Referee 1:

We sincerely appreciate the constructive feedback from the reviewer in improving the quality of the manuscript. We have addressed all the review comments in the revised manuscript.

Anonymous Referee:

Thanks for this interesting and informative paper. In general the paper was easy to read, well-structured and complete. The topic of the paper fits to the scope of Natural Hazards and Earth System Sciences in this case to flooding and inundation. The content is relevant to the scientific community and gives substantial contribution to the knowledge in this domain.

The paper is in his core a case study for a specific flood event in Germany. I recommend to specify the natural hazards and target of the 2D modelling (flooding/ inundation) in the title. A generalization of the method to other case studies or other application scenarios would be beneficial for the reader. This could be done in a minor or a major revision. However, the conclusions of the work done should be described and highlighted beyond the model case study in Germany as added value for the reader of the paper. The question, in which way the paper can help other modellers for other case studies, should be answered explicitly.

Authors:

The title has been updated to specify the hazard. The new title following the recommendation is

“Reducing uncertainties in flood inundation outputs of a two-dimensional hydrodynamic model by constraining roughness”

The conclusion section has been revised in the updated manuscript in order to generalization results to other case studies. In addition, more discussion is added as to how this paper can help other modellers.

The followings are our point-by-point responses to the reviewer’s quotes

Anonymous Referee:

1. Page 2 line 11 The coefficient is either measured in the field -> How did you measure the Manning coefficient in the field ? I think the coefficient is not measured but derived from measurements. see same page line 15 -> "therefore, it cannot be measured

exactly"

Authors:

The line has been corrected to “derived from measurements in the field”. Page 2: Line 11-12

“and the term is denoted as Manning’s roughness coefficient or simply Manning’s n in most of HD models”

Anonymous Referee:

2. Introduction- The spatial distribution of the roughness (e.g. in the river bed, in flood plains and in areas with inundation), is missing in the introduction, maybe you can add 1,2 sentences to clarify this problem/challenge.

Authors:

To clarify the problem of the spatial distribution, these sentences have been added in introduction. Page 2:Line 15-17.

"The spatial distribution of the Manning’s n in floodplains is challenging and depend on many factors, such as vegetation type, soil surface and imperviousness (Sellin et al., 2013). Traditionally, this coefficient can be best estimated based on lookup tables of land use types (Werner et al., 2005b)."

Anonymous Referee:

3. The last sentence about the case study in Kulmbach is too short, reading up to here, it is not clear how the flood is triggered (heavy rain -> flash flood in the city, river flood wave inundation, ...) maybe you can add some key words / numbers to classify the case study area in more sentence to characterize the type of flood case study. 3.1 will gives the details later

Authors:

We have provided more details of the flood event. It was induced by a combination of intense rainfall and snowmelt in the catchment. Page 4: Line 17-23

"Intense rainfall and snow melting in the Fichtel mountains caused floods in several rivers of Upper Franconia. On 14th January, the maximum discharge of 92.5 m^3/s was recorded at gauge Kauerndorf and 75.3 m^3/s at gauge Ködnitz. It was one of the biggest in terms of its magnitude and corresponded to a discharge of the 100-year return period at gauge Kauerndorf and the 10-year return period at gauge Ködnitz. Agricultural land and traffic routes were flooded, but no serious damage was reported. In Kulmbach, a dyke in the region of Burghaig was about to collapse due to the large volume of water. The Water Management Authority opened the weir in Kulmbach which saved potential damages (Hof, 2011)."

Anonymous Referee:

4. Page 4 line 15 Please add the term "site" in the sentence, as the 8 bridges are shown as site 1-8 in Figure 1. line 16 Please add a reference to the levelling instrument Ni2 and add some numbers to "high accuracy".

Authors:

The measurements were taken by the experts in the Water Management Authority in Hof, Germany during the flood event. It is believed that they are accurate, however, we are not able to provide any numbers regarding the accuracy. The instrument has its own uncertainties (details in Faig and Kahmen, 2012) but it will be very subjective to add in this paper and not the scope of this paper.

The term "bridges" has been corrected and reference to the instrument has been provided. Page 4: Line 24-25.

"Water levels at eight sites during the winter flood of January 2011 were collected by the Water Management Authority in Hof, Germany in Kulmbach (see Fig. 1a). The water levels were measured using a levelling instrument Ni 2 (Faig & Kahmen 2012)."

Anonymous Referee:

5. line 26 Unterzetlitz is not mentioned in chapter 3.2 as "previous section", please add a sentence in 3.2 as only Kodnitz and Kaurndorf are mentioned and only these two hydrographs are shown. Maybe the discharge of Red Main / Unterzetlitz is not critical for the flooding area, but if you mention it in 3.3 the information should be complete

Authors:

Based on the recommendation, we have omitted Unterzetlitz from the manuscript. The river Red Main (gauging station Unterzetlitz) is downstream of the city and the eight sites assessed in the study. Hence, we believe that presenting discharge data for that particular gauge is irrelevant for this study. Nevertheless, all the discharge data is open and downloadable from the data source provided in Fig. 3: Bavarian Hydrological Service (www.gkd.bayern.de).

Anonymous Referee:

6. line 28 What is "high-quality" DEM, please mention the resolution e.g. in m and how

this is represented and combined in the numerical mesh (terrain, river bed) ?

Authors:

The description has been updated in Page 5: Line 7-12.

"Digital elevation model for this study was provided by the Water Management Authority, Hof and presented in Fig. 1b. In the provided elevation model, the terrain is determined by airborne laser scanning and airborne photogrammetry with a high-resolution of 1 meter, whereas the river bed was mostly recorded by the terrestrial survey. The combined elevation data were used to generate a triangulated irregular network (TIN) of the topography, which was then resampled to an irregular mesh of the 2D HD model. Special attention was given in resampling in order to preserve important features, such as rivers, dykes, buildings and roads."

Anonymous Referee:

7. Chapter 3.2 the time steps given in table 2, assuming it is a global time step. I'm missing in the paper the simulation period (2,5 days ?) maybe one sentence about the required time for one simulation on a specified hardware would be also helpful. Not everyone is reading your two papers 2018a and 2018b before reading this paper, as only 2018b is available at the moment.

Authors:

More details regarding the simulation time is provided in revised version and also in Table 2 for readers .Page 5: Line 16-20

"The HD models were simulated starting at 13.01.2011 00:00 to 14.01.2011 18:00, which requires approximately five hours to simulate an event of 42 hours on an eight-core, Intel® Core™ 2 Duo CPU T7700 @ 2.40 cloud computer with 64 GB RAM. Eight cloud computers using the LRZ Compute Cloud, provided by the Leibniz Supercomputing Centre of the Bavarian Academy of Sciences and Humanities, were used to complete 1000 simulation in two weeks."

Anonymous Referee:

8. Page 5 line 2 Why did you performed 1000 simulations, not 500, not 2000, please add a sentence to validate the number of performed simulations

Authors:

A justification is given in the revised manuscript behind 1000 simulations on Page 5: Line 14-17.

"For the study, we have performed 1000 simulations based on uniformly distributed parameter sets for five land use classes. The sample size does contain enough samples of different behavioural models and the estimate was based on the recommendation in the literature (Aronica et al., 1998; Romanowicz and Beven, 2003) as well as the computational resources available."

Anonymous Referee:

9. line 6 What is a "simple" model ? Is there any model reflecting the "true" distribution of the parameters ? what is the "basin" ? Do you mean model region/area ? line 11 cotton fields and small boulders are confusing here

Authors:

The sentence has been updated in Page 5: Line 24-26

"The model parameter consists of roughness coefficient Manning's n for five land use classes. A simple model structure, such as diffusive wave approximation, does not represent the accurate values of roughness as this parameter is scale-dependent effective values that compensate for varying conceptual errors in the model (Néelz et al., 2009)."

In addition, cotton fields and small boulders have been updated to parks to gravels Page 5: Line 30

“0.040 – 0.080, parks to gravels in urban areas (Arcement and Schneider, 1989).”

