StormSense: A New Integrated Network of IoT Water Level Sensors in the Smart Cities of Hampton Roads, VA

Derek Loftis^{1*}, David Forrest², Sridhar Katragadda³, Kyle Spencer⁴, Tammie Organski⁵, Cuong Nguyen⁶, and Sokwoo Rhee⁶

*corresponding author: jdloftis@vims.edu

⁵City of Newport News, Department of Information Technology, 2400 Washington Ave., Newport News, VA 23607, U.S.A.

⁶Smart Grid and Cyber-Physical Systems Program Office, National Institute of Standards and Technology, 100 Bureau Dr., Gaithersburg, MD 20899, U.S.A.

Abstract

Propagation of cost-effective water level sensors powered through the Internet of Things (IoT) has expanded the available offerings of ingestible data streams at the disposal of modern smart cities. StormSense is an IoT-enabled inundation forecasting research initiative and an active participant in the Global City Teams Challenge seeking to enhance flood preparedness in the smart cities of Hampton Roads, VA for flooding resulting from storm surge, rain, and tides. In this study, we present the results of the new StormSense water level sensors to help establish the "regional resilience monitoring network" noted as a key recommendation from the Intergovernmental Pilot Project. To accomplish this, the Commonwealth Center for Recurrent Flooding Resiliency's Tidewatch tidal forecast system is being used as a starting point to integrate the extant (NOAA) and new (USGS and StormSense) water level sensors throughout the region, and demonstrate replicability of the solution across the cities of Newport News, Norfolk, and Virginia Beach within

¹Center for Coastal Resources Management, Virginia Institute of Marine Science, College of William and Mary, 1208 Greate Road, Gloucester Point, VA 23062, U.S.A.

²Department of Physical Sciences, Virginia Institute of Marine Science, College of William and Mary, 1208 Greate Road, Gloucester Point, VA 23062, U.S.A.

³City of Virginia Beach, Department of Communications and Information Technology, 2405 Courthouse Dr., Virginia Beach, VA 23456 U.S.A.

⁴City of Norfolk, Department of Communications and Technology, 3661 E. Virginia Beach Blvd., Norfolk, VA 23502, U.S.A.

Hampton Roads, VA. StormSense's network employs a mix of ultrasonic and radar remote sensing technologies to record water levels during 2017 Hurricanes Jose and Maria. These data were used to validate the inundation predictions of a street-level hydrodynamic model (5-m resolution), while the water levels from the sensors and the model were concomitantly validated by a temporary water level sensor deployed by the USGS in the Hague, and crowd-sourced GPS maximum flooding extent observations from the Sea Level Rise app, developed in Norfolk, VA.

Keywords:

Hurricane Maria, Hurricane Jose, King Tide, Hydrodynamic Modeling, Internet of Things, Smart City, Global City Teams Challenge, Replicability, Citizen Science, Sea Level Rise

1 1. Introduction

2 The modern smart city of today is tantamount to a complex system. Such systems are frequently 3 subjected to innumerable non-linear influences on how to efficiently allocate their limited resources (Rhee, 2016). The protocols by which these cities respond to emergency inundation conditions in 4 the near-future could be adapted using models informed and validated by an expanded water level 5 sensor network to advise how best to prepare for the imminent flood-related disasters of the future 6 (Fig. 1). Analysis of the local sea level trend from the longest period record in Hampton Roads at 7 8 Sewells Point in the City of Norfolk depicts a long-term linear increase in mean sea level of 9 4.59±0.23 mm/year since its establishment in 1928 (Fig. 2). The data from a new sea level trend study conducted at the Virginia Institute of Marine Science (VIMS) focuses on trends since the 10 11 Anthropocene (1969-present) to suggest that rising sea levels will inevitably exacerbate flooding 12 conditions from storm events in the nearer-future than initially projected by the IPCC's fifth assessment report, leading to a linear increase in mean sea-level of 0.29 m by 2050 (Mitchell et al., 13 14 2013; NOAA Tides and Currents, 2017). When considering a quadratic fit of these data, the curve

suggests an elevated trend of 0.49m by 2050 (Fig. 2) (Boon *et al.*, 2018). Cities, counties, town governments, local institutions, and private contractors, provide myriad 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 citizens rely upon.

Many existing smart cities solutions are designed to have a measurable impact on specific key 19 performance indicators relevant to their communities. Because many of today's smart 20 21 city/community development efforts are isolated and customized projects, the National Institute of Standards and Technology (NIST) launched the Global City Teams Challenge (GCTC) to 22 encourage collaboration and the development of standards for smart cities. The GCTC's long-term 23 24 goal is to demonstrate a scalable and replicable model for incubating and deploying interoperable, 25 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 26 improve efficiency and lower costs. NIST also created the Replicable Smart City Technology 27 28 (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 29 30 replicable solutions (RSCT, 2016). The RSCT program was designed to support standards-based platform approaches to smart cities technologies that can provide measurable performance metrics. 31 32 Together these two programs work to advance state-of-the-art of smart city standards.

