

Assessing the impact of different sources of topographic data on 1D hydraulic modelling of floods

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Abstract

Topographic data, such as digital elevation models (DEMs), are essential input in flood inundation modelling. DEMs can be derived from several sources either through remote sensing techniques (space-borne or air-borne imagery) or from traditional methods (ground survey). The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), the Shuttle Radar Topography Mission (SRTM), the Light Detection and Ranging (LiDAR), and topographic contour maps are some of the most commonly used sources of data for DEMs. These DEMs are characterized by different precision and accuracy. On the one hand, the spatial resolution of low-cost DEMs from satellite imagery, such as ASTER and SRTM, is rather coarse (around 30 m to 90 m). On the other hand, LiDAR technique is able to produce a high resolution DEMs (around 1m), but at a much higher cost. Lastly, contour mapping based on ground survey is time consuming, particularly for higher scales, and may not be possible for some remote areas. The use of these different sources of DEM obviously affects the results of flood inundation models. This paper shows and compares a number of hydraulic models developed using HEC-RAS as model code and the aforementioned sources of DEM as geometric input. The study was carried out on a reach of the Johor River, in Malaysia. The effect of the different sources of DEMs (and different resolutions) was investigated by

1 considering the performance of the hydraulic models in simulating flood water levels as well
2 as inundation maps. The outcomes of our study show that the use of different DEMs has
3 serious implications to the results of hydraulic models. The outcomes also indicates the loss
4 of model accuracy due to re-sampling the highest resolution DEM (i.e. LiDAR 1 m) to lower
5 resolution are much less compared to the loss of model accuracy due to the use of low-cost
6 DEM that have not only a lower resolution, but also a lower quality. Lastly, to better explore
7 the sensitivity of the hydraulic models to different DEMs, we performed an uncertainty
8 analysis based on the GLUE methodology.

9

10 **1 Introduction**

11 In hydraulic modelling of floods, one of the most fundamental input data is the geometric
12 description of the floodplains and river channels often provided in the form of digital
13 elevation models (DEM). During the past decades, there has been a significant change in data
14 collection for topographic mapping technique, from conventional ground survey to remote
15 sensing techniques (i.e. radar wave and laser altimetry; e.g. Mark and Bates, 2000; Castellarin
16 et al., 2009). This shift has a number of advantages in terms of processing efficiency, cost
17 effectiveness and accuracy (Bates, 2012; Di Baldassarre and Uhlenbrook, 2012).

18 DEMs can be acquired from many sources of topographic information ranging from the high
19 resolution and accurate, but costly, LiDAR (Light Detection and Ranging) obtained from
20 lower altitude to low-cost, and coarse resolution, space-borne data, such as ASTER
21 (Advanced Spaceborne Thermal Emission and Reflection Radiometer), and SRTM (Shuttle
22 Radar Topography Mission). DEMs can also be developed from traditional ground surveying
23 (e.g. topographic contour maps) by interpolating a number of elevation points.

24 DEM horizontal resolution, vertical precision and accuracy differ considerably. This diversity
25 is caused by the types of equipment and methods used in obtaining the topographic data.
26 When used as an input to hydraulic modelling, the differences in the quality of each DEM
27 subsequently result in differences in model output performance. In addition, re-sampling
28 processes of raster data via Geographic Information System (GIS) may also deteriorate the
29 accuracy of the DEMs. The usefulness of diverse topographic data in supporting hydraulic
30 modelling of floods is subject to the availability of DEMs, economic factors and geographical
31 conditions of survey area (Cobby and Mason, 1999; Casas et al., 2006; Schumann et al.,
32 2008).

1 To date, a number of studies have been carried out with the aim of evaluating the impact of
2 accuracy and precision of the topographic data on the results of hydraulic models (e.g. Table
3 1).

4 Werner (2001) investigated the effect of varying grid element size on flood extent estimation
5 from a 1D model approach based on a LIDAR DEM. The study found that the flood extent
6 estimation increased as the resolution of the DEM becomes coarser.

7 Horrit and Bates (2001) demonstrated the effects of spatial resolution on a raster based flood
8 model simulation. Simulation tests were performed at resolution sizes of 10, 20, 50, 100, 250,
9 500, and 1000 m and the predictions were compared with satellite observations of inundated
10 area and ground measurements of floodwave travel times. They found that the model reached
11 a maximum performance at resolution of 100 m when calibrated against the observed
12 inundated area. The resolution of 500 m proved to be adequate for the prediction of water
13 levels. They also highlighted that the predicted floodwave travel times are strongly dependent
14 on the model resolution used.

15 Wilson and Atkinson (2005) set up a two-dimensional (2D) model, LISFLOOD-FP, using
16 three different DEMs (contour dataset, synthetic-aperture radar (SAR) dataset, and differential
17 global positioning system (DGPS)) used to predict flood inundation for 1998 flood event in
18 the United Kingdom. The results showed that the contour datasets resulted in a substantial
19 difference in the timing and the extent of flood inundation when compared to the DGPS
20 dataset. Although the SAR dataset also showed differences in the timing and the extent, it was
21 not as massive as the contour dataset. Nevertheless, the authors also highlighted a potential
22 problem with the use of satellite remotely sensed topographic data in flood hazard assessment
23 over small areas.

24 Casas et al. (2006) investigated the effects of the topographic data sources and resolution on
25 one-dimensional (1D) hydraulic modelling of floods. They found out that the contour-based
26 digital terrain model (DTM) was the least accurate in the determination of the water level and
27 inundated area of the floodplain, however the global positioning system (GPS)-based DTM
28 lead to a more realistic estimate of the water surface elevation and of the flooded area. The
29 LiDAR-based model produced the most acceptable results in terms of water surface elevation
30 and inundated flooded area compared to the reference data. The authors also pointed out that
31 the different grid sizes used in LiDAR data has no significant effect on the determination of
32 the water surface elevation. In addition, from an analysis of the time-cost ratio for each DEMs

1 used, they concluded that the most cost effective technique for developing a DEM by means
2 of an acceptable accuracy is from laser altimetry survey (LIDAR), especially for large areas.

3 Schumann et al. (2008) demonstrated the effects of DEMs on deriving the water stage and
4 inundation area. Three DEMs at three different resolutions from three sources (LiDAR,
5 contour and SRTM DEM) were used for a study area in Luxembourg. By using the HEC-RAS
6 1D hydraulic model to simulate the flood propagation, the result shows that, the LiDAR DEM
7 derived water stages by displaying the lowest RMSE, followed by the contour DEM and
8 lastly the SRTM. Considering the performance of the SRTM (it was relatively good with
9 RMSE of 1.07 m), they suggested that the SRTM DEM is a valuable source for initial vital
10 flood information extraction in large, homogeneous floodplains.

