Emerging Flood Model Validation Frameworks for Street-Level Inundation Modeling with StormSense

Jon Derek Loftis
College of William and Mary
Gloucester Point, VA, USA
jdloftis@vims.edu

Harry Wang
College of William and Mary
Gloucester Point, VA, USA
wanghv@vims.edu

David Forrest
College of William and Mary
Gloucester Point, VA, USA
drf@vims.edu

Sokwoo Rhee
NIST
Gaithersburg, MD, USA
sokwoo.rhee@nist.gov

Cuong Nguyen
NIST
Gaithersburg, MD, USA
cuong.nguyen@nist.gov

ABSTRACT

Technological progress in flood monitoring and the proliferation of cost-efficient IoT-enabled water level sensors are enabling new streams of information for today's smart cities. StormSense is an inundation forecasting research initiative and an active participant in the GCTC seeking to enhance flood preparedness in the Hampton Roads region for flooding resulting from storm surge, rain, and tides and demonstrating replicability of the solution. Herein, we present street-level hydrodynamic modeling results at 5m resolution with conventional flood validation sources alongside new emergent techniques for validating model predictions during three prominent recent flooding events in Hampton Roads during Fall 2016: Hurricane Hermine, Tropical Storm Julia, and Hurricane Matthew. Emerging validation techniques include: (1) IoT-water level sensors, (2) crowd-sourced GPS maximum flood extent measurements, and (3) geospatial flooded area comparisons with drone-surveyed flood extents via ESRI's Drone2Map. Model uncertainty was validated against 5 newly-established tide gauges within the domain for an aggregate vertical root mean squared error of ±8.19 cm between the sensor observations and model predictions. Also, geospatial uncertainty was assessed using mean horizontal distance difference as ±4.97 m via 206 crowd-sourced GPS flood extents from the Sea Level Rise App.

CCS CONCEPTS

•Computer systems organization → Embedded and cyber-physical systems; •Software and its engineering → Design patterns;

KEYWORDS

Hurricane Matthew, Hydrodynamic Modeling, Internet of Things, Smart City, Global City Teams Challenge, Replicability, Citizen Science, Sea Level Rise, Drone2Map

SCOPE 2017, Pittsburgh, PA USA

978-1-4503-4989-5/17/04…$15.00
DOI: http://dx.doi.org/10.1145/3063386.3063764

ACM Reference format:
Jon Derek Loftis, Harry Wang, David Forrest, Sokwoo Rhee, and Cuong Nguyen. 2017. Emerging Flood Model Validation Frameworks for Street-Level Inundation Modeling with StormSense. In *Proceedings of The 2nd Workshop on Science of Smart City Operations and Platforms Engineering, Pittsburgh, PA USA, 21 April 2017 (SCOPE 2017),* 6 pages.
DOI: http://dx.doi.org/10.1145/3063386.3063764

1 INTRODUCTION

Cities are inherently complex systems subject to innumerable non-linear influences on how to efficiently allocate their limited resources [17]. This is certainly true for handling emergency flooding conditions in the near-present and how best to prepare for the imminent flood-related disasters of the future. Analysis of the local sea level trend from one water level monitoring sensor at Sewells Point in the City of Norfolk depict a long-term increase in mean sea level of 4.59 mm/year ±0.23 mm/year since its establishment in 1928, projecting that rising sea levels will inevitably exacerbate flooding conditions from storm events in the future [3, 16].Cities, counties, and town governments, local institutions, and private contractors, provide many solutions, each of which must be evaluated in its own way. However, provision of these serviceable flooding solutions often impacts the availability of other services. Many existing smart cities solutions, such as those implemented in the Global City Teams Challenge (GCTC) action clusters, are designed to have a measurable impact on specific key performance indicators. Because many of today's smart city/community development efforts are isolated and customized projects, the National Institute of Standards and Technology (NIST) has launched the GCTC to encourage collaboration and the development of standards. The GCTC's long-term goal is to demonstrate a scalable and replicable model for incubating and deploying interoperable, adaptable, and configurable Internet of Things (IoT)/Cyber-Physical Systems technologies in smart cities/communities. This program aims to help communities benefit from working with others to improve efficiency and lower costs. NIST created the Replicable Smart City Technology (RSCT) cooperative agreement program to provide funding to enable awardee City/Community Partners to play a lead role in the team-based GCTC effort to pursue measurement science for replicable solutions [1]. The RSCT program was designed to support standards-based platform approaches to smart cities technologies that can provide measurable performance metrics.

