Flood-inundation modeling in an operational context: sensitivity to topographic resolution and Manning's *n*

Sarah Praskievicz, Shawn Carter, Juzer Dhondia and Michael Follum

ABSTRACT

Streamflow forecasts from operational hydrologic models can be converted into forecasts of flood-inundation extent using either physically based hydraulic models or simpler terrain-based approaches. Two factors that influence simulated flood-inundation extent are spatial resolution of topographic data and in-channel and overland-flow roughness characterized by the Manning's *n* parameter. Here, AutoRoute, a raster-based flood-inundation model, was used to simulate two recent flood events in Florida (a forested floodplain) and Texas (an urban floodplain) using two different topographic resolutions and a range of Manning's *n* values. The AutoRoute-simulated flood-inundation extents were evaluated using observed extents from remotely sensed imagery. For comparison, the same flood events were also simulated using a one-dimensional Hydrologic Engineering Center River Analysis System (HEC-RAS) model. Results indicated that model performance was much improved with higher topographic resolution for the forested floodplain site and that the urban site was more sensitive to Manning's *n*. For the three different rivers analyzed, the fit for HEC-RAS was 5–10% higher than that for AutoRoute. Despite being only slightly less accurate than HEC-RAS in its simulation of flood extent, AutoRoute was much simpler to set up and required less computational time to run.

Key words | AutoRoute, emergency response, flooding, HEC-RAS, inundation modeling, Landsat

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HIGHLIGHTS

- Applies a simple terrain-based model for use in operational flood forecasting.
- Compares the performance of a simple terrain-based model with that of a standard physically based hydraulic model.
- Uses the observed inundation extent from remote sensing to quantitatively validate model performance.
- Assesses model sensitivity to topographic resolution and Manning's *n*.
- Provides a framework that can potentially be adapted for near real-time operational flood forecasting for large spatial domains.

INTRODUCTION

Floods are among the deadliest and most destructive natural disasters globally. To save lives and protect property, emergency responders must have accurate, real-time, high-resolution forecasts of flood-inundation extent. Such forecasts allow emergency responders to make the best possible decisions about evacuations and staging of resources (Fagan 2016). Because flood events range from local to watershed-scale, efforts within the United States are ongoing to develop operational hydrologic models that can forecast streamflow for a continental domain, at high

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spatial resolution, and in near real time (Salas *et al.* 2018). Although these efforts are beneficial, they currently only focus on producing accurate flow rates, not flood-inundation or streamflow velocity, which may be more helpful to first responders.

There are two potential approaches to simulating the inundation extent associated with a streamflow magnitude. One is to use a physically based hydraulic model, such as the United States Army Corps of Engineers (USACE) Hydrologic Engineering Center River Analysis System (HEC-RAS) model (USACE 2016), the Finite Element Surface Water Modeling System for 2D flow in the Horizontal Plane (FESWMS-2DH), Flow and Sediment Transport with Morphological Evolution of Channels (FaSTMECH), MIKE FLOOD 1D/2D, SOBEK 1D/2D, BreZo/HiRes-Flood, Flood Wave Dynamic Model (FLDWAV), or LISFLOOD-FP (Afshari *et al.* 2018). Many physically based hydraulic models can be run in either 1D or 2D modes; here, our focus is on 1D HEC-RAS in order to make the results comparable to those of the simple terrain-based model we are testing. Because physically based models solve many of the hydraulic equations that govern flow, they produce highly accurate results that meet engineering specifications. Physically based hydraulic models, however, require significant amounts of input data such as cross-sections and/or high-resolution topographic data, roughness values, and the characteristics of hydraulic structures (Bates 2004). These data are not available everywhere, especially cross-section data that resolve the shape of river channels. Moreover, physically based hydraulic models are computationally expensive to run. Because of these data and computational limitations, it is challenging to use physically based hydraulic models to operationally forecast flood inundation for continental domains, where thousands or even millions of stream reaches must be simulated. Although 1D hydraulic models exist for large river basins or even entire countries or continents in places like the Mississippi River basin, Bangladesh, and the European Union, forecasting flood inundation in near real time during an actual flood event using physically based models would be subject to these data and computational limitations.

An alternative to physically based models that can feasibly be implemented at a continental scale is to use simple terrain-based approaches. Because the primary control on the extent of inundation is topography, it is reasonable to use a digital elevation model (DEM) to estimate the inundation extent associated with a streamflow amount (Casas *et al.* 2006). The expectation is that results using a simple terrain-based model will be less accurate than for a physically based hydraulic model because of lack of dynamic representation of processes such as those related to backwaters, but the advantage is that the data and computational requirements are much simpler (Horritt & Bates 2002). The main dataset needed for terrain-based approaches is a DEM, which is available at approximately 10-m resolution for the entire continental United States from the National Elevation Dataset (Gesch *et al.* 2002). Using only a DEM (albeit one that must be pre-processed to be useful hydraulically, such as by filling sinks and removing artifacts) and a relatively simple and computationally efficient terrain-based model, it is feasible to forecast flood-inundation extent associated with streamflow forecasts at a continental scale.

Regardless of whether physically based or terrain-based approaches are used, much of the uncertainty in forecasts of flood-inundation extent stems from uncertainty in the input data. There are uncertainties in each of the three main types of input data: the forcing, the topographic data, and the roughness data (Cook & Merwade 2009). Uncertainty in the forcing means that the incoming streamflow (in the case of hydraulic models) or rainfall (in the case of hydrologic–hydraulic models) is not known or specified with perfect accuracy, especially because river gages can be destroyed during large floods, smaller streams are often ungaged, and the model's ability to represent spatial variability in rainfall is limited by the resolution of input grids.