The StormSense project brings together 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), to develop a regional resilience monitoring network, with the installation of 28 new publicly-broadcasting water level sensors. This was a notable recommendation from the

Intergovernmental Pilot Project's working group (Steinhilber et al., 2016). StormSense is poised to develop the network as Phase 1, and develop a street-level flood forecasting and monitoring solution across the entire region for Phase 2, which begins with integration of observed water-levels into VIMS' Tidewatch tidal forecasting system, which now operates under the <u>Commonwealth Center</u> for Recurrent Flooding Resiliency (CCRFR) (Fig. 1).

Hampton Roads, VA, experiences nuisance flooding fatigue with such frequency that it is easy to 43 44 forget that flooding events cost our cities, their first responders, and their residents time and money (VanHoutven et al., 2016). In one neighborhood in the City of Newport News that is subjected to 45 frequent flooding, typically many emergency responders were required to assist in evacuating the 46 47 complex (Lawlor, 2012; Alley, 2017). However, by remotely alerting residents that the water was rising quickly on the local stream, the past two flooding events have not required any emergency 48 responders to assist in evacuating and were subsequently able to dedicate their emergency services 49 elsewhere (Smith, 2016; Alley 2017). The goal of establishing a flood monitoring network can be 50 51 expensive, but in the long term, the anticipated benefits of improved quality of life for a region's citizens are monumental. The goal is to replicate this level of success throughout the cities of 52 53 Hampton Roads by providing a greater density of water level sensors. As an added benefit, more publicly-available water level sensors empower property owners to take responsibility for their 54 55 assumed risk of living adjacent to floodplains. This has resulted in a marked spike in the number of residents who have opted for flood insurance, with 2,231 claims totaling \$25M in damage attributed 56 to 2016 Hurricane Matthew (FEMA, 2016). Many of these properties are insured through the 57 58 Federal Emergency Management Agency's (FEMA) National Flood Insurance Program (NFIP), but many properties outside of the designated floodplain do not have preferred risk policies 59 (VanHoutven et al., 2016). 60

A stakeholder workshop conducted on January 19, 2016, with representatives from Hampton Roads 61 regional emergency management, storm water engineering, and planning municipal staff, as well 62 63 as academic and non-government organization partners uncovered a need for near-term, locally scaled, and 'realistic' scenarios to communicate risk (Flooding Mitigation Stakeholder Workshop, 64 2016). Emergency managers are currently limited in their communications tools and know them to 65 be inadequate (CoreLogic, Inc., 2015; Yusuf et al., 2017). A better understanding of the decisions 66 people are making to adapt to flooding is needed. Differences are expected in both flood perception 67 and behavior between urban and rural audiences. A pilot study conducted in 2015 examining 68 information logistics for drivers on flooded roads in Norfolk found that decisions made about 69 driving were strongly situational, based upon the importance, timing, and location of the driving 70 plans, but that a regional approach to communication was needed and lacking (CoreLogic, Inc., 71 2015). Time living in Hampton Roads was an important factor in risk perception and that 72 information comes from local knowledge, recognized sources of information, and sometimes a 73 74 haphazard mix of both. Examining these issues in Hampton Roads and these recent studies, the context of flood communication and further elucidating the currently vague appropriate flood model 75 76 parameters for accurate inundation prediction using hydrodynamic models at the street-level scale 77 in a broader context is needed. This leads 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 disseminated 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 10 water level sensors by the United States Geological Survey (USGS) in the City of Virginia Beach, along with 5 new street inundation sensors and 1 tide gauge in Norfolk, and 7 new water level sensors in Newport News through StormSense will be compared during Hurricanes Jose and Maria in Hampton Roads in September 2017.

90 2. Study Area and Model Inputs

Hampton Roads, VA, is the second-largest population center at risk from sea level rise in the 91 92 United States. The region has more than 400,000 properties that are exposed to flood or storm surge inundation (Sweet *et al.*, 2014). The region has a population of over 1.7 million people, 93 94 living and traveling on roads exposed to both severe and increasing frequent chronic "nuisance" flooding (Ezer and Atkinson, 2014; Ezer and Atkinson, 2017). Existing flood communication and 95 messaging systems have not yet responded to the changing risk patterns brought by sea level rise 96 and have not been able to meet the diverse needs of a growing populous in an expanding floodplain. 97 A better understanding of flood risk perception, information seeking behavior and decision-98 making can inform the development of new communications tools and flood risk messaging (Wahl 99 100 et al., 2015). This is the percieved intersect between new IoT-technologies and emerging flood model validation methods. For each storm event, water levels driven via 36-hour Tidewatch 101 forecasts provided by VIMS at Sewells Point were used to drive surge and tides, alongside wind 102 103 and pressure inputs used to drive the model atmospherically, similar to Loftis, Wang, and Forrest