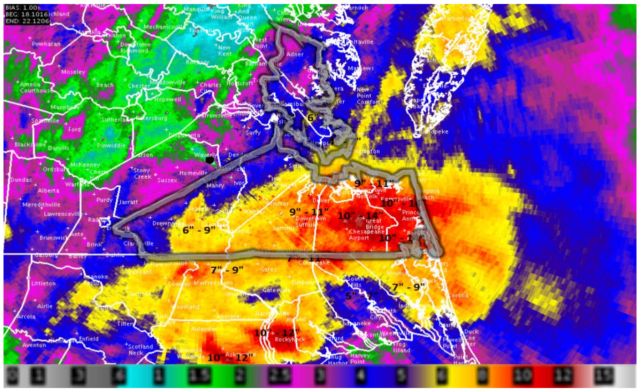

Figure 1: Map of the Hampton Roads Region of Virginia with StormSense partner agreement cities outlined in gray superposed with radar-derived rainfall totals (in.) over 72 hours from Sept. 19-22, 2016, during Tropical Storm Julia. The region has an area of 1,365 sq. km. (527 sq. mi.) and can be modeled using lidar elevations and high-res. bathymetry at 5 m resolution.

The StormSense project brings together partnering municipal governments in Hampton Roads, Virginia, including: Newport News, the RSCT grant recipient, Norfolk, Virginia Beach, Hampton, Chesapeake, Portsmouth, Williamsburg, and York County along with the Virginia Institute of Marine Science (VIMS), with emphasis on replicating a flood forecasting and monitoring solution across the entire region (Figure 1). As an example, in one neighborhood in the City of Newport News that is subject to frequent flooding, typically a large number of emergency responders were required to assist in evacuating the complex [2, 10]. However, by remotely alerting residents that the water is rising quickly on the local stream, the past two flooding events have not required any emergency responders to assist them in evacuating, who were subsequently able to dedicate their emergency services elsewhere [18]. The goal of establishing a flood monitoring network can be cost-prohibitive, but in the long term, the anticipated benefits of improved quality of life for a region's denizens are sizable. The goal is to replicate this level of success throughout the cities of Hampton Roads by providing a greater density of water level sensors. As an added benefit, residents are taking responsibility for their assumed risk of living adjacent to floodplains, resulting in a marked spike in the number of residents who have opted for flood insurance, with 2,231 claims totaling $25M in damage attributed to Hurricane Matthew [9]. Many of these properties are insured through the Federal Emergency Management Agency's (FEMA) National Flood Insurance Program (NFIP), but many properties outside of the surveyed floodplain do not have preferred risk policies.

A stakeholder workshop conducted on January 19, 2016 with representatives from Hampton Roads regional emergency management, storm water engineering and planning municipal staff, as well as academic and non-government organization partners uncovered a need for near-term, locally scaled, and 'realistic' scenarios to communicate risk [5]. Emergency managers are currently limited in their communications tools and know them to be inadequate [5, 6]. A better understanding of the decisions people are making