Anonymous Referee:

10. Page 6 line 6 I instead of II (2*II)

Authors: Thank you for pointing it out, it has been corrected to cases II and III

Anonymous Referee:

11. line 3 ff This sentence is not clear for me: The sites are located at bridges in the water bodies, this is clear. But the water level is less depending on the landuse at the location more on the upstream flow situation, which type of landuse is there and how much area is flooded (besides water bodies) at upstream. In Figure 2 is shown that the main upstream landuse is water body and agriculture and only for extended

inundation small areas of forest, urban region and transportation -> as there is no Figure with a DEM or with a typical flow situation (flood map), the impact is not clear except for site 1. I propose to add at least one flood map to argument for this sensitivity. As all this is important for interpreting the Figure 5 (a) - (p), maybe a more detailed, structured description of the landuse impact to site 1-8 might be helpful. If finally only two roughness coefficients are sensitive (as first result of the analysis), why the three other parameters has not been eliminated for a 2nd step to rerun the 1000 simulations (with two parameters only, maybe less simulations are needed) and to concentrate on the changes of these two parameters in the parameter sets?

Authors:

We have added both DTM in Fig. 1b and a flood inundation map in Fig. 5 of the study area for the flood event of January 2011.

We appreciate the reviewers' suggestion to concentrate on the changes of these two parameters, however, two roughness were found out to be sensitive as an outcome of the methodology and the idea or focus of this study was not to perform an iterative analysis. We believe that in other study areas using another model structure, might show sensitivity towards other land uses as well. In addition, we also believe that the sensitivity also depends on the land use type of the site. A conclusive remark can only be made if the measured sites are evenly distributed in the model domain in all the land uses

Furthermore, a description of the land use impact has been provided in Page 6: Line 22-27.

"The main reason for the lack of sensitivity can be explained by the location of the sites since they were mainly located next to bridges upstream from water bodies or agriculture land uses. Nonetheless, there are other influencing factors, such as the inundation area, velocity, and topography that could also play a role (Werner et al., 2005b). Fig. 5 shows the maximum flood inundation map for the January 2011 flood event simulated using the optimal model parameters, which were obtained by the least absolute error of 0.20 m. The inundation upstream to the sites is mainly constrained in the water bodies and agricultural land uses, which explains the impact on sensitivity of water levels to these two land uses."

Anonymous Referee:

12. Page 7 The conclusion is more a summary and a outlook, but no conclusion. A generalization of the finding is missing, in which way the reader can benefit from this study ? Are there recommendations to do a similar approach in similar case or a general guideline to reduce the uncertainty bounds for flood modelling

Authors:

We thank the reviewer for pointing it out and we have updated to improve the conclusion section. This part has been added to the generalization of the finding. Page 8: Line 17-22.

"The method is easy to incorporate into other study areas, provided that there are measured water levels available. The uncertainty analysis presented in this study allows a better understanding of the model roughness variability in HD models. The ranges researched for Manning's n in this study can represent a good starting point (prior distribution) for other studies. Our study has shown that there are significant uncertainties in HD model roughness and should be considered in decision-making. In addition, the study highlights the importance of field surveys for reducing the uncertainty in flood inundation outputs."

Anonymous Referee:

What is the consequence for the flood modelling for the city of Kulmbach ? Maybe this question can be discussed in Chapter 4. I can follow the description in Chapter 4, but I missed the consequences for the modelling tasks.

Authors:

The consequence for the flood modelling is highlighted in chapter 4.4. Page 7: Line 7-8

"The impact of reducing the uncertainty is clear in the simulated flood inundation for the city of Kulmbach".

Anonymous Referee:

13. Page 8 line 13-15 the short-cuts for the authors should be not used, who is BGM ?

Authors:

BGM was there by mistake, thank you for pointing it out. The short cut of authors are as per the recommendation of author contributions guidelines and kept the same.

Anonymous Referee:

14. Figure 1 Why did you not use the full width of the page? the figure size could be increased

Authors:

The figure has been increased to full page width. Nevertheless, all the figures will be provided in original form and high-resolution of 300dpi to the journal to ensure high quality.

Anonymous Referee:

15. Figure 2 1st image is fine, but difficult to discover the river bed without zooming in

Authors:

We have replaced Figure 2b, where the river bed is visible, however, there is still some vegetation cover.

Referee 2

Guy J.-P. Schumann:

This paper describes a case study of constraining the model roughness parameter as a means to reduce the overall uncertainty in 2D inundation models.

In general, the paper is well written and, as so many papers around this topic that now start to become quite dated, is an interesting read and debates a very important topic: quite straightforward uncertainty reduction methods are available and should be used and applied much more in practice. Although, this argument was made a lot quite some years ago, I kind of welcome this paper, as it refreshes this important point.

Authors:

We sincerely appreciate the detailed and positive feedback from the reviewer. We also second the opinion of the reviewer that the argument of uncertainty reduction is outdated, especially in operational-use. We hope that we have addressed all the comments satisfactorily in the revised manuscript, which improves the quality of this paper.

The followings are our point-by-point responses to the reviewer's quotes

Guy J.-P. Schumann:

Here are some points that I feel need to be addressed before publication:

In my mind Keith Beven and Florian Pappenberger wrote two of the best papers on this topic, both in 2006 so 13 (or more) years ago, namely:

Beven: https://www.sciencedirect.com/science/article/pii/S002216940500332X
Pappenberger:

https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2005WR004820

While the latter is cited by the authors, the former is not I believe and I think it should because I think it would be very useful in this presented study if the authors put their work in context of those two papers and build a justification around them to state why their presented case study is needed and what makes it different to existing literature, which, although now dated, is substantially large, especially the the 10 years 1998-2009.

Without such a "putting in context", this paper only really refreshes this very well known problem. It is my opinion, that with such a justification, the paper could be published subject to "minor/moderate" revisions but without it, I think it is unclear what new message is presented here.

Authors:

We thank the reviewer for this suggestion, The reference Beven (2006) has been added in the review in the revised manuscript. Page 2: Line 24-29.

“However, effective roughness identified for one flood event might not hold true for another (Romanowicz and Beven, 2003), and a range of parameters should be defined where equifinality can be observed. Beven (2006) argued that the prior selected for the range of parameters should potentially cover all the accepted or behavioural models (modeller types 2 or 3). In HD models, selecting such a prior distribution for model parameter introduces the issue of too wide bounds.”

In addition, the novelty or the research gap has been clearly addressed in the revised version. Page 3: Line 6-8.

“These methods, although widely used in research, are not employed in operational practice, and a straightforward approach is needed to reduce the bounds. Furthermore, there is a need to ensure efficiency in searching model parameter spaces for behavioural models (Beven, 2006).”

Guy J.-P. Schumann:

Also, the authors need to clarify why they did not consider other sources of uncertainty

in their model, such as discharge or downstream boundary condition or indeed topography?

Why only roughness? Also, they should explain why they decided to do 1000

simulations and how this number was decided?

Authors:

A justification is given in the revised manuscript behind 1000 simulations on Page 5: Line 14-17.

"For the study, we have performed 1000 simulations based on uniformly distributed parameter sets for five land use classes. The sample size does contain enough samples of different behavioural models and the estimate was based on the recommendation in the literature (Aronica et al., 1998; Romanowicz and Beven, 2003) as well as the computational resources available."

In addition, more information is provided as to why other sources were not considered in this paper, Page 2: Line 5-7

"In the case of hindcasting a flood event based on measured discharges or water levels as the input boundary conditions and a fine-resolution elevation, roughness remains the main source of uncertainty in HD models; hence we focus this study on roughness uncertainty."

Reducing uncertainties in flood inundation outputs of a two-dimensional hydrodynamic model by constraining roughness

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Abstract. The consideration of uncertainties in flood risk assessment has received increasing attention over the last two decades. However, the assessment is not reported in practice due to the lack of best practices and too wide uncertainty bounds. We present a method to constrain the model roughness based on measured water levels and reduce the uncertainty bounds of a two-dimensional hydrodynamic model. Results show that the maximum uncertainty in roughness generated an uncertainty bound in the water level of 1.26 m (90% confidence interval) and by constraining roughness, the bounds can be reduced as much as 0.92 m.

1 Introduction

Uncertainties in flood risk assessment have received increasing attention from researchers over the last two decades. In Germany, flood risk management plans rely on hydrodynamic (HD) models to determine the impact of flooding for areas of potential flood risk (Thieken et al., 2016). Two-dimensional (2D) HD models are widely used to simulate flood hazards in the form of water depth, inundation extent and flow velocity (Disse et al., 2018). The hazard maps depict inundated areas for floods above certain exceedance levels, which leads to an improvement in flood risk assessment through increased spatial planning and urban development (Hagemeier-Klose, 2007).