(2016). VIMS employs a street-level hydrodynamic model, which incorporates a non-linear solver 104 and variable sub-grid resolutions, capable of being embedded with lidar-derived topography to 105 106 scale resolution for inundation where it is needed down to 5 m or even 1 m resolution in known areas where flooding frequency is high. The model has been used to simulate every major storm 107 event in Hampton Roads that has occurred in the last 20 years, and has been used in many other 108 109 places along the U.S. East and Gulf Coasts as well (Loftis, 2014; Wang et al., 2014; Wang et al., 2015; Loftis et al. 2016; Loftis et al., 2017). For more information on the model, please refer to 110 these cited studies. 111

112 **2.1 Groundwater Inputs**

Recent advancements in hydrodynamic computation have enabled models to predict the mass and 113 movement of flood waters to predict water velocities at increasingly finer scales. However, the 114 current version of the sub-grid inundation model VIMS has developed does not fully incorporate 115 a comprehensive groundwater model that slowly returns flood waters that infiltrate through the 116 soil back to the nearest river (Loftis, 2014). This is a valuable aspect of flooding relevant for city 117 planning perspectives using sub-grid hydrodynamic modeling that has been successfully 118 119 developed and employed throughout the Netherlands, Germany, and Italy (Casulli, 2015). There is an array of groundwater wells that exist in the Hampton Roads Region, bored and monitored by 120 121 the USGS (USGS Groundwater Monitoring Sites, 2017). These temporally-varying values for hydraulic conductivity could provide some valuable input information for the hydrodynamic 122 model via Richard's equation (Loftis et al., 2016). However, this does not currently account for 123 the standard practice of near-surface groundwater displacement via pumping prior to anticipated 124 flooding events conducted by cities with residents in the floodplains where a high water table 125 regularly exacerbates even minor rainfall events (Loftis et al., 2017). Nevertheless, values 126

observed near these sites prior to forecast simulations were used as the model's initial condition to
estimate infiltration through pervious surfaces, to counterbalance precipitation inputs, similar to
Loftis *et al.* (2016).

In forecast approaches, groundwater influence is usually neglected, since typically storm surge is 130 a short-term event, and groundwater recharge is more of a delayed and long-term process, 131 132 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 5 133 or more tidal cycles. VIMS has been incorporating different forms of percolation of flood waters 134 through different types of ground cover ranging from vegetated to impervious within the sub-grid 135 model in recent years (Loftis et al., 2016; Loftis, Wang, and DeYoung, 2013). It is worth noting 136 that there are potential applications for storm water systems that could be manually added to the 137 existing sub-grid model version to account for surge flooding backups through storm water 138 drainage without sufficient backflow prevention (Loftis et al., 2017). 139

140 **2.2 Precipitation Inputs**

The inundation model could be used to guide decisions related to storm water management by 141 142 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 143 144 stations in the localities, and from the Hampton Roads Sanitation District (HRSD), which combined currently amounts to ~130 sensors. With an iteratively interpolated series of 145 precipitation measurements, further research could also be conducted with these sensors and the 146 new water level sensors to model the impacts of localized microburst precipitation events, like 147 those experienced during 2016 Hurricane Matthew, or most recently on August 29, 2017, in some 148 neighborhoods in southside Hampton Roads. This could aid researchers to help model ways that 149

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 provided by HRSD.

154 **3. Water Level Sensors**

StormSense has recently deployed 28 IoT-bridge-mounted ultrasonic and microwave radar water 155 level sensors in Newport News, Virginia Beach, and Norfolk, as outlined on the StormSense 156 project's website at: http://www.stormsense.com. These sensors will complement the previously 157 158 installed array of 6 gauges operated by NOAA, 19 relatively new gauges recently installed in 2015-2016 via Hurricane Sandy relief funds operated by the USGS, and 1 gauge operated by VIMS in 159 160 Hampton Roads. While the extant remote sensors in the region are largely radar sensors transmitting 161 data through satellite signals, the new StormSense IoT-sensors enlist the use of ultrasonic sensors 162 and transmit data via cellular transmission protocols or Long Range (LoRa) Wireless Area 163 Networks (WAN), with the focus of creating a replicable cost-effective network of sensors. Some realized utilities for a dense network of water level sensors are noted as follows: 164

- 165 1) Archiving of water level observations for flood reporting
- 166 2) Automated targeted advance flood alert messaging
- 167 3) Validation/inputs for hydrodynamic flood models
- 168 **3.1 Sensor Types and Applications**

A collaboration between VIMS and the 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 173 new sensors to the cities' current Everbridge notification systems for alert messaging when the 174 175 sensor observes flooding at user-specified elevations, and integration with model predictions for timely forecasted tidal inundation alerts through Tidewatch once the sensors are tidally-calibrated. 176 Fig. 3 shows an internal look at some sensors in Newport News, VA. The city employed a mix of 177 178 2 radar sensors (Fig. 3A) and 6 ultrasonic sonar sensors (Fig. 3B) from Valarm, a California-based sensor vendor with a cloud-based virtual alarm messaging platform. The Valarm Tools cloud 179 platform will use the newly-installed sensors to provide subscriber-based alerts (Fig. 3C) based 180 upon water level observations (and eventually tidal forecast predictions once incorporated into 181 Tidewatch), to provide a unique flood-preparedness service to their citizens and potentially bolster 182 the flood warning portion of their FEMA NFIP application to participate in the Community Rating 183 System (CRS). This is important, as each higher participation level the city achieves in the 184 hierarchical CRS program is commensurate with an additional 5% decrease in flood insurance 185 186 premiums for the citizen homeowners in participating communities.

