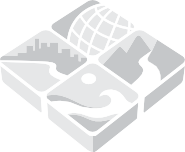
# JOURNAL OF THE AMERICAN WATER RESOURCES ASSOCIATION

August 2018



Vol. 54, No. 4

AMERICAN WATER RESOURCES ASSOCIATION

A HYDRAULIC MULTIMODEL ENSEMBLE FRAMEWORK FOR VISUALIZING FLOOD INUNDATION UNCERTAINTY1

*Christopher M. Zarzar , Hossein Hosseiny, Ridwan Siddique, Michael Gomez, Virginia Smith, Alfonso Mejia, and Jamie Dyer2*

ABSTRACT: While deterministic forecasts provide a single realization of potential inundation, the inherent uncertainty associated with forecasts also needs to be conveyed for improved decision support. The objective of this study was to develop an ensemble framework for the quantification and visualization of uncertainty associ- ated with flood inundation forecast maps. An 11-member ensemble streamflow forecast at lead times from 0 to 48 hr was used to force two hydraulic models to produce a multimodel ensemble. The hydraulic models used are

(1) the International River Interface Cooperative along with Flow and Sediment Transport with Morphological Evolution of Channels solver and (2) the two-dimensional Hydrologic Engineering Center-River Analysis Sys- tem. Uncertainty was quantified and augmented onto flood inundation maps by calculating statistical spread among the ensemble members. For visualization, a series of probability flood maps conveying the uncertainty in forecasted water extent, water depth, and flow velocity was disseminated through a web-based decision support tool. The results from this study offer a framework for quantifying and visualizing model uncertainty in fore- casted flood inundation maps.

(KEY TERMS: flooding; uncertainty mapping; risk assessment; decision support system; ensemble modeling; uncertainty analysis.)

Zarzar, Christopher M., Hossein Hosseiny, Ridwan Siddique, Michael Gomez, Virginia Smith, Alfonso Mejia, and Jamie Dyer, 2018. A Hydraulic Multimodel Ensemble Framework for Visualizing Flood Inundation Uncer- tainty. *Journal of the American Water Resources Association* (JAWRA) 54 (4): 807–819. [https://doi.org/10.1111/](https://doi.org/10.1111/1752-1688.12656) [1752-1688.12656](https://doi.org/10.1111/1752-1688.12656)

# INTRODUCTION

Floods are one of the costliest natural disasters in the United States (U.S.) (Pielke and Downton 2000). Each year floods are responsible for numerous weather-related fatalities alongside billions of dollars in damages to properties (NWS 2015). Effective and efficient flood preparation efforts rely heavily on the

accuracy and communication of forecasted flood risks. Forecasted flood inundation maps are typically based on deterministic model output generated using a hydraulic model forced with a single discharge output from a hydrologic model (e.g., Merwade et al. 2008; Grimaldi et al. 2013). These deterministic flood inundation maps are subject to uncertainty due to imperfect forcing, initial conditions, model parameteri- zations, and numerical limitations (Merwade et al.

1Paper No. JAWRA-17-0040-P of the *Journal of the American Water Resources Association* (JAWRA). Received April 13, 2017; accepted April 24, 2018. © 2018 American Water Resources Association. Discussions are open until six months from issue publication.

2Department of Geosciences (Zarzar, Dyer), Mississippi State University, Mississippi State, Mississippi, USA; Department of Civil and Environmental Engineering (Hosseiny, Smith), Villanova University, Villanova, Pennsylvania, USA; and Department of Civil and Environ- mental Engineering (Siddique, Gomez, Mejia), Pennsylvania State University, University Park, Pennsylvania, USA (Correspondence to Zarzar: [chris.zarzar@gmail.com).](mailto:chris.zarzar@gmail.com)

[](http://crossmark.crossref.org/dialog/?doi=10.1111%2F1752-1688.12656&domain=pdf&date_stamp=2018-06-07)Journal of the American Water Resources Association

807

# JAWRA

Zarzar, Hosseiny, Siddique, Gomez, Smith, Mejia, and Dyer

2008; Christian et al. 2013); therefore, by not incorpo- rating these uncertainties, deterministic flood inunda- tion maps fail to communicate the full risk for potential flooding.

Ensemble modeling techniques have been widely used as a method for improving forecast accuracy and for quantifying uncertainties in model predictions (Pal- mer 2000; Pappenberger et al. 2005; Pappenberger et al. 2006; Hagedorn et al. 2008; Hamill et al. 2008; Leutbecher and Palmer 2008; Cloke and Pappenberger 2009; Sanyal et al. 2010; Buahin et al. 2017). An ensemble is composed of a series of simulations pro- duced by a single underlying model to encompass the range of possible model outcomes. The greater range of outcomes, or lower agreement among members, coin- cides with higher uncertainty in the model prediction. Three common approaches to generating an ensemble are to use statistical models to generate a time-lagged ensemble (Regonda et al. 2013), perturb initial condi- tions of a single model (Toth and Kalnay 1997; Dyer et al. 2016), or vary the physics of the single model (Stensrud et al. 2000; Du et al. 2004; Dyer et al. 2016). A challenge with multi-physics ensembles is that the underlying distribution cannot be attributed to a com- mon probability density function (PDF) or climatology. As such, a change to the underlying model would not necessarily affect the members of the ensemble. Another ensemble generation approach is to generate a multimodel ensemble where the ensemble is com- posed of realizations from different models (Beven and Binley 1992; Nutter et al. 2004). A multimodel ensem- ble encounters challenges similar to the multi-physics ensemble because each model member belongs to its own PDF; however, even though each model has its own PDF, improvements to the underlying models will improve the entire framework.

Hydrologic and hydraulic models include inherent uncertainty associated with input data, model parame- ters, and the structure of the models (Kauffeldt et al. 2016). Subjective choices made by the modeler in developing and calibrating the simulational frame- work may generate substantial error depending on the model (Zarriello 1998). Additionally, model calibration problems may not necessarily be addressed by better and more field data (Gupta et al. 1998). These factors make the selection of a model for a desired application quite complex. In fact, there is not a unique model that can be known as the “best” model for all conditions (Vela´zquez et al. 2010; Afshari et al. 2018). An option to account for subjectivity in model selection is to com- bine multiple and different model realizations, or a multimodel ensemble. Each model will produce specific information that can supplement the final multimodel predicted scenario (Oudin et al. 2006). This will also help eliminate some of the uncertainties by rejecting improbable output produced by a single model

(Kauffeldt et al. 2016). Subjectivity is decreased with the multimodel technique because attention is directed to locations where models are in agreement. Locations where model agreement is strong translate to greater confidence in the potential for that scenario indepen- dent of a single modeler’s subjectivity and a single model’s accuracy.

It is important to also consider how to communicate flood information in disseminated products. While comparing the communication of flood information as deterministic maps vs. probabilistic maps, Di Baldas- sarre et al. (2010) concluded that it is most appropriate to communicate flood maps as probabilistic surfaces given the uncertainties associated with simplifying complex river dynamics in a modeling environment. Frick and Hegg (2011) showed that the communication of forecast uncertainty improves end users’ situational awareness and decision making; however, there are numerous caveats that need consideration when com- municating uncertainty in hydrometeorological fore- casts (Ramos et al. 2010). Ramos et al. (2010) found that one of the most prominent caveats is the end user’s understanding of how to use the uncertainty information to make decisions. Even so, Ramos et al. (2010) and Frick and Hegg (2011) concluded that the communication of uncertainty using probabilistic tech- niques has the greatest potential for successful imple- mentation. Furthermore, Leedal et al. (2010) demonstrated the ability to develop and disseminate real-time probabilistic flood forecast products.

The National Oceanic and Atmospheric Administra- tion’s (NOAA) Hydrologic Ensemble Forecast Service (HEFS) uses similar methods to provide this proba- bilistic uncertainty information to end users through an online graphics interface that generates products including spaghetti plots, expected values charts, exceedance probability for some variables, and current vs. historical exceedance probability distribution plots (Demargne et al. 2014). However, HEFS and other uncertainty visualization tools (e.g., Ensemble-vis: Potter et al. 2009; Noodles: Sanyal et al. 2010) are con- fronted with the paradox of decreasing the end user’s understanding of the situation by providing too much information. During time-sensitive decision-making situations, Frick and Hegg (2011) found that users often abandon the additional information and revert back to habitual routines; therefore, rather than intro- duce a new system to the end user’s routine, a more effective method for the communication of uncertainty is to augment current products with probabilistic uncertainty information so the information can be seamlessly integrated into current routines.

The objective of this study was to explore the advan- tages of using hydrometeorological ensembles and a hydraulic multimodel framework for forecasting and visualizing flood inundation uncertainty information.

# JAWRA

17521688, 2018, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1752-1688.12656 by University Of Alabama, Wiley Online Library on [05/06/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

808

Journal of the American Water Resources Association

A Hydraulic Multimodel Ensemble Framework for Visualizing Flood Inundation Uncertainty

This study quantifies forecast flood inundation uncer- tainty using a combined hydrometeorological and hydraulic multimodel ensemble approach. This approach allows for the generation of numerous ensem- ble members without changing model physics schemes, allowing for a more direct assessment of individual model uncertainty. The incorporation of this flood inun- dation uncertainty information into an interactive web- based application will demonstrate new techniques for rapid dissemination of flood inundation forecast prod- ucts. Through the linkage of existing systems, the framework allows for the seamless integration of uncer- tainty information into operational products, which will provide critical information to help decision makers prepare for and respond to potential flood events.

