CASE STUDY: A RAPID URBAN INUNDATION FORECASTING TECHNIQUE BASED ON QUANTITATIVE PRECIPITATION FORECAST FOR HOUSTON AND HARRIS COUNTY FLOOD CONTROL DISTRICT

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Abstract

This research explored the operational feasibility of quantitative precipitation forecasting (QPF) using high resolution numerical weather prediction models at the urban landscape scale for flood inundation forecasting in the city of Houston for Harris County Flood Control District (HCFCD). The authors propose and test a rapid-refresh technique for generating forecasted flood inundation maps. The time required to process such maps for an urban flood management agency is controlled only by the time required for generating high resolution QPF. The study investigated hurricane (e.g. Harvey) and non-hurricane type storms. Using the dense gauge network operated by the HCFCD, it was found that hurricane type storms are generally more challenging for precipitation forecasting than the less intense and more frequent winter storm events. The investigation of gauge-based water level measurements indicated that it is possible to forecast inundation level at water level gauging points based on rainfall forecast using pre-developed rating curves between forecast rainfall and expected increase in water level. Using this rating curve approach, it was found that the median of relative RMSE (percentage) and correlation of forecasted water level at gauge locations are consistently below 10% and higher than 0.7, respectively for up to 4 day of lead-time, subject to availability of adequate computational

resources. In terms of spatial detection of flooded (non-flooded) areas, our technique yields qualitative consistency during peak inundation episodes in Houston at 1 day of lead-time when compared against satellite radar imagery or in-situ based technique. In general, it is found that flood inundation forecast accuracy during peak episodes is not as compromised as QPF skill for hurricane-strength storms, indicating that the highly urbanized nature of Houston is more ideally suited for inundation mapping using the rating curve approach.

Keywords: Houston, urban flooding, hurricane, Harris County, Harvey, forecasting, WRF

1. INTRODUCTION

Houston has frequently experienced the nation's worst urban flooding events (Zelinski and Zaveri 2018). With its flat and saucer-like terrain, highly urbanizing landscape, inadequate storm drainage capacity and intense precipitation events, there is no doubt that Houston will experience urban flooding in the foreseeable future. For example, in one study using remote sensing imagery of land cover, asphalt and concrete increased 21% during 1984–1994, 39% in 1994–2000 and 114%, from 2000 to 2003, while vegetation suffered an overall decrease (Khan 2005). Such rapidly urbanizing landscape appears more alarming when considered in the context of recent studies on projected trends of extreme rainfall for the state of Texas. One study estimated that the annual probability of a 500 mm of area-integrated rainfall was about 1% in the period 1981–2000 and that this is likely to increase to 18% over the period 2081–2100 under Intergovernmental Panel on Climate Change (IPCC) AR5 representative concentration pathway 8.5 (Emanuel 2017). Furthermore, if it was assumed that the frequency of such events increases linearly in time, then an event like Hurricane Harvey probably had a 6% chance of occurrence in 2017, which is a six-fold increase since the late 20th century (Emanuel 2017).

Given this increasing propensity for Houston to frequently experience more catastrophic urban flooding, it is opportune time to explore the operational potential of quantitative precipitation forecast (QPF) from numerical weather prediction (NWP) models for real-time urban flood management. QPF can be considered a low-hanging fruit that is freely available to any agency for real-time forecasting of weather events (e.g. Liguori et al. 2012, Liu et al. 2015). The goal here was to understand the operational sustainability of using the publicly available and real-time QPF produced by the National Oceanic and Atmospheric Administration (NOAA) Global Forecasting system (GFS). This research studied the hurricane strength extreme storm

Harvey and lesser magnitude events. Since, GFS-based weather forecasts available at a high frequency are available at a coarse spatial resolution of 0.25 degree (25 km), dynamic downscaling to higher spatial resolution (1 km) using a cloud resolving NWP model is necessary for flood forecasting at the urban landscape scale (Chen and Hossain 2016, Sikder and Hossain 2016).

In order to explore a sustainable operational strategy for rapid forecasting of flood inundation, the authors engaged closely with Harris County Flood Control District (HCFCD), which is the main agency with the mandate for urban flood management for the city of Houston. Towards this goal, this study posed the following research questions:

1. How does skill of high resolution QPF vary as a function of lead time for Harvey and non-Harvey type extreme storm events over Houston?
2. Can high resolution QPF be used for water level/inundation forecasting?
3. What is a feasible and sustainable approach for HCFCD (and similar agencies) to take advantage of high resolution QPF in urban flood disaster management?