This approach demonstrates the benefits of replicating shared smart city solutions across multiple 187 cities and communities that are facing similar flood challenges and it aligns with the goals of 188 189 GCTC and RSCT programs. For a different innovative example, Fig. 4A shows a map of Norfolk's LoRaWAN ultrasonic sensor network established in The Hague, in August 2017. The sensor 190 191 network is currently comprised of one tide monitoring sensor mounted over The Hague walking 192 bridge near where the USGS mounts their temporary rapid deployment gauge, and five inundation sensors, strategically positioned over frequently flooded streets (Fig. 4B). The LoRaWAN sensors 193 were purchased through a Norfolk-based vendor, GreenStream, Inc., and use long range WiFi 194 195 instead of cellular data transmissions, and like the Newport News sensors. They are currently

publicly reporting water level observations in Tidewatch, as depicted in Fig. 4C. Public Application
 Programming Interface (API) URLs are available at: <u>http://www.vims.edu/people/loftis_jd/</u>
 HRVASensorAssets/index.php.

199 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 200 201 using these ultrasonic sensors will be evaluated as reputable and replicable monitoring methods after a longer-term study. In pursuit of this, Fig. 5 shows three examples of temporary StormSense 202 ultrasonic sensors deployed on the same bridges as the USGS' radar sensors over tidal rivers and 203 creeks throughout the City of Virginia Beach. A later paper will evaluate the differences between 204 these sensor accuracies and types, fault tolerance in data transmissions, and solar power 205 management schemes. An initial comparison with a temporary Rapid Deployment Gauge (RDG) 206 established by the USGS allowed for a favorable short-term data comparison with Norfolk's 207 LoRaWAN sensor collocated there during a nine-day overlap period during Hurricane Maria in 208 209 Fig. 6.

3.2 Sensor Configurations, Accuracies, and Costs

After an evaluation period of 6-9 months, these sensors will be relocated to unique monitoring locations in Virginia Beach. A small number of white papers and vendor brochures evaluate the accuracies of the ultrasonic and radar sensors in laboratories or for the application of level monitoring of water treatment reservoirs or chemical vats. However, these are not comparable to tidal water bodies or areas with significant wave action, such as during the extratropical storm surge events presented in this study during Hurricanes Jose and Maria.

A cursory comparison from the initial deployments of the sensors in Summer 2017 revealed that the ultrasonic sonar units are from Valarm are accurate in the lab to a Root Mean Squared Error

(RMSE) of ± 5 mm, and accurate in the field to an average of ± 18 mm, while the two radar sensors 219 in Newport News are accurate in the lab to ± 1 mm and accurate as deployed in the field to ± 9 mm. 220 221 The cost to purchase a solar-powered cellular transmission station was approximately \$3000/each for the ultrasonic sensors, and \$4400/each to purchase the radar units. The street inundation sensors 222 employed in Norfolk through the vendor, Green Stream, are accurate in the lab to approximately 223 224 ± 15 mm, and accurate in the field ± 45 mm, and sensors were purchased for \$400/each, plus the cost of the LoRa transmission gateway, which has an effective transmission range of 225 approximately one mile, less the distances occluded by high-rises and buildings (Loftis, Wang, 226 and Forrest, 2017). 227

228 **3.3 Water Level Sensor Data Comparisons**

229 A comparison of the five new street inundation sensors and one water level sensor in Norfolk, and 230 eight new water level sensors in Newport News were used to temporally and vertically validate a 231 street-level hydrodynamic model's predictions during the offshore passage of Hurricanes Jose and 232 Maria, which detected increased water levels in Hampton Roads by 76.2 cm. (2.5 ft.) and 60.9 cm. (2 ft.), respectively. These six gauges resulted in an aggregate vertical RMSE of ± 8.93 cm. over a 233 72-hour Hurricane Jose model forecast simulation (Loftis, Wang, and Forrest, 2017). The time 234 series plots shown in Fig. 7A-E compared well with the maximum period of spatial inundation 235 extents predicted by the model at 19:00 UTC on 9/19/2017 in Fig. 7F. The labeled location for 236 each of the sensors in The Hague in Fig. 7F also shows the surface elevations of city-maintained 237 light poles in ft. above NAVD88, which accounts for relative depths of flood waters and puddles 238 detected by the sensors and the model. Interestingly enough, the sensor in Fig. 7E detects latent 239 240 ponding of water on the outskirts of the intersection for several hours after the nearby over-water sensor at the walking bridge in The Hague shows the tidal-driven surge subsiding after the peak 241

of several tidal cycles. This is likely a result of storm water drainage backup in the storm drainsnearest to the sensor.

