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Accounting for model structure, parameter and input forcing uncertainty in flood inundation modeling using Bayesian model averaging

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ABSTRACT

Reliability of flood stage and inundation extent predictions are affected by the performance of a hydraulic model. However, uncertainties at all times exist in the model setup process. Therefore, prediction from a single hydraulic model implementation may be subject to huge uncertainty. Bayesian model averaging (BMA) is applied in this study to combine ensemble predictions from different hydraulic model implementations and to develop a robust deterministic water stage prediction as well as the prediction distribution. The BMA approach is tested over the Black River watershed in Missouri and Arkansas based on water stage predictions from 81 LISFLOOD-FP model configurations that integrate four sources of uncertainty including channel shape, channel width, channel roughness and flow input. Model ensemble simulation outputs are trained with observed water stage data during one flood event to obtain the weight and variance for each model member, and BMA prediction ability is then validated for another flood event. The results indicate that the BMA approach is able to provide consistently good and reliable deterministic flood stage prediction across the basin, though it does not always outperform the best model in the ensemble. The BMA water stage prediction has better performance than the ensemble mean prediction. Additionally, high-chance flood inundation extent derived from a BMA probabilistic flood map is more accurate than the probabilistic flood inundation extent based on the equal model weights in the Black River watershed.

1. Introduction

With the increasing threat of frequently occurring intense storms, hydrodynamic models are expected to play a bigger role in understanding and predicting the floods and their corresponding extents. There are several ongoing efforts to simulate floods at multiple spatial scales ranging from single reach to continental scale stream networks (Cook and Merwade, 2009; de Paiva et al., 2013; Horritt and Bates, 2002; Knebl et al., 2005; Schumann et al., 2013). Additionally, all these efforts use different approaches ranging from simplistic digital elevation model (DEM) based models such as HAND (Nobre et al., 2011) to more sophisticated 1D or 2D hydraulic models such as HEC-RAS and LISFLOOD-FP (Pappenberger et al., 2005a; Wood et al., 2016). All approaches require two primary inputs including the topography to construct the river geometry and flow magnitude to simulate the hydraulics. Simulation of hydraulics require adjustment of model parameters, which is primarily the channel roughness specified in the form of Manning's n. Depending on the flood modeling approach, the final result is affected by several sources of uncertainty including the model structure, flow magnitude, topography and model parameters, among others (Bermúdez et al., 2017; Cook and Merwade, 2009; Dottori et al., 2013; Mukolwe et al., 2016; Teng et al., 2017).

The uncertainty in flood inundation modeling can be categorized into three major types: model structure, model parameter and input forcing. Model structure broadly includes the type of the model, one-dimensional or two-dimensional, type and form of numerical equations, and the assumptions in the model. For a specific model, structural uncertainty could also include how the river geometry, including the channel cross-sectional shape and planform, is extracted and represented in the model (Liu et al., 2018; Pappenberger et al., 2006; Teng et al., 2017). For instance, commonly used DEMs do not have information on channel bed, and thus assuming a shape for the channel bed could add substantial uncertainty to the model output. Most hydraulic models are calibrated for different flows using channel roughness parameter, and thus when these models are used to simulate flows that are outside the range used during calibration, the calibrated channel roughness value can add uncertainty to the model results. This is typically the case when hydraulic models are used for simulating 100-year or higher return period design flows as observed data for such flows may not exist. Finally, observed or simulated input forcing data

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such as streamflows and water stage used in hydraulic models also add significant uncertainty to the simulation results. (Beven and Hall, 2014; Demeritt et al., 2007; Merwade et al., 2008; Pappenberger et al., 2005b). Therefore, reliance on a single hydraulic model implementation for flood prediction typically increases the statistical bias of the forecast.

One way to handle model uncertainties is by using a multi-model combination approach, in which results are extracted from a group of existing model implementations to provide a robust prediction based on the model prediction ensemble. Multi-model combining for ensemble predictions is widely used in hydrology and climate forecast using a variety of methods, including SMA (simple model average), WMA (weighted model average), MMSE (multi-model super-ensemble) and M3SE (a variant of MMSE), among others (Ajami et al., 2006; Chowdhury and Sharma, 2009; Hamill, 2001; Liu et al., 2014; Najafi and Moradkhani, 2015a; Najafi and Moradkhani, 2015b; Shamseldin et al., 1997; Xiong et al., 2001). Additionally, the performance of probabilistic ensemble merging techniques have been evaluated and compared with the deterministic model predictions for climate model and streamflow predictions (Najafi and Moradkhani, 2015a; Najafi and Moradkhani, 2015b). In recent years, the Bayesian model averaging (BMA) technique (Merlise, 1999; Raftery et al., 2005) has been used widely in surface water hydrology (Ajami et al., 2007; Duan et al., 2007; Jiang et al., 2017; Rings et al., 2012; Zhang et al., 2009), groundwater hydrology (Neuman, 2003), climatology (Zhang et al., 2016), biology (Yeung et al., 2005), ecology (Wintle et al., 2003), public health (Morales et al., 2006), and economics (Fernandez et al., 2001). The rationale behind the BMA method lies in the fact that some models are superior to other models and each model should not be treated exactly the same. The BMA approach evaluates model implementations and assigns each of them a weight and variance based on the model performance in the training period. The advantage of this approach over other model combing methods is that BMA not only provides a deterministic model weighted average prediction of the interested variable, but also produces the forecast distribution which reflects the uncertainty associated with the deterministic prediction (Raftery et al., 1997; Rings et al., 2012).