2. THE SELECTED STORMS

Two storm events were selected in this study. The first storm was Hurricane Harvey, while the second one was of a lesser magnitude (with a typical 2-year return period). In both cases, the specific date was selected, when rainfall (hereafter interchangeably used with precipitation) total was maximum as the target date for forecasting up to 96 hours ahead of time (i.e., 4-day lead-time). The specific peak rainfall dates for the storms are:

Harvey storm – August 26, 2017 (daily and areal averaged rainfall total= 276 mm)

Non-Harvey Class storm – February 21, 2018 (daily and areal averaged rainfall total= 25 mm)

Another Non-Harvey storm event was selected for further analysis in this study, which had the maximum magnitude on January 18, 2017 (daily and areal averaged rainfall total= 65 mm). This storm event along with the above two events were used to develop the precipitation-water level rise relation (i.e., rating curve), which later used to generate the water level forecast.

3. DATA AND MODELS

3.1 In-Situ Rainfall and Water Level Data

Harris County Flood Control District has a very dense rainfall gauge and water level monitoring network. For ground rainfall data, the authors had access to 139 recording gauges distributed in the county with an average density of 1 gauge in a 5X5km grid. Figure 1 shows the location of these gauges that transmitted rainfall and water level every 5 minutes to HCFCD headquarters via a telemetered network.

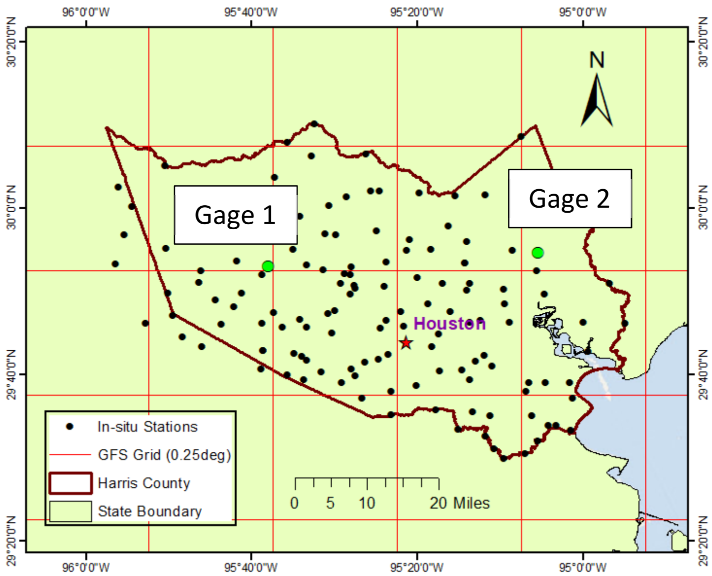

Fig. 1. Location of HCFCD rainfall and water level gauges in the county where Houston is located. The larger grids are 25 km in size and typical size for NOAA's QPF (GFS). Location of two selected gages are shown as green to demonstrate the response of water level change to precipitation spells in figure 5.

3.2 The Global Forecasting System (GFS) for NWP Forecasts

The Global Forecasting System (GFS) developed by the National Oceanic and Atmospheric Administration (NOAA) was used as the key source of NWP model based QPF. GFS produces global-scale weather forecast up to 16 days lead time at a spatial resolution ranging from 0.25 degree to 1 degree. This is perhaps the only publicly available weather forecast at a global scale for operational use. The motivation for exploring the GFS forecast is further based on the authors' previous experience and success in operational flow forecasting for South and Southeast Asian agencies (Sikder and Hossain 2018, Sikder and Hossain 2016). As a publicly available and real-time product for the world, GFS is therefore ideal for short-term weather prediction applications, particularly in urban flood management agencies that traditionally do not use such modern atmospheric science based solutions. The historical and real-time data are available from National Center for Environmental Information (NCEI) at https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/global-forcast-system-gfs. For first 10 days of lead time, the GFS provides forecasts for every 3 hours, and the outputs are available at 0.25, 0.5, 1.0, and 2.5 degree resolutions.