# DATA AND METHODS

*Study Area*

The river selected for this project is a segment of Darby Creek, located in urban Philadelphia, Pennsyl- vania, and stretching from the Mt. Moriah Cemetery to its confluence with the Delaware River (Figure 1). The floodplains of Darby Creek are highly urbanized, and have been for some time (Figures 2a and 2b). The mean slope of the river is 0.001 m/m with an average width of 50 m. The length of the reach is approximately 15 km. Tidal impacts are apparent in

the downstream portion of the Darby Creek segment. A previously calibrated and verified one-dimensional (1D) Hydrologic Engineering Center-River Analysis System (HEC-RAS) model for the main stem of the Delaware River from Philadelphia to Marcus Hook showed that the stage varies depending on the tidal condition (Gomez 2017).

Due to the highly urbanized floodplains in the study area, it was necessary to use high-resolution elevation data to correctly represent the terrain. A high-resolu- tion (1 m) LiDAR-derived digital elevation model (DEM) obtained from the Pennsylvania Spatial Data Access was used in combination with a bathymetry dataset collected by NOAA. The river bed elevation underneath bridges was set to average bed elevation of the upstream and downstream of the bridge to ensure the connectivity of the flow from upstream to downstream.

*Selected Flood Event and Flow Observations*

The flood event that occurred on April 30, 2014 was selected to demonstrate the proposed framework. For this event, the U.S. Geological Survey (USGS) Cobb Creek gage at Mt. Moriah Cemetery (USGS 01475548) measured the second highest streamflow on record at the gage reaching 99 m3/s at 1900 EDT. The precipitation gage located at Philadelphia Inter- national Airport recorded 121.92 mm of rain during the last two days of April 2014, indicating a five-year precipitation event (according to NOAA Atlas 14).

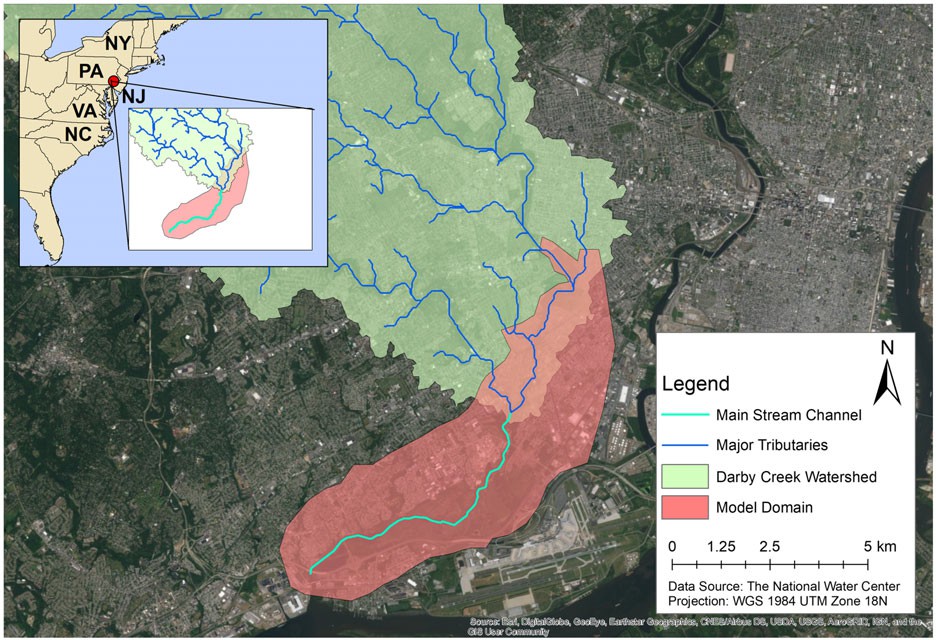


FIGURE 1. Darby Creek, PA model domain and watershed for the stream reach examined.

PA, Pennsylvania; NY, New York; NJ, New Jersey; VA, Virginia; NC, North Carolina.

Journal of the American Water Resources Association

17521688, 2018, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1752-1688.12656 by University Of Alabama, Wiley Online Library on [05/06/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

809

# JAWRA

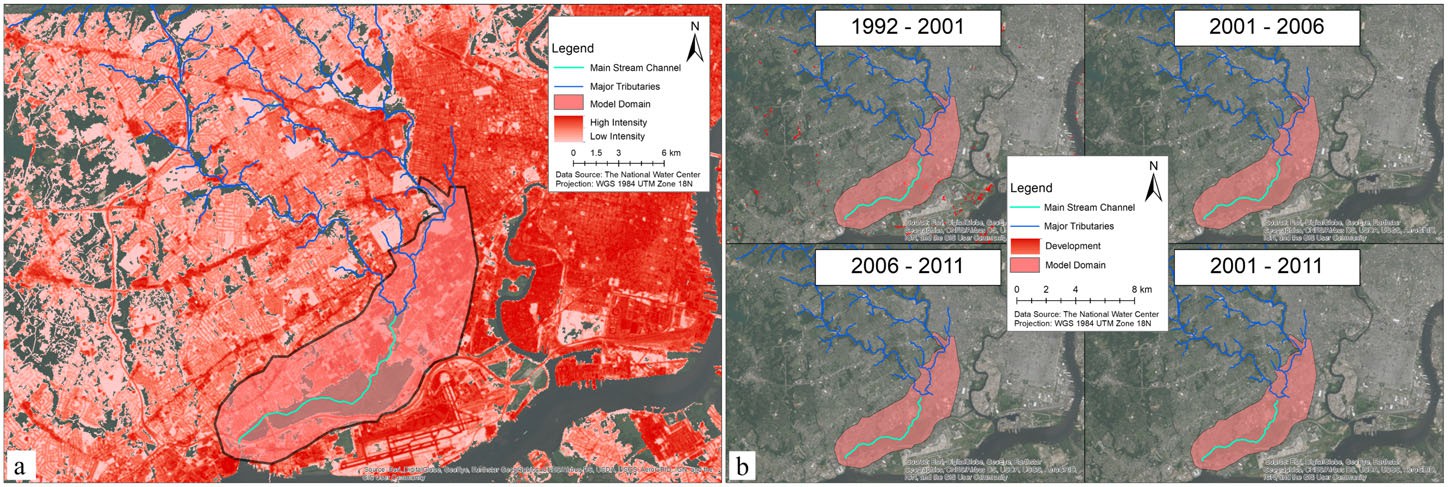


FIGURE 2. (a) 2006 National Land Cover Database (NLCD) impervious land cover classification and (b) NLCD land cover classification change developed from 1991–2001, 2001–2006, 2006–2011, and 2001–2011.

*Obtaining Ensemble Streamflow Forecasts*

The first component of the framework was the gen- eration of ensemble streamflow forecasts, which were obtained from a previously developed and fully veri- fied regional hydrological ensemble prediction system (RHEPS) (Figure 3) (Sharma et al. 2017; Siddique and Mejia 2017). The RHEPS uses weather ensemble forecasts (precipitation and near-surface tempera- ture) from the National Centers for Environmental Prediction 11-member Global Ensemble Forecast Sys- tem Reforecast version 2 (GEFSRv2) to force the

NOAA’s Hydrology Laboratory-Research Distributed Hydrologic Model (HL-RDHM) (Siddique and Mejia 2017). Thus, 11 different realizations or ensembles of streamflow forecasts are generated. The 11-member GEFSRv2 precipitation forecasts (Siddique et al. 2015; Sharma et al. 2017) as well as the 11-member streamflow forecasts (Siddique and Mejia 2017) gen- erated with HL-RDHM were previously verified. Fur- ther details about the RHEPS are provided elsewhere (see Siddique and Mejia 2017; Sharma et al. 2018), including all the different system components and the data used by the system to generate ensemble

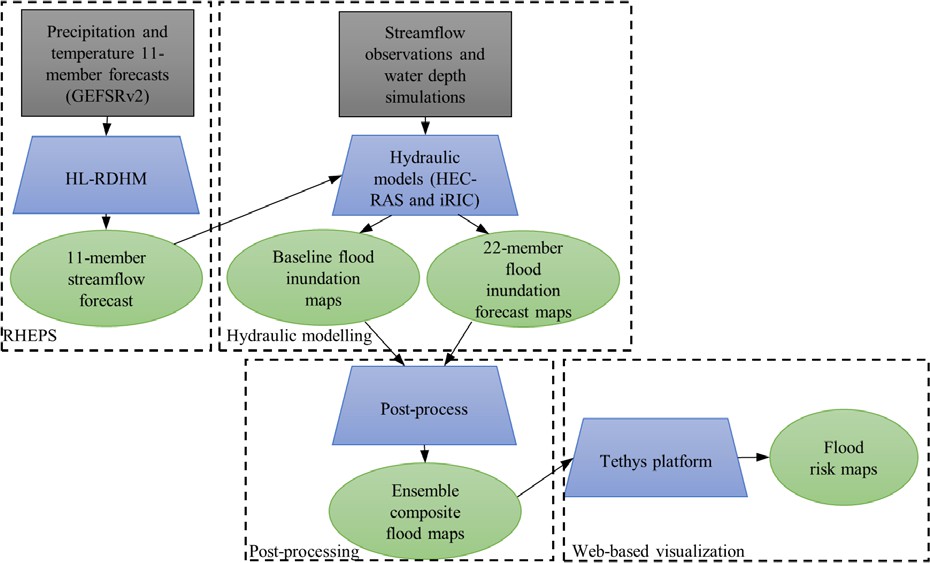


FIGURE 3. Schematic illustrating the major components and subcomponents of the framework used to generate and visualize the ensemble flood inundation forecasts. The major components consist of the regional hydrological ensemble prediction system (RHEPS), hydraulic model- ing, postprocessing, and web-based visualization. The minor components include all the steps followed to translate the ensemble flow fore- casts from the RHEPS into web-based flood risk maps. GEFSRv2, Global Ensemble Forecast System Reforecast version 2; HL-RDHM, Hydrology Laboratory-Research Distributed Hydrologic Model; HEC-RAS, Hydrologic Engineering Center-River Analysis System; iRIC, Inter- national River Interface Cooperative.