244 The seven gauges present during Hurricane Maria (including the USGS rapid deployment gauge installed from 9/21-9/29/2017) yielded a more favorable aggregate RMSE of ±6.28 cm when 245 compared with the model. Both storms produced minimal surge-related coastal flooding, yet 246 247 inundation impacts were equally profound in some tidal-connected inland areas, making the comparison with Norfolk's new street inundation sensors interesting to observe and practical for 248 verification of inland inundation extents and depths. Fig. 6A shows how the USGS RDG 249 measurements temporarily co-located (similarly to Fig. 5) at the same site during Maria's passage 250 were used to apply a vertical adjustment of +4.5 cm. (0.15 ft.), based upon the Mean Absolute 251 Error (MAE) as an offset, to improve the Root Mean Squared Error (RMSE) metric for this event, 252 and likely many events in the future. This change resulted in an improvement in sensor estimated 253 RMSE from 6.08 to 0.71 cm., a difference of 5.37 cm. (0.17 ft.). 254

255 4. Crowdsourced GPS Flood Extents during Hurricane Jose

Hurricane Jose had a more significant storm surge measured by water level sensors in Hampton 256 257 Roads and less rain, while the opposite was true for Hurricane Maria. The relatively new citizen science 'Sea Level Rise' mobile app provided 393 points of geospatial data for use with validating 258 predicted flood extents in the Larchmont Neighborhood of Norfolk during Hurricane Jose (Fig. 8) 259 with a favorable Mean Horizontal Distance Difference (MHDD) of ±3.36 m (Loftis, Wang, and 260 Forrest, 2018). This indicates that the modeled maximum flooding extents calculated by the street-261 level hydrodynamic model in the flood-prone Larchmont neighborhood of Norfolk compared 262 263 reasonably well with these observations during the event, and the average depth of inundation in this area reported by the model (and the underlying digital elevation model's contour) was 24.4 cm.
(0.8 ft.).

The street-level model's Lidar-derived DEM, embedded in the model's sub-grid, was recently 266 scaled to 1 m resolution in the Larchmont, Chesterfield Heights, and The Hague neighborhoods in 267 Norfolk as part of an ongoing NASA Mid-Atlantic Resiliency Demonstration Study. Larchmont is 268 positioned on a peninsula bounded by the Elizabeth River to the west and the Lafayette River to the 269 270 north and east, and the area frequently experiences tidal 'nuisance' flooding. By measuring the horizontal distances from the GPS-reported points of maximum flooding extents from the 'Sea 271 Level Rise' App, to the edge of the model predicted maximum flooding extent contour line, an 272 273 assessment of geospatial accuracy may be reached with minimal processing effort using the standard distance formula (Loftis et al., 2016; Loftis et al., 2017). An inherent caveat of this 274 geospatial MHDD approach is that it is only a relevant metric in areas with minimal surficial slope, 275 like those that characterize Hampton Roads, VA. In areas with steeper slopes immediately adjacent 276 277 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 (Loftis et al., 2016). 278

279 **5. Discussion**

The hydrodynamic model in Hampton Roads, VA, was effectively validated using 5 street inundation sensors and 2 water level sensors during the passage of Hurricanes Jose and Maria in September 2017. An aggregate of the results in Newport News during Hurricane Jose yielded a RMSE of ± 6.2 cm. 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. The USGS provided a valuable service in the form of surveying and installing a temporary rapid deployment gauge during Hurricane Maria that provided an additional form of data

validation not present during Hurricane Jose the previous week. The data from this sensor, 287 positioned on the same walking bridge in The Hague, compared quite well between the new 288 ultrasonic sonar sensor and this temporary radar gauge, with an $R^2=0.9235$, a MAE=4.57 cm., and 289 an RMSE=6.08 cm. It was noted that an offset using the sensor's MAE during Jose could be applied 290 as a minor vertical adjustment of +4.5 cm. (0.15 ft.) to improve the statistical comparison during 291 Jose to R²=0.9979, a MAE=0.01 cm., and RMSE=0.71 cm., along with likely improving future 292 observations at the site, as suggested in the examples from Fig. 4. This minimal, yet consistent, bias 293 of +4.5 cm. (1.8 in.) is likely due to minor measurement error or differences in vertical datum 294 measurements at this specific site relative to the bottom of the sensor's emitter to NAVD88, as its 295 application to the other sites in Norfolk made inconsistent changes in results. 296

Typically, the USGS collects valuable high water marks after major flood events. However, as none 297 of these events were truly catastrophic flood events in Hampton Roads, VA, relative to if they had 298 made landfall, high water marks in the form of GPS maximum flood extent points from the citizen 299 300 science App, 'Sea Level Rise' were compared with the model instead as a secondary form of model validation. Results from 393 data points at one site in the western peninsula side of the Larchmont 301 neighborhood in Norfolk during Jose yielded a favorable MHDD of ±3.36 m. This characterized 302 the relative error as equivalent to approximately 2/3 of a single 5×5 m sub-grid cell pixel, from the 303 304 model's perspective.