Topographic data are uncertain because measured cross-sections are often unavailable, models must interpolate between cross-sections, and high-resolution elevation data (such as from LiDAR) are not available everywhere. For example, Sanders (2007) found that flood-inundation models based on coarser-resolution DEMs tend to overestimate flood extent compared with the most accurate LiDAR-based DEMs. Abily *et al.* (2016) found that urban flood simulations are highly sensitive to modeler choices relative to measurement errors in high-resolution topographic datasets. Li & Wong (2010) compared flood-inundation simulation results based on different topographic datasets and found significant differences among simulations associated with resolution of the input elevation data. These findings suggest that improving the spatial resolution of DEMs that are available across the United States, for example by increasing the LiDAR coverage, is critical for improving flood-inundation forecasts. An additional issue with most available DEMs is that they include only the elevation of the water surface at the time of data acquisition and do not incorporate river bathymetry. On deep rivers, the channel-storage capacity is large, so flood inundation may be significantly overestimated if river bathymetry is not considered. Cook & Merwade (2009) compared flood-inundation modeling results from six different topographic datasets and found that an inundated area is reduced with improved horizontal accuracy and vertical resolution, and further reduced when river bathymetry is incorporated into the topographic data.

Another source of uncertainty in flood-inundation modeling is input data on in-channel and overland-flow roughness, usually parameterized using Manning's n. For example, Bozzi *et al.* (2015) found that uncertainty in roughness leads to probability density functions (PDFs) with heavier right tails for water level, meaning that the assumption of symmetrical PDFs can lead to underestimation of flooding. For both physically based and terrain-based models, Manning's n or other roughness parameters are needed to estimate the flow velocity using Manning's equation:

$$V = \frac{k}{n} R_h^{2/3} S^{1/2} \tag{1}$$

where V is the cross-sectional average velocity, k is a conversion factor between SI and English units, n is the Manning's roughness coefficient, R_{h} is the hydraulic radius, and S is the hydraulic slope. Manning's equation is empirically derived, and it is generally not possible to accurately predict Manning's n from theoretical principles. Instead, Manning's n can be estimated in the field using variables such as bed-particle size, surface irregularities, obstructions, and vegetation. Where detailed information on the particle size and channel or floodplain characteristics are unavailable, Manning's n can be estimated using geospatial datasets such as land cover (e.g., Moore 2011). Nevertheless, the lack of theoretical basis for Manning's n results in uncertainty about how to parameterize it. Analyzing the sensitivity of flood-inundation extent to different Manning's n ranges is useful for assessing alternative assumptions about how land cover and other geospatial attributes affect roughness.

Here, we test the AutoRoute model, a simple raster-based model developed by USACE Coastal and Hydraulics Laboratory (Follum 2013; Follum *et al.* 2017) to simulate flood events over large regions for the military, as a potential tool to estimate the extent of flooding based on streamflow forecasts. The advantage of AutoRoute is its minimal time (for both computation and, even more importantly, model setup) and data requirements (a DEM, flowline, land cover, and streamflow data, all easily available for the continental United States), which make it feasible to apply at a continental scale using real-time, high-resolution streamflow forecasts. For example, Follum *et al.* (2017) used streamflow from the RAPID routing model (David *et al.* 2011a, 2011b) to estimate high-resolution flood maps for the June 2008 flood events in the Midwest and the April–June 2011 flood events in the Mississippi Delta. Afshari *et al.* (2018) compared flood-simulation results for two low-complexity models, including AutoRoute, with those from HEC-RAS 2D. They found that the low-complexity models, especially AutoRoute, were able to produce inundation extents similar to HEC-RAS 2D, concluding that 'low-complexity flood models can be considered as a suitable alternative for fast predictions in large-scale hyper-resolution operational frameworks' (Afshari *et al.* 2018). There are, therefore, potential advantages of AutoRoute over more advanced hydraulic models in terms of data requirements and computational efficiency, which make AutoRoute more feasible to apply in operational flood-forecasting contexts.

In this study, we evaluate the performance of AutoRoute-simulated flood-inundation extents for two flood events (one in a forested floodplain and the other in an urban floodplain) using observed inundation extents derived from remotely sensed imagery. We test the model's sensitivity to topographic resolution and Manning's n. For comparison, we also simulated the same floods using HEC-RAS, to evaluate the effectiveness of the simple raster-based AutoRoute relative to a more standard physically based hydraulic model. The goal of the comparison is to determine whether AutoRoute can feasibly be used to produce simulations of inundation extent using streamflow forecasts in an operational context with similar accuracy to the engineering-standard HEC-RAS 1D shallow-water equation-based modeling approach. Although our study areas are small, the goal is to test the extent to which flood events in different river types (large forested floodplain versus small urban streams) can be accurately simulated by AutoRoute and how sensitive the results are to differing input datasets (topographic resolution and Manning's n). These results can inform the development of AutoRoute as a tool for continental-scale applications. The novelty of the study is its evaluation of AutoRoute's performance for operational flood forecasting, by comparing AutoRoute flood extents with those simulated by HEC-RAS and observed from remote sensing, and how their sensitivity to topographic resolution and Manning's n varies in different types of rivers.

METHODS

AutoRoute

AutoRoute was developed for supporting military operations by determining route vulnerability caused by flooding (McKinley *et al.* 2012; Follum 2013). AutoRoute is a one-dimensional, raster-based program with spatial inputs of a DEM, stream mask (rasterized stream network), and land-cover map. For each stream cell (defined by the stream mask), the model internally samples cross-sections from the DEM and estimates hydraulic roughness (Manning's n) from the land-cover map. Peak flow estimates are also defined for each stream cell, which can be input using a constant flow value, a flow-regression equation, or output from a river-flow model (see Follum *et al.* (2017) as an example). For each cross-section, an iterative volume-fill method of Manning's equation is used to calculate the flow velocity, normal-flow depth, and flood extent. Following Follum *et al.* (2017), the hydraulic roughness for each cross-section is defined by correlating Manning's n roughness coefficients with land-cover classifications from the National Land Cover Database (NLCD). The output from AutoRoute is a flow depth along each stream cell. A post-processing script then creates flood-depth rasters and flood-inundation polygons (Follum *et al.* 2019). For a more detailed description of the AutoRoute model, the reader is guided to Follum (2013), Follum *et al.* (2017), and Follum *et al.* (2019).