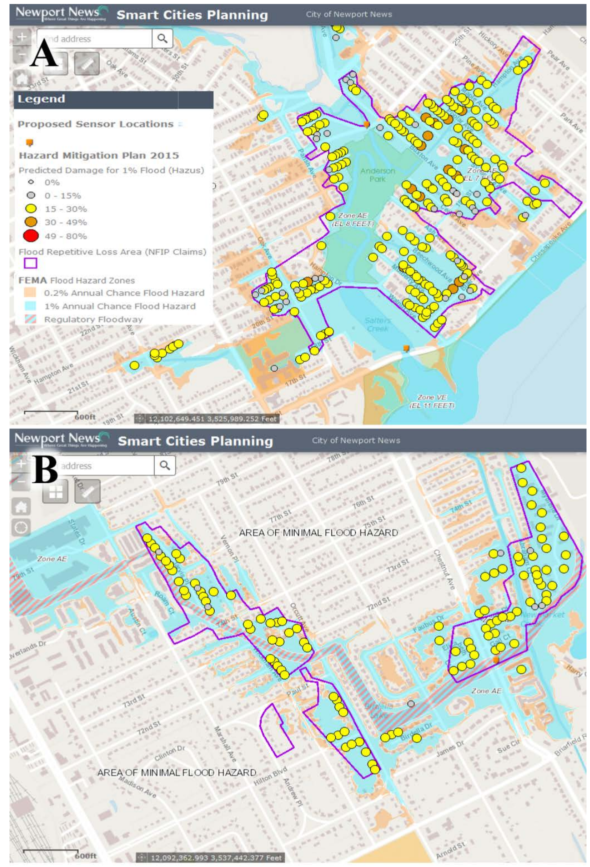

Figure 2: Prototype of Newport News Smart Cities Planning Dashboard with water level sensor installation sites relative to FEMA's flood zones and NFIP repetitive loss claims, and GIS flood-vulnerable properties identified via Hazus for a 100-year flood scenario in: A) Salters Creek, vulnerable to Coastal Flooding, and B) along Newmarket Creek, an inland regulatory floodway vulnerable to rainfall-induced flooding.

to adapt to flooding is needed. Differences are expected in both flood perception and behavior between urban and rural audiences. A pilot study conducted in 2015 examining information logistics for drivers on flooded roads in Norfolk found that decisions made about driving were strongly situational, based upon the importance, timing and location of the driving plans, but that a regional approach to communication was needed and lacking [6]. Time living in the area was an important factor in risk perception and that information comes from local knowledge, recognized sources of information, and sometimes a haphazard mix of both. Examining these issues in the context of flood communication and further elucidating the currently vague appropriate flood model parameters for accurate inundation prediction at 5 m scale in a broader context is needed, leading to the following flood research questions:

- How should bottom friction be appropriately parameterized for high-resolution street-level sub-grid inundation models?

- How should percolation/infiltration of rainwater through different density surfaces present in urban and rural environments be accurately accounted for in a high-resolution sub-grid model?
- How should model results be deseminated to enhance flood preparedness, and what communication methods and messages influence flood risk decision-making and behaviors (including information-seeking and adaptive response)?

To attempt to address these questions, examples from a recent installment of water level sensors by the United States Geological Survey (USGS) and the City of Norfolk will be used as a proxy for a suite of ultrasonic water level sensors currently being installed in Hampton Roads via StormSense. The sensors will be fed into a geographic information system (GIS) flood risk dashboard (example depicted in Figure 2) to demonstrate the utility of a higher-density water level sensor network and how future flood forecasting efforts can be augmented for the betterment of citizen safety. The system can be used to study inundation extents and timing during flooding events in order to:

(1) Build public awareness of inundation, and recurrent flooding through predictable geospatially locatable events,
(2) Collect quality crowd-sourced inundation extent data to test and validate the numerical model via citizen science, and
(3) Enhance both the scientific understanding of the physical systems involved and the public understanding of the science of inundation.

In pursuit of this, the StormSense model will be spatially validated during three 2016 flooding events: Hurricane Hermine, Tropical Storm Julia, and Hurricane Matthew, via the following emergent data sources in the subsequent sections: 1) IoT-water level sensors, 2) Crowd-sourced GPS maximum flood extent measurements collected using the crowd-sourced data-collection app, *'Sea Level Rise'*, and 3) Geospatial flooded area comparisons with drone-surveyed flood extents via Drone2Map software.

2 STUDY AREA AND MODEL INPUTS

Hampton Roads has been described as the second-largest population center at risk from sea level rise, with ¿400,000 properties exposed to flood or storm surge inundation [19]. The region has a population of over 1.7 million people, living and traveling on roads exposed to both severe and increasing frequent chronic "nuisance" flooding [8]. Existing flood communication and messaging systems have not yet responded to the changing risk patterns brought by sea level rise and have not been able to meet the needs of diverse at-risk communications audiences. A better understanding of flood risk perception, information seeking behavior and decision-making can inform the development of new communications tools and flood risk messaging [20]. This is the perceived intersect between new IoT-technologies and emerging flood model validation methods. For each storm event, water levels driven via 36-hour tidewatch forecasts provided by VIMS at Sewells Point were used to drive surge and tides, alongside wind and pressure inputs used to drive the model atmospherically, similar to [14].