305 6. Conclusions

In the future, smart city systems could evaluate tenable candidate blueprint solutions for floodrelated problems, whether they be attributed to storm surge, heavy rainfall, and tides, as was the case during the offshore passage of Hurricanes Jose and Maria, using a decision matrix. This could help key decision-makers make informed decisions regarding how flood-related solutions could be best addressed with the new StormSense water level sensor network being integrated into Tidewatch to creating a resilience monitoring network throughout Hampton Roads, VA, to directly address a key recommendation from the Intergovernmental Pilot Project. Ways the new sensors could be used to drive a street-level inundation model and be parameterized for specific flooding scenarios are *noted in italics* below:

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

In cases of heavy rainfall, the street-level sub-grid hydrodynamic modeling approach also performs the function of a hydrologic transport model to predict flow accumulation and 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.

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such products are necessarily the best available for the purpose.

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procedure; this does not imply endorsement or recommendation by NIST, nor does it imply that

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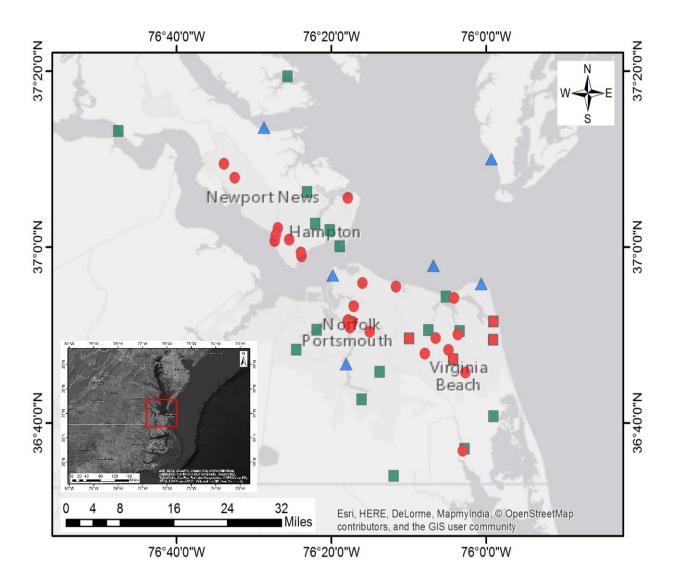


Fig. 1. Map of 57 publicly-streaming water level monitoring stations throughout Hampton Roads, VA. The StormSense sensor network has contributed 28 sensors to the 29 existing sensors maintained by federal entities. Of these, NOAA has 6 (marked in blue) and USGS maintains 19 (noted in green). Additionally, VIMS has 1, and WeatherFlow has 3 (also marked in red). Click Fig. or http://arcg.is/14aCe1 for interactive station map.

Norfolk, Virginia

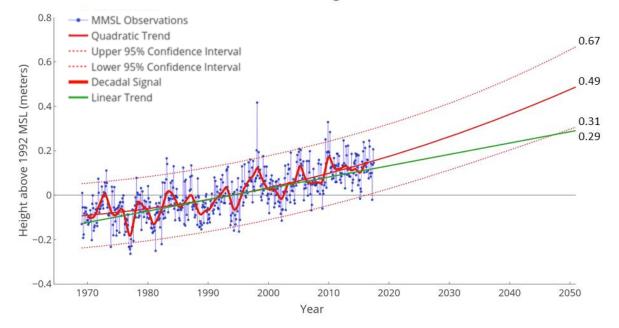


Fig. 2. Hampton Roads Sea Level Rise Projections for Sewells Point through 2050 from VIMS Anthropocene Sea Level Change Report at <u>http://www.vims.edu/test/dlm/slrc/index.php</u> (Boon *et al.*, 2018).