3.3 The Weather Research and Forecasting (WRF) Model

The Weather Research and Forecasting (WRF) model V3.7.1 was used for dynamic downscaling of coarse resolution global NWP weather forecasts, such as from GFS. Such physical downscaling can generate high resolution precipitation forecast over an urban landscape that requires flood inundation model at a very high spatial resolution (in this case 1 km grids). WRF is a mesoscale cloud resolving NWP model, which is the successor of the MM5 model. It uses non-hydrostatic Euler equations, which are fully compressible in nature. WRF offers various features like advanced dynamics, physics, and numerical schemes. For computation, the model uses Arakawa-C grid staggering for horizontal discretization, and second or third order Runge-Kutta integration scheme for time separation. WRF uses terrain-flowing pressure coordinate system. Thus, the upper boundary of the model maintained by a constant pressure level. Further description of WRF physics and dynamics can be found in Skamarock et al. 2008.

Since the focus in this study was on urban scale flooding triggered by extreme storm events, the initial WRF setup used in this study was based on a previous study optimized for simulating urban precipitation event during the Nashville 2010 flood (Chen et al. 2017a). Previous studies suggest that WRF performance is mostly affected by the choices of cloud microphysics and cumulus parameterization schemes (Chen et al. 2017a). Model resolution and initial/boundary conditions (IC/BC) also affect the simulation quality. However in this case, as the goal is to enable real-time forecasting, the GFS forecast fields were used as Initial and boundary conditions. The initial model configuration further refined in this study, based on extensive sensitivity studies for various parameterizations, carried out earlier for heavy storms in the US (reported in Chen and Hossain 2016). Based on these extensive sensitivity studies to identify the optimal WRF configuration, a two-way nesting with three domains (9km-3km-1km) was selected with Morrison microphysics and Kain-Fritsch cumulus schemes (Figure 2).

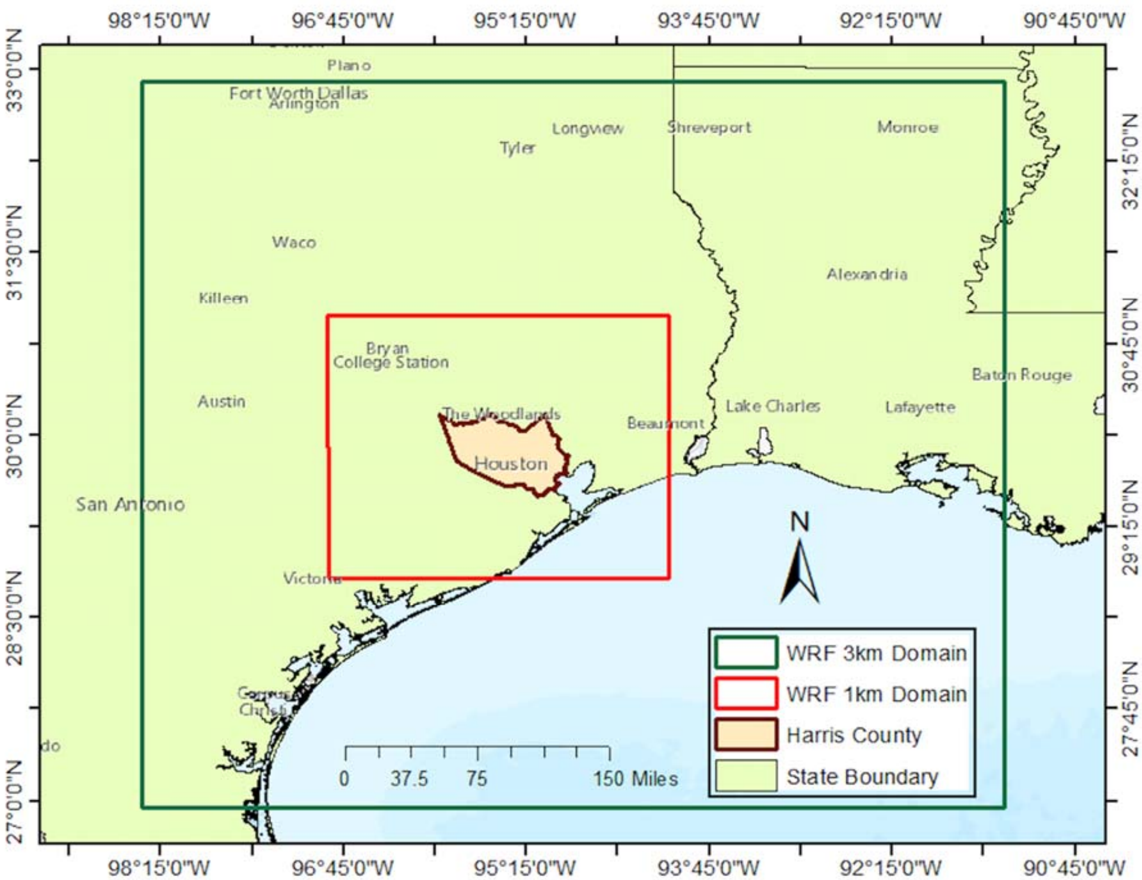

Fig. 2. WRF nested domain set up over Houston and Harris County. The inner domain has a grid spacing of 1 km and covers all of HCFCD's jurisdiction, while the outer domain has spacing of 3km.