11 For the large flood prone area, the availability of DEM from public domain (e.g. ASTER,
12 SRTM) makes it easier to conduct a study. Patro et al. (2009) selected a study area in India
13 and demonstrated the usefulness of using SRTM DEM to derive river cross section for the use
14 in hydraulic modelling. They found that the calibration and validation results from the
15 hydraulic model performed quite satisfactory in simulating the river flow. Furthermore, the
16 model performed quite well in simulating the peak flow which is important in flood
17 modelling. The study by Tarekegn et al. (2010) carried out on a study area in Ethiopia used a
18 DEM which was generated from ASTER image. Integration between remote sensing and GIS
19 technique were needed to construct the floodplain terrain and channel bathymetry. From the
20 results obtained, they concluded that the ASTER DEM is able to simulate the observed
21 flooding pattern and inundated area extends with reasonable accuracy. Nevertheless, they also
22 highlighted the need of advanced GIS processing knowledge when developing a digital
23 representation of the floodplain and channel terrain.

24 Schumann et al. (2010) demonstrates that near real-time coarse resolution radar imagery of a
25 particular flood event on the River Po (Italy) combined with SRTM terrain height data leads
26 to a water slope remarkably similar to that derived by combining the radar image with highly
27 accurate airborne laser altimetry. Moreover, it showed that this spaceborne flood wave
28 approximation compares well to a hydraulic model thus allowing the performance of the
29 latter, calibrated on a previous event, to be assessed when applied to an event of different
30 magnitude in near real time.

31 Paiva et al. (2011) demonstrated the use of SRTM DEM in a large-scale hydrologic model
32 with a full one-dimensional hydrodynamic module to calculate flow propagation on a

1 complex river network. The study was conducted on one of the major tributaries of the
2 Amazon, the Purus River basin. They found that a model validation using discharge and water
3 level data is capable of reproducing the main hydrological features of the Purus River basin.
4 Furthermore, realistic floodplain inundation maps were derived from the results of the model.
5 The authors concluded that it is possible to employ full hydrodynamic models within large-
6 scale hydrological models even when using limited data for river geometry and floodplain
7 characterization.

8 Moya Quiroga et al. (2013) used Monte Carlo simulation sampling SRTM DEM elevation,
9 and found a considerable influence of the SRTM uncertainty on the inundation area (the
10 HEC-RAS hydraulic model of the Timis-Bega basin in Romania was employed).

11 Most recently, Yan et al. (2013) made a comparison between a hydraulic model based on
12 LiDAR and SRTM DEM. Besides the DEM inaccuracy, they also introduced the uncertainty
13 analysis by considering parameter and inflow uncertainty. The results of this study showed
14 that the differences between the LiDAR-based model and the SRTM-based model are
15 significant, but within the accuracy that is typically associated with large-scale flood studies.

16 Yet, the aforementioned studies explored the impact of topographic input data on the results
17 flood inundation models by considering either the accuracy (or quality) or the precision (or
18 resolution) of the DEMs (Table 1). When both accuracy and precision were considered
19 (Casas, 2006), model results were not compared to observations via calibration and validation
20 exercises. This paper continues the presented line of research and deals with the assessment of
21 the effects of using different DEM data source and resolution in a 1D hydraulic modelling of
22 floods. The novelty of our study is that both accuracy and precision of the DEM are explicitly
23 considered and their impacts on hydraulic model results is evaluated in terms of both water
24 surface elevation and inundation area. Furthermore, we compare model results via
25 independent calibration and validation exercises and by explicitly considering parameter
26 uncertainty and its potential compensation of inaccuracy of topographic data.

27 Hence, the goal of our paper is not to validate a specific approach for producing flood
28 inundation maps, but rather to contribute to the existing literature with an original approach
29 assessing the impact of topographic input data on hydraulic modelling of floods.

30

1 **2 Study area and available data**

2 **2.1 Study area**

3 The study area is located within the Johor River Basin in the State of Johor, Malaysia. The
4 river basin has a total area of 2,690 km². The test site is a 30 km reach of the Johor River. The
5 Johor River channel has a bankfull depth between 5 and 8 m and average slope around 0.03%.
6 The river reach under study is characterised by a stable main channel from 50 m to 250 m
7 wide. The study area consists of agricultural land, residential and commercial areas (see Fig.
8 1). As reported by Department of Irrigation and Drainage, Malaysia (DID, 2009), this test site
9 has been experiencing some major historical flood events since 1948. The most recent ones
10 happened in December 2006 and January 2007 when more than 3,000 families were
11 evacuated.

12 **2.2 Hydraulic modelling**

13 Flood inundation modelling was carried out by using the model code HEC-RAS , which was
14 developed by Hydrologic Engineering Center (HEC) of the United States Army Corps of
15 Engineers Hydrologic Engineering Center (USACE, 2010). HEC-RAS is a 1D model that can
16 simulate both steady and unsteady flow conditions. In this study, all simulations were
17 performed under unsteady flow conditions. To simulate open channel flows, HEC-RAS
18 numerically solves the full 1D Saint-Venant equations. The HEC-RAS model was set up
19 using 32 cross-sections, whose topography is derived by different DEMs (see below). The
20 observed flow hydrograph at an hourly time step was used as upstream boundary condition,
21 while the friction slope was used as downstream boundary condition. The next section reports
22 the different sources of topographic data used to define the geometric input. To develop flood
23 inundation maps, the results were post-processed by using HEC-GeoRAS, an ArcGIS
24 extension.

25 1D hydraulic modelling does not properly simulate river hydraulics and floodplain flows.
26 However, while 2D models tend to schematize better flood inundation processes, they do not
27 necessarily perform better when applied to real world case studies because, besides model
28 structure, many other sources of uncertainty affect model results (Werner 2001; Bates et al.,
29 2003; Pappenberger et al., 2005; Merwade et al., 2008; Di Baldassarre et al., 2009; Di
30 Baldassarre et al., 2010). A number of authors have carried out comparative studies and

1 showed that the performance of 1D models are often very close to the one of 2D models (e.g.
2 Horrit and Bates 2002; Castellarin et al., 2009; Cook and Merwade 2009). Also, 1D models
3 are typically more efficient than 2D models from a computation viewpoint, allowing for
4 numerous simulations and uncertainty analysis to be carried out. In our case study, for a given
5 flow, topography, river reach and a number of simulations, a HEC-RAS simulation
6 (excluding post-processing GIS) took only 4 hours to predict inundated area, whereas
7 LISFLOOD-FP took around 26 hours.

8 Anyhow, to properly test our model selection, we carried out a number of additional
9 experiments (see Section 4.2) and compared the results of 1D models to the results obtained
10 with a 2D model (LISFLOOD-FP; e.g. Hunter et al., 2006; Bates et al., 2010; Neal et al.,
11 2012; Coulthard et al., 2013).

12 **2.3 Digital Elevation Model**

13 The required input data for the HEC-RAS include the geometry of the floodplain and the
14 river, which is provided by a number of cross sections. We identified several sources of DEM
15 data for our study area (details are given below) with different spatial resolution and accuracy
16 (Fig. 2):

- 17 i. DEMs derived from an original 1 m LiDAR dataset (obtained from DID).
- 18 ii. 20 m resolution DEM generated from the vectorial 1:25000 cartography map obtained
19 from DID with a permission of the Department of Survey and Mapping, Malaysia
20 (DSMP).
- 21 iii. 30 m resolution DEM derived from the globally and freely available ASTER data
22 retrieved from the United States Geological Survey (USGS,
23 <http://earthexplorer.usgs.gov>)
- 24 iv. 90 m resolution DEM derived from the globally and freely available SRTM data
25 retrieved from a Consortium for Spatial Information (CGIAR-CSI, [www.cgiar-](http://www.cgiar-csi.org)
26 [csi.org](http://www.cgiar-csi.org)).