2.1 Groundwater Inputs

Recent advancements in hydrodynamic computation have enabled models to predict the mass and movement of flood waters to predict water velocities at increasingly finer scales. However, the current version of the sub-grid inundation model VIMS has developed does not fully incorporate a comprehensive groundwater model that slowly returns flood waters that infiltrate through the soil back to the nearest river. This is a valuable aspect of flooding relevant for city planning perspectives using sub-grid hydrodynamic modeling that has been successfully developed and employed throughout the Netherlands, Germany, and Italy [7]. There is an array of groundwater wells that exist in the Hampton Roads Region, bored and monitored by the USGS [4]. These temporally-varying values for hydraulic conductivity could provide some valuable input information for the hydrodynamic model via Richard's equation [13]. However, this does not currently account for the standard practice of near-surface groundwater displacement via pumping prior to anticipated flooding events conducted by cities with residents in the floodplains where a high water table regularly exacerbates even minor rainfall events [15]. Nevertheless, values observed near these sites prior to forecast simulations were used as the model's initial condition to estimate infiltration through previous surfaces, to counterbalance precipitation inputs, similar to [13].

In forecast approaches, groundwater influence is usually neglected, since typically storm surge is a short-term event, and groundwater recharge is more of a delayed and long-term process, however, it is becoming increasingly important to also consider in forecasting longer-term extratropical flooding events such as nor'easters where flooding and high winds can persist for 5 or more tidal cycles. Although, VIMS have been incorporating different forms of percolation of flood waters through different types of ground cover ranging from vegetated to impervious within the sub-grid model more recently [12, 13] there are still some potential applications of storm water that could be manually added to the existing sub-grid model version to account for surge flooding backups through storm water drainage without sufficient backflow prevention [13].

2.2 Precipitation Inputs

The inundation model could be used to guide decisions related to storm water management by using existing sensor-derived precipitation data in several cities. This could be expanded to include data observations from rain gauges that are currently operating on sewer and storm water pump stations in the localities, and from the Hampton Roads Sanitation District (HRSD), which combined currently amounts to $\sim$ 130 sensors. With an iteratively interpolated series of precipitation measurements, further research could also be conducted with these sensors and the 10 proposed water level sensors to model localized microburst precipitation events. As evidenced in the series of interpolated rainfall images in Figure 1, a combination of these rainfall data with new observations from a high-density water level sensor network, would help better explain why one neighborhood experienced a drizzle and a neighboring community experienced a deluge during Hurricane Matthew. Furthermore, this could aid researchers to help model ways that the city's systems could potentially be augmented for greater resilience to precipitation -induced flooding threats in the future. In the simulations presented herein, model results are calculated with temporally-varying precipitation inputs from the currently-private rain gauge data from HRSD.

3 WATER LEVEL SENSOR COMPARISON

StormSense is currently in the process of identifying and surveying sites for new IoT-bridge-mounted ultrasonic and microwave radar water level sensors in Newport News, Virginia Beach, and Norfolk, as outlined on the StormSense project's website at stormsense.com. These sensors will complement the previously installed array of 2 gauges operated by NOAA, 9 gauges recently installed in 2015-2016 via Hurricane Sandy relief funds operated by the USGS, and 1 gauge operated by VIMS in Hampton Roads. While these remote sensors are largely X-band radar sensors transmitting data through satellite signals, the IoT-sensors will enlist ultrasonic sensors and transmit data via cellular transmission protocols with the focus of creating a replicable cost-effective network of sensors. Some perceived utilities of water level sensors are viewed as follows:

(1) Archiving of water level observations for flood reporting
(2) Automated targeted advance flood alert messaging
(3) Validation/inputs for hydrodynamic flood models

A collaboration between VIMS and the constituent partner Cities of: Newport News, Hampton, Norfolk, Virginia Beach, Portsmouth, Chesapeake, Williamsburg, and York County, in Hampton Roads, VA, will provide a prototype for strengthening emergency response times by providing spatial flood extent predictions in interactive map form at 5 m resolution. The plan for integrating the inundation model into a more permanent warning system involves planned connection with the new sensors to the citiesfi current Everbridge notification systems for alert messaging when the sensor observes flooding at user-specified elevations, and integration with model predictions for timely forecasted alerts once the sensors are tidally-calibrated. This approach demonstrates the benefits of replicating shared smart city solutions across multiple cities and communities that are facing similar flood challenges and it aligns with the goals of GCTC and RSCT programs. It is the hope that the recent installation of water level sensors provided by the efforts of the USGS can be used as an opportunity to demonstrate some of the benefits of added water level sensors while the alternative model validation approaches described herein may be replaced with more reputable and replicable monitoring methods soon.