Study areas and flood events

We used two flood events in two study areas (Figure 1). These study areas were selected because of the availability of remotely sensed images of inundation extent during recent floods from the U.S. Flood Inundation Map Repository (USFIMR) at the Surface Dynamics Modeling Lab at the University of Alabama (SDML 2019). The first study area is the Choctawhatchee River, which originates in southeastern Alabama and flows for 227 km to its mouth on Choctawhatchee Bay in the Florida panhandle, with a total drainage area of 11,888 km^2. Land use in the basin is predominantly rural, with approximately 52% forest, 31% cropland (mostly soybeans, corn, peanuts, cotton, hay, fruits, and nuts), 12% pasture, and 3% urban. The Choctawhatchee River is free of any major dams and supports extensive bottomland hardwood forest on its undeveloped floodplain.

Because of the subtropical climate – with frequent heavy rainfall and occasional hurricane landfalls – as well as the flat terrain and lack of flow regulation, the Choctawhatchee River is highly flood-prone. One of the largest floods on record in the southeastern United States occurred on the Pea River, the largest tributary of the Choctawhatchee, in Elba, Alabama, in March 1929. After this flood, a levee was built to protect Elba. Nevertheless, a highly destructive flood occurred in Elba in March 1990, when the levee was breached, and the town was completely inundated for 4 days by flows from Whitewater Creek. This event also caused flooding on the mainstem Choctawhatchee River in Geneva, Alabama, and Caryville, Florida, and caused a total of $120 million in damage. Serious floods also affected Elba in 1994 and 1998.

The first flood event used in this study occurred on the Choctawhatchee River in Alabama and Florida between 22 December 2015 and 15 January 2016. This event followed several weeks of heavy rainfall, with over 254 mm of rain during December 2015, more than twice the December average of 117 mm. For this flood event, we modeled an approximately 75-km segment from the Alabama–Florida

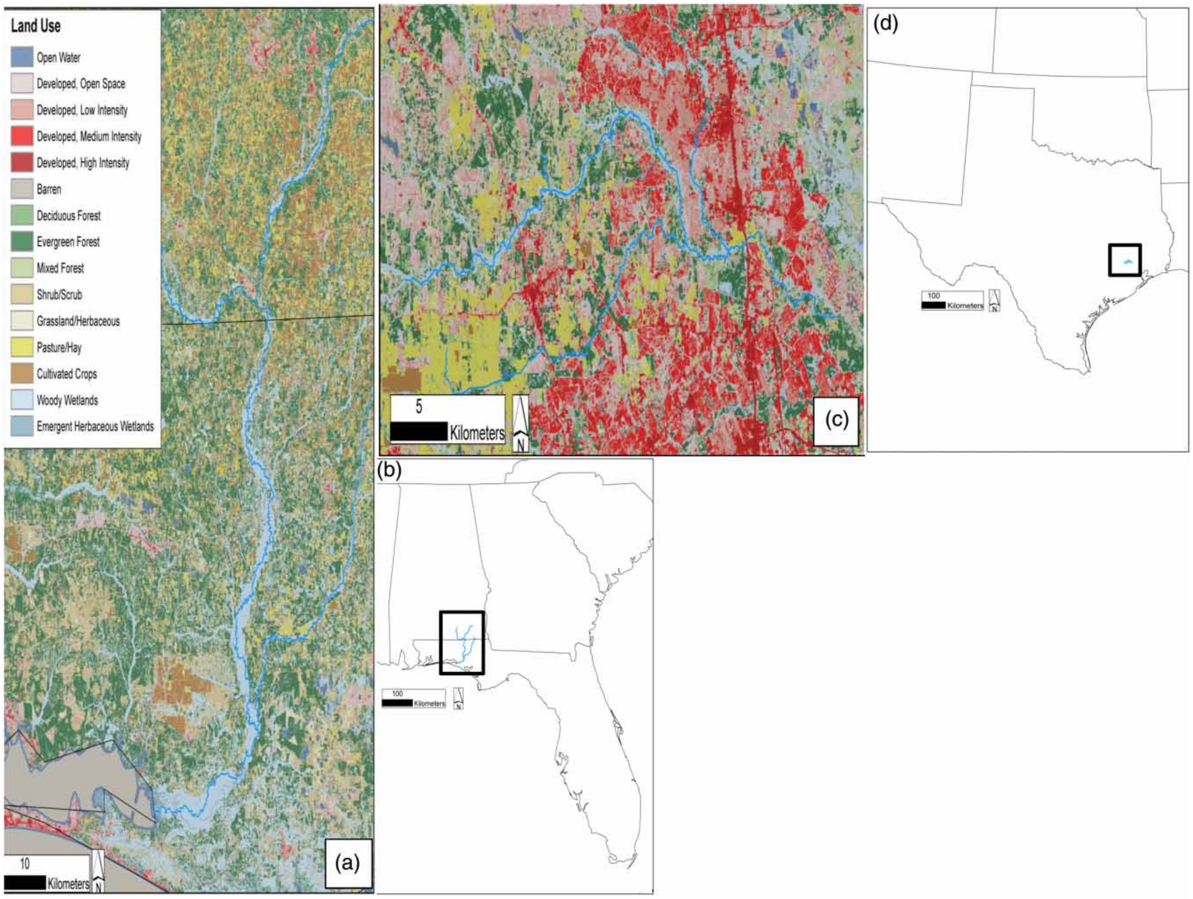

Figure 1 | Choctawhatchee River basin (a) land cover; and (b) location; Spring and Willow creeks (c) land cover; and (d) location.

border to Choctawhatchee Bay in Florida. This segment was selected because there was a cloud-free Landsat overpass on 4 January 2016, when the river was still in flood, and our model domain begins at the Florida border because 3-m NED data were not available for the Alabama portion of the basin. Discharge at the time of Landsat image acquisition was 1,141 $m^3 s^{-1}$ (a small flood with a recurrence interval of approximately 3.7 years) at the United States Geological Survey (USGS) gage at Caryville, Florida (02365500), past the crest on 29 December 2015, of 1,580 $m^3 s^{-1}$. The Landsat 8 Operational Land Imager (OLI) 30-m image was classified by the Spatial Dynamics Modeling Lab (SDML) at the University of Alabama to determine the flood-inundation extent (SDML 2019). To make the observed Landsat-based inundation extents comparable to the AutoRoute-simulated extents, we used the ArcGIS Boundary Clean tool on the observed extents.