27 To analyse the influence of spatial resolution and separate it out from the impact of different
28 accuracy, four additional DEMs were obtained by rescaling the original LiDAR DEM (1 m
29 resolution) to the spatial resolutions of the DEMs derived from vectorial cartography (20 m),
30 ASTER (30 m) and SRTM (90 m). Hence, a total of eight DEMs were used (see Table 2) to
31 explore the impact of different topographic information on the hydraulic modelling of floods.

1 Given that the laser/radar waves used in the remote sensing techniques are not capable of
2 penetrating the water surface and capture the river bed elevations, all the DEMs were
3 integrated with river cross section data derived from traditional ground survey. The ground
4 survey of the river cross sections within the study area was systematically carried out at about
5 1000 m intervals. Then, the flood simulation results across different data sets were compared
6 to evaluate the effects of data spatial resolutions and data source differences.

7

8 **3 Methodology**

9 **3.1 Evaluating the DEMs quality**

10 At first, the vertical error of each DEM was evaluated through comparison between the
11 topographic data and 164 Global Positioning System (GPS) ground points taken at random
12 positions within the study area. The value of each reference elevation points were extracted
13 from the study area using GPS survey equipment. The quality of each DEM is referred by the
14 Root Mean Square Error ($RMSE_{DEM}$) and Mean Error (ME_{DEM}). The equation is as follows:

$$15 \quad RMSE_{DEM} = \sqrt{\frac{\sum_{i=1}^n (Elev_{GPS} - Elev_{DEM})^2}{n}} \quad (1)$$

16 where $Elev_{GPS}$ is the reference elevation (m) derived from GPS, $Elev_{DEM}$ is the corresponding
17 value derived from each DEM, and n corresponds to the total numbers of points.

18 **3.2 Model calibration and validation**

19 Then, data from two recent major flood events that occurred along the Johor River in 2006
20 and 2007 were used for independent calibration and validation of the models. The estimated
21 peak flow of the 2006 event is approximately 375 m³/s, while the one of the 2007 event is
22 around 595 m³/s. Both discharge data were measured and recorded at Rantau Panjang
23 hydrological station. The 2006 flood data were used for the calibration exercise, while the
24 2007 flood data were used for model validation.

25 To assess the sensitivity of the different models to the model parameters, the Manning's n
26 roughness coefficients for all the models were sampled uniformly from 0.02 to 0.08 m^{-1/3}s for
27 the river channel, and between 0.03 and 0.10 m^{-1/3}s for the floodplain, by steps of 0.0025 m^{-1/3}s

1 ^{1/3}s. The performance of the hydraulic models in producing the observed water levels was
2 assessed by means of the Mean Absolute Error (MAE):

$$3 \quad MAE = \frac{1}{T} \sum_{t=1}^T |O_t - S_t| \quad (2)$$

4 where T is the number of steps in time series, O_t is the observed water level at time t , and S_t is
5 the simulated water level at time t .

6 **3.3 Quantifying the effect of the topographic data source on the water surface** 7 **elevation and inundation area (sensitivity analysis)**

8 The effects of DEM source and spatial resolution were further investigated by examining the
9 sensitivity of model results in terms of maximum water surface elevation (WSE), inundation
10 area and floodplain boundaries. For this additional analysis, the model results obtained with
11 the most accurate and precise DEM source (LiDAR at 1 m resolution) was used as a
12 reference. For WSE analysis, each model was compared to the reference model (Jhr L1, see
13 Table 1) by means of the following measures:

$$14 \quad MAD_{WSE} = \frac{1}{x} \sum_{x=1}^x |WSE_{Ref} - WSE_{DEM}| \quad (3)$$

15 where WSE_{Ref} denotes the WSE simulated by the reference model (Jhr L1), WSE_{DEM} the WSE
16 estimated by the models based on DEMs of lower resolution or different source (Table 1), and
17 x corresponds to the total number of cross sections where models results were compared.

18 To analyse the sensitivity to different topographic input in terms of simulated flood extent, we
19 used the following measure of fit:

$$20 \quad F(\%) = \frac{M_1 \cap M_2}{M_1 \cup M_2} \cdot 100 \quad (4)$$

21 where M_1 and M_2 are the simulated and observed (i.e. simulated by the reference model)
22 inundation areas, and \cup and \cap are the union and intersection GIS operations respectively. F
23 equal to 100% indicates that the two areas are completely coincidental.

24 **3.4 Uncertainty Estimation – GLUE analysis**

25 In hydraulic modelling, multiple sources of uncertainty can emerge from several factors, such
26 as model structure, topography, and friction coefficients (Aronica et al., 2002; Trigg et al.,

1 2009; Brandimarte and Baldassarre, 2012; Dottori et al., 2013). A methodological approach to
 2 estimate the uncertainty is the generalised likelihood uncertainty estimation (GLUE)
 3 methodology (Beven and Binley, 1992), a variant of Monte Carlo simulation. Although some
 4 aspects of this methodology are criticized in several papers (e.g. Hunter et al., 2005;
 5 Mantovan and Todini, 2006; Montanari, 2005; Stedinger et al., 2008), it is still widely used in
 6 hydrological modelling because of its easiness in implementation and a common-sense
 7 approach to use only a set of the “best” models for uncertainty analysis (e.g. Hunter et al.,
 8 2005; Shrestha et al., 2009; Vázquez et al., 2009; Krueger et al., 2010; Jung and Merwade,
 9 2012; Brandimarte and Woldeyes, 2013).

10 According to the GLUE framework (Beven and Binley, 1992), each simulation, i , is
 11 associated to the (generalized) likelihood weight, W_i , ranging from 0 to 1. The weight, W_i is
 12 expressed as a function of the measure fit, ε_i , of the behavioural models.

$$13 \quad W_i = \frac{\varepsilon_{max} - \varepsilon_i}{\varepsilon_{max} - \varepsilon_{min}} \quad (5)$$

14 where, ε_{max} and ε_{min} are the maximum and minimum value of MAE of behavioural models.
 15 To identify the behavioural of the models, a threshold value (rejection criteria) has been set as
 16 follows:

- 17 i. simulations associated with MAE larger than 1.0 m; and
- 18 ii. Manning’s n roughness coefficient of the floodplain smaller than the Manning’s n
 19 roughness coefficient of the channel.

20 Then, the likelihood weights are the cumulative sum of 1 and the weighted 5th, 50th and 95th
 21 percentiles. The likelihood weights were calculated as follow:

$$22 \quad L_i = \frac{W_i}{\sum_{i=1}^n W_i} \quad (6)$$

23 For this study, the applications of uncertainty analysis considered only the parameter
 24 uncertainty and implemented for all DEMs based model.