Considering the wide applicability of BMA in other areas of hydrology, its application in flood inundation modeling can help address the issue of accounting and presenting model structure, parameter, and input forcing uncertainty. Although the BMA approach is usually being used to account only for model structure uncertainty, there do exist previous studies in other fields to incorporate forcing/boundary condition and parameter uncertainty using the BMA method (Chitsazan and Tsai, 2015; Yen, 2012). Accordingly, the objectives of this study are to: (1) determine whether BMA can provide accurate and reliable deterministic flood predictions for a stream network by considering various uncertainty sources; (2) compare the performance of BMA prediction with predictions from model members and ensemble mean; and (3) quantify uncertainty associated with the BMA deterministic prediction. The above objectives are accomplished by applying a large scale hydraulic model for the Black River watershed that is located in Arkansas and Missouri in the U.S.

We acknowledge that uncertainty quantification is not a new topic in flood inundation mapping because several past studies have addressed uncertainties related to parameter, input data and boundary conditions (Aronica et al., 2002; Jung and Merwade, 2011; Pappenberger et al., 2005a, 2013; Tiwari and Chatterjee, 2010; Yu et al., 2015). However, the results from these studies are somewhat limited due to the use of isolated flood events on a single reach in the analysis. With the growing need to simulate the river hydrodynamics over an entire stream network at basin to continental scales (Huang and Hattermann, 2018; Jafarzadegan and Merwade, 2017; Merwade et al., 2018; Schumann et al., 2013; Wilson et al., 2007), it is expected that multiple sources of uncertainties will play different roles in different streams to contribute to the overall uncertainty in the final result. Hydrodynamic modeling in a stream network will involve a mix of large and small reaches. Many large reaches could be well described in the model in terms of their cross-sectional shape, roughness characterization and channel width, but the same may not apply to many low order contributing streams. As a result, many low order streams may be affected by structural, parameter and input forcing uncertainties, but the large streams may only be affected by input forcing uncertainties. Thus, there is a need to understand the cumulative effect of different uncertainty sources in flood inundation modeling over a larger stream network. This study attempts to address this need by using the BMA methodology. Once the cumulative effect of all uncertainties is accounted, the hierarchical BMA can then be used to understand the relative impact of individual uncertainties.

2. Study area and data

The 20,000 km^2 Black River watershed located across Arkansas and Missouri states in the U.S. is selected for this study. Historical records indicate that this region has experienced numerous flood events in the past including the recent one that occurred in May 2017. The recorded water level data for the 2017 event are available from the United States Geological Survey (USGS) gauges (Fig. 1 and Table 1), and are used in validating the results from this study. Additionally, the Black River watershed has four major rivers including Black river, Current River, Eleven Point River and Spring River, which drain towards the watershed outlet in Arkansas. These four major rivers provide distinct topographical, geomorphic settings as well as varying reach lengths and sinuosity, thus making Black River watershed a good test bed for this study. The daily streamflow data (input to the hydraulic model) and stage data (for validation) used in this study are unaffected by any major hydraulic structures, and are thus considered natural. The topography and land use dataset are obtained in the form of national elevation dataset 90 m DEM (http://ned.usgs.gov) and NLCD 2011 land use data (http://www.mrlc.gov/nlcd2011.php), respectively. A 90 m DEM instead of 30 m or finer resolution DEM is selected for this study to strike a balance between predication accuracy and the computational demand for a large number of simulations needed for uncertainty analysis. Although the prediction accuracy might be affected by using the 90 m DEM, many large scale models use 90 m or coarser DEM for flood modeling as well (Neal et al., 2012; Schumann et al., 2013). Inundation extents for selected storms, which will be used for validation of results, are derived by classifying Landsat images from the USGS earth explorer website (http://earthexplorer.usgs.gov/). The Landsat images are classified into water and non-water area with a supervised classification technique using the ArcGIS classification tools. The classification is formed using the following three steps: (i) train the tool by delineating water and non-water areas; (2) use the maximum likelihood classification approach to classify the entire Landsat image based on information obtained from the training areas; and (iii) extract the "water" area from the classified image and treat it as observed inundation extent around the streams.

3. Methodology

3.1. Hydraulic modeling

Many one-, two- or three-dimensional models exist for conducting flood simulations. One-dimensional (1D) models use discrete cross-sections to describe the rivers and assumes that water moves only longitudinally along the direction of river; whereas two-dimensional models (2D) use continuous mesh or raster grid to define the channels and assumes water moves both longitudinally and laterally; and a three-dimensional (3D) model adds the vertical movement to the 2D flow. One of the most commonly used models in the U.S. is the Hydrological Engineering Center's River Analysis System (HEC-RAS) (USACE, 2015) which includes the classic 1D and the recently developed (2D) versions.