Even though HD models are physically deterministic, they contain numerous uncertainties in model outputs (Bates et. al., 2014; Beven et al., 2018). Information about the type and magnitude of these uncertainties is crucial for decision making and to increase confidence in model predictions (Oubennaceur et al., 2018). Despite uncertainties, decision making in practice is based on first-hand data, expert judgement and/or a calibrated model output (Henonin et al., 2013; Uusitalo et al., 2015). Uncertainties associated with exceedance level scenarios are usually not quantified for at least five reasons: 1) most of the sources of uncertainty are not recognized (Bales and Wagner, 2009); 2) the data required to quantify uncertainty are seldom available (Werner et al., 2005a); 3) high computational resources are required to perform an extensive uncertainty assessment; 4) the wide uncertainty bounds cannot be incorporated into the decision making process (Pappenberger and Beven, 2006); and 5) the uncertainty analysis is complex and is not considered for the final decision (Merwade et al., 2008).

The major sources of uncertainty in HD models can be categorized as model structure, model input, model parameters and the modeller (Matott et al., 2009; Schumann et al., 2011). The model structure, essentially either 1D, 2D or hybrid 1D-2D HD code, is generally selected based on the purpose and scale of the modelling (Musall et al., 2011; Bach et al., 2014). In addition, there is no general agreement on the best approach to consider model structure uncertainty; hence, it is often neglected (Oubennaceur et al., 2018). In the case of hindcasting a flood event based on measured discharges or water levels as the input boundary conditions and a fine-resolution elevation, roughness remains the main source of uncertainty in HD models; hence we focus this study on roughness uncertainty.

The precise meaning of *roughness* changes based on a model's physical properties, such as grid resolution and time step (Bates et. al., 2014), and the term is denoted as Manning's roughness coefficient or simply Manning's n in most of HD models. Various studies point out that HD models can be very sensitive to Manning's n, which implies a higher degree of uncertainty (Aronica et al., 1998; Pappenberger et al., 2005; Werner et al., 2005a). The coefficient is either derived from measurements in the field or estimated from the relevant literature on the basis of land use types, but it has proven very difficult to demonstrate that such models can provide accurate predictions using only measured or estimated parameters (Hunter et al., 2007). In addition, Manning's n is not only related to bottom friction but also includes incorrect representation of turbulence losses, 3D effects and incorrect geometry (profiles); therefore, it cannot be measured exactly. The spatial distribution of the Manning's n in floodplains is challenging and depend on many factors, such as vegetation type, soil surface and imperviousness (Sellin et al., 2013). Traditionally, this coefficient can be best estimated based on lookup tables of land use types (Werner et al., 2005b).

In order to understand views on uncertainty analysis, it is important to look at the different modeller types. According to Pappenberger and Beven (2006), there are different modeller types: physically based modellers who believe that their models are physically accurate and that the roughness must not be adjusted under any circumstances; the second modeller type believes that the roughness should be calibrated within a strictly known range (Wagener and Gupta, 2005); and the third modeller type uses effective roughness beyond the accepted range (Pappenberger et al., 2005). The first modeller type would reject any calibration or uncertainty analysis; however, HD models make simplifying assumptions and do not consider all known processes that occur during a flood event (Romanowicz and Beven, 2003). Hence, models are subjected to a degree of structural errors that are typically compensated for by calibrating Manning's n (Bates et. al., 2014). However, effective roughness identified for one flood event might not hold true for another (Romanowicz and Beven, 2003), and a range of parameters should be defined where equifinality can be observed. Beven (2006) argued that the prior selected for the range of parameters should potentially cover all the accepted or behavioural models (modeller types 2 or 3). In HD models, selecting such a prior distribution for model parameter introduces the issue of too wide bounds.

Significant work has been done thus far in the quantification of HD model uncertainties and an overview of selected publications, including model roughness, is presented in Table 1. The major issue of wide uncertainty bounds raised by researchers and practitioners reflects in the table. It shows the maximum bounds reported in each publication and in some cases, these bounds are more than 50% of the available water depth (Aronica et al., 1998; Hall et al., 2005; Werner et al., 2005a; Jung and Merwade, 2012). This is indeed an issue but not a reason to ignore uncertainties in predicting hazards.

Moreover, decision makers must be made aware of potential risks associated with the possible outcomes of predictions, such as water levels and inundation extent (Pappenberger and Beven, 2006; Uusitalo et al., 2015).

The associated uncertainties can be constrained on measured data, if available, using a suitable goodness-of-fit or with the help of a sophisticated framework for assessment (Werner et al., 2005a). Few researchers have used frameworks, such as *Generalized Likelihood Uncertainty Estimation* (GLUE), the *Point Estimate Method* and *Global Sensitivity Analysis*, to reduce the bounds. These methods, although widely used in research, are not employed in operational practice, and a straightforward approach is needed to reduce the bounds. Furthermore, there is a need to ensure efficiency in searching model parameter spaces for behavioural models (Beven, 2006).

This study investigates the use of measured water levels to reduce uncertainties bounds of HD model outputs. We begin with the approach of the third modeller type and select extreme ranges of model roughness in literature and gradually shift to the approach of the second modeller type by reducing the uncertainty bounds based on the measured data. The main focus of this paper is to constrain literature-based ranges of roughness using measured water levels and to assess uncertainties in water levels. Uncertainty is quantified for the flood event of January 2011 in the city of Kulmbach, Germany.

2 Methods

To investigate the effect of measured data on constraining parameters, an ensemble of parameter sets was sampled using a prior distribution. In the HD model, distributed roughness values were used based on land use and a single value was used for each land use class. The model domain was spatially discretized based on the classification of land use and parameter sets were sampled using a prior. The choice of the distribution influences the outcome hence, it should be selected carefully. The 2D HD model was then run with each parameter set. The acceptance of each simulation was assessed by comparing the model outputs and measured data. The measured data can be static or time-series water level measurements in the model domain and/or inundation extent gathered by field survey or post-event satellite images.

The performance of the simulations can be accessed using a suitable goodness-of-fit, such as Nash Sutcliffe efficiency, the coefficient of determination, absolute error etc., based on the purpose of application and measured data available. A behaviour threshold was applied to divide simulations with acceptable performances from those with unacceptable performances. Parameter sets that perform below the threshold were then selected at each location and an intersection at all the locations resulted in the final number of accepted simulations (r) using equation 1

$$r = \bigcap_{i=1}^{n} P_i(GoF \leq e) \qquad (1)$$

Where n is the total number of observations, GoF is the goodness-of-fit used, e is the threshold and P is the array of models that satisfy the criteria of GoF below the threshold.

3 Materials

3.1 Study area and land use

The city of Kulmbach is located in the North-East of the federal state of Bavaria in Southern Germany. The city is categorized as a great district city inhabiting around 26,000 people and a population density of 280 inhabitants per km^2 in an area of 92.8 km^2. The city is crossed by the river White Main and Mühl canal, which is a diversion canal for flood protection. Schorgast and Red Main are two main tributaries that meet the White Main upstream and downstream of the city respectively. In the north, the small tributary Dobrach meets the White Main and from the south side, two stormwater canals join the Mühl canal (see Fig. 1a). Main gauging stations upstream of the city are Ködnitz at White Main and Kauerndorf located at the river Schorgast.

The land use is shown in Fig. 1a and it generally consists of agricultural land (62%) that includes floodplains and grassland. The water bodies make up 7% of the total model area and include rivers, canals and lakes. The urban area covers around 26% of the land and includes industrial and residential areas as well as transport infrastructures like roads and railway tracks, whereas forests form barely 5% of the total area. Fig. 2 shows images of the main channel and flood plain of the river White Main near site 1.

3.2 Measured discharges and water levels

Hydrological measurement data for the winter flood event of January 2011was collected by the Bavarian Hydrological Services. Fig. 3 shows the discharge at the main two gauges upstream of the city, Ködnitz and Kaurndorf. Intense rainfall and snow melting in the Fichtel mountains caused floods in several rivers of Upper Franconia. On 14th January, the maximum discharge of 92.5 m³/s was recorded at gauge Kauerndorf and 75.3 m³/s at gauge Ködnitz. It was one of the biggest in terms of its magnitude and corresponded to a discharge of the 100-year return period at gauge Kauerndorf and the 10-year return period at gauge Ködnitz. Agricultural land and traffic routes were flooded, but no serious damage was reported. In Kulmbach, a dyke in the region of Burghaig was about to collapse due to the large volume of water. The Water Management Authority opened the weir in Kulmbach which saved potential damages (Hof, 2011).