# JAWRA

17521688, 2018, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1752-1688.12656 by University Of Alabama, Wiley Online Library on [05/06/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

810

Journal of the American Water Resources Association

streamflow forecasts at any forecast location in the middle Atlantic U.S. An 11-member, 48-h (i.e., lead times from 1 to 48 h at 1-h resolution) streamflow forecast ensemble was obtained from this system at the upstream boundary of the hydraulic model for the selected flood event (April 30, 2014 to May 1, 2014) (Figure 4). The ensemble streamflow forecasts from the regional system (Siddique and Mejia 2017) were used because forecasts from the National Water Model (NWM) were not available for the selected flood event; however, the quality of the forecasts from the regional system should be representative of the quality of forecasts from the NWM since they both rely on similar weather forcing from NOAA.

*Hydrologic Engineering Center-River Analysis System*

The HEC-RAS (Brunner 2016) is a hydraulic model with 1D and two-dimensional (2D) modeling capabili- ties. The HEC-RAS model has been widely employed in simulation and forecasting applications (Mashriqui et al. 2014). The 2D component of the model solves the shallow water equations over an unstructured computational mesh; this allows the user to add more detail where needed such as dikes, roads, buildings, etc. To reduce the computation time, the model uses a subgrid bathymetry approach (Casulli 2009). The subgrid approach consists of using a coarse computa- tional grid and at each cell associated properties from the underlying terrain data are precomputed, thus accounting for the fine terrain data through mass conservation.

In our application of the 2D component of HEC- RAS to Darby Creek, the model mesh is composed of 82,349 irregularly shaped cells (three to eight sides),

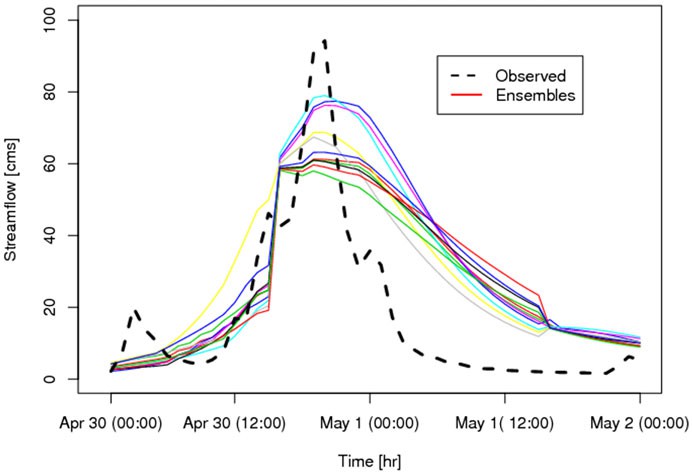


FIGURE 4. Ensemble forecasts (solid color lines) generated by the RHEPS for the selected flood event (April 30–May 1). The observation from United States Geological Survey gage station

(black dashed line) at Cobbs Creek near Mt. Moriah is also shown.

with an average cell size of 385 m2. The Manning’s *n*

value for the main channel was initially set to

0.035 m3/s. The spatial variability of the roughness parameter in the floodplains was determined by using the 2011 National Land Cover Database (NLCD) data, and it varied from 0.04 to 0.15 m3/s.

Boundary Conditions and Model Calibra- tion. The model was calibrated using water surface elevation and discharge data from the USGS Cobb Creek gage at Mt. Moriah Cemetery. The flooding event of August 30, 2009 with a peak discharge of 184 m3/s and maximum water surface elevation of 12 m (NAVD88) was selected for calibration. The cali- bration of the model was done by forcing the upstream boundary with 72-h observed flow data starting from August 29, 2009 and the stage data at the downstream boundary for the same period. The Manning’s *n* values were adjusted to ensure the model output matched the observed water surface elevation until no further improvement was observed.

Baseline Simulation and Forecast Runs. The calibrated model was used to create two sets of maps for the selected flood event: (1) baseline flood inunda- tion maps and (2) forecast flood inundation maps (Figure 3). The former is obtained by forcing the model with observed discharge data at the upstream boundary and the simulated data from the Delaware River at the downstream boundary. Without a ground-referenced dataset of the flood extent data in the reach for this event, this flood extent map gener- ated from the observed upstream discharge data is considered the best representation of the actual flood inundation for comparison against the HEC-RAS out- put. The second set of forecast maps were obtained by forcing the model at the upstream boundary with the 11-member hydrometeorological forecast. To understand the effect of the forecast lead time on the flood maps, two separate flood inundation forecasts per member, namely the 24- and 48-h forecast flood inundation maps, were considered. These were obtained by forcing the hydraulic model with the 24- and 48-h lead time hydrometeorological ensemble streamflow forecast, respectively.

*International River Interface Cooperative*

The International River Interface Cooperative (iRIC) software provides a multidimensional river simulation medium along with various steady and unsteady solvers (Nelson et al. 2010). Among the solvers, the Flow and Sediment Transport with Mor- phological Evolution of Channels (FaSTMECH), a quasi-steady vertically averaged model, was used to

Journal of the American Water Resources Association

17521688, 2018, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1752-1688.12656 by University Of Alabama, Wiley Online Library on [05/06/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

811

# JAWRA

simulate flood extent and to calculate depth and velocity domains over the study area.

The topographic data used were the same data used in the HEC-RAS model, which consisted of 1-m LiDAR data merged with surveyed bathymetry. The same discharge data from the Mt. Moriah Cemetery USGS gage (01475548) used by the HEC-RAS model were used in the calibration of iRIC. The topographic data used in iRIC were mapped over a grid mesh

approximately 5 9 5 m2. Although higher resolution of topographic LiDAR data (1 9 1 m2) was available, this decrease in spatial resolution saved substantial

computational time and assisted with model stability.

Boundary Conditions and Model Calibra- tion. FaSTMECH is a quasi-steady state solver, which assumes that average hydraulic parameters are relatively constant through time. This means that the discharge variations in the momentum equa- tion are negligible (Nelson et al. 2010); thus, the model requires both upstream and downstream boundary conditions. The Cobbs Creek USGS gage at Mt. Moriah Cemetery provided discharge at the upstream of the domain. The data for downstream were the same as the data used for HEC-RAS calibra- tion to ensure consistent downstream boundary con- ditions between iRIC and HEC-RAS.

As with the HEC-RAS model, the iRIC model was calibrated with a known water surface elevation at the upstream USGS Cobb Creek gage at Mt. Moriah Cemetery using the flood event of August 30, 2009. The frictional coefficients within iRIC (in the form of drag coefficients) were selected initially based off of the HEC-RAS roughness values. Also, the spatial dis- tribution of the frictional coefficients was set the same as HEC-RAS to ensure similarity in the param- eter values of the hydraulic models. However, minor adjustments were made to ensure that the upstream water surface elevation reached the expected value.

Baseline Simulation and Forecast Runs. The iRIC model was used to generate both baseline simula- tion and ensemble forecast flood inundation maps (Fig-

ure 3), same as with the HEC-RAS model. Specifically,

information system (GIS) environment to resample the output from the models to a common 5 9 5 m2 gridded raster format. In the case of iRIC, data were output as a single numerical value at the center of

each grid. This required the employment of an inverse distance-weighted interpolation to convert the data to a continuous raster grid prior to the resam- pling and reclassification procedure.

The resampling procedure extracted information from each of the model ensemble member grid cells and reclassified the data into discrete classes (0 or 1) based on whether a predetermined threshold was exceeded in the respective grid cell. These predeter- mined thresholds were based on hazardous levels for flood extent, water depth, flow velocity, and critical conditions — which is a combination of hazardous water depth and flow velocity conditions (Table 1). The flood extent threshold can be viewed as the event total flood inundation because flood extent illustrates all flood inundation that exceeded a water depth of

0.05 m. A threshold of 0.05 m was selected because it described the flooding while removing potential verti- cal errors in the DEM. As shown in Table 1, water depth and flow velocity provide a series of threshold values rather than providing continuous data. This discrete approach was used to simplify the dissemi- nated product and increase the effectiveness of the products in risk assessment applications. The critical condition threshold was a unique variable derived with flood preparation and response efforts in mind. For example, a critical condition threshold extracted from the ensemble members identified whether conditions in a grid would exceed a water depth of 0.30 m (1 foot) and a flow velocity faster than 1.80 m/s (4 miles/h). These conditions are hazardous to try to stand in, much less walk (Jonkman and Penning-Rowsell 2008); therefore, the critical conditions variable will help inform decision makers of extraordinarily hazardous

TABLE 1. Flood threat thresholds extracted during postprocessing of model output.

