters, model input and evaluation data to drive and constrain a combination of rainfall–runoff and hydraulic models

Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-496, 2016
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Published: 28 September 2016

Hydrology and Earth System Sciences
Open Access
Discussions

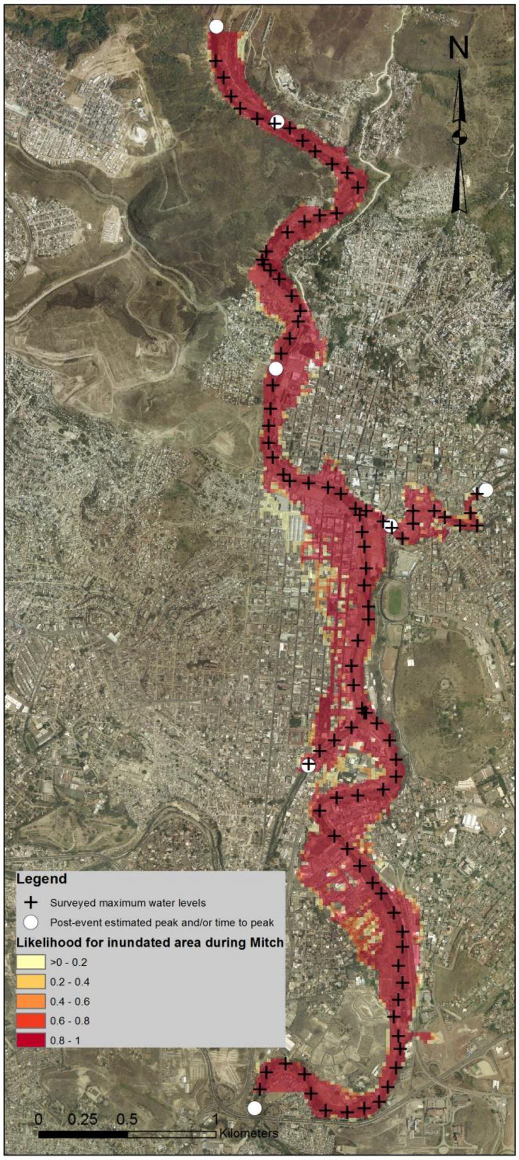

Figure 11 Likelihood of inundated area during the Mitch event on 30–31 October 1998, considering uncertainty in model parameters, model input and evaluation data to drive and constrain a combination of rainfall–runoff and hydraulic models.