Water levels at eight sites during the winter flood of January 2011 were collected by the Water Management Authority in Hof, Germany in Kulmbach (see Fig. 1a). The water levels were measured using a levelling instrument *Ni 2* (Faig & Kahmen 2012). Based on the locations, the sites are categorized in four groups: sites 1, 2, and 3 at the river White Main; site 4 at Dobrach canal in the north; site 5 at a side canal; and sites 6, 7, and 8 at Mühl canal.

3.3 2D HD model

HEC-RAS 2D was used as the 2D hydrodynamic model to quantify uncertainties in the inundation. The model uses an implicit finite difference solution algorithm to discretise time derivatives and hybrid approximations, combining finite differences and

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finite volumes to discretise spatial derivatives (Brunner, 2010). Table 2 shows the model properties and information of the cell size. We have used the unsteady diffusive wave model presented in previous work in Bhola et al. (2018a and 2018b). Measured discharge hydrographs described in the previous section were used as the upstream boundary condition at river gauges Ködnitz and Kauerndorf, and an energy slope value of 0.0096, based on the river slope, at the downstream boundary where the water flows out of the model domain. Along with the major rivers, canals were also represented as discharge hydrograph type.

Digital elevation model for this study was provided by the Water Management Authority, Hof and presented in Fig. 1b. In the provided elevation model, the terrain is determined by airborne laser scanning and airborne photogrammetry with a high-resolution of 1 meter, whereas the river bed was mostly recorded by the terrestrial survey. The combined elevation data were used to generate a triangulated irregular network (TIN) of the topography, which was then resampled to an irregular mesh of the 2D HD model. Special attention was given in resampling in order to preserve important features, such as rivers, dykes, buildings and roads.

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4 Results and discussion

For the study, we have performed 1000 simulations based on uniformly distributed parameter sets for five land use classes. The sample size does contain enough samples of different behavioural models and the estimate was based on the recommendation in the literature (Aronica et al., 1998; Romanowicz and Beven, 2003) as well as the computational resources available. The HD models were simulated starting at 13.01.2011 00:00 to 14.01.2011 18:00, which requires approximately five hours to simulate an event of 42 hours on an eight-core, Intel® Core™ 2 Duo CPU T7700 @ 2.40 cloud computer with 64 GB RAM. Eight cloud computers using the LRZ Compute Cloud, provided by the Leibniz Supercomputing Centre of the Bavarian Academy of Sciences and Humanities, were used to complete 1000 simulation in two weeks. Measured water levels at eight sites (see section 3.2) were used for the analysis of the model output. The absolute error between the simulated and measured water level is used as the goodness-of-fit to reach the objective.

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4.1 Roughness range and distribution

The model parameter consists of roughness coefficient Manning's n for five land use classes. A simple model structure, such as diffusive wave approximation, does not represent the accurate values of roughness as this parameter is scale-dependent effective values that compensate for varying conceptual errors in the model (Néelz et al., 2009). Hence, it is recommended to use extreme feasible upper and lower ranges for the parameters in the literature (Aronica et al., 1998; Bhola et al., 2018b). In this study, ranges of Manning's n were set as: 0.015 – 0.15 for water bodies, which covers a range from very weedy reaches to rough asphalt; 0.025 – 0.110 for agriculture, short grass to medium-dense brush; 0.110 – 0.200 for forests, dense trees (Chow, 1959); 0.012 – 0.020 for transportation, firm soil to concrete; and 0.040 – 0.080, parks to gravels in urban areas

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(Arcement and Schneider, 1989). Latin hypercube sampling was used to generate 1000 parameter sets using the upper and lower ranges of Manning's n set as prior and HEC-RAS 2D model was simulated for each set.

4.2 Error tolerance

For the analyses, the absolute error between the simulated and the measured water levels was calculated at eight sites. The simulations that produced an absolute error below a threshold at all the sites were selected. Fig. 4 shows that as we increase the threshold, the number of accepted simulations increases. To find one calibrated parameter set, the least value of tolerance can be set at 0.20 m that gives two simulations that result in the least error at all site. Having said that, the calibrated roughness set will probably hold true only for the January 2011 event as discussed in the study (Romanowicz and Beven, 2003). In order to generalize the results to other events and collect enough samples to produce uncertainty bounds, the tolerance needs to be increased. In this study, we have used 1.5 m, 0.70 and 0.50 m as the tolerance at sites to evaluate the roughness sensitivity, which results in 1000, 339 and 143 selected simulations, respectively. Nevertheless, tolerance can be changed depending on the requirements of the user. To summarize, three thresholds are used to evaluate the performance of the method in order to reduce the uncertainty bounds and are termed as follows

- Case I: Absolute error of 1.5 m resulting in 1000 simulations
- Case II: Absolute error of 0.7 m resulting in 339 simulations
- Case III: Absolute error of 0.5 m resulting in 143 simulations

4.3 Roughness sensitivity

The sensitivity of the model roughness was investigated, and it was observed that the sites were only sensitive to land use of water bodies and agriculture and no sensitivity was observed with respect to urban, transportation and forest. Table 3 presents the coefficient of determination (R^2) between Manning's n for all the land uses and absolute error for case I. Site-specific dependency in Manning's n and sites was observed for the cases in which the value of R^2 are found to be above *0.18* (in italic). The main reason for the lack of sensitivity can be explained by the location of the sites since they were mainly located next to bridges upstream from water bodies or agriculture land uses. Nonetheless, there are other influencing factors, such as the inundation area, velocity, and topography that could also play a role (Werner et al., 2005b). Fig. 5 shows the maximum flood inundation map for the January 2011 flood event simulated using the optimal model parameters, which were obtained by the least absolute error of 0.20 m. The inundation upstream to the sites is mainly constrained in the water bodies and agricultural land uses, which explains the impact on sensitivity of water levels to these two land uses.

The sensitivity to the land uses is apparent in the scatter plots between the absolute error and Manning's n shown in Fig. 6. In the figure, it can be observed that the cases II and III (with 339 and 143 accepted simulations) result in an absolute error of less than 0.70 m and 0.50 m at the sites respectively. The selected simulations were further used in refining the uncertainty bounds. Sites 1, 2 and 3 (White Main) show a pattern with agriculture (flood plain): as Manning's n increases, the error reduces until an optimal roughness is obtained and further increase in the roughness value results in an increased error. Sites 6, 7 and

8, located at Mühl canal, show similar sensitivity towards water bodies. In the case of sites 4 and 5, sensitivity is observed for both land use types. The sensitivity found here is also reflected in other studies, such as sensitivity to flood plains (agriculture) (Aronica et al., 1998) and main channel (water bodies) (Hall et al., 2005), and insensitivity to other land uses for flood events (Horritt and Bates, 2002; Werner et al., 2005a).

4.4 Uncertainty of water levels

Table 4 shows 90% confidence interval of the absolute error bounds of the simulated and measured water levels for three cases along with the measured available water depth. The impact of reducing the uncertainty is clear in the simulated flood inundation for the city of Kulmbach; the average uncertainty bound was 0.87 m and after constraining with the measured data, it was reduced to 0.55 m for case II and further reduced to 0.38 in case III. The maximum bound of 1.26 m was observed at site 1, which was reduced to 0.59 and 0.34 m in case II and III respectively. Sites 7 and 8, located on Mühl canal, showed the least effect of 0.12 and 0.11 m reduction in the bounds respectively (case III). Fig. 7 presents a box plot of the difference in the simulated and measured water levels. The pre-selected literature values of Manning's n tend to over-predict the water levels as the mean water level is well above zero at sites in case I. After constraining Manning's n, the mean drops considerably and is still above zero for all sites except 7 and 8 in both cases II and III. The figures also suggest that the simulations can both under- and over-predict the inundation, which might not be desired in some applications, such as early warning and evacuation planning. Furthermore, in situations where few sites are more sensitive/important than others, a weighted goodness-of-fit can also be realized. However, in this study, we have focused on the overall uncertainties, both positive and negative, for a comprehensive assessment.

4.5 Constrained parameter set

The main objective of this study was to reduce the uncertainty bounds of the model output by constraining the prior set for the roughness. In this section, it is shown that the literature-based prior used for Manning's n can be reduced using measured water levels. Fig. 8 presents the box plot of water bodies and agriculture roughness for three cases (1000, 339 and 143 accepted simulations). As stated in the previous section, no sensitivity was observed between the sites and other three land use types. Hence, the uncertainty bounds for other land use classes remain the same after the analysis.