Flow

the calibrated model was run by changing the

Water depth

velocity Critical conditions

upstream 72-h hydrograph for the 11 different stream- flow ensemble members. Simulation iteration was set accordingly to ensure convergence in calculations and to ensure continuity error achieved <5%. The computa- tion took less than one hour for each run.

*Hydraulic Model Output Postprocessing*

Ensemble members from the HEC-RAS and iRIC models were postprocessed in a geographic

>0.15 m >0.45 m/s >0.15 m water flowing at >1.80 m/s

>0.30 m >0.90 m/s >0.30 m water flowing at >1.80 m/s

>0.61 m >1.80 m/s >0.61 m water flowing at >1.80 m/s

>0.91 m >2.70 m/s >0.15 m water flowing at >2.70 m/s

>1.20 m >3.60 m/s >0.30 m water flowing at >2.70 m/s

>1.50 m >0.61 m water flowing at >2.70 m/s

>1.80 m >0.91 m water flowing at >0.90 m/s

>1.20 m water flowing at >0.90 m/s

>1.50 m water flowing at >0.45 m/s

>1.80 m water flowing at >0.45 m/s

Note: Flood extent is defined as any cell inundated by >0.05 m of water.

# JAWRA

17521688, 2018, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1752-1688.12656 by University Of Alabama, Wiley Online Library on [05/06/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

812

Journal of the American Water Resources Association

situations that may require specialized resources, such as switch water rescue teams.

The numerous flood extent, water depth, flow velocity, and critical condition threshold rasters extracted from the ensemble members for the iRIC and the HEC-RAS were combined into composite threshold rasters for each of the hydraulic model out- put separately (Figure 3). Each grid cell value in the composite rasters corresponds to the percentage of ensemble member agreement that a defined threshold will be exceeded. As shown in Figure 5, this process used the binary output from the GIS postprocessed ensemble output to calculate the sum of each ensem- ble agreement in each grid cell divided by the total number of ensemble members to calculate the per- centage of ensemble agreement. This agreement also provides insight into the uncertainty of flood inunda- tion forecasts. That is, where the model ensemble member agreement is high, there is lower uncertainty that a predetermined threshold will be exceeded; where the model ensemble member agreement is low, there is higher uncertainty that a predetermined threshold will be exceeded. To help describe the uncertainty among ensemble members and the tem- poral change in uncertainty between the 24- and 48-h predictions, a nonparametric value called interquar- tile range (IQR) was used to assess the uncertainty in aerial coverage of inundation between the model ensembles and model forecast periods.

Finally, the outputs from both the iRIC and the HEC-RAS ensemble members were combined into a single composite using the same procedures outlined above and in Figure 5. This procedure created the final multimodel flood inundation ensemble rasters for flood extent, water depth, flow velocity, and criti- cal conditions. From these rasters, the total ensemble agreement is used as a proxy to communicate forecast uncertainty for flood inundation extent, water depth, flow velocity, and critical conditions at each grid cell.

*Product Dissemination*

The final linkage in the framework is the dissemina- tion of the multimodel flood inundation ensemble

raster layers. There are many methods that can be used to disseminate ensemble information including spaghetti plots, static map overlaid layers, and interac- tive online GIS environments (e.g., HEFS: Demargne et al. 2014; Ensemble-vis: Potter et al. 2009; Noodles: Sanyal et al. 2010). It was decided that an online GIS interactive environment would be the best method for helping users personalize and locate local flood haz- ards; therefore, the multimodel flood inundation ensemble raster layers were disseminated using a web- based mapping and decision support software develop- ment framework called Tethys (Figure 3) (Jones et al. 2014). This open-source software development suite allows for the creation of web-based applications that can ingest geospatial data using a web map service into a user-friendly interactive environment. The current study built an example web application called the Flood Threat Viewer in the Tethys platform and is accessible on the BYU Hydroinformatics Lab Apps Portal.

# RESULTS

*Comparing Ensemble Flood Inundation Forecasts from iRIC and HEC-RAS*

An advantage to the multimodel ensemble approach is that each hydraulic model has its own set of ensemble members. For comparison, baseline deterministic maps of flood inundation (i.e., flood extent threshold) were created for each hydraulic model by using the observed streamflow as the input into iRIC (Figures 6a and 7a) and HEC-RAS (Fig- ures 6d and 7d). This was compared to the compos- ited flood inundation maps (i.e., flood extent threshold) output for each model that were created using the streamflow ensemble as input for iRIC (Fig- ures 6b and 7b) and HEC-RAS (Figures 6c and 7c). Greater uncertainty is illustrated in Figures 6 and 7 as green, or where there is less agreement between the ensemble members. Lower uncertainty is illus- trated as red in Figures 6 and 7, or where there is greater agreement between the ensemble members

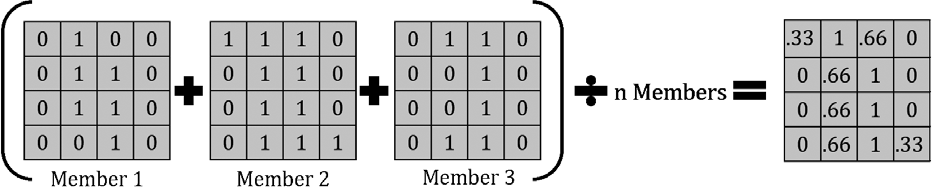


FIGURE 5. Diagram for the calculation of ensemble agreement. After categorizing the hydraulic model output rasters into binary format, the rasters are added together and divided by the total number of rasters to obtain the percentage of ensemble agreement.

Journal of the American Water Resources Association

17521688, 2018, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1752-1688.12656 by University Of Alabama, Wiley Online Library on [05/06/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

813

# JAWRA

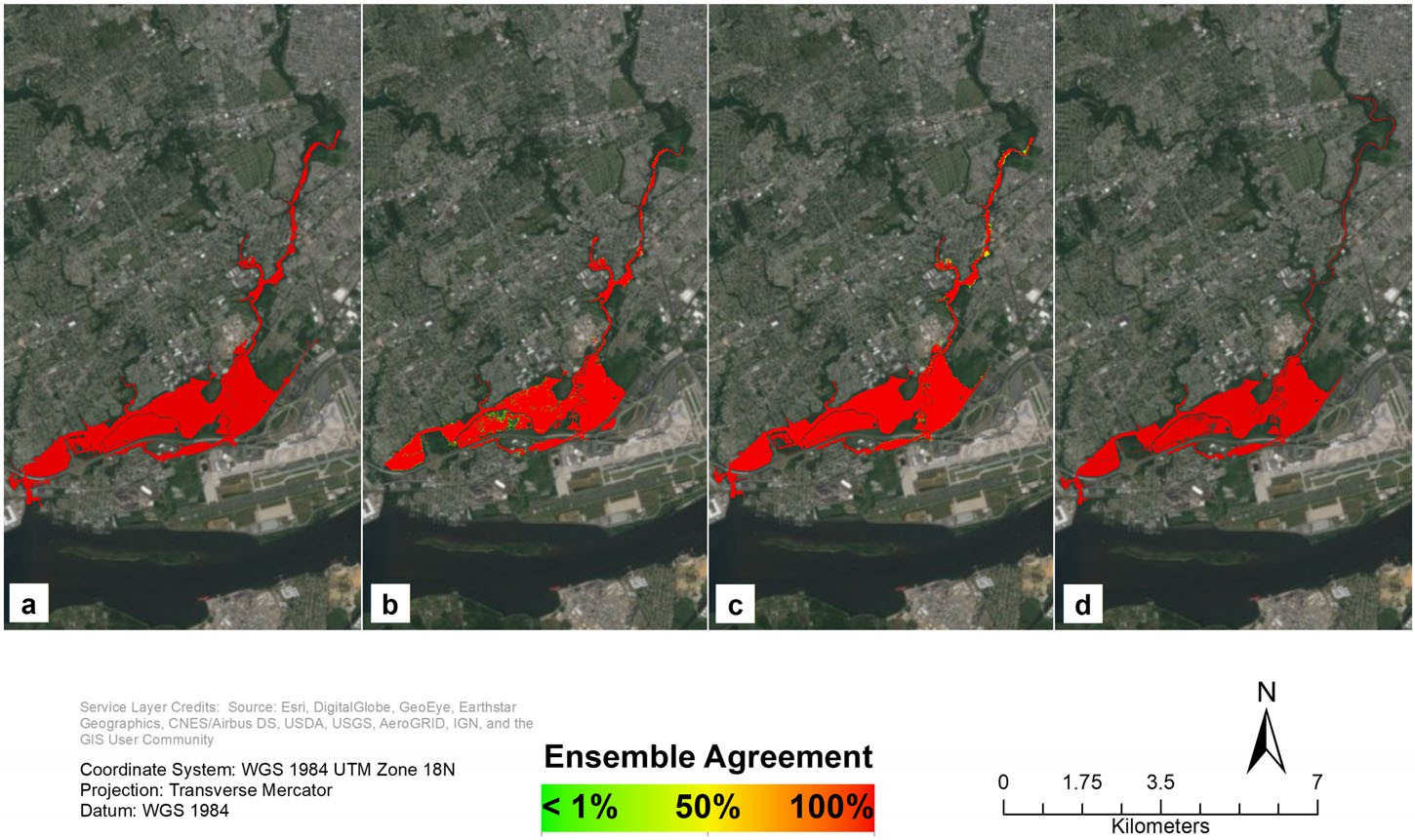


FIGURE 6. Comparison of (a) iRIC baseline flood inundation map, (b) 24-h forecast for iRIC ensemble flood inundation map,

(c) 24-h forecast for HEC-RAS ensemble flood inundation map, and (d) HEC-RAS baseline flood inundation map.

and, therefore, interpreted as greater risk for flood inundation at those grid cells.