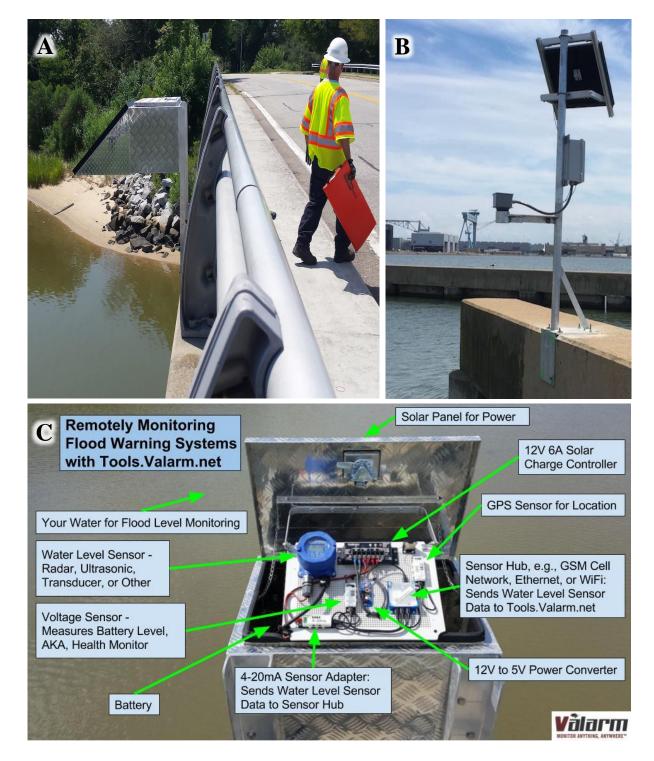


Fig. 3. Internal look at Newport News' sensor from Valarm: A) a standard bridge-mounted remote radar sensor control box configuration on the 16th St. Bridge over Salters Creek vs. B) a pole-mounted ultrasonic sonar sensor on a solid breakwater at Leeward Municipal Marina. C) The internal view of the control board and the sensor in panel A.

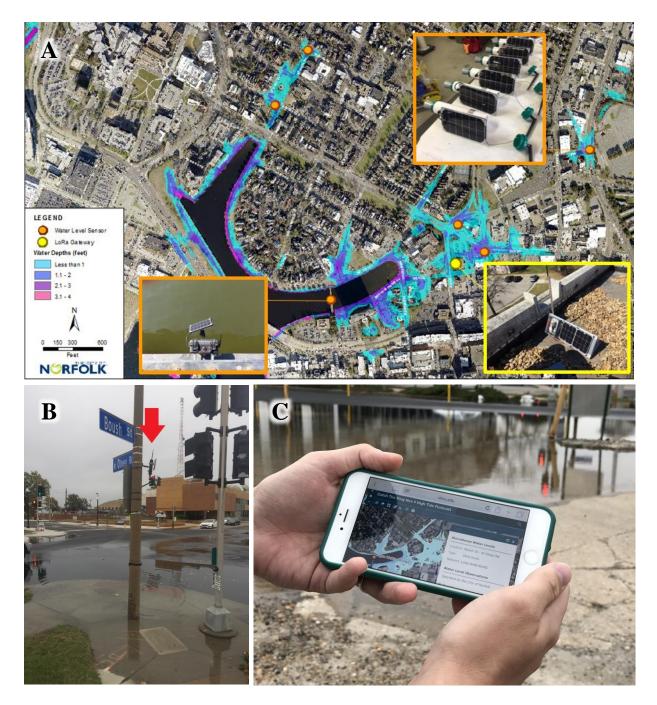
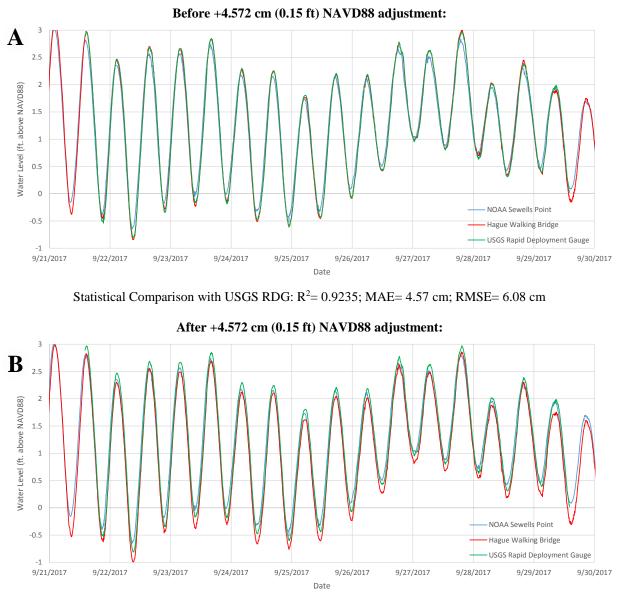


Fig. 4. A) Map of Norfolk's LoRaWAN ultrasonic sensor network established in The Hague. The group currently consists of one tide monitoring sensor mounted over The Hague Walking Bridge near where the <u>USGS mounts their temporary rapid deployment gauge</u>, and five inundation sensors, strategically positioned over frequently flooded streets. One such street is featured in B) at the intersection of Boush St. and Olney Rd. during the King Tide flooding on the morning of Nov. 4, 2017. C) The sensor data are currently publicly reporting water level observations in Tidewatch and the user interface provided by the manufacturer, Green Stream, Inc. (https://greenstream.io/Dashboard).



Fig. 5. Examples from three StormSense ultrasonic sonar sensors co-located in the field adjacent to USGS radar sensors in Virginia Beach for direct comparison of monitoring accuracy. These sensors will temporarily be stationed adjacent to each other for a period of 6-9 months to provide a long term data record for comparison of water level measurements, data transmission speeds, and solar power efficiency.