In the case of water bodies, Manning's n gradually concentrated in the range of 0.029 – 0.055 (25 – 75%, case III). The physical interpretation of the constrained coefficient ranges in main channels with stones to sluggish reaches (Chow, 1959). However, for agriculture, the mean dropped considerably from case I to case II and remains consistent in case III. The 25 – 75% bounds of the coefficient were 0.032 – 0.047 (case III) and can be interpreted as high grass to medium brush in the flood plains (Chow, 1959). This compares well to the results of Horritt and Bates (2002) in which they achieved an optimum in the range 0.03 – 0.05 for the main channel and 0.02 – 0.10 for the flood plain roughness of the 2D HD models.

Both the main channel and flood plains are homogenous in the model area and the presence of stones and high grass is observed in the field (see Fig. 2). It was discussed previously in the Introduction, that the second modeller type believes that Manning's n should be varied in a strictly known range based on field experiments. But these ranges can also be defined using a data-driven approach with the method presented. However, a detailed field experiment in the study area will be required to make a conclusive remark for a comparison between the field and evaluated coefficients. Furthermore, these ranges may vary for summer and winter events and various HD models can be build up depending on the season.

5 Conclusions

We have quantified the uncertainty associated with the model parameter for the flood event of January 2011 in the city of Kulmbach, Germany. Moreover, the study provides a comprehensive review of HD model uncertainty and explores the issue of high uncertainty bounds, which hinder users to analyse uncertainties. We have provided a straightforward approach to practitioners for searching model parameter spaces for behavioural models and subsequently reduce the flood inundation uncertainty bounds. Extreme ranges of model roughness in the literature were selected and 1000 uniformly distributed models were run, which resulted in wide uncertainty bounds of up to 1.26 m (90% confidence interval). To reduce the bounds, measured water levels at eight sites were used and three cases were selected on the basis of absolute error threshold values of 1.5, 0.7 and 0.5 m, which resulted in 1000, 343 and 143 accepted simulations respectively. By constraining the roughness, the bounds were reduced to a maximum of 0.34 m. In addition, the model roughness was constrained, and the physical interpretation of the constrained roughness was discussed. The model roughness was spatially distributed based on five land uses and the model was sensitive only to water bodies and agriculture.

The method is easy to incorporate into other study areas, provided that there are measured water levels available. The uncertainty analysis presented in this study allows a better understanding of the model roughness variability in HD models. The ranges researched for Manning's n in this study can represent a good starting point (prior distribution) for other studies. Our study has shown that there are significant uncertainties in HD model roughness and should be considered in decision-making. In addition, the study highlights the importance of field surveys for reducing the uncertainty in flood inundation outputs.

On an urban scale, the uncertainty assessment presented would substantially improve emergency responses by assessing the potential consequences of flood events (Molinari et al., 2014), and disaster relief organisations, such as the Federal Agency for Technical Relief (THW), the German Red Cross, and the Bavarian Water Authorities, would indeed benefit from prioritising and coordinating evacuation planning. For advanced users such as decision-makers in water management authorities, the uncertainty assessment should further serve as a tool for enhanced risk assessment. In addition, by visualising inundation scenarios, improved flood mitigation and flood forecast planning strategies can be developed using a multi-model ensemble (Bhola et al., 2018d) and potential damage can be estimated for various quantiles.

Under-prediction of a simulated inundation is not desired in most case studies; therefore, the goodness-of-fit used in this study could be a critical issue. Future work should include other evaluation measures to constrain the parameter ranges. As the high-computational resources hinder a comprehensive uncertainty assessment of a full dynamic HD model, it is worth exploring

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transferability of the evaluated uncertainty bounds of Manning's n of the simple model structure (diffusive wave) to a complex model structure. Furthermore, other sources of uncertainty, such as model input (hydrological model in Disse et al., 2018), discharge measurement error, or flood frequency estimations; and digital elevation map) and measured water level, which is assumed to have no error, should also be incorporated for a comprehensive assessment. The parameter ranges were constrained based on a single event in this study; however, the values can be further validated using another flood event of higher magnitude. Land use in this study is divided into five classes; in future, further reclassification of land use, especially in urban areas, will help further reduce the bounds (Bhola et al., 2018c).

The inundation model should be extended to simulate urban pluvial flooding in future by including a 1D-2D sewer/overland flow coupled-model structure (Leandro et al., 2011). This will bring other sources of uncertainties as there are numerous uncertain parameters associated with this model structure (Djordjević et al., 2014). With an ever-increasing computational performance and the introduction of cloud computing, the integration of more complex models will become feasible.

Author contribution

The study was conceptualized by PKB and MD, PKB conceptualized and completed the formal analysis of uncertainty analysis. PKB wrote the original draft and subsequently reviewed and edited by all co-authors. All authors contributed to writing the paper.

Competing interests

The authors declare that they have no conflict of interest.

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References

Arcement Jr. and G. J., Schneider, V. R.: Guide for selecting manning's roughness coefficients for natural channels and flood plains, Water-Supply paper 2339, United States Department of Transportation, Denver, USA, 1989.

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, 349-365, https://doi.org/10.1016/S0309-1708(98)00017-7, 1998.

Bach, P.M., Rauch, W., Mikkelsen, P.S., McCarthy, D.T. and Deletic, A.: A critical review of integrated urban water modelling – urban drainage and beyond, Environ. Modell. Softw., 54, 88-107, https://doi.org/10.1016/j.envsoft.2013.12.018, 2014.

Bales, J.D. and Wagner, C.R.: Sources of Uncertainty in flood inundation maps, J. Flood Risk Manag., 2, 139–147, https://doi.org/10.1111/j.1753-318X.2009.01029.x, 2009.

Bates, P.D., Pappenberger, F. and Romanowicz, R.J.: Uncertainty in flood inundation modelling, in: Applied uncertainty analysis for flood risk management, edited by: Beven, K. and Hall, J., Imperial College Press, London, UK, 232–269, https://doi.org/10.1142/9781848162716_0010, 2014.

Beven, K.: A manifesto for the equifinality thesis, J. Hydrol., 320, 18-36, https://doi.org/10.1016/j.jhydrol.2005.07.007, 2006.

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Beven, K.J., Almeida, S., Aspinall, W.P., Bates, P.D., Blazkova, S., Borgomeo, E., Freer, J., Goda, K., Hall, J.W., Phillips, J.C., et al.: Epistemic uncertainties and natural hazard risk assessment – part 1: A review of different natural hazard areas, Nat. Hazards Earth Syst. Sci., 18, 2741-2768, https://doi.org/10.5194/nhess-18-2741-2018, 2018.

Bhola, P.K., Bhavna, N., Leandro, J., Rao, S.N. and Disse, M.: Flood inundation forecasts using validation data generated with the assistance of computer vision, J. Hydroinform., 21, 240-256, 10.2166/hydro.2018.044, 2018.

Bhola, P., Leandro, J. and Disse, M.: Framework for offline flood inundation forecasts for two-dimensional hydrodynamic models, Geosciences, 8, 346, https://doi.org/10.3390/geosciences8090346, 2018b.

Bhola, P.K, Ginting, B.M., Leandro, J., Broich, K., Mundani, R.P. and Disse, M.: Model parameter uncertainty of a 2D hydrodynamic model for the assessment of disaster resilience, EnviroInfo, Garching, Munich, 5-7 September 2018, 2018c.

Bhola, P.K., Leandro, J., Videkhina, I. and Disse, M.: Dynamic risk mapping in fluvial flood application using a two-dimensional hydrodynamic model incorporating the model parameter uncertainties, International Conference on Natural Hazards and Risks in a Changing World, University of Potsdam, Potsdam, Germany, 4-5 October 2018, 97, 2018d.

Brunner, G.W.: HEC-RAS River Analysis System Hydraulic Reference Manual, Report for US Army Corps of Engineers, Hydrologic Engineering Center (HEC), Davis, CA, USA, 2010.

Chow, V. T.: Development of uniform flow and its formulas, in: Open-channel hydraulics, McGraw-Hill Book Company, edited by: HARMER D.E., USA, 89–114,1959.