Both iRIC and HEC-RAS produced quality 24-h lead time forecasts relative to the baseline map pro- duced by each model (Figure 6). In Figure 8, all 11 ensemble members in each of the hydraulic model ensembles are in agreement that a large number of grid cells will become inundated; however, for the 24- h lead time, it is apparent that the iRIC model ensemble members have greater disagreement in those grid cells predicted to be inundated than HEC- RAS. The iRIC 24-h lead time has 4,529 grid cells where only one ensemble member predicts inunda- tion, whereas HEC-RAS has 1,040 grid cells where only one ensemble member predicts inundation. While the model agreement dropped substantially for the iRIC 48-h lead time forecast (Figure 7b), the 48-h HEC-RAS model agreement stayed relatively consis- tent with the 24-h lead time (Figure 7c). For the iRIC 48-h lead time forecast, there are 31,963 grid cells where only one ensemble member predicts the grid cells will become inundated. In contrast, the HEC- RAS 48-h lead time forecast is relatively consistent with the 24-h forecast with 608 grid cells where only

one ensemble member predicts the grid cells will become inundated.

The substantial increase in uncertainty during the iRIC 48-h lead time forecast is reiterated in a plot depicting the area inundated relative to each ensem- ble member (Figure 9). Predicted flood inundation area forecasted by the ensemble members was consis- tent across all members in each corresponding model ensemble except for the iRIC 48-h lead time forecast. Where the 24-h iRIC, 24-h HEC-RAS, and 48-h HEC- RAS lead time flood inundation area forecasts between ensemble members produced an IQR < 0.1 km2, the IQR for the 48-h iRIC lead time forecasts was nearly 0.4 km2. This inconsistency and lower agreement translates into higher uncertainty in the iRIC 48-h lead time flood inundation forecast. The iRIC 48-h lead time ensemble members also pro- duced more widespread inundation than was fore- casted during the iRIC 24-h lead time ensemble members (Figure 9). While the uncertainty was not as pronounced for the HEC-RAS 48-h lead time ensemble members, the HEC-RAS ensemble members did produce slightly more inundation during the 48-h lead time forecasts than the 24-h lead time forecasts.

# JAWRA

17521688, 2018, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1752-1688.12656 by University Of Alabama, Wiley Online Library on [05/06/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

814

Journal of the American Water Resources Association

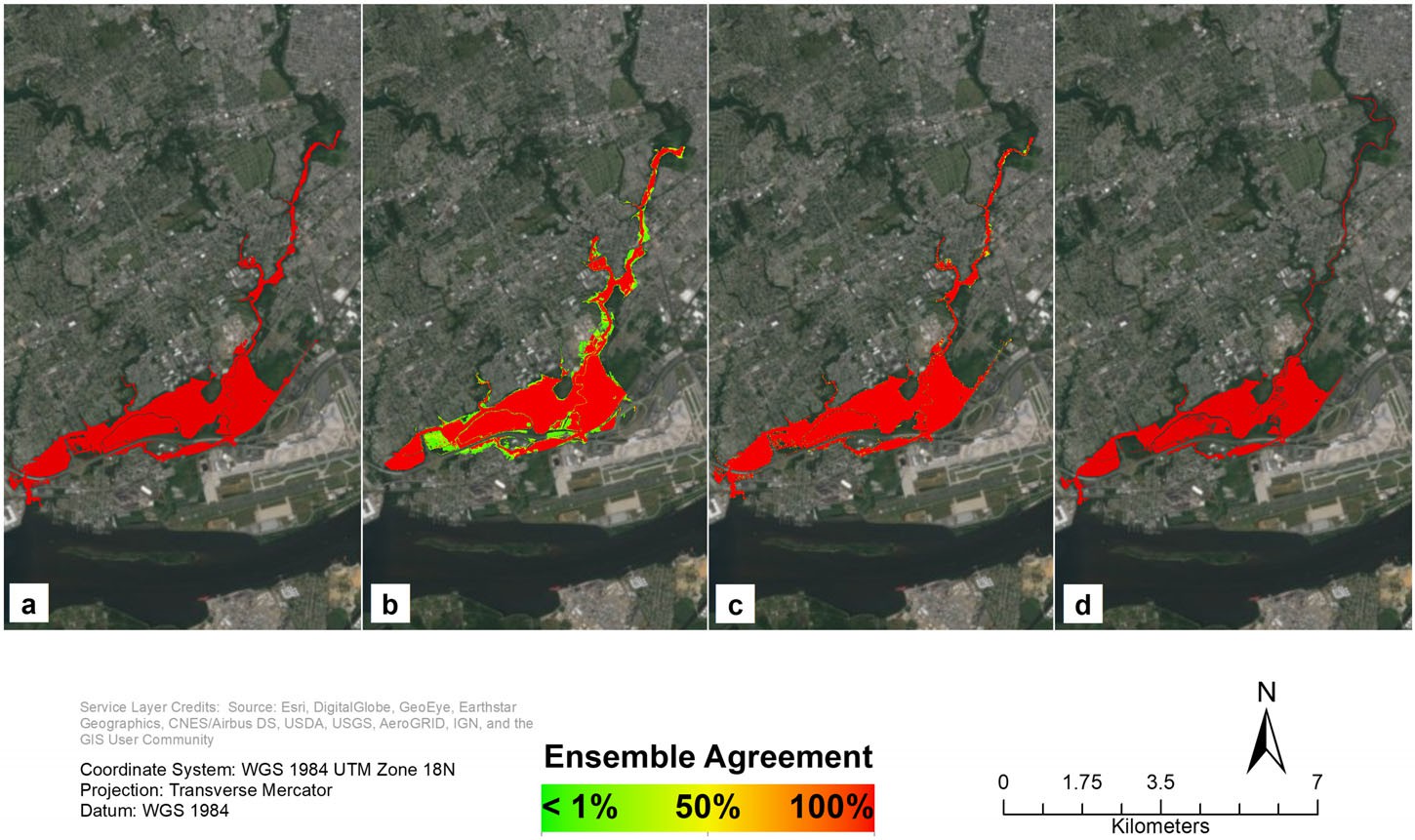


FIGURE 7. Comparison of (a) iRIC baseline flood inundation map, (b) 48-h forecast for iRIC ensemble flood inundation map,

(c) 48-h forecast for HEC-RAS ensemble flood inundation map, and (d) HEC-RAS baseline flood inundation map.

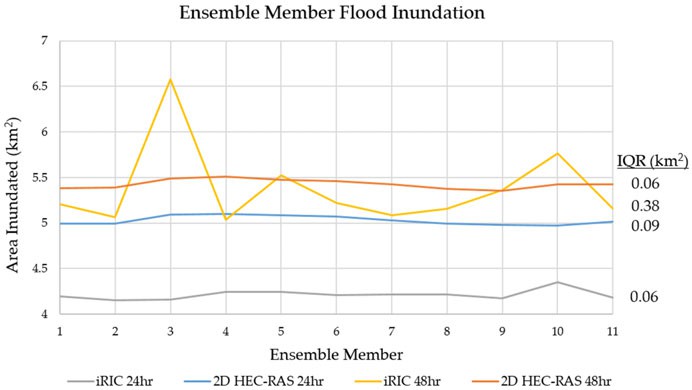
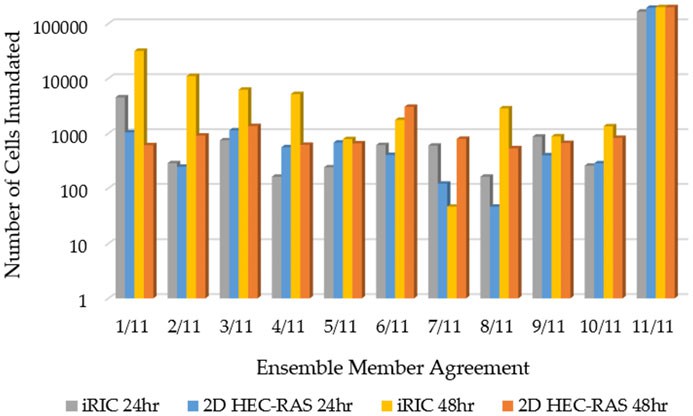


FIGURE 8. Number of cells inundated relative to ensemble member agreement from 1/11 to 11/11 agreement.