25

1 **4 Results and discussion**

2 **4.1 Quality of DEMs compared with the reference points**

3 Table 3 shows the calculated statistical vertical errors for each different DEM for the same
4 study area. As anticipated, LiDAR is not only the most precise DEM because of its highest
5 resolution, but also the most accurate. The RMSE of each LiDAR DEMs increased from 0.58
6 m (Jhr L1) to 1.27 m (Jhr L90) as the resolution of the DEMs reduced from 1 m (original
7 resolution) to 90 m.

8 Overall, the terrain is considered well defined under the LiDAR DEMs even though the
9 calculated errors are higher compared to the vertical accuracy reported in product
10 specification (around 0.15 m). Fig. 3 show the distribution of each DEMs compared to the
11 GPS ground elevation.

12 Although LiDAR DEM gives the lowest error, it is useful to note that this type of DEM has a
13 number of limitations as highlighted in the several papers (see Sun et al., 2003; Casas et al.,
14 2006; Schumann et al., 2008):

- 15 i. it provides only discrete surface height samples and not continuous coverage,
- 16 ii. its availability is very much limited by economic constraint,
- 17 iii. its inability to capture the river bed elevations due to the fact the laser does not
18 penetrate the water surface, and
- 19 iv. its incapability to penetrate the ground surface in densely vegetated areas especially
20 for the tropical region.

21 The RMSE value of the other DEMs is 4.66 m for contour maps, 7.01 m for ASTER and 6.47
22 m for SRTM. It's also noticeably that the RMSE of the SRTM DEM for this particular study
23 area is within the average height accuracy found in other SRTM literature either global or at
24 particular continent (see Table 4). Nevertheless, it is proven that this type of DEM gives an
25 acceptable result when used in large scale flood modelling (e.g. Patro et al., 2009; Paiva et al.,
26 2012; Yan et al., 2013).

27 Despite having the lowest vertical accuracies, the ASTER and contour DEMs are still widely
28 used in the field of hydraulic flood research as they are globally available and free (e.g.
29 Tarekegn et al., 2010; Wang et al., 2011; Gichamo et al., 2012). The differences in the vertical
30 accuracies may partly due to the lack of information in topographical flats areas such as

1 floodplains. However, the further use of each DEM in this study is subject to its performance
2 in the hydraulic flood modelling during the calibration and validation stages, which are
3 described in the following sub-section.

4 **4.2 Model calibration and validation**

5 The panels a) to h) of Fig. 4 show the model responses in terms of MAE provided by the eight
6 HEC-RAS models in simulating the 2006 flood event. The models were built using the eight
7 DEMs with different accuracy and precision (Table 2) as topographic input.

8 In general, all models (Fig. 4a-h) showed to be more sensitivity to the changing of Manning's
9 n roughness coefficient of main channel than the Manning's n roughness coefficient of
10 floodplain areas. The results of the calibration showed that the best-fit models based on
11 LiDAR DEM with different resolutions (Jhr L2, Jhr L20, Jhr L30 and Jhr L90) generally gave
12 good performances with only slight variations in the MAE value from 0.38 m to 0.41 m.
13 Nevertheless, the optimum channel and floodplain Manning's n roughness coefficient are
14 centred on similar values at $n_{\text{channel}} = 0.0425$ to 0.0500 and $n_{\text{floodplain}} = 0.0575$ for Jhr L1, Jhr
15 L2, Jhr L20, Jhr L30 and Jhr L90. While, the best-fit models based on topographic map and
16 SRTM also performed well with MAE of 0.31 m and 0.50 m. On the other hand, ASTER-
17 based model completely failed (exceptionally high value of MAE in Fig. 4g are due to model
18 instabilities) and was therefore eliminated from further analysis.

19 Moreover, the panel i) of Fig. 4 shows the outcomes of the additional experiment we carried
20 out to test the appropriateness of selecting a 1D model. In particular, a LISFLOOD-FP model
21 was built using the LiDAR topography rescaled at 90 m and is called here Jhr LF90. The
22 specific topographic input was chosen as a trade-off between computational times and the
23 need for an as-accurate-as-possible DEM for a proper comparison between 1D and 2D
24 modelling. By comparing the calibration results of the LISFLOOD-FP model (Fig. 4i) to the
25 corresponding (i.e. using the same topography) ones of the HEC-RAS model (Fig. 4e), one
26 can observe that differences are not significant. Lastly, Fig.4i shows that LISFLOOD-FP is
27 also more sensitive to the main channel roughness coefficient than to the floodplain one.

28 The best-fit models, using the optimum Manning's n roughness coefficients (Table 5), were
29 then used to simulate the January 2007 flood event for model validation. This was carried out
30 for all models except ASTER based model due to its poor performance (see Fig. 4g). Table 5
31 summarises the MAE of each model obtained during model validation. It is noted that the

1 MAE values for all LiDAR based models (first five rows) with different resolutions remained
2 almost the same with the difference within +0.03 m. The MAE values for the models based on
3 topographic contour maps and SRTM DEM both provides MAE of 0.60 m.

4 The model validation exercise also supports the use of 1D hydraulic models for this river
5 reach. In particular, Table 5 also shows that the LISFLOOD-FP model (Jhr LF90) provided a
6 MAE of 0.52 m, while the corresponding HEC-RAS model (Jhr L90) provided a MAE equal
7 to 0.39 m. Thus, the 1D model performed even (slightly) better than the 2D model.

8 The results of this first analysis suggest that the reduction in the resolution of LiDAR DEMs
9 (from 1 m to 90 m) does not significantly affect the model performance. However, the use of
10 topographic contour maps (Jhr T20) and SRTM (Jhr S90) DEMs as geometric input to the
11 hydraulic model produces a slight increase of model errors. For instance, Jhr L90 and Jhr S90
12 have the same resolution (90 m), but the different accuracy results into increased (though not
13 remarkably) errors in model validation (from 0.39 m to 0.60 m). This limited degradation of
14 model performance (Table 5), in spite of the much lower accuracy of topographic input (Table
15 2) can be attributed to the fact that models are compared to water levels observed in two
16 cross-sections. A spatially distributed analysis (comparing the simulated flood extent and
17 flood water profile along the river) might show more significant differences (see Section 4.3).

18 **4.3 Quantifying the effect of the topographic data source on the water surface** 19 **elevation and inundation area on 1D model**

20 **4.3.1 Inundation area (sensitivity analysis)**

21 This section reports an additional analysis aiming to better explore the sensitivity of model
22 results to different topographic data (see Section 3.3). Fig. 5 shows the simulated flood extent
23 maps obtained from the seven different topographic input data. The floodplain areas
24 simulated by the five LiDAR-based models (Jhr L1, Jhr L2, Jhr L20, Jhr L30 and Jhr L90) are
25 very similar. In contrast, the floodplain areas simulated by the models based on topographic
26 contour maps (Jhr T20) and SRTM DEM (Jhr S90) are substantially different (see Fig. 5 and
27 Table 6).

28 Table 6 shows the comparison between the different models in terms of simulating flood
29 extent. The aforementioned measure of fit F was found to decrease for both decreasing
30 resolution and lowering accuracy. This sensitivity analysis also shows that the results of flood

1 inundation models are more affected by the accuracy of the DEM used as topographic input
2 than its resolution.