Disse, M., Konnerth, I., Bhola, P.K. and Leandro, J.: Unsicherheitsabschätzung für die Berechnung von Dynamischen Überschwemmungskarten – Fallstudie Kulmbach, in: Vorsorgender und nachsorgender Hochwasserschutz, edited by: Heimerl S., Springer Vieweg, Wiesbaden, Germany, 350-357, https://doi.org/10.1007/978-3-658-21839-3_50, 2018.

Djordjević, S., Vojinović, Z., Dawson, R. and Savić, D.A.: Uncertainties in flood modelling in urban areas, in: Applied uncertainty analysis for flood risk management, edited by: Beven, K. and Hall, J., Imperial College Press, London, UK, 297-334, https://doi.org/10.1142/9781848162716_0012, 2014.

Faig, W., and Kahmen, H.: Differential levelling, in: Surveying, edited by: Kahmen, H., and Faig, W., De Gruyter, Berlin, Germany, 321–386, 2012.

Hagemeier-Klose, M.: Results of formative evaluation of information tools in flood risk communication, final report on formative evaluation - EU-Life project FloodScan, Technical University of Munich, Germany, 2007.

Hall, J.W., Tarantola, S., Bates, P.D. and Horritt, M.S.: Distributed sensitivity analysis of flood inundation model calibration, J. Hyd. Eng., 131, 117-126, https://doi.org/10.1061/(ASCE)0733-9429(2005)131:2(117), 2005.

Henonin, J., Russo, B., Mark, O. and Gourbesville, P.: Real-time Urban Flood Forecasting and Modelling—a State of the Art, J. Hydroinform., 15, 717–736, https://doi.org/10.2166/hydro.2013.132, 2013.

Hof: Gebiet des Mains: https://www.wwa-ho.bayern.de/hochwasser/hochwasserereignisse/januar2011/main/index.htm, access: 27.03.2019, 2011.

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

Hunter, N.M., Bates, P.D., Horritt, M.S. and Wilson, M.D.: Simple spatially-distributed models for predicting flood inundation: A review, Geomorphology, 90, 208-225, https://doi.org/10.1016/j.geomorph.2006.10.021, 2007.

Jung, Y. and Merwade, V.: Uncertainty quantification in flood inundation mapping using generalized likelihood uncertainty estimate and sensitivity analysis, J. Hydrol. Eng., 17, 507-520, https://doi.org/10.1061/(ASCE)HE.1943-5584.0000476, 2012.

Leandro, J., Djordjević, S., Chen, A. S., Savić, D. A. and Stanić, M.: Calibration of a 1D/1D urban flood model using 1D/2D model results in the absence of field data, J. Water Sci. Tech., 64, 1016–1024, https://doi.org/10.2166/wst.2011.467, 2011.

Matott, L.S., Babendreier, J.E. and Purucker, S.T.: Evaluating uncertainty in integrated environmental models: A review of concepts and tools, Water Resour. Res., 45, https://doi.org/10.1029/2008WR007301, 2009.

Merwade, V., Olivera, F., Arabi, M. and Edleman, S.: Uncertainty in flood inundation mapping: Current issues and future directions, J. Hydrl.Eng., 13, 608-620, https://doi.org/10.1061/(ASCE)1084-0699(2008)13:7(608), 2008.

Molinari, D., Ballio, F., Handmer, J. and Menoni, S.: On the modeling of significance for flood damage assessment, Int. J. Disaster Risk Reduct., 10, 381–391, https://doi.org/10.1016/j.ijdrr.2014.10.009, 2014.

Musall, M., Oberle, P. and Nestmann, F.: Hydraulic modelling, in: Flood risk assessment and management: How to specify hydrological loads, their consequences and uncertainties, edited by: Schumann, A.H., Springer, Dordrecht, Netherlands, 187-209, https://doi.org/10.1007/978-90-481-9917-4_9, 2011.

Néelz, S., Pender, G., Agency, G. B. E., Great Britain. Department for Environment, F., and Affairs, R.: Desktop review of 2D hydraulic modelling packages, Environment Agency, 2009.

Oubennaceur, K., Chokmani, K., Nastev, M., Tanguy, M. and Raymond, S.: Uncertainty analysis of a two-dimensional hydraulic model, Water, 10, 272, https://doi.org/10.3390/w10030272, 2018.

Pappenberger, F. and Beven, K.: Ignorance is bliss: Or seven reasons not to use uncertainty analysis, Water Resour. Res., 42, https://doi.org/10.1029/2005WR004820, 2006.

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, 46-69, https://doi.org/10.1016/j.jhydrol.2004.06.036, 2005.

Romanowicz, R. and Beven, K.: Estimation of flood inundation probabilities as conditioned on event inundation maps, Water Resour. Res., 39, 3, https://doi.org/10.1029/2001WR001056, 2003.

Schumann, A.H., Wang, Y. and Dietrich, J.: Framing uncertainties in flood forecasting with ensembles, in: Flood risk assessment and management: How to specify hydrological loads, their consequences and uncertainties, edited by: Schumann, A.H., Springer, Dordrecht, Netherlands, 53-76, https://doi.org/10.1007/978-90-481-9917-4_4, 2011.

Thieken, A.H., Kienzler, S., Kreibich, H., Kuhlicke, C., Kunz, M., Mühr, B., Müller, M., Otto, A., Petrow, T., Pisi, S. and Schröter, K.: Review of the flood risk management system in Germany after the major flood in 2013, Ecol. Soc., 21, 1–12, http://dx.doi.org/10.5751/ES-08547-210251, 2016.

Uusitalo, L., Lehikoinen, A., Helle, I. and Myrberg, K.: An overview of methods to evaluate uncertainty of deterministic models in decision support, Environ. Modell. Softw., 63, 24-31, https://doi.org/10.1016/j.envsoft.2014.09.017, 2015.

Wagener, T. and Gupta, H.V.: Model identification for hydrological forecasting under uncertainty, Environ. Res. Ris. Assess., 19, 378-387, https://doi.org/10.1007/s00477-005-0006-5, 2005.

Werner, M., Blazkova, S. and Petr, J.: Spatially distributed observations in constraining inundation modelling uncertainties, Hydrol. Processes, 19, 3081-3096, https://doi.org/10.1002/hyp.5833, 2005a.

Werner, M. G. F., Hunter, N. M., and Bates, P. D.: Identifiability of distributed floodplain roughness values in flood extent estimation, J. Hydrol., 314, 139-157, https://doi.org/10.1016/j.jhydrol.2005.03.012, 2005b.

Tables

Table 1. A summary of selected publications including the maximum uncertainty bound reported. GLUE, PEM, GSA and SD stands for *Generalized Likelihood Uncertainty Estimation*, *Point Estimate Method*, *Global Sensitivity Analyses*, and standard deviation respectively.

Model dimension	HD Model	Identified sources	Method	Sample size	Max bound	Literature
1D	HEC-RAS	Manning's n	GLUE	10000	~	Pappenberger et al. (2005)
1D	HEC-RAS	Flow Topography Manning's n	GLUE	5000	~2.5 m (95%) in 8 m	Jung and Merwade (2012)
1D-2D	SOBEK	Topography Manning's n	GLUE		1.64 m (90%) in 1.51 m	Werner et al. (2005a)

2D		Manning's n	GLUE	1000	~7m (90%) in 10.5 m	Aronica et al. (1998)
2D	H2D2	Flow Topography Manning's n	PEM	108	0.27 m SD in 12.06 m	Oubennaceur et al. (2018)
2D	Lisflood-FP	Flow Topography Manning's n Channel width	GSA	1792	6 m SD in 11 m	Hall et al. (2005)

Table 2. 2D hydrodynamic model properties.