*Ensemble vs. Deterministic Flood Inundation Forecasts*

Unique to this study is the use of a hydrometeoro- logical ensemble used to drive two different modeler approaches (HEC-RAS and iRIC) to forecast flood inundation. By compositing the ensemble flood inun- dation maps from both hydraulic models, modeler subjectivity is decreased and there is greater

FIGURE 9. Area inundated as predicted by each ensemble member in the iRIC ensemble (dashed) and by each ensemble member in the two-dimensional (2D) HEC-RAS ensemble (solid) for the 24- and 48-h forecasts. Interquartile range (IQR) values from each model run are annotated next to the corresponding model run line segment.

confidence in the forecasted inundation where both hydraulic modeling approaches for flood inundation converge. The resourcefulness of this approach is demonstrated when comparing the deterministic flood extent generated by a single hydraulic model using a single streamflow value as input to the flood extent

Journal of the American Water Resources Association

17521688, 2018, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1752-1688.12656 by University Of Alabama, Wiley Online Library on [05/06/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

815

# JAWRA

generated by the multimodel (HEC-RAS and iRIC) composite using the streamflow ensemble as input (Fig- ure 10). The flood extents in Figures 10a and 10b appear similar, but the advantages of the multimodel ensemble flood inundation map can be seen when zoomed in to a commercial and residential area (Fig- ures 10c and 10d). Where it appears imminent that Locations 1, 2, and 3 will flood based on the determinis- tic flood inundation map, the actual risk of inundation is not so certain. When augmented with probability surfaces (Figures 10b and 10d), it turns out that the risk for inundation, based on ensemble agreement, is highest for Location 1, followed by Locations 2 and 3, respectively. This provides important information in the decision-making process because this may indicate that resources should be allocated to Location 1, but maybe not immediately deployed to Location 3.

*Interactive Web-Based Visualization of Flood Inundation*

In addition to the flood extent, it was mentioned that other threshold values useful in flood prepara- tion efforts were extracted for water depth, flow velocity, and critical conditions (Table 1). It would be challenging to sift through the great amount of infor- mation contained in this series of rasters in a typical

GIS platform, especially if these products are used in emergency response situations; therefore, the rasters were incorporated into a web-based application, the Flood Threat Viewer app, built in the Tethys develop- ment environment (Figure 11). The simplicity of the geospatial web environment enhances the usefulness of the framework. Layers produced from the numer- ous flood extent, water depth, flow velocity, and criti- cal conditions threshold rasters can be viewed by interacting with the provided radio buttons. End users are able to zoom in to areas of interest and can interact with the layers to quickly conduct a flood risk assessment for their areas of interest.

By simplifying the dissemination of this large amount of information, the current framework offers an effective and efficient tool for flood preparation activities. The Flood Threat Viewer created in the current paper overlaid a flood inundation forecast with ensemble agreement (i.e., uncertainty) informa- tion to communicate a level of risk in the flood inun- dation forecast. This can be used to prioritize resources to those locations where risk for hazardous conditions is high. For example, when zoomed in to a crude oil storage tank farm, it appears that a couple of these oil tanks are at a moderate risk for flooding in the current event (Figure 11a). There is no risk for the velocity of the water to exceed 0.9 m/s (2 mph) (Figure 11c) and no risk for exceeding the critical

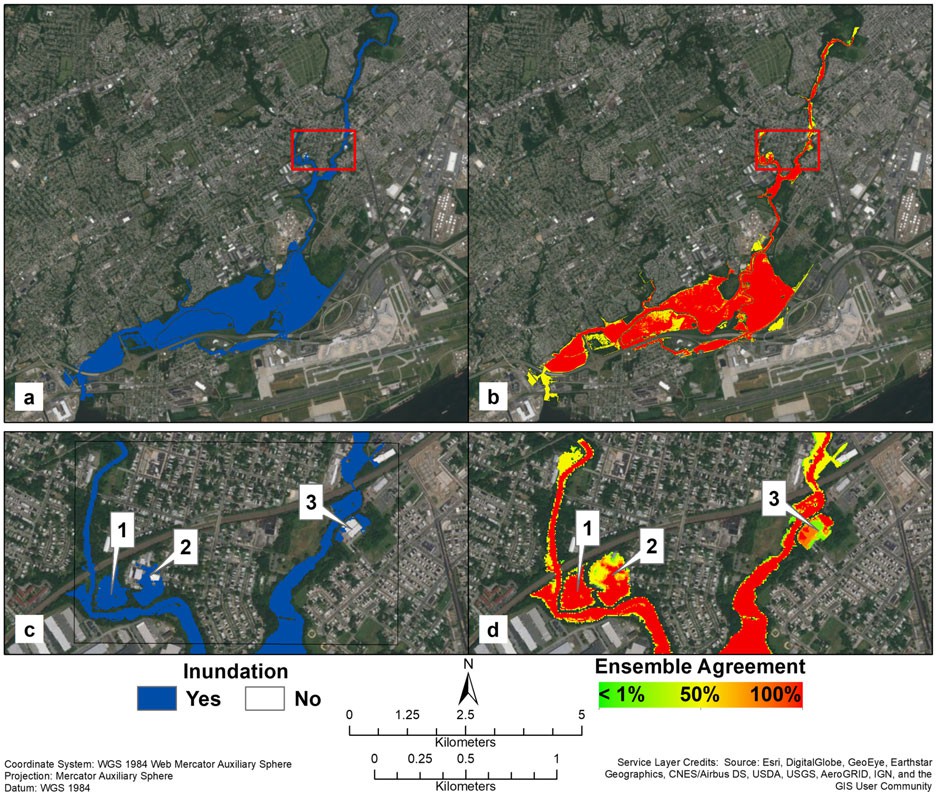


FIGURE 10. Side-by-side comparison of (left) 2D HEC-RAS deterministic flood inundation map and (right) 24-h lead time multimodel (2D HEC-RAS/iRIC composited) ensemble flood inundation map over (a, b) the full domain extent and (c, d) zoomed in to an area of interest.

# JAWRA

17521688, 2018, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1752-1688.12656 by University Of Alabama, Wiley Online Library on [05/06/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

816

Journal of the American Water Resources Association



FIGURE 11. Screenshots from the Flood Threat Viewer application zoomed to a crude oil storage tank farm. Panels correspond to the Table 1 threat metrics of (a) flood extent, (b) water depth, (c) flow velocity, and (d) critical conditions.

conditions that would require a swift water team (Figure 11d); therefore, if it is known that the tanks can withstand 0.3 m (1 ft) of standing water, which is forecasted to be a low risk of occurrence, then resources can be allocated to another location where there is greater risk of hazardous conditions during the event.

# SUMMARY AND CONCLUSIONS

Flood inundation forecasts based on deterministic model output fail to depict the complete flood inunda- tion scenario because they do not communicate the uncertainties due to imperfect forcing, initial condi- tions, model parameterizations, and numerical limita- tions. The ensemble approach implemented in this study linked existing platforms to develop a feasible framework for augmenting flood inundation forecasts with the underlying uncertainty information. Ensem- bles were generated using a hydrometeorological fore- casting system and a hydraulic multimodel approach. Specifically, an 11-member streamflow forecast ensem- ble was used as input in two hydraulic models, iRIC and 2D HEC-RAS, to generate a range of estimates for flood extent, water depth, and flow velocity.

Uncertainty was quantified by assessing the spread among ensemble members and was visualized as prob- abilistic raster surfaces. Probabilistic raster surfaces

were created for numerous flood extent, water depth, flow velocity, and critical condition thresholds to com- municate the risk of exceedance for hazardous condi- tions. The final linkage in this framework was the dissemination of the output and communication of flood risk using a web-based application. Through the framework presented, it was shown how ensembles can be readily generated and incorporated into opera- tional platforms to augment deterministic forecasts with valuable uncertainty information. Therefore, by using hydrometeorological ensembles to force two dif- ferent hydraulic modeling techniques, this framework provides a viable approach for reducing modeler sub- jectivity, quantifying uncertainty, and providing flood inundation mapping products in an interactive online environment.

An important outcome from this project is a frame- work that links between existing hydraulic models, GIS, and web-based application platforms. With this process now semiautomated, there are opportunities to adapt the framework to new study areas. It is also possible to change the models, add additional hydrau- lic models, or substitute an entirely different method for estimating flood inundation. For example, with the implementation of the NWM, future work can substitute the regional hydrometeorological forecast system in the framework to produce nationwide flood inundation uncertainty information.

A challenge with the presented framework is that the intensive nature of the hydraulic models limits the spatial applicability of the framework; therefore,

Journal of the American Water Resources Association

17521688, 2018, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1752-1688.12656 by University Of Alabama, Wiley Online Library on [05/06/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

817

# JAWRA

Zarzar, Hosseiny, Siddique, Gomez, Smith, Mejia, and Dyer

alternatives to the intensive hydraulic models for flood inundation mapping would expand the application of this framework beyond the local-scale analysis. It is possible that future work can use terrain-based models such as Height Above Nearest Drainage, which could be a reasonable substitute for the computationally intensive hydraulic models (Zheng et al. 2018). How- ever, in areas with highly dynamic flow conditions, such as in tidal river reaches, the proposed framework offers a viable approach.

In the absence of ground-truth data, baseline inun- dation maps were used for the comparison of model output. This provided the best representation of inun- dation against which to compare the model output; however, it is still subject to errors and, in that sense, it does not account for the full uncertainty of the inun- dation forecasts. While the current study was focused on the development of a framework to quantify and communicate uncertainty information, not model veri- fication, it sheds light on the need for new methods to collect ground-truth flood extent data, such as unmanned aircraft systems. In addition to adapting this framework to study areas with available ground- truth data, case studies are needed to provide a thorough assessment of this framework in flood prepa- ration and planning activities. This could be in the form of an emergency management training exercise where the forecasted flood inundation situation can be pre- sented to the group. Then a comparison can be made between the decisions made in the 2009 event to how the individuals involved in the emergency management training exercise make decisions about the event with access to the Flood Threat Viewer application.