3 **4.3.2 Water surface elevation**

4 Fig. 6 compares the flood water profiles simulated by the reference model (Jhr L1) with the
5 flood water profiles (WSE) obtained from the other six models (Jhr L2, Jhr L20, Jhr L30, Jhr
6 L90, Jhr T20 and Jhr S90). All these flood water profiles were obtained by simulating the
7 2007 flood event. Despite having different resolutions, the flood water profiles simulated
8 from all LiDAR-based models portray a similar flood water profiles to the reference model
9 [see Fig. 6(a) to 6(d)]. This is consistent with the findings about the inundation area (Fig. 5).
10 Whereas, flood water profiles simulated by the models based on topographic contour maps
11 and SRTM DEMs [see Fig. 6(e) and 6(f)] are rather different.

12 The discrepancies between the reference model (Jhr L1) and the other models visualized in
13 Fig. 6 are quantified in terms of Mean Absolute Difference (MAD). This shows that the re-
14 sampled LiDAR data (Jhr L2, Jhr L20, Jhr L30 and Jhr L90) have all a low MAD: between
15 0.05 to 0.08 m. Higher discrepancies are found with the models based on SRTM DEM (0.76
16 m) and contour maps (1.12 m). The great differences obtained using the topographic contour
17 maps may be partly due to the way that the DEM height is sampled. For instance, contour
18 DEM in this study were based on topographic contours at 20 m intervals and required
19 interpolation technique to generate a DEM. Table 7 shows the summary of MAD in terms of
20 water surface elevation simulated by the models.

21 **4.3.3 Uncertainty in flood profiles obtained from different DEMs model by** 22 **considering parameter uncertainty**

23 To better interpret the differences that have emerged in comparing the results of models based
24 on different topographic data, we carried out a set of numerical experiments to explore the
25 uncertainty in model parameters. As mentioned, we varied the Manning's n roughness
26 coefficient between 0.02 and 0.08 $\text{m}^{-1/3}\text{s}$, for the river channel, and from 0.03 to 0.10 $\text{m}^{-1/3}\text{s}$,
27 for the floodplain, with steps 0.0025 $\text{m}^{-1/3}\text{s}$. Then, a number of simulations are reject as
28 described in Section 3.4. Fig. 7 shows the uncertainty bounds for the different models. The
29 width of these uncertainty bounds was found to be between 1.5 m and 1.6 m for all models
30 (only parameter uncertainty is considered here). Nevertheless, the model based on contour

1 maps lead to significant differences from the LiDAR based model, even when the uncertainty
2 induced by model parameters is explicitly accounted for [see Fig. 7(e)].

3

4 **5 CONCLUSIONS**

5 This study assessed how different DEMs (derived by various sources of topographic
6 information or diverse resolutions) affect the output of hydraulic modelling. A reach of the
7 Johor River, Malaysia, was used as the test site. The study was performed using a 1D model
8 (HEC-RAS), which was found to perform as better as a 2D model (LISFLOOD-FP) in this
9 case study. The sources of DEMs were LiDAR at 1 m resolution, topographic contour maps at
10 20 m resolution, ASTER data at 30 m resolution, and SRTM data at 90 m resolution. The
11 LiDAR DEM was also re-sampled from its original resolution dataset to 2, 20, 30 and 90 m
12 cell size. Different models were built by using them as geometric input data.

13 The performance of the five LiDAR-based models (characterised by different resolutions
14 ranging from 1 to 90 m; see Table 5) did not show significant differences. Neither in the
15 exercise of independent calibration and validation based on water level observations in an
16 internal cross section, nor in the sensitivity analysis of simulated flood profiles and inundation
17 areas. Another striking result of our study is that the model based on ASTER data completely
18 failed because of major inaccuracies of the DEM.

19 In contrast, the models based on SRTM data and topographic contour maps did relatively well
20 in the validation exercise as they provided a mean absolute error of 0.6 m, which is only
21 slightly higher than the ones obtained with LiDAR-based models (all around 0.4 m). However, this
22 outcome could be attributed to the fact that validation could only be performed by using the
23 water level observed in a two internal cross-sections. As a matter of fact, higher discrepancies
24 emerged when LiDAR-based models are compared to the models based on SRTM data or
25 topographic contour maps in terms of inundation areas or flood water profiles. These
26 differences were found to be relevant even when parameter uncertainty is accounted for.

27 The study also showed that, to support flood inundation models, the quality and accuracy of
28 the DEM is more relevant than the resolution and precision of the DEM. For instance, the
29 model based on the 90 m DEM obtained by re-sampling the LiDAR data performed better
30 than model based on the 90 m DEM obtained from SRTM data. These outcomes are
31 unavoidably associated to the specific test site, but the methodology proposed here can allow

1 a comprehensive assessment of the impact of diverse topographic data on hydraulic modelling
2 of floods for different rivers around the world.

3

4 **Acknowledgments**

5 The authors would like to thank to the Department of Irrigation and Drainage, Malaysia
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7 Service Department, Malaysia for providing a PhD Fellowship funding and study leave for
8 the first author.

9

10

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1 **List of Table**

2 **Table 1.** Summary of studies assessing the impact of topographic input data on the results of flood inundation models

3

Author(s)	Numerical modelling	Calibration ⁺ / validation ⁺⁺ data	Source of DEMs	Type of assessment	Study area
Horrit & Bates (2001)	LISFLOOD-FP/NCFS	SAR flood imagery ⁺	LiDAR	Precision	River Severn, UK.
Werner (2001)	HEC-RAS	N.A.	Laser altimetry data	Precision	River Saar, Germany.
Wilson and Atkinson (2005)	LISFLOOD-FP	SAR flood imagery ⁺⁺	InSAR, topography & GPS	Accuracy	River Nene, UK.
Casas et al. (2006)	HEC-RAS	N.A	GPS, bathymetry, LiDAR & topography	Accuracy & precision	River Ter, Spain.
Schumann et al. (2008)	REFIX & HEC-RAS	Field data ⁺ /1D model output ⁺⁺	LiDAR, SRTM topography	Accuracy	River Alzette, Luxembourg.
Schumann et al. (2010)	HEC-RAS	Field data ⁺ /LiDAR derived water levels ⁺⁺	LiDAR & SRTM	Accuracy	River Po, Italy.
Yan et al. (2013)	HEC-RAS	Field data ⁺ /SAR flood imagery ⁺⁺	LiDAR & SRTM	Accuracy	River Po, Italy.

1 **Table 2.** Information about the eight digital elevation models used as topographical input

Model name	DEM type	Resolution (m)
Jhr L1	LiDAR	1 m
Jhr L2	(re-scaled from LiDAR)	2 m
Jhr L20	(re-scaled from LiDAR)	20 m
Jhr L30	(re-scaled from LiDAR)	30 m
Jhr L90	(re-scaled from LiDAR)	90 m
Jhr T20	Contours maps	20 m
Jhr A30	ASTER	30 m
Jhr S90	SRTM	90 m

2

3 **Table 3.** Statistics of errors (m) of each DEMs with respect to the GPS control points.