Data	Value
Model area	11.5 km^2
Total number of cells	430,485
Δt	20 s
Flood event duration	42 hours
Model run-time	5 hours
Minimum cell area	6.8 m^2
Maximum cell area	59.8 m^2
Average cell area	24.8 m^2

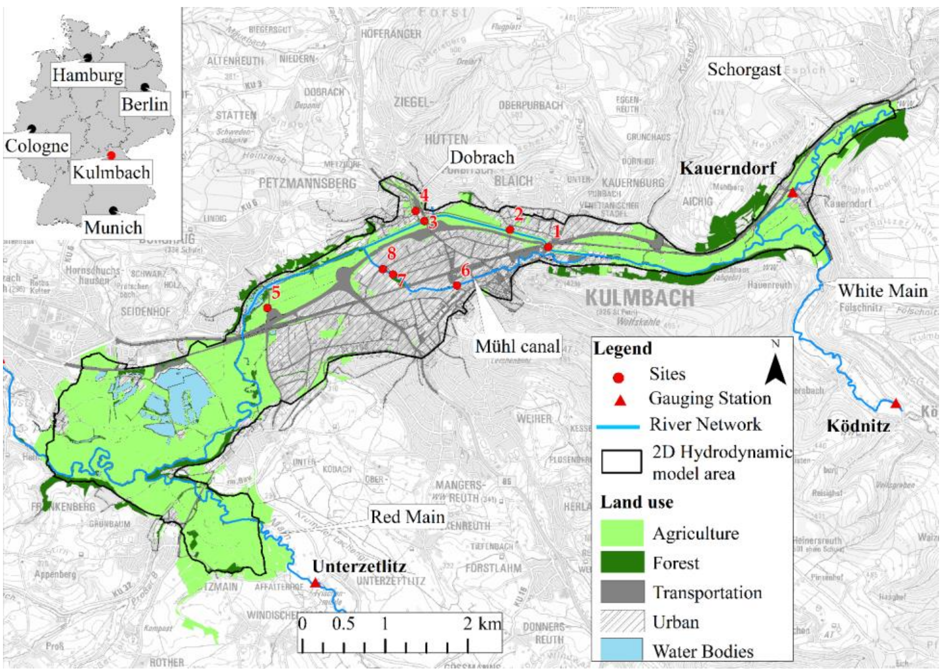
Table 3. Coefficient of determination (*R^2*) between Manning's n and absolute error for case I.

Site	Coefficient of determination [-]				
	Water bodies	Agriculture	Forest	Transportation	Urban
1	0.04	*0.89*	0.00	0.00	0.00
2	0.05	*0.85*	0.00	0.00	0.00
3	*0.18*	*0.69*	0.00	0.00	0.00
4	*0.34*	*0.54*	0.00	0.00	0.01
5	*0.45*	*0.37*	0.00	0.00	0.00
6	*0.97*	0.00	0.00	0.00	0.00
7	*0.23*	*0.18*	0.00	0.00	0.00
8	*0.19*	*0.22*	0.00	0.00	0.00

Table 4. 90% confidence interval absolute error bounds (in m) for three cases along with measured water depth (in m) at eight sites for the January 2011 event.

Site	Measured water depth[1]	90% absolute error bounds		
		Case I	Case II	Case III
1	2.78	1.26	0.59	0.34
2	2.90	1.04	0.55	0.34
3	2.93	1.01	0.59	0.36
4	1.43	0.97	0.64	0.46
5	1.75	0.78	0.46	0.32
6	0.89	0.85	0.65	0.43
7	2.31	0.52	0.46	0.40
8	2.36	0.51	0.46	0.40

Figures


Hamburg
Berlin
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Kulmbach
Munich
Schorgast
Dobrach
Kauerndorf
1
2
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8
KULMBACH
White Main
Mühl canal
Ködnitz
Red Main
Unterzetlitz
0
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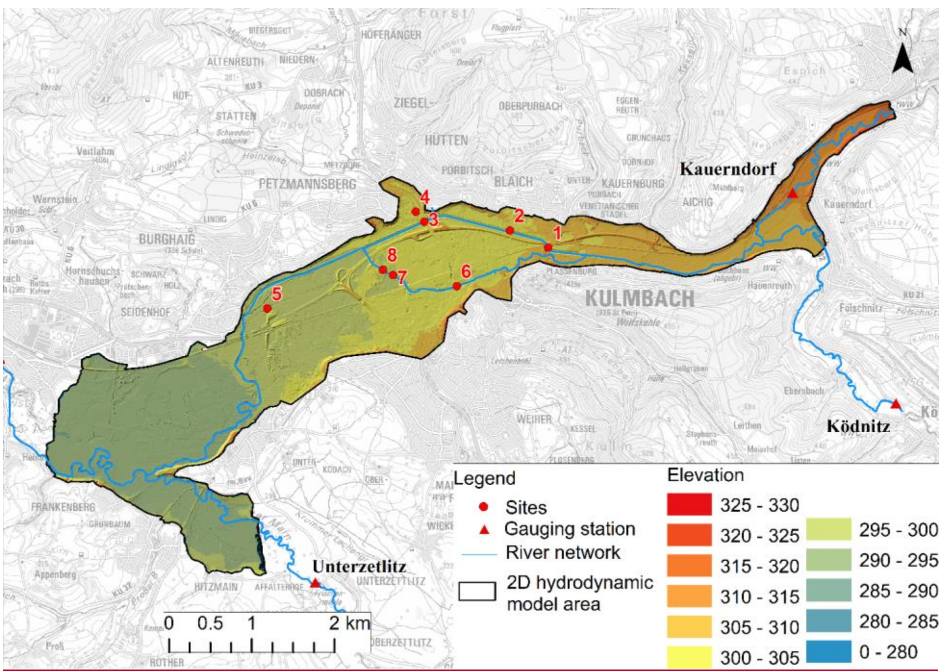
River Network
2D Hydrodynamic model area
Land use
Agriculture
Forest
Transportation
Urban
Water Bodies

(a) Land use



(b) Digital elevation model

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Figure 1: Land use and the digital elevation model of the city of Kulmbach. Data source: Water Management Authority Hof.

Figure 2: Main channel and flood plain of the river White Main near site 1 (image taken on 23.07.2015).

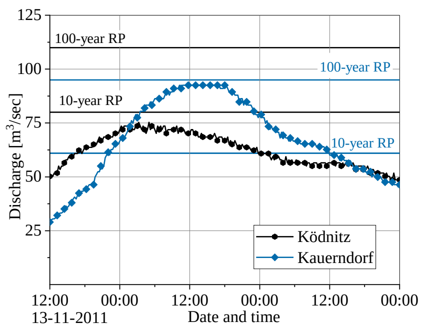


Figure 3: Discharge hydrographs at gauging stations upstream of the city, Ködnitz and Kauerndorf. RP stands for return period. Data source: Bavarian Hydrological Service (www.gkd.bayern.de).

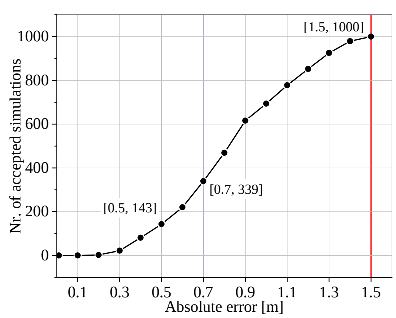


Figure 4: Accepted number of simulations vs. absolute error.

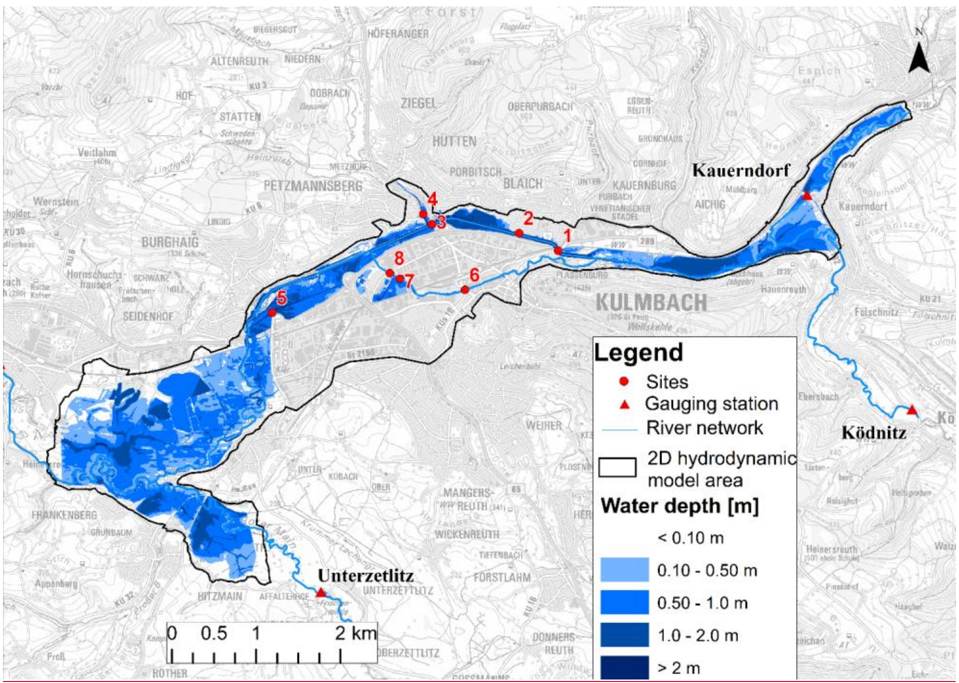
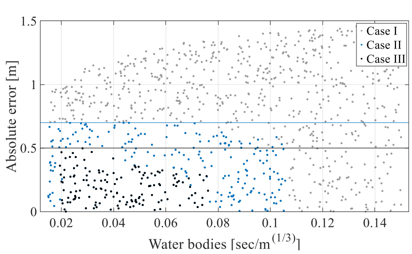
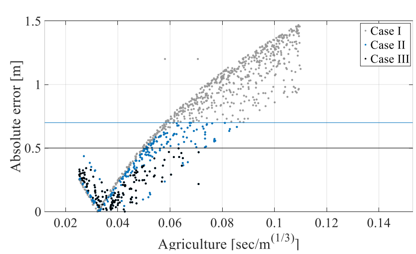


Figure 5: Inundation map for the flood event of January 2011 using the optimal model parameters, obtained using a least absolute error of 0.20 m.