A comparison of five existing water level sensors were used to temporally and vertically validate the hydrodynamic model's predictions. These sensors are located at: 1) National Oceanic and Atmospheric Administration (NOAA)'s Money Point sensor, the USGS's permanent sensors at 2) Rt. 17 near Portsmouth, and 3) Bailey Creek at Dock Landing Rd. in Chesapeake, a temporary USGS rapid-deployment gauge at 4) the Hague in Norfolk deployed only during Hurricane Hermine, and 5) water level sensor at Mayflower Crescent pump station maintained by the City of Norfolk. These 5 gauges resulted in an aggregate vertical root mean squared error (RMSE) of ±8.19 cm over the 36-hour Hurricane Hermine forecast simulation [14]. The four gauges present during Hurricane Matthew yielded a more favorable aggregate RMSE of ±4.69 cm. Tropical Storm Julia resulted in 12-14" of rainfall a week prior to Hurricane Matthew, ameliorating high water table drainage issues during the storm (Figure 1). Both storms produced minimal surge related coastal flooding and inundation impacts were far more profound inland, making coastal and estuarine water level sensors less practical for verification of inland inundation extents or depths.

4 CROWDSOURCED GPS FLOOD EXTENTS

Hurricane Hermine had a more significant storm surge measured by water level sensors in Hampton Roads and less rain, while the opposite was true for Hurricane Matthew. The relatively new citizen science 'Sea Level Rise' mobile app provided 206 points of geospatial data for use with validating predicted flood extents in Norfolk during Hurricane Hermine with a favorable Mean Horizontal Distance Difference (MHDD) of ±4.97 m (Figure 3A). Sites labelled B-D in Figure 3 represent the modeled maximum flooding extents calculated by the street-level hydrodynamic model in the flood-prone Larchmont neighborhood of Norfolk. Positioned on a peninsula bounded by the Elizabeth River to the west and the Lafayette River to the north and east, the area is no stranger to tidal 'nuisance' flooding. By measuring the horizontal distances from the GPS-reported points of maximum flooding extents from the 'Sea Level Rise App', to the edge of the model predicted maximum flooding extent contour line, an assessment of geospatial accuracy may be reached with minimal processing effort using the standard distance formula [17,18]. In Figure 3B at the houses along Richmond Crescent, the MHDD between the 65 GPS observation points and the model-predicted maximum flood extent contour line is ±6.72 m. Figure 2C depicts a slightly more favorable comparison with a MHDD of ±3.92 m along Cambridge and Carroll Crescent's 74 points. Finally, in Figure 3D, 48th Street near ODU and Hampton Blvd's 67 GPS observations were in agreement with model-predicted flooding extents with a MHDD of ±4.48 m.

An apparent caveat of this geospatial MHDD approach is that it is only a relevant metric in areas with minimal surficial slope [17,18], like those that characterize Hampton Roads, VA. In areas with steeper slopes immediately adjacent to the shoreline, model over-prediction of several inches or even feet in the vertical may only manifest in minuscule increments of change on the horizontal scale. However, lack of these app data or crowdsourced data on ArcGIS online in the region during tropical Storm Julia or Hurricane Matthew (due to mass power outages) led to the use of emerging data validation methods from image analysis of drone videos via Drone2Map.

5 DRONE2MAP FLOODED AREA COMPARISONS

Useful information can be extracted from iterative image analysis of publicly uploaded drone footage to internet video repositories (e.g. YouTube, Vimeo, etc.) released under the umbrella of the shared creative commons license for research. Often, the rapid battery drain constraints of flight control and video streaming result in short drone flight times of ¡30 minutes. Thus, accompanying auxiliary data collection alongside flight-control information is often an afterthought. Through estimation of altitudes and retroactive construction of pre-programmed flight plans, a video may be parsed