Model name	Min. error (m)	Max. error (m)	RMSE (m)
Jhr L1	-0.59	1.00	0.58
Jhr L2	-0.64	1.38	0.58
Jhr L20	-0.83	1.83	0.68
Jhr L30	-0.93	3.98	0.79
Jhr L90	-5.46	3.73	1.27
Jhr T20	-15.38	10.55	4.66
Jhr A30	-33.37	7.58	7.01
Jhr S90	-3.59	4.32	6.47

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1 **Table 4.** Reported vertical accuracies of SRTM data

Reference	Average height accuracy (m)	Continent
Rabus et al. (2003)	6.00	European
Sun et al. (2003)	11.20	European
SRTM mission specification (Rodriguez et al., 2005)	16.00	Global
Berry et al. (2007)	2.54	Eurasia
	3.60	Global
Farr et al. (2007)	6.20	Eurasia
Wang et al. (2011)	13.80	Eurasia

2

3 **Table 5.** Model validation results

Model name	Calibrated Manning's n roughness coefficient		MAE (m) (validation)
	channel	Floodplain	
Jhr L1	0.0500	0.0575	0.40
Jhr L2	0.0450	0.0575	0.38
Jhr L20	0.0425	0.0575	0.37
Jhr L30	0.0450	0.0575	0.38
Jhr L90	0.0450	0.0550	0.39
Jhr T20	0.0500	0.0750	0.60
Jhr S90	0.0375	0.0500	0.60
Jhr LF90	0.0550	0.0700	0.52

4

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1

2 **Table 6.** Effects of DEMs (source and resolution) on HEC-RAS simulations

Model name	Inundation area (km ²)	Area difference (%)	<i>F</i> (%)	<i>F</i> (%) ⁺
Jhr L1	25.86	-	-	-
Jhr L2	25.78	- 0.3	96.6	-
Jhr L20	25.96	0.4	92.9	-
Jhr L30	26.18	1.2	92.2	-
Jhr L90	25.84	- 0.1	89.4	-
Jhr T20	29.23	13.0	73.7	74.2
Jhr S90	16.58	- 35.9	48.9	49.6

3 ⁺*Overlap-fit percentage *F* (%) of the floodplain inundated area with those from LiDAR DEMs*
4 *of the same resolutions (Jhr L20, Jhr L90)*

5

6 **Table 7.** Summary of Mean Absolute Difference (MAD) in terms of water surface elevation
7 simulated by the models

Model name	MAD _{WSE} (m)
Jhr L1	-
Jhr L2	0.06
Jhr L20	0.05
Jhr L30	0.05
Jhr L90	0.08
Jhr T20	1.12
Jhr S90	0.76

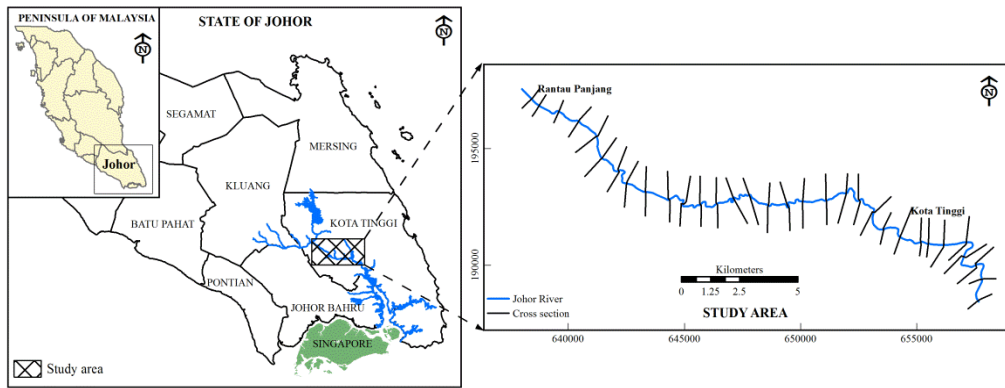
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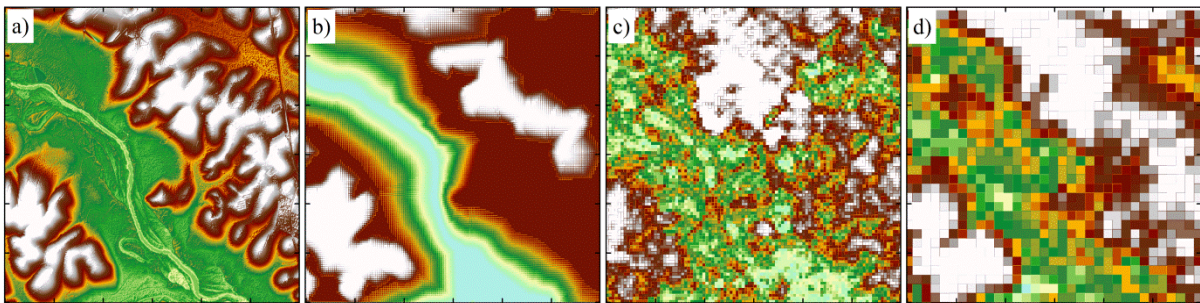
1 **List of Figure**

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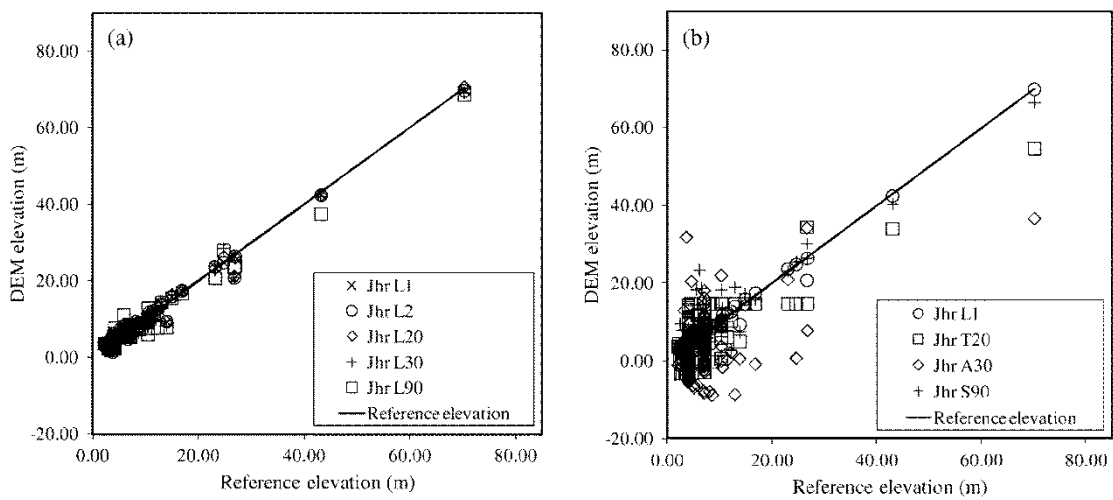
3