Statistical Comparison with USGS RDG: R²=0.9979; MAE= 0.01 cm; RMSE= 0.71 cm

Fig. 6. Comparison of Norfolk LoRaWAN ultrasonic tide sensor (in red) with temporary Rapid Deployment Gauge (in green) installed by the USGS measuring water levels via radar at Hague Walking Bridge from 9/21-9/29/2017 during the passage of Hurricane Maria. Results in panel A) depict measurements recorded prior to a vertical adjustment of +4.572 cm (0.15 ft), which was applied for future reporting and improves results in B) after the sensor was consistently lower than the USGS sensor, temporarily mounted to the same bridge at the same site. Observations from NOAA's Sewells Point sensor (in blue) represent the water levels at the mouth of the Elizabeth River as the next nearest tide gauge from the Hague located 12.39 km (7.7 mi) downriver.

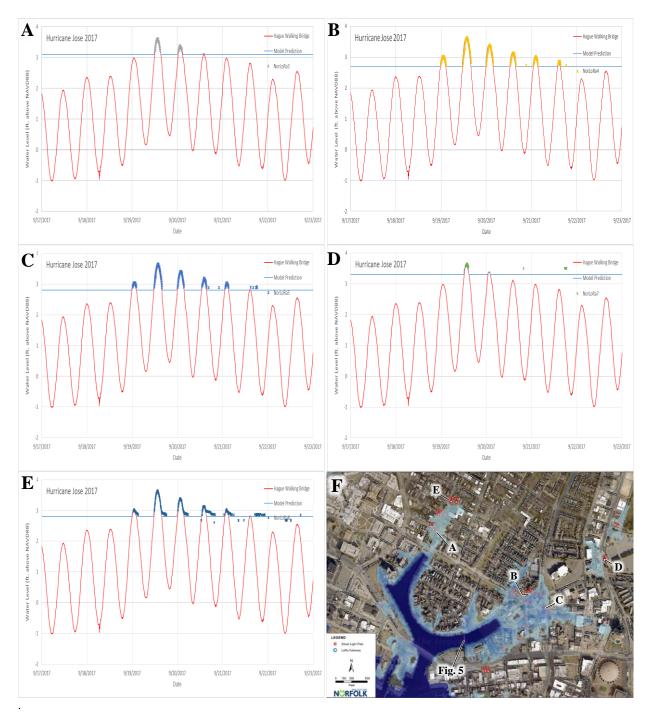


Fig. 7. Norfolk LoRaWAN ultrasonic street inundation sensor comparisons from 9/17-9/23/2017 during the passage of Hurricane Jose. Each sensor's observations featured in Panels A-E) are compared with the nearby LoRa tide gauge featured in Fig. 5 (in red) and the street-level hydrodynamic model's predictions (in blue) at five locations in Norfolk's Hague region. Panel F depicts the spatial inundation extents predicted by the model at 19:00 UTC on 9/19/2017, with the labeled location of each inundation sensor alongside surface elevations of city-maintained light poles in ft above NAVD88, which were used to aid decision-making for sensor placement.

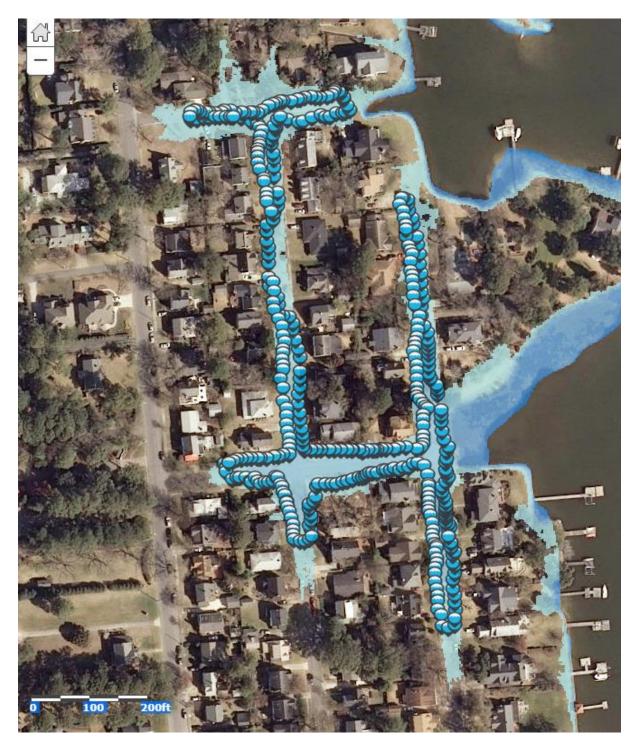


Fig. 8. Street-level model flood prediction at 14:00 UTC on 09/19/2017 while Hurricane Jose was hovering offshore of just outside of the Chesapeake Bay mouth. The blue dots represent 393 High Water Marks tracing the extent of inundation collected via citizen science volunteer users of the Sea Level Rise mobile App between 9:50-10:17 EDT (13:50-14:17 UTC).