ACKNOWLEDGMENTS

This work was conducted during the 2016 National Flood Inter- operability Experiment (NFIE) Summer Institute supported by the Consortium of Universities for the Advancement of Hydrologic Science, Inc. (CUAHSI) and the Office of Water Prediction (OWP). The authors thank all those involved in the coordination and exe- cution of the very successful 2016 NFIE Summer Institute. The authors also thank Christian Kesler, Savannah Keane, and Zhiyu (Drew) Li for their help in integrating this work into the BYU Tethys platform.

LITERATURE CITED

Afshari, S., A.A. Tavakoly, M.A. Rajib, X. Zheng, M.L. Follum, E. Omranian, and B.M. Fekete. 2018. “Comparison of New Genera- tion Low-Complexity Flood Inundation Mapping Tools with a Hydrodynamic Model.” *Journal of Hydrology* 556: 539–56. <https://doi.org/10.1016/j.jhydrol.2017.11.036>.

Beven, K., and A. Binley. 1992. “The Future of Distributed Models: Model Calibration and Uncertainty Prediction.” *Hydrological Processes* 6 (3): 279–98. <https://doi.org/10.1002/hyp.3360060305>.

Brunner, G.W. 2016. *HEC-RAS, River Analysis System Hydraulic Reference Manual. Version 5.0*. Davis, CA: US Army Corps of Engineers—Hydrologic Engineering Center (HEC). [http://www.](http://www.hec.usace.army.mil/software/hec-ras/documentation/HEC-RAS%205.0%20Reference%20Manual.pdf) [hec.usace.army.mil/software/hec-ras/documentation/HEC-RAS%](http://www.hec.usace.army.mil/software/hec-ras/documentation/HEC-RAS%205.0%20Reference%20Manual.pdf) [205.0%20Reference%20Manual.pdf](http://www.hec.usace.army.mil/software/hec-ras/documentation/HEC-RAS%205.0%20Reference%20Manual.pdf).

Buahin, C.A., N. Sangwan, C. Fagan, D.R. Maidment, J.S. Hors- burgh, E.J. Nelson, V. Merwade, and C. Rae. 2017. “Probabilis- tic Flood Inundation Forecasting Using Rating Curve Libraries.” *Journal of the American Water Resources Association* 53 (2): 300–15. <https://doi.org/10.1111/1752-1688.12500>.

Casulli, V. 2009. “A High-Resolution Wetting and Drying Algorithm for Free-Surface Hydrodynamics.” *International Journal for Numerical Methods in Fluids* 60 (4): 391–408. [https://doi.org/10.](https://doi.org/10.1002/fld.1896) [1002/fld.1896](https://doi.org/10.1002/fld.1896).

Christian, J., L. Duenas-Osorio, A. Teague, Z. Fang, and P. Bedi- ent. 2013. “Uncertainty in Floodplain Delineation: Expression of Flood Hazard and Risk in a Gulf Coast Watershed.” *Hydrologi- cal Processes* 27 (19): 2774–84. <https://doi.org/10.1002/hyp.9360>.

Cloke, H.L., and F. Pappenberger. 2009. “Ensemble Flood Forecast- ing: A Review.” *Journal of Hydrology* 375 (3–4): 613–26. <https://doi.org/10.1016/j.jhydrol.2009.06.005>.

Demargne, J., L. Wu, S.K. Regonda, J.D. Brown, H. Lee, M. He,

D.J. Seo, R. Hartman, H.D. Herr, M. Fresch, and J. Schaake. 2014. “The Science of NOAA’s Operational Hydrologic Ensemble Forecast Service.” *Bulletin of the American Meteorological Soci- ety* 95 (1): 79–98. <https://doi.org/10.1175/BAMS-D-12-00081.1>.

Di Baldassarre, G., G. Schumann, P.D. Bates, J.E. Freer, and K.J. Beven. 2010. “Flood-Plain Mapping: A Critical Discussion of Deterministic and Probabilistic Approaches.” *Hydrological Sciences Journal* 55 (3): 364–76. [https://doi.org/10.1080/](https://doi.org/10.1080/02626661003683389)

[02626661003683389](https://doi.org/10.1080/02626661003683389).

Du, J., J. McQueen, G.J. DiMego, T.L. Black, H. Juang, E. Rogers,

B.S. Ferrier, B. Zhou, Z. Toth, and S. Tracton. 2004. “The NOAA/NWS/NCEP Short Range Ensemble Forecast (SREF) Sys- tem: Evaluation of an Initial Condition Versus Multiple Model Physics Ensemble Approach.” In *Preprints, 20th Conference on Weather Analysis and Forecasting/16th Conference on Numeri- cal Weather Prediction* (Volume 21, Issue 3, pp. 1–10). Seattle, WA: American Meteor Society. [http://ams.confex.com/ams/](http://ams.confex.com/ams/pdfpapers/71107.pdf) [pdfpapers/71107.pdf.](http://ams.confex.com/ams/pdfpapers/71107.pdf)

Dyer, J., C. Zarzar, P. Amburn, R. Dumais, J. Raby, and J.A. Smith. 2016. “Defining the Influence of Horizontal Grid Spacing on Ensemble Uncertainty within a Regional Modeling Frame- work.” *Weather and Forecasting* 31: 1997–2017. [https://doi.org/](https://doi.org/10.1175/WAF-D-16-0030.1) [10.1175/WAF-D-16-0030.1.](https://doi.org/10.1175/WAF-D-16-0030.1)

Frick, J., and C. Hegg. 2011. “Can End-Users’ Flood Management Decision Making Be Improved by Information About Forecast Uncertainty?” *Atmospheric Research* 100 (2): 296–303. [https://](https://doi.org/10.1016/j.atmosres.2010.12.006) [doi.org/10.1016/j.atmosres.2010.12.006](https://doi.org/10.1016/j.atmosres.2010.12.006).

Gomez, M. 2017. “Medium-Range Ensemble Flood Forecast Inunda- tion Maps: The Case of the Delaware River Near Philadelphia.” Master’s thesis, Pennsylvania State University, University Park, PA.

Grimaldi, S., A. Petroselli, E. Arcangeletti, and F. Nardi. 2013. “Flood Mapping in Ungauged Basins Using Fully Continuous Hydrologic-Hydraulic Modeling.” *Journal of Hydrology* 487: 39–

47. <https://doi.org/10.1016/j.jhydrol.2013.02.023>.

Gupta, H.V., S. Sorooshian, and P.O. Yapo. 1998. “Toward Improved Calibration Model of Hydrologic Models: Multiple and Non Commensurable Measures of Information.” *Water Resources Research* 34 (4): 751–63. [https://doi.org/10.1029/97WR0349](https://doi.org/10.1029/97WR03495)5.

Hagedorn, R., T.M. Hamill, and J.S. Whitaker. 2008. “Probabilistic Forecast Calibration Using ECMWF and GFS Ensemble Refore- casts. Part I: Two-Meter Temperatures.” *Monthly Weather Review* 136: 2608–19. <https://doi.org/10.1175/2007MWR2410.1>.

Hamill, T.M., R. Hagedorn, and J.S. Whitaker. 2008. “Probabilistic Forecast Calibration Using ECMWF and GFS Ensemble

# JAWRA

17521688, 2018, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1752-1688.12656 by University Of Alabama, Wiley Online Library on [05/06/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

818

Journal of the American Water Resources Association

Reforecasts. Part II: Precipitation.” *Monthly Weather Review*

136: 2620–32. [https://doi.org/10.1175/2007MWR2411.1.](https://doi.org/10.1175/2007MWR2411.1)

Jones, N., J. Nelson, N. Swain, S. Christensen, D. Tarboton, and P. Dash. 2014. “Tethys: A Software Framework for Web-Based Modeling and Decision Support Applications.” International Congress on Environmental Modelling and Software, San Diego, California. Paper 25. [https://scholarsarchive.byu.edu/iemssconfe](https://scholarsarchive.byu.edu/iemssconference/2014/Stream-A/25) [rence/2014/Stream-A/25](https://scholarsarchive.byu.edu/iemssconference/2014/Stream-A/25).

Jonkman, S.N., and E. Penning-Rowsell. 2008. “Human Instability in Flood Flows.” *Journal of the American Water Resources Associa- tion* 44: 1208–18. <https://doi.org/10.1111/j.1752-1688.2008.00217.x>. Kauffeldt, A., F. Wetterhall, F. Pappenberger, P. Salamon, and J. Thielen. 2016. “Technical Review of Large-Scale Hydrological Models for Implementation in Operational Flood Forecasting Schemes on Continental Level.” *Environmental Modelling and Software* 75: 68–76. <https://doi.org/10.1016/j.envsoft.2015.09.009>.

Leedal, D., J. Neal, K. Beven, P. Young, and P. Bates. 2010. “Visu- alization Approaches for Communicating Real-Time Flood Fore- casting Level and Inundation Information.” *Journal of Flood Risk Management* 3: 140–50. [https://doi.org/10.1111/j.1753-318X.](https://doi.org/10.1111/j.1753-318X.2010.01063.x) [2010.01063](https://doi.org/10.1111/j.1753-318X.2010.01063.x).x.