The second study area is Spring Creek and Willow Creek, in the San Jacinto River basin near Houston, Texas. Willow Creek, with a drainage area of 209 km^2, is a tributary of Spring Creek, with a total drainage area of 1,099 km^2. Spring Creek flows into the San Jacinto River, which enters Galveston Bay. Land use in the Spring Creek subbasin is dominated by agriculture (31%), developed land (25%), and forest (24%, predominantly pine). The subbasin is affected by urban development from the Houston metropolitan region, the fifth-largest metropolitan area in the United States. Although the mainstem San Jacinto River is regulated, Spring Creek is mostly free-flowing.

The risk of flooding is substantial throughout the Houston metropolitan region, due to intense rainfall and low relief, as well as high amounts of impervious surface area associated with urban development. The hazards associated with flooding are especially severe because of the high population density exposed to floods. Major floods were common early in the history of the city, with 16 major floods from 1836 to 1936. In response to especially destructive floods in 1929 and 1935, the Harris County Flood Control District was formed and began constructing flood-control structures and a flood early-warning system. After the 1940s, there were approximately 30 floods in Harris County, causing hundreds of millions of dollars in damage, including widespread flooding caused by Tropical Storm Allison in 2001. Most recently, the Houston metropolitan region and the Texas Gulf Coast experienced catastrophic flooding in August 2017, when Hurricane Harvey set new North American rainfall records, with some locations receiving up to 1,300 mm of rain in less than 48 h.

The second flood event used in this study occurred on Spring and Willow creeks in Texas between 25 May and 2 June 2016. Houston experienced its wettest April on record in 2016, with approximately 356 mm of rainfall. Another series of heavy rainfall events occurred in late May, including one storm that dropped over 483 mm of rain in 48 h, resulting in widespread flooding that caused 10 deaths. The San Jacinto River basin was among the areas to be flooded, including Spring and Willow creeks. For this flood event, we modeled an approximately 75-km segment of Spring Creek and an 11-km segment of Willow Creek near Tomball, Texas. This flood event was selected because of the availability of cloud-free Landsat 8 OLI imagery from 28 May 2016 (SDML 2019), when discharge was 1,266 $m^3 s^{-1}$ (large flood with a recurrence interval of approximately 55 years) at the USGS Tomball, Texas, gage on Spring Creek (08068275) (just past the crest of 1,286 $m^3 s^{-1}$ on 27 May) and 89 $m^3 s^{-1}$ at the Tomball, Texas, gage on Willow Creek (08068325).

Streamflow data

We used AutoRoute to simulate flood-inundation extent for the two flood events under steady-flow forcing data, using observed flow-regression equations to estimate peak flow in each river reach. AutoRoute is a steady-flow model, and the intention was to simulate the peak (or near-peak) inundation at the time of Landsat image acquisition. Using peak inundation is appropriate because the goal of any flood-inundation model in forecasting mode is to map the maximum inundation extent for the current forecast. Observed flow data from USGS gaging stations during the high-flow events were combined with peak flow-regression equations developed by the USGS to estimate flow rates along ungaged river sections. For the Choctawhatchee River, we used the regression developed for Region 4 of Alabama (Gulf Coastal Plain), which is a power-law function of contributing drainage area (Hedgecock & Feaster 2007). For Spring and Willow creeks, we used a power-law regression developed for Texas, based on mean annual precipitation, channel slope, and drainage area (Asquith & Roussel 2009). We applied the functions to each National Hydrography Dataset Plus (NHDPlus) stream reach in the study area using the NHDPlus attributes of drainage area and channel slope. For the Texas regression equation, we used the Parameter-elevation Regressions on Independent Slopes Model (PRISM) to estimate mean annual precipitation. The result was the observed streamflow from the upstream USGS gaging station routed through the NHDPlus network, so that each reach has a streamflow value. The hydrologic input for AutoRoute was the streamflow for each NHDPlus reach from USGS gaging stations and regression equations.

Sensitivity analysis

We assessed the sensitivity of AutoRoute to two different inputs: topographic resolution and Manning's n. To assess the sensitivity of the model to spatial resolution of topographic data, we ran AutoRoute with both the 3-m and 10-m NED. To assess whether optimum ranges of Manning's n vary by land cover, we ran the AutoRoute model for each flood event under three different sets of Manning's n values. The values used, from Moore (2011), are shown in Table 1. In all cases, AutoRoute generates a Manning's n raster in which the n value for each pixel is determined based on the NLCD land-cover class for that pixel, but the values differ across the three ranges. For example, for high-intensity development, the low value is 0.075, the medium value is 0.100, and the high value is 0.125. Although we cannot say for certain which Manning's n values best characterize the actual conditions of the study sites, because Manning's n has no independent physical basis, the values tested are within the ranges commonly used in flood modeling.