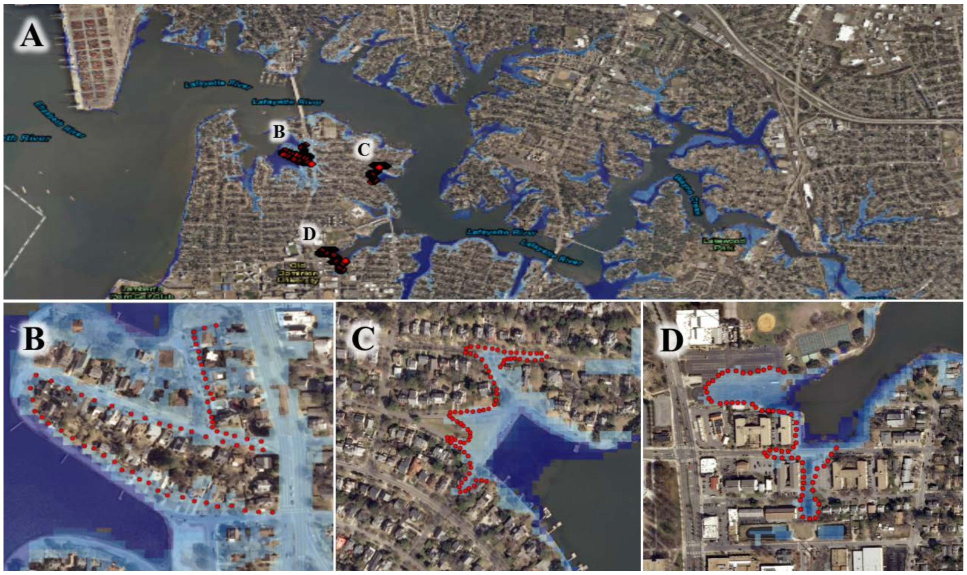

Figure 3: Maximum flooding extents predicted for 2016 Hurricane Hermine on Sept. 2nd validated via crowdsourced GPS monitoring of maximum flooding extents on Sept 3rd in the Larchmont neighborhood of Norfolk, VA.

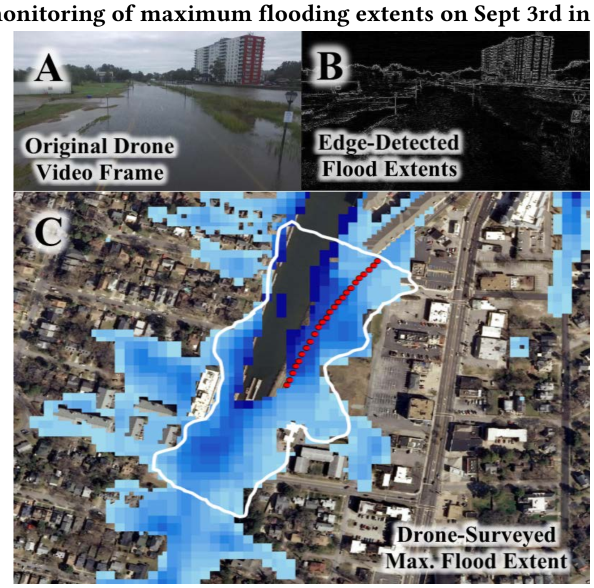

Figure 4: A) Single flooding image frame from drone video over drone video footage of Llewellyn Ave near Haven Creek Boat Ramp in Norfolk at 2:30pm on Oct. 10, 2016 after Hurricane Matthew. B) Laplace transform of pixel values for edge detection of water's edge. C) Resulting polygon (white) of water's edge from Drone2Map stitched edge-detected imagery representing extracted flood extents [14]. Source Video: https://youtu.be/PkvjnqDlTcQ

into a series of image frames that may be individually prescribed estimated GPS metadata to aid in flood model validation in places where there is an absence of validated reputable water level sensor measurements. Figure 4 depicts an estimated Drone2Map flooding extent captured via drone at 2:30pm on October 10th, 2016 on Llewellyn Ave of a mostly oblique segment of video. Figure 4 depicts drone video footage at the intersection of Monticello Ave and Jefferson Ave in Norfolk from an overhead aerial view shows a more uniform depiction of flooding, although there are complications in each series of images form uniform edge detection methods. The oblique view suffers from line of sight complications with taller buildings, while the overhead viewpoint can be hampered by shadows. This can have potentially worse implications for detecting the dark transition between the water's edge and shadows cast by tall infrastructure becoming more apparent later in the day as the shadows elongate. When calculating the mean horizontal distance difference of the resulting edge-detected interface between wet and dry pixel values, the example is Figure 4 at the Haven Creek Boat Ramp in Norfolk at 3:00pm on Oct. 10, 2016, resulted in an AHDD of ±14.39 m from 137 points artificially constructed at 5 m regular intervals along the interface line.