Leutbecher, M., and T.N. Palmer. 2008. “Ensemble Forecasting.” *Journal of Computational Physics* 227: 3515–39. [https://doi.org/](https://doi.org/10.1016/j.jcp.2007.02.014) [10.1016/j.jcp.2007.02.01](https://doi.org/10.1016/j.jcp.2007.02.014)4.

Mashriqui, H.S., J.S. Halgren, and S.M. Reed. 2014. “1D River Hydraulic Model for Operational Flood Forecasting in the Tidal Potomac: Evaluation for Freshwater, Tidal, and Wind-Driven Events.” *Journal of Hydraulic Engineering* 140: 04014005. [https://doi.org/10.1061/%28ASCE%29HY.1943-7900.0000862.](https://doi.org/10.1061/%28ASCE%29HY.1943-7900.0000862)

Merwade, V., F. Olivera, M. Arabi, and S. Edleman. 2008. “Uncer- tainty in Flood Inundation Mapping: Current Issues and Future Directions.” *Journal of Hydraulic Engineering* 13: 608–20. [https://doi.org/10.1061/%28ASCE%291084-0699%282008%2913%](https://doi.org/10.1061/%28ASCE%291084-0699%282008%2913%3A7%28608%29) [3A7%28608%29.](https://doi.org/10.1061/%28ASCE%291084-0699%282008%2913%3A7%28608%29)

Nelson, J.M., Y. Shimizu, H. Takebayashi, and R.R. McDonald. 2010. “The International River Interface Cooperative: Public Domain Software for River Modeling.” 2nd Joint Federal Intera- gency Conference, Las Vegas, NV.

Nutter, P., D. Stensrud, and M. Xue. 2004. “Effects of Coarsely Resolved and Temporally Interpolated Lateral Boundary Condi- tions on the Dispersion of Limited-Area Ensemble Forecasts.” *Monthly Weather Review* 132: 2358–77. https://doi.org/10.1175/

1520-0493(2004) 132<2358:EOCRAT>2.0.CO;2.

NWS. 2015. “Hydrologic Information Center—Flood Loss Data.” [http://www.nws.noaa.gov/hic/.](http://www.nws.noaa.gov/hic/)

Oudin, L., V. Andr´eassian, T. Mathevet, C. Perrin, and C. Michel. 2006. “Dynamic Averaging of Rainfall-Runoff Model Simulations from Complementary Model Parameterizations.” *Water Resources Research* 42 (7): 1–10. [https://doi.org/10.1029/2005WR004636.](https://doi.org/10.1029/2005WR004636)

Palmer, T. 2000. “Predicting Uncertainty in Forecasts of Weather and Climate.” *Reports on Progress in Physics* 63: 71–116.

Pappenberger, F., K.J. Beven, N.M. Hunter, P.D. Bates, B.T. Gou- weleeuw, J. Thielen, and A.P.J. De Roo. 2005. “Cascading Model Uncertainty from Medium Range Weather Forecasts (10 Days) Through a Rainfall-Runoff Model to Flood Inundation Predic- tions Within the European Flood Forecasting System (EFFS).” *Hydrology and Earth System Sciences Discussions* 9: 381–93. <https://hal.archives-ouvertes.fr/hal-00304846>.

Pappenberger, F., P. Matgen, K.J. Beven, J.B. Henry, L. Pfister, and P. Fraipont. 2006. “Influence of Uncertain Boundary Condi- tions and Model Structure on Flood Inundation Predictions.” *Advances in Water Resources* 29: 1430–49. [https://doi.org/10.](https://doi.org/10.1016/j.advwatres.2005.11.012) [1016/j.advwatres.2005.11.012](https://doi.org/10.1016/j.advwatres.2005.11.012).

Pielke, R.A., and M.W. Downton. 2000. “Precipitation and Damag- ing Floods: Trends in the United States, 1932–97.” *Journal of*

*Climate* 13: 3625–37. https://doi.org/10.1175/1520-0442(2000) 013<3625:PADFTI>2.0.CO;2.

Potter, K., A. Wilson, P.T. Bremer, D. Williams, C. Doutriaux, V. Pascucci, and C.R. Johnson. 2009. “Ensemble-Vis: A Framework for the Statistical Visualization of Ensemble Data.” In Data Mining Workshops, 2009. ICDMW’09. IEEE International Con- ference, 233–40. <https://doi.org/10.1109/icdmw.2009.55>.

Ramos, M.H., T. Mathevet, J. Thielen, and F. Pappenberger. 2010. “Communicating Uncertainty in Hydro-Meteorological Fore- casts: Mission Impossible?” *Meteorological Applications* 17 (2): 223–35. <https://doi.org/10.1002/met.202>.

Regonda, S.K., D.J. Seo, B. Lawrence, J.D. Brown, and J. Demargne. 2013. “Short-Term Ensemble Streamflow Forecast- ing Using Operationally-Produced Single-Valued Streamflow Forecasts—A Hydrologic Model Output Statistics (HMOS) Approach.” *Journal of Hydrology* 497: 80–96. [https://doi.org/10.](https://doi.org/10.1016/j.jhydrol.2013.05.028) [1016/j.jhydrol.2013.05.028](https://doi.org/10.1016/j.jhydrol.2013.05.028).

Sanyal, J., S. Zhang, J. Dyer, A. Mercer, P. Amburn, and R. Moor- head. 2010. “Noodles: A Tool for Visualization of Numerical Weather Model Ensemble Uncertainty.” *IEEE Transactions of Visualization and Computer Graphics* 16: 1421–30. [https://doi.](https://doi.org/10.1109/TVCG.2010.181) [org/10.1109/TVCG.2010.181.](https://doi.org/10.1109/TVCG.2010.181)

Sharma, S., R. Siddique, N. Balderas, J.D. Fuentes, S. Reed, P. Ahnert, R. Shedd, B. Astifan, R. Cabrera, A. Laing, and M. Klein. 2017. “Eastern US Verification of Ensemble Precipitation Forecasts.” *Weather and Forecasting* 32 (1): 117–39. [https://doi.](https://doi.org/10.1175/waf-d-16-0094.1) [org/10.1175/waf-d-16-0094.1.](https://doi.org/10.1175/waf-d-16-0094.1)

Sharma, S., R. Siddique, S. Reed, P. Ahnert, P. Mendoza, and A. Mejia. 2018. “Relative Effects of Statistical Preprocessing and Postprocessing on a Regional Hydrological Ensemble Prediction System.” *Hydrology and Earth System Sciences Discussions*. [https://doi.org/10.5194/hess-2017-514.](https://doi.org/10.5194/hess-2017-514)

Siddique, R., and A. Mejia. 2017. “Ensemble Streamflow Forecast- ing Across the U.S. Mid-Atlantic Region with a Distributed Hydrological Model Forced by GEFS Reforecasts.” *Journal of Hydrometeorology* 18: 1905–28. [https://doi.org/10.1175/JHM-D-](https://doi.org/10.1175/JHM-D-16-0243.1)

[16-0243.1](https://doi.org/10.1175/JHM-D-16-0243.1).

Siddique, R., A. Mejia, J. Brown, S. Reed, and P. Ahnert. 2015. “Verification of Precipitation Forecasts from Two Numerical Weather Prediction Models in the Middle Atlantic Region of the USA: A Precursory Analysis to Hydrologic Forecasting.” *Journal of Hydrology* 529: 1390–406. [https://doi.org/10.1016/j.jhydrol.](https://doi.org/10.1016/j.jhydrol.2015.08.042)

[2015.08.042](https://doi.org/10.1016/j.jhydrol.2015.08.042).

Stensrud, D.J., J. Bao, and T.T. Warner. 2000. “Using Initial Con- dition and Model Physics Perturbations in Short-Range Ensem- ble Simulations of Mesoscale Convective Systems.” *Monthly Weather Review* 128: 2077–107. https://doi.org/10.1175/1520- 0493(2000)128<2077:UICAMP>2.0.CO;2.

Toth, Z., and E. Kalnay. 1997. “Ensemble Forecasting at NCEP and the Breeding Method.” *Monthly Weather Review* 125: 3297–

319. https://doi.org/10.1175/1520-0493(1997)125<3297:EFANAT>

2.0.CO;2.

Vela´zquez, J.A., F. Anctil, and C. Perrin. 2010. “Performance and Reliability of Multimodel Hydrological Ensemble Simulations Based on Seventeen Lumped Models and a Thousand Catch- ments.” *Hydrology and Earth System Sciences* 14 (11): 2303–17. <https://doi.org/10.5194/hess-14-2303-2010>.

Zarriello, P. 1998. “Comparison of Nine Uncalibrated Runoff Mod- els to Observed Flows in Two Small Urban Watersheds.” *First Federal Interagency Hydrologic Modeling Conference* 1: 7–170.

Zheng, X., D.G. Tarboton, D.R. Maidment, Y.Y. Liu, and P. Pas- salacqua. 2018. “River Channel Geometry and Rating Curve Estimation Using Height above the Nearest Drainage.” *Journal of the American Water Resources Association*. [https://doi.org/10.](https://doi.org/10.1111/1752-1688.12661) [1111/1752-1688.12661](https://doi.org/10.1111/1752-1688.12661).

Journal of the American Water Resources Association

17521688, 2018, 4, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/1752-1688.12656 by University Of Alabama, Wiley Online Library on [05/06/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

819

JAWRA