Table 1 | Manning's *n* roughness values associated with different land covers for the low, medium, and high ranges (from Moore (2011))

Land cover	Manning's *n* (low)	Manning's *n* (medium)	Manning's *n* (high)
Water	0.025	0.030	0.033
Developed (open space)	0.010	0.013	0.016
Developed (low intensity)	0.038	0.050	0.063
Developed (medium intensity)	0.056	0.075	0.094
Developed (high intensity)	0.075	0.100	0.125
Barren land	0.025	0.030	0.035
Deciduous forest	0.100	0.120	0.160
Evergreen forest	0.100	0.120	0.160
Mixed forest	0.100	0.120	0.160
Shrub	0.035	0.050	0.070
Grass/herbaceous	0.025	0.030	0.035
Pasture/hay	0.030	0.040	0.050
Cultivated crops	0.025	0.035	0.045
Woody wetlands	0.880	0.100	0.120
Emergent herbaceous wetlands	0.075	0.100	0.150

HEC-RAS 1D shallow-water equation modeling approach

Although AutoRoute has been used often by the U.S. Army in austere environments, it is not commonly used within the United States. Therefore, the more widely used HEC-RAS 1D shallow-water equation-based modeling approach is also used in this effort to compare the performance of AutoRoute to a more standard-practice model. Like the AutoRoute model, one-dimensional HEC-RAS uses cross-sections and observed flow to simulate flow depth, which can then be used to generate a flood-inundation map. When measured cross-sections are unavailable, the HEC-GeoRAS program in ArcGIS can be used to sample cross-sections from DEM data. Although using DEM-derived cross-sections is likely to reduce the accuracy of the HEC-RAS simulations, using the same input elevation data for both modeling approaches ensures that output from the two models is comparable. All HEC-RAS model inputs (DEM, from which we extracted cross-sections using the HEC-GeoRAS program; Manning's n; and upstream discharge and downstream stage boundary conditions) were the same as for AutoRoute. We used the optimized NED resolution and Manning's n values from the sensitivity analysis to do the AutoRoute/HEC-RAS comparison. Different than AutoRoute, HEC-RAS can simulate flood events using steady-flow or dynamic-flow inputs, but we used the same steady-state input flow for both AutoRoute and HEC-RAS for comparability (the streamflow value at the time of Landsat image acquisition). We exported the HEC-RAS modeling results to ArcGIS and used HEC-GeoRAS to generate the water surface and delineate the floodplain. We subjected the resulting water-depth raster to the same Boundary Clean and shapefile conversion post-processing steps as were used for the AutoRoute flood-depth rasters.

Index of fit

We used a simple index of percent fit to compare the flood-inundation extents. Two sets of comparisons were performed: (1) the sensitivity analysis, in which the AutoRoute-simulated flood-inundation extent was compared with the observed remotely sensed extent, using 10-m and 30-m NED and low, medium, and high ranges of Manning's n, for a total of six runs for each river and (2) the AutoRoute/HEC-RAS comparison, in which AutoRoute- and HEC-RAS-simulated flood-inundation extent was compared with the observed remotely sensed extent, using optimal values of topographic resolution and Manning's n. For both sets of comparisons, we used the following index:

$$F = 100 * \frac{\mathrm{A_a} \cap \mathrm{A_b}}{\mathrm{A_a} \cup \mathrm{A_b}} \quad (2)$$

where F is the percent fit, A_a and A_b are the inundation extents predicted separately from two data sources (in this case, by the remote sensing and the model simulation), $A_a \cap A_b$ is the intersection of the two extents, and $A_a \cup A_b$ is the union of the two extents (Bates & De Roo 2000). A perfect prediction by the model would yield a fit of 100%, and both under- and over-predictions of inundation extent are penalized by the index, so that the fit indicates the percentage of pixels that are classified correctly as inundated or not inundated. The sensitivity analysis can be considered a calibration of the AutoRoute model, because it involved iterative adjustments of parameters (in this case, topography and Manning's *n*) to evaluate the fit to observed data (the remotely sensed flood extents). The AutoRoute/HEC-RAS comparison can be considered an evaluation of the performance of the calibrated model.

RESULTS AND DISCUSSION

Sensitivity analysis

Table 2 shows the fit to the observed extent for the AutoRoute simulations of the two events using the two topographic resolutions and three sets of Manning's *n* values. For the Choctawhatchee River, which has a mostly forested floodplain, the fit to observed data was much better for the higher-resolution run (66% versus 50%), but the fit for Spring and Willow creeks, the urban site, was higher for 10-m compared with 3-m NED (59% versus 50% for Spring Creek and 48% versus 33% for Willow Creek). For the Choctawhatchee River, the fit to the observed inundation extent was slightly higher for low Manning's *n* values but was very similar for all three sets of Manning's *n* values (approximately 66%). For Spring and Willow creeks, the highest accuracy was for the high Manning's *n* set (59% versus 56% for Spring Creek, 48% versus 47% for Willow Creek).

Table 2 | Fit for AutoRoute-simulated inundation extent, compared with the observed (Landsat) inundation extent, using 10-m and 3-m NED and low, medium, and high ranges of Manning's *n* roughness

Topographic resolution	Manning's *n* roughness range	Choctawhatchee	Spring	Willow
10 m*	Low	50	56	47
	Medium	48	59	47
	High	48	59	48
3 m*	Low	66	45	27
	Medium	66	48	30
	High	66	50	33

*t-test indicates significant (at $p = 0.05$ level) differences in fit between 10-m and 3-m resolution for all three sites. Differences among low, medium, and high ranges of Manning's *n* roughness are not significant.

AutoRoute/HEC-RAS comparison

Figure 2(a)–2(d) show the observed and AutoRoute-simulated inundation extents for the floods on the Choctawhatchee River and on Spring and Willow creeks using optimized topographic resolution and optimized Manning's *n* from the sensitivity analysis. AutoRoute classifies 48–66% of pixels correctly for the three rivers (Table 3). In all cases, the AutoRoute-simulated flood extent was somewhat greater than the observed flood extent. This difference is not necessarily a problem with AutoRoute, but in some cases may be attributed to the discontinuous nature of the Landsat-based extent resulting from canopy or other obstructions of water in the channel. Underestimations of flood extent, however, occurred mostly on the large main channels, possibly because of AutoRoute's lack of ability to simulate backwater effects (Figure 3). Another area in which the AutoRoute underestimated flood extent is for off-channel low-lying areas. These are likely areas of pluvial (direct rainfall) flooding. Although pluvial flooding can sometimes be more significant than riverine flooding when it comes to impact, it is beyond the capabilities of river models like AutoRoute or HEC-RAS to simulate these flooded areas.