6 CONCLUSIONS

The hydrodynamic model in Hampton Roads, VA, was effectively validated using 5 water level sensors within the model domain during Hurricane Hermine to yield a vertical RMSE of 8.19cm, as a primary time-honored model validation method that has been embraced by the hydrodynamic modeling community as a staple for determining the uncertainty of their predictions. Typically, the USGS provides a valuable service in the form of surveying high water marks after major flood events, but as none of these events were truly catastrophic flood events in Hampton Roads, VA, relative to the southern U.S. Eastern Seaboard, high water lines in the form of GPS maximum flood extent points from the citizen science App, 'Sea Level Rise' were used instead as a secondary form of model validation. Results from 3 sites in Norfolk yielded a MHDD of ±4.97 m during Hurricane Hermine. A tertiary flood validation approach involving the use of the newly-released Drone2Map software from ESRI was employed to successfully develop maximum flooding extent polygons from aerial drone survey footage. The footage was parsed into frames at quarter-second intervals, and batch-processed through image analysis to run an edge detection algorithm using a Laplacian filter. This highlighted areas of the images where stark contrasts in wet/dry (dark/light) pixel values were used to highlight flooding extents at the time of the flight. The frames were georeferenced and mosaicked together in the software, and then compared with the analogous time-aware raster model output layer for a reasonably agreeable estimated AHDD of 14.39 m (±3 of 5 m resolution sub-grid cells). It is worth noting that in cases of heavy rainfall, this street-level sub-grid hydrodynamic modeling also performs the function of a hydrologic transport model to predict flow accumulation to aid in identification of areas that are most susceptible to flooding. This is useful for resilient building practices, as the model could also identify potential areas where development of green infrastructure could commence, with the understanding that a sub-grid model represents infrastructural features and many city lifelines better than most conventional hydrodynamic models [11]. In the future, smart city systems could evaluate the efficacy of candidate blueprint solutions to flood-related problems, and suggest how they could be addressed with a street-level inundation model (bold):

- Reduction of impervious surfaces is addressed by **changes to spatially-varying soil infiltration values**
- Land use changes is addressed by the **model grid mesh modification to remove/add buildings/ infrastructure AND changes to spatially-varying soil infiltration values**
- Combination gray and green infrastructure opportunities are tested by **changes to spatially-varying soil infiltration values in areas where modified green infrastructure lie**
- Increase in storm water "holding" management systems is modeled by **Digital Elevation Model modification and adding sources/sinks for new holding reservoirs/ ponds**

ACKNOWLEDGMENTS

The authors would like to thank the USGS and the City of Norfolk for their efforts in establishing and maintaining the recent suite of water level sensors in Hampton Roads used to help validate the results presented herein. Our thanks is extended to the Hampton Roads Sanitation District, and the public utilities, public works, and water works divisions in the Cities of Newport News, Norfolk, and Virginia Beach for making their privately-collected rainfall measurements at pump stations throughout Hampton Roads accessible for this research endeavor. Portions of this publication and research efforts are made possible through the encouragement and support of NIST via federal award #70NANB16H277.

REFERENCES

[1] Federal Funding Opportuninty Announcement: Replicable Smart City Technologies Cooperative Agreement Program. https://www.nist.gov/document-360. (????). Accessed: 2017-03-02.

[2] Letter regarding flooding on Newmarket Creek and City Line Apartments from City of Newport News Fire Chief. https://wm1693.box.com/s/qwsfc722peihdb70xsvfhzwxas348y0u. (????). Accessed: 2017-03-02.

[3] NOAA Tides and Currents: Sewells Point Sea level Trends. https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?stnid=8638610. (????). Accessed: 2017-03-02.

[4] USGS Groundwater Monitoring Sites: Tidewater Virginia. https://groundwaterwatch.usgs.gov/StateMap.asp?sa=VA&sc=51. (????). Accessed: 2017-03-02.