(a) Site 1: Water bodies



(b) Site 1: Agriculture

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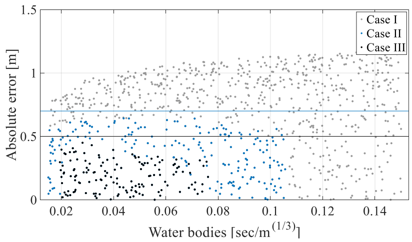
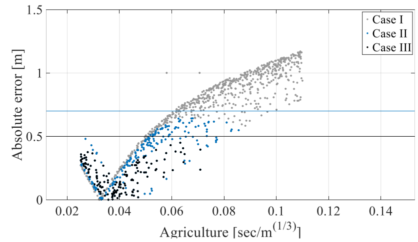
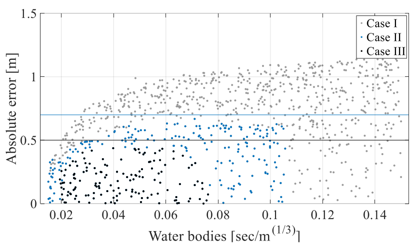


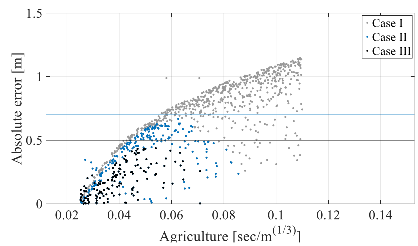
(c) Site 2: Water bodies



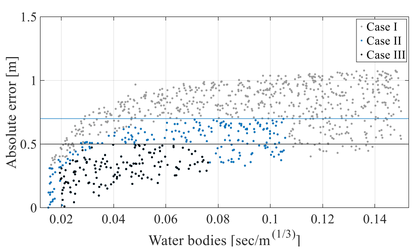
(d) Site 2: Agriculture



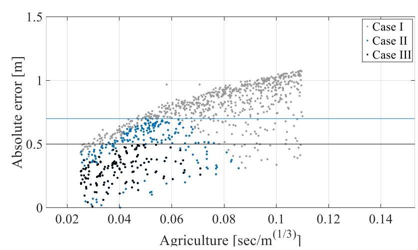
(e) Site 3: Water bodies



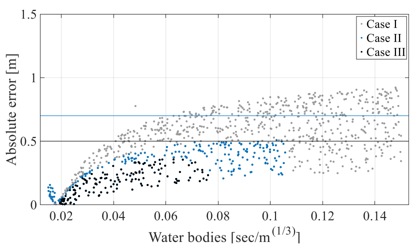
(f) Site 3: Agriculture



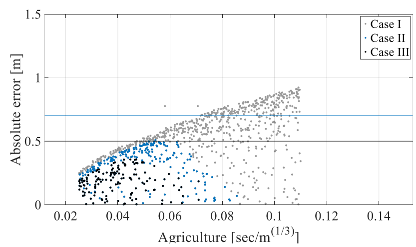
(g) Site 4: Water bodies



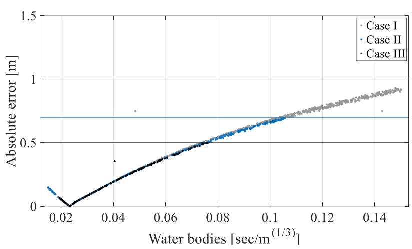
(h) Site 4: Agriculture



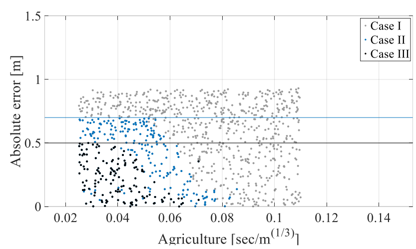
(i) Site 5: Water bodies



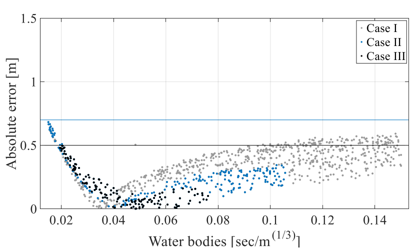
(j) Site 5: Agriculture



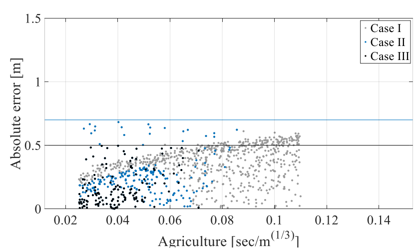
(k) Site 6: Water bodies



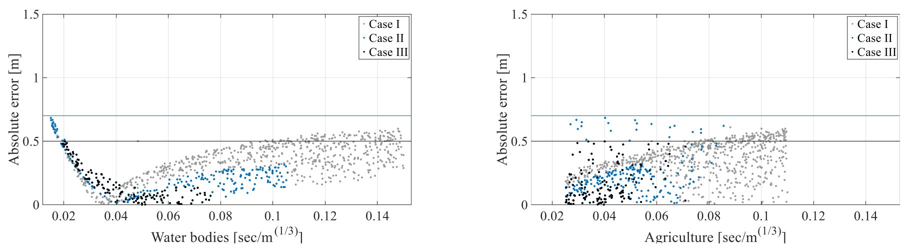
(l) Site 6: Agriculture



(m) Site 7: Water bodies

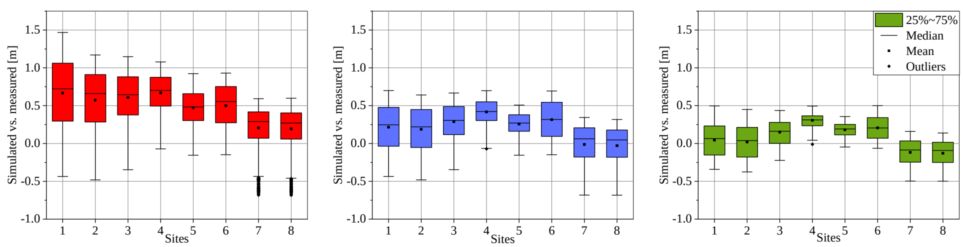


(n) Site 7: Agriculture



(o) Site 8: Water bodies **(p) Site 8: Agriculture**

Figure 6: Scatter plot of the absolute error of 1000 simulation in relation to water bodies and agriculture. Three cases I, II and III shows accepted simulations based on threshold values of 1.5, 0.7 and 0.5 m respectively.



(a) Case I **(b) Case II** **(c) Case III**

Figure 7: Error in simulated vs. measured water levels for a) Case I, b) Case II, and c) Case III.

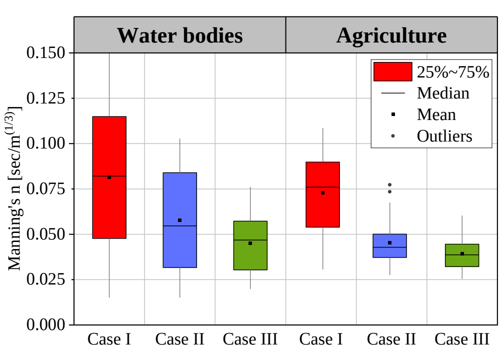


Figure 8: Box plot of Manning's n of water bodies and agriculture for three cases.