Figure 2(e)–2(h) show the observed and HEC-RAS-simulated inundation extents for the floods on the Choctawhatchee River and on Spring and Willow creeks. As with AutoRoute, the HEC-RAS simulation of both floods matches well with observed extent, with 58–74% of pixels classified correctly for the three rivers (Table 3). The fact that HEC-RAS, like AutoRoute, estimates a somewhat larger flood extent than observed provides further support for the assumption that the Landsat-based extent may be underestimated because of tree canopy or other obstructions. Overall, the spatial distribution of error is similar between AutoRoute and HEC-RAS.

Figure 4 shows the AutoRoute- and HEC-RAS-simulated inundation extents for the floods on the Choctawhatchee River and on Spring and Willow creeks. The flood-inundation extents simulated by the two models are similar, with 47–62% overlap (Table 3). The main difference is that AutoRoute simulates a more continuous flood-inundation extent than HEC-RAS. This difference is likely the result of AutoRoute's automatic extraction of cross-sections from the

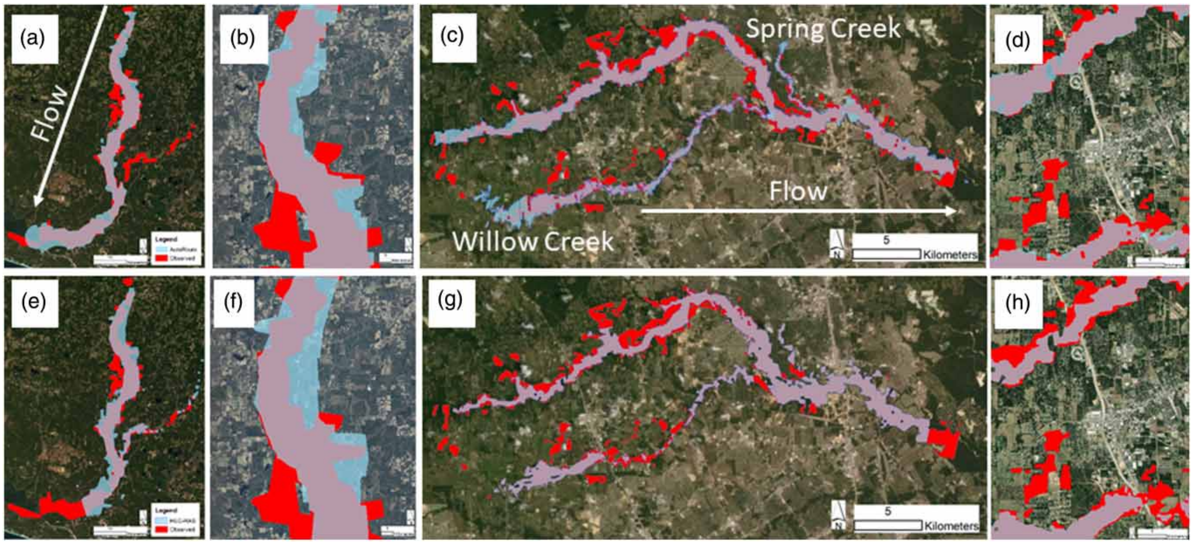

Figure 2 | Observed and simulated flood-inundation extent for (a) Choctawhatchee River flood using AutoRoute; (b) zoomed-in version of Choctawhatchee River flood using AutoRoute; (c) Spring and Willow creeks flood using AutoRoute; (d) zoomed-in version of Spring and Willow creeks flood using AutoRoute; (e) Choctawhatchee River flood using HEC-RAS 1D shallow-water equation modeling approach; (f) zoomed-in version of Choctawhatchee River flood using HEC-RAS 1D shallow-water equation modeling approach; (g) Spring and Willow creeks flood using HEC-RAS 1D shallow-water equation modeling approach; and (h) zoomed-in version of Spring and Willow creeks flood using HEC-RAS 1D shallow-water equation modeling approach.

Table 3 | Fit for AutoRoute and HEC-RAS 1D shallow-water equation modeling approach using optimized topographic resolution and Manning's *n*, compared with the observed (Landsat) inundation extent and with one another

Model	Choctawhatchee	Spring	Willow
AutoRoute	66	59	48
HEC-RAS	74	65	58
AutoRoute versus HEC-RAS	55	62	47

t-test indicates that differences in fit between AutoRoute and HEC-RAS are not statistically significant.

DEM at a uniform dense spacing, while cross-sections must be delineated by the user in one-dimensional HEC-RAS.

Table 3 shows the fit values for the AutoRoute- and HEC-RAS-simulated flood extents relative to observed. The HEC-RAS simulation matches the observed flood extent more closely than does the AutoRoute simulation, but the difference is relatively minor. This finding indicates that AutoRoute, which is simpler to set up than HEC-RAS, does similarly well in simulating the flood-inundation

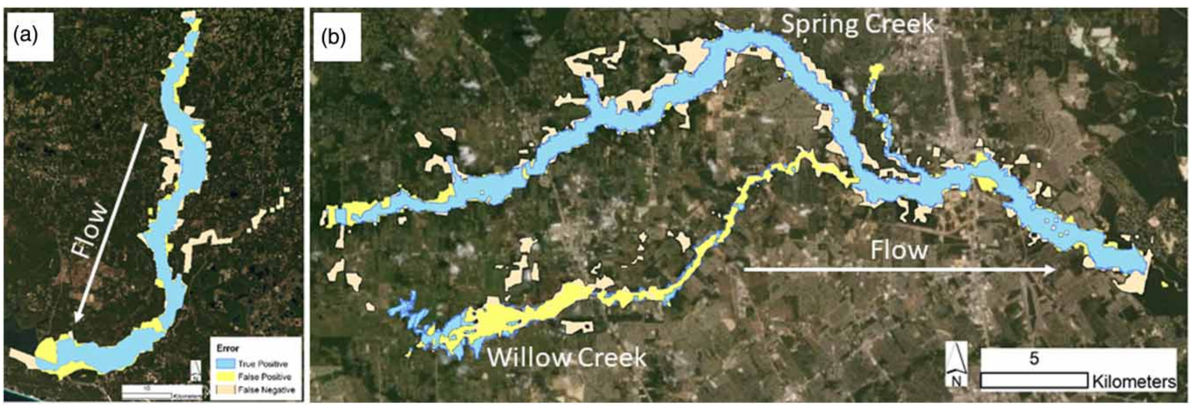

Figure 3 | Spatial distribution of errors in the AutoRoute-simulated flood extent, including true positives (no error), false positives (model overestimates flood extent), and false negatives (model underestimates flood extent), for (a) Choctawhatchee River flood and (b) Spring and Willow creeks flood.