[5] 2016. Hampton Roads Planning District Commission Flooding Mitigation Stakeholder Workshop. (Jan. 2016).

[6] Howard Botts, Thomas Jeffrey, Wei Du, and Logan Suhr. 2015. *Storm Surge Report.* Technical Report. CoreLogic. http://www.corelogic.com/research/storm-surge/corelogic-2015-storm-surge-report.pdf

[7] V. Casulli. 2015. A conservative semi-implicit method for coupled surface-subsurface flows in regional scale. *International Journal for Numerical Methods in Fluids* 79, 4 (2015), 199–214.

[8] T. Ezer and L. P. Atkinson. 2014. Accelerated flooding along the US East Coast: on the impact of sea-level rise, tides, storms, the Gulf Stream, and the North Atlantic oscillations. *Earth's Future* 2, 8 (2014), 362–382.

[9] FEMA. 2016. National Flood Insurance Program coverage isn't the same as homeowner insurance or FEMA assistance. http://www.vaemergency.gov/national-flood-insurance-program-/ /coverage-isnt-homeowner-insurance-fema-assistance/. (Dec. 2016).

[10] J. Lawlor. 2012. City Line Apartments: flood prone and no solutions in sight. *Daily Press* (2012). http://articles.dailypress.com/2012-08-29/news/dp-nws-city-line-apts-20120829_1_city-line-apartments-apartment-investment-and-management-government-ditch

[11] J. D. Loftis. 2014. *Development of a Large-Scale Storm Surge and High-Resolution Sub-Grid Inundation Model for Coastal Flooding Applications: A Case Study during Hurricane Sandy.* Ph.D. Dissertation. College of William & Mary.

[12] J. D. Loftis, H. Wang, and R. DeYoung. 2013. *Storm Surge and Inundation Modeling in the Back River Watershed for NASA Langley Research Center.* Technical Report NASA/TM-2013-218046. NASA.

[13] J. D. Loftis, H. V. Wang, R. J. DeYoung, and W. B. Ball. 2016. Using Lidar Elevation Data to Develop a Topobathymetric Digital Elevation Model for Sub-Grid Inundation Modeling at Langley Research Center. *Journal of Coastal Research* Special Issue, 76 (2016), 134–148.

[14] J. D. Loftis, H. V. Wang, and D. R. Forrest. 2016. *Street-Level Inundation Modeling of Hurricanes Matthew and Hermine and Emerging Flood Monitoring Methods in Hampton Roads.* Technical Report. VIMS Department of Physical Sciences. http://doi.org/10.21220/V5XW2G

[15] J. D. Loftis, H. V. Wang, S. E. Hamilton, and D. R. Forrest. 2017. Combination of Lidar Elevations, Bathymetric Data, and Urban Infrastructure in a Sub-Grid Model for Predicting Inundation in New York City during Hurricane Sandy. *Computers, Environment, and Urban Systems* (2017). In Review.

[16] Molly Mitchell, Carl Hershner, Julie Herman, Dan Schatt, Pam Mason, and Emily Eggington. 2013. *Recurrent Flooding Study for Tidewater Virginia.* Technical Report. Virginia Institute of Marine Science. http://ccrm.vims.edu/recurrent_flooding/Recurrent_Flooding_Study_web.pdf

[17] Sokwoo Rhee. 2016. Catalyzing the Internet of Things and Smart Cities: Global City Teams Challenge. In *1st International Workshop on Science of Smart City Operations and Platforms Engineering (SCOPE).* Global City Teams Challenge (GCTC), 1.

[18] [7] H. Smith. 2016. After yet another City Line Apartments flood, FEMA steps in to help. *Daily Press* (2016). http://www.dailypress.com/news/newport-news/dp-nws-fema-city-line-20161112-story.html

[19] W. V. Sweet, J. Park, J. J. Marra, C. Zervas, and S. Gill. 2014. *Sea level rise and nuisance flood frequency changes around the United States.* Technical Report. NOAA Technical Report NOS COOPS 73.

[20] T. Wahl, S. Jain, J. Bender, S. D. Meyers, and M. E. Luther. 2015. Increasing risk of compound flooding from storm surge and rainfall for major US cities. *Nat. Clim. Change* (2015). DOI: http://dx.doi.org/10.1038/nclimate2736