4 **Fig. 1.** Layout map of study area: Johor River, Malaysia



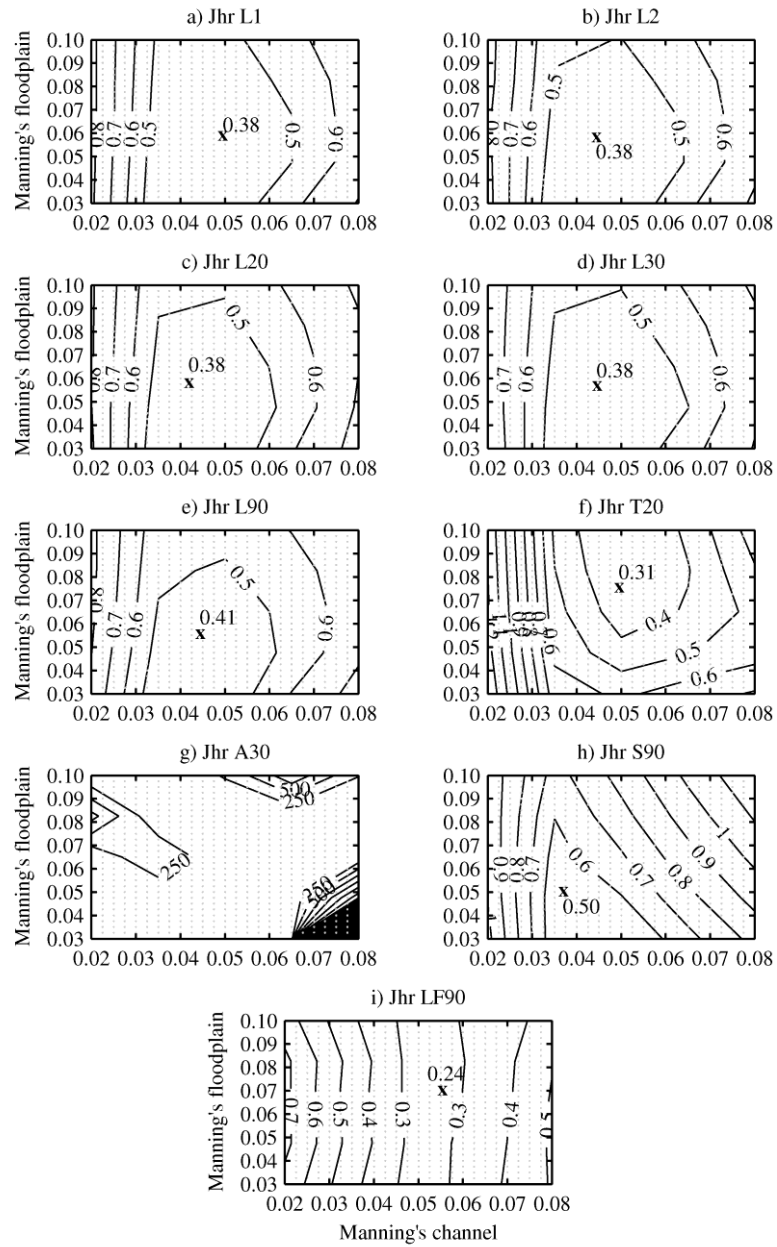
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6 **Fig. 2.** Original DEMs used in this study, based on: a) LiDAR data; b) Contour map; c)
7 ASTER data; and d) SRTM data.



8

9 **Fig. 3.** Comparison between GPS point elevations and elevations derived by the different
10 DEMs: a) LiDAR DEM at different resolution; and b) different sources of DEMs