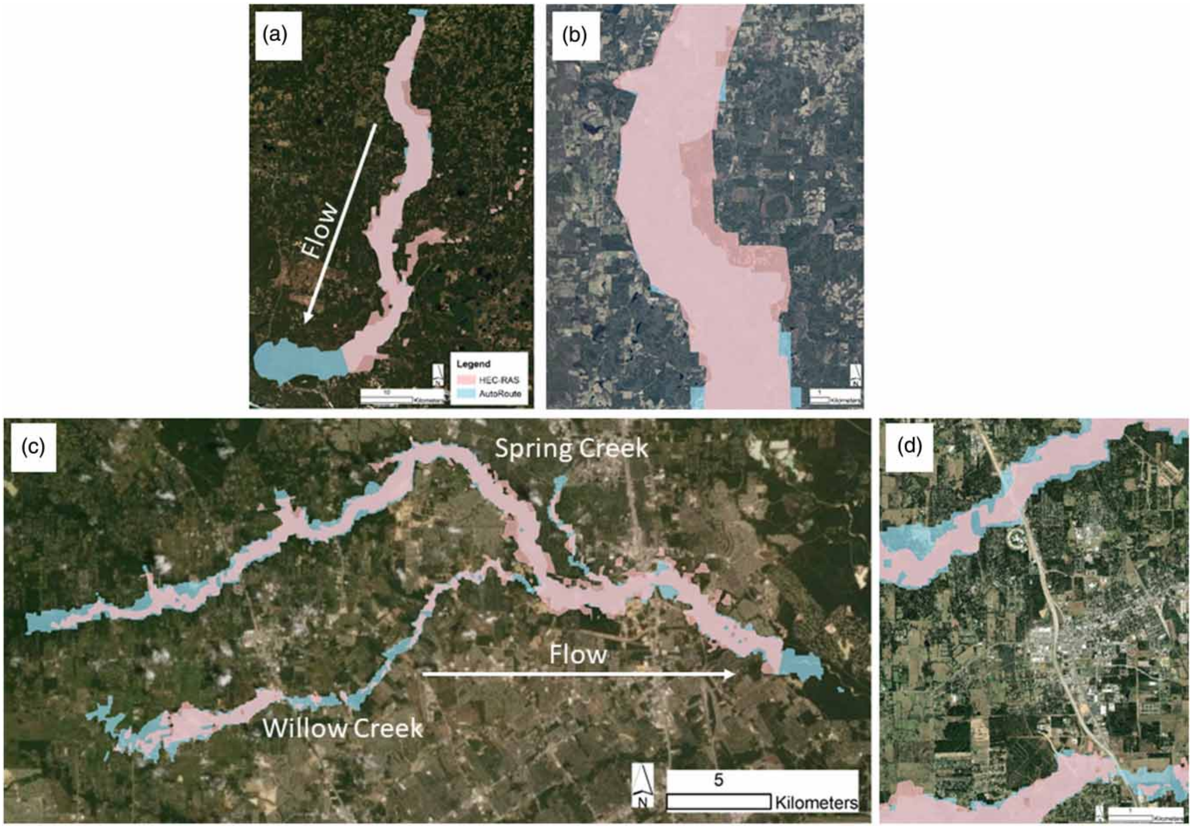

Figure 4 | AutoRoute- and HEC-RAS-simulated flood-inundation extent for (a) Choctawhatchee River flood; (b) zoomed-in version of Choctawhatchee River flood; (c) Spring and Willow creeks flood; and (d) zoomed-in version of Spring and Willow creeks flood.

extent when using the same input elevation data (Table 4). For comparison, the setup for AutoRoute involved running Python scripts to rasterize the stream network, create the input flow file, and generate the Manning's n raster for the input dataset, each of which took <10 s to run. HEC-RAS took approximately 30 s to run (a substantial difference in processing time when scaled up to larger spatial domains), but also involved hours of pre-processing work, such as using HEC-GeoRAS to specify cross-sections. Comparison of the fit values of the AutoRoute- and HEC-RAS-simulated flood extents to one another confirms that the two models give very similar results.

Table 4 | Advantages and disadvantages of AutoRoute and HEC-RAS 1D shallow-water equation modeling approach

Model	Advantages	Disadvantages
AutoRoute	Minimal data requirements	Uses steady flow
	Computationally efficient	Is one-dimensional
	Simple to set up and run for operational applications	Does not simulate backwater
HEC-RAS	Can use steady or unsteady flow	Requires cross-sections or 2D elevation grid
	Can be run in 1D or 2D	Can be computationally expensive
	Uses physically based approach	Complicated setup makes it difficult to use for operational applications

DISCUSSION

Our modeling results were highly sensitive to the spatial resolution of the topographic input data. Although our results for the Choctawhatchee River found that the best-fit model with 3-m resolution had a higher fit (66%) than the best-fit 10-m model (48%), the same was not true for Spring and Willow creeks, where the best fit for the 3-m model (50%

for Spring and 33% for Willow) was less than the best-fit 10-m model (59% for Spring and 48% for Willow). A possible explanation is that, in the urban environment of Spring and Willow creeks, combining DEM cells as a mean reduces the vertical error of the DEM. In urban regions with heterogeneous surface characteristics, smoothing out the cell-to-cell variability may result in fewer errors.

The differences in the accuracy of inundation extents among the three sets of Manning's n values were not dramatic. Using low Manning's n values for the Choctawhatchee River resulted in an accuracy improvement of less than 1% over using high values, and using high values for Spring and Willow creeks resulted in an improvement of 1–3% over using low values. These results indicate that the AutoRoute model is modestly sensitive to Manning's n, at least when the variation is confined within typical ranges, and that additional sources of uncertainty (hydrologic forcing and topographic data) are more significant than uncertainty in Manning's n in affecting the overall inundation uncertainty. It is worth noting that the optimal set of Manning's n parameters in our results was lower Manning's n for the forested floodplain (when forested land has relatively high roughness) and higher Manning's n for the urban floodplain (when urban land has relatively low roughness). AutoRoute is DEM-based and lacks bathymetric data, which allows Manning's n to be partially a function of adjusting for the unknown channel volume that is not captured by the DEM. Just as high (low) values of Manning's n translate into low (high) flow velocity and therefore into high (low) flood inundation, high (low) amounts of channel conveyance result in low (high) flood inundation. In the forested floodplain, lower values of Manning's n were selected, which could be a function of the low channel conveyance (large amounts of channel storage) in a forested floodplain river with multiple side channels. In the urban floodplain, higher values of Manning's n may have been selected because of the high channel conveyance (small amounts of channel storage) in urban streams. Although more research is needed to establish this connection between Manning's n and channel conveyance and storage, it is worth exploring because of its potential applicability in flood-inundation forecasting. In areas in which the amount of channel storage is unknown (which is the case for most rivers because of lack of coupled topographic–bathymetric datasets), the first-order estimate of Manning's n could be the traditional roughness estimate based on land cover or other geospatial data, but values could then be adjusted upward or downward to reflect the expected channel conveyance and storage, based on knowledge of the channel characteristics from land cover or physiographic region.

In evaluating the potential applicability of AutoRoute for forecasting the flood-inundation extent at a continental scale, two potential issues that must be considered are input data requirements and computational efficiency. One advantage of AutoRoute is that its input data requirements are minimal and are easily obtained from existing geospatial datasets for the continental United States. Like the one-dimensional version of HEC-RAS, AutoRoute is based on cross-sections. Unlike HEC-RAS, the process for extracting cross-sections from a DEM is fully automated within the AutoRoute model. Although it is expected that HEC-RAS would yield more accurate results than AutoRoute if actual measured cross-sectional data were used, we found that its results were only marginally more accurate than those of AutoRoute when based on the same input elevation data. AutoRoute is not the only model that can automatically extract cross-sections, but its ability to automatically create all the required input datasets (cross-sections, Manning's n raster, stream lines, and input flow data) does make it suitable for operational forecasting, as it is currently used for military applications outside the United States. Our finding that the physically based HEC-RAS and simple terrain-based AutoRoute produced very similar inundation estimates for our study floods suggests that AutoRoute can be a useful tool in initial estimates of flood inundation.

In addition to requiring minimal input data, another advantage of AutoRoute for continental-scale flood-inundation forecasting is its simplicity. Even though AutoRoute uses only an iterative calculation of Manning's equation rather than the solution of the full continuity and momentum equations implemented in HEC-RAS, we found that its results were comparable to those of HEC-RAS for our study floods. HEC-RAS 2D might be expected to provide more accurate results, but the input data requirements and computational expense of two-dimensional simulations basically prohibit their high-resolution applications at a continental scale for operational flood forecasting. AutoRoute's simple one-dimensional approach is much more efficient. Moreover, such simple flood models can be feasibly run as ensembles using different parameterizations to generate probabilistic flood maps that depict forecast uncertainty.

Despite the advantages of AutoRoute for operational flood forecasting, it has several major limitations as well. As described in Follum *et al.* (2017), areas affected by backwaters are not accurately modeled within AutoRoute. Accordingly, physically based models such as HEC-RAS are essential for areas with backwater effects. Moreover, unlike in HEC-RAS, structures such as bridges and levees are not explicitly represented in AutoRoute. Levees can be implicitly incorporated into AutoRoute simulations if a DEM of sufficiently high resolution (e.g., from LiDAR) is used to generate the cross-sections, although AutoRoute is not capable of simulating breaching events. Bridges, on the other hand, must be removed from high-resolution DEMs used to generate AutoRoute cross-sections, because the model will treat them as dams. This means that AutoRoute cannot be used to dynamically simulate the interactions between flooding and engineered structures such as bridges. A final major limitation of AutoRoute is that it uses steady flow, which limits its usefulness for continuous simulation of a flood wave over the course of an event. Instead, AutoRoute is intended to simulate the potential peak inundation during a flood, which is useful for purposes such as planning evacuation routes and staging of resources.

CONCLUSIONS

In this paper, we used the simple raster-based flood-inundation model AutoRoute to simulate two recent flood events and compared simulated with observed inundation extents from remote sensing. We ran AutoRoute using two different spatial resolutions of topographic data and three different sets of Manning's n roughness values to assess the model's sensitivity to these parameters and to optimize the topographic resolution and n values for the different rivers. For comparison, we also simulated the same flood events using a HEC-RAS 1D shallow-water equation modeling approach, the standard in physically based hydraulic modeling. We found higher-resolution AutoRoute simulations matched observed extents better for the forested floodplain of the Choctawhatchee River and that relatively high values of Manning's n were optimal for the urban Spring and Willow creeks. AutoRoute was reasonably successful (fit of 48–66%) at reproducing observed flood extents. Flood-inundation extents simulated by the HEC-RAS 1D shallow-water equation modeling approach matched observed extents somewhat better (fit of 58–74%) than those simulated by AutoRoute, but the flood extents simulated by the two models were similar, most likely because both were based on extracting cross-sections from the same input DEM. These findings provide support for using AutoRoute to forecast initial flood-inundation estimates at a continental scale.

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