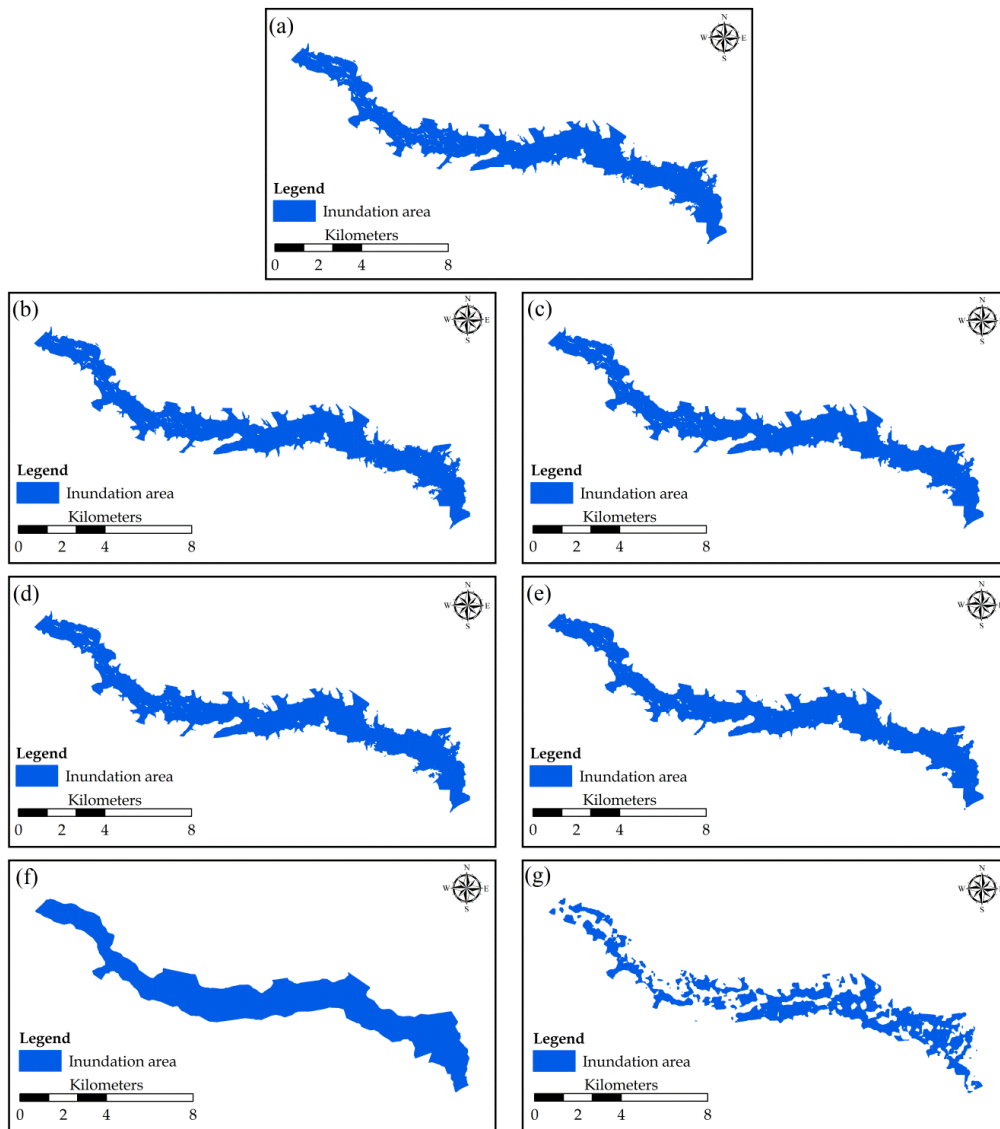


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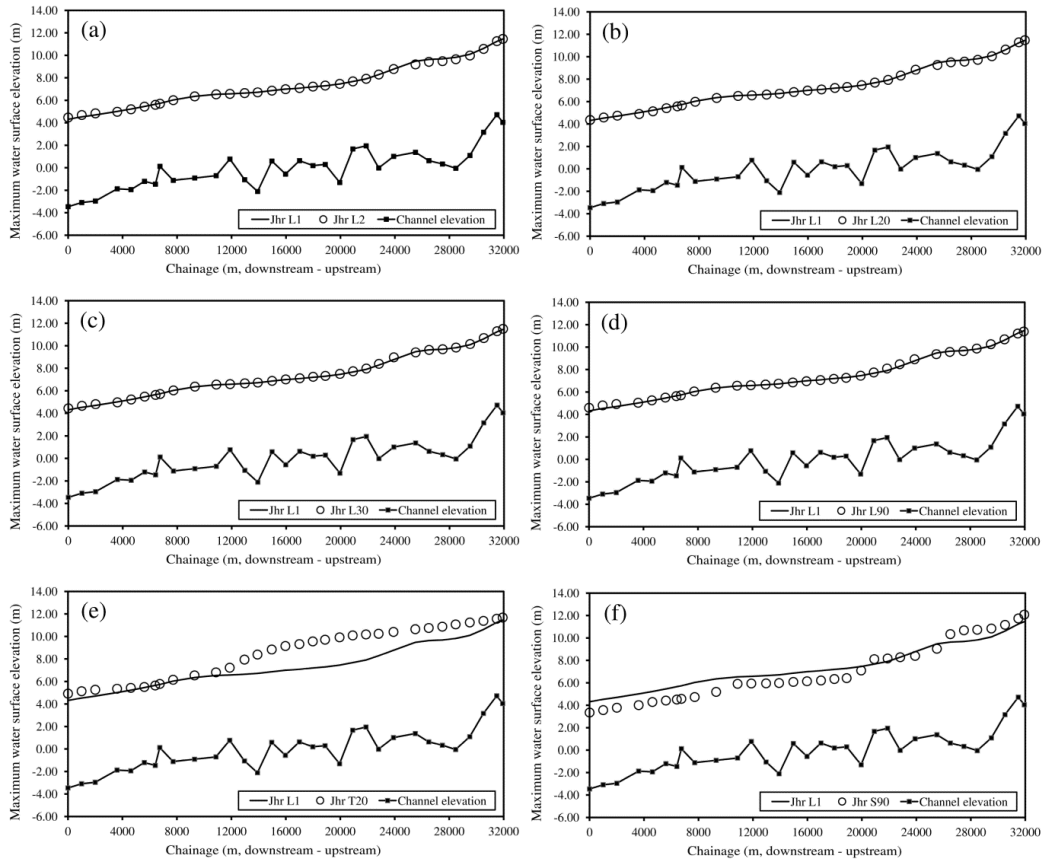
Fig. 4. Model calibration: contour maps of MAE across the parameter space for (a-h) eight different 1D models (HEC-RAS) and (i) for the 2D model (LISFLOOD-FP)

5

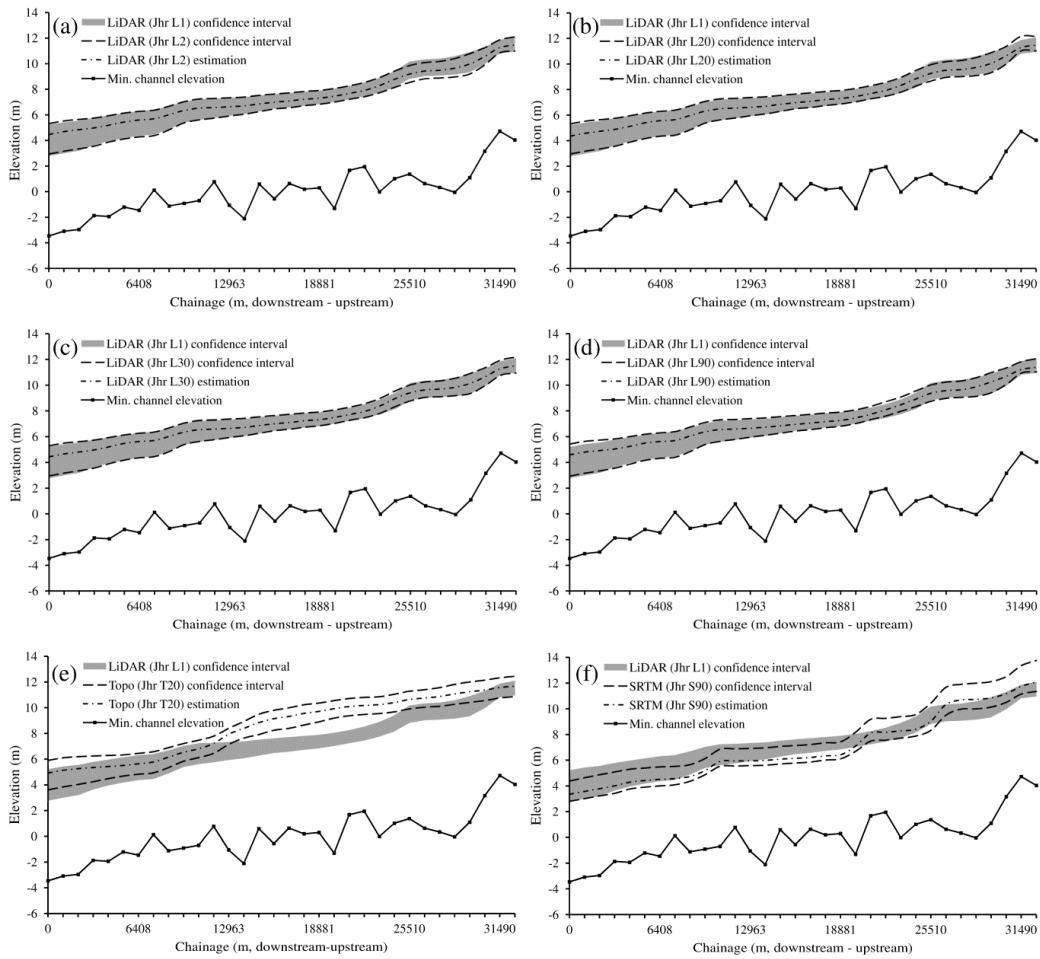


1

2 **Fig. 5.** Effect of DEMs on Johor River. Inundation map resulting from (a) Jhr L1; (b) Jhr L2;
 3 (c) Jhr L20; (d) Jhr L30; (e) Jhr L90; (f) Jhr T20 and (g) Jhr S90



1
 2 **Fig. 6.** Maximum water surface elevation along the Johor River for the six hydraulic models
 3 compared to that simulated by the reference model.



1

2 **Fig. 7.** Comparison of uncertainty bounds (5th, 50th and 95th percentiles by considering
 3 parameter uncertainty only) between the reference model and the other models. The reference
 4 model uncertainty bound are shown in gray areas, while the uncertainty bound of the other six
 5 models are shown in dashed line.

6

7