4. CPU RESOURCES AND COMPUTATIONAL RUN TIME

For operational (real-time) urban flood management, time is of the essence for any agency. Any forecast must be generated significantly faster than the natural evolution of the flooding so that the forecasts can be analyzed, processed and disseminated with considerable lead time to make appropriate decisions. Since, QPF generation using high-resolution NWP models can be computationally prohibitive; this study was performed on affordable CPU resources of varying hardware configurations that are likely to be operationally sustainable in the

HCFCD work environment. In particular, the computational run time was tested on the following CPU configurations:

MACHINE 1 (price: 4000 USD): 32 core Intel Xeon 2.4 GHz Linux Workstation

MACHINE 2 (price: 3000 USD): 24 core Intel Xeon 2.4 GHz Linux Workstation

MACHINE 3 (price: 2000 USD): 12 core Intel Xeon 2.4 GHz Linux Workstation

The CPU run time on various machines are shown in Table 1 as a function of lead time.

Table 1. The CPU run time for 1 day and 4 day (96 hour) lead times

Lead	**MACHINE 1**	**MACHINE 2**	**MACHINE 3**
1 day only	7 hrs	7.5 hrs	20 hrs
4 days (96 hrs) total	28 hrs	30 hrs	80 hrs

Assuming that a CPU machine worth 4000 USD with 32 cores can be sustainably maintained by a flood agency like HCFCD, it appears that generating forecasts only for the 72 hour lead time (or longer) would be meaningful due to the runtime of 7 hours per lead day. It should be noted that the computational efficiency of the WRF downscaling can be optimized further through a Graphics Processor Unit (GPU) or parallel version of WRF that runs an order faster. In addition, the inner domain resolution of 1km and outer domain resolution of 3km could be relaxed and assessed of the precipitation forecast skill in a manner similar to the author's previous studies with Nashville 2010 flood (Chen et al. 2017a) or other extreme events studied for Probable Maximum Precipitation in Chen and Hossain (2016). Finally, if flood control districts like HCFCD are willing to invest modestly in cloud-based high performance based computing infrastructure (with some of the costs transferred to users of forecasts), it is quite feasible to generate these forecasts in timescales of 30 minutes to an hour each instant an update is needed.

5. SKILL OF HIGH RESOLUTION QUANTITATIVE PRECIPITATION FORECAST

5.1 HURRICANE HARVEY (AUGUST 2017)

Figure 3 shows the rainfall forecast up to 4 day lead time at 25 km (GFS) and 1 km (WRF downscaled) resolution over Harris County. Table 2 summarizes the performance metrics of the forecasted rainfall. It is clear from the assessment that hurricane-strength storms like Harvey are somewhat challenging to forecast unless adequate attention is given to the storm-specific WRF set up. Dynamic downscaling with WRF does not seem to add value to GFS forecast. This is not entirely surprising as past studies have reported on the general difficulty of simulating precipitation during Hurricanes (Emanuel 2017, Rotunno et al. 2008). However, it appears that given sufficient investigation of the choice of WRF model variants, one might be able to simulate high-resolution precipitation forecast at the urban scale for Hurricane events. For example, Dodla et al. 2011 had studied the life cycle of Hurricane Katrina using three variations of the high-resolution WRF model. One particular variation was Hurricane WRF (HWRF) designed specifically for hurricane studies while the other two WRF models had different dynamic cores. For Katrina, the HWRF exhibited superior performance in tracking the evolution of the Hurricane.

The specific WRF high resolution NWP model used in this study was derived based on an atmospheric river event (Durkee et al. 2012) that flooded Nashville city in 2010. Due to differing dynamics behind the precipitation process, the choice of cumulus and cloud microphysics parameterizations need to be revisited and calibrated uniquely for Harvey class storms within perhaps HWRF if the forecast skill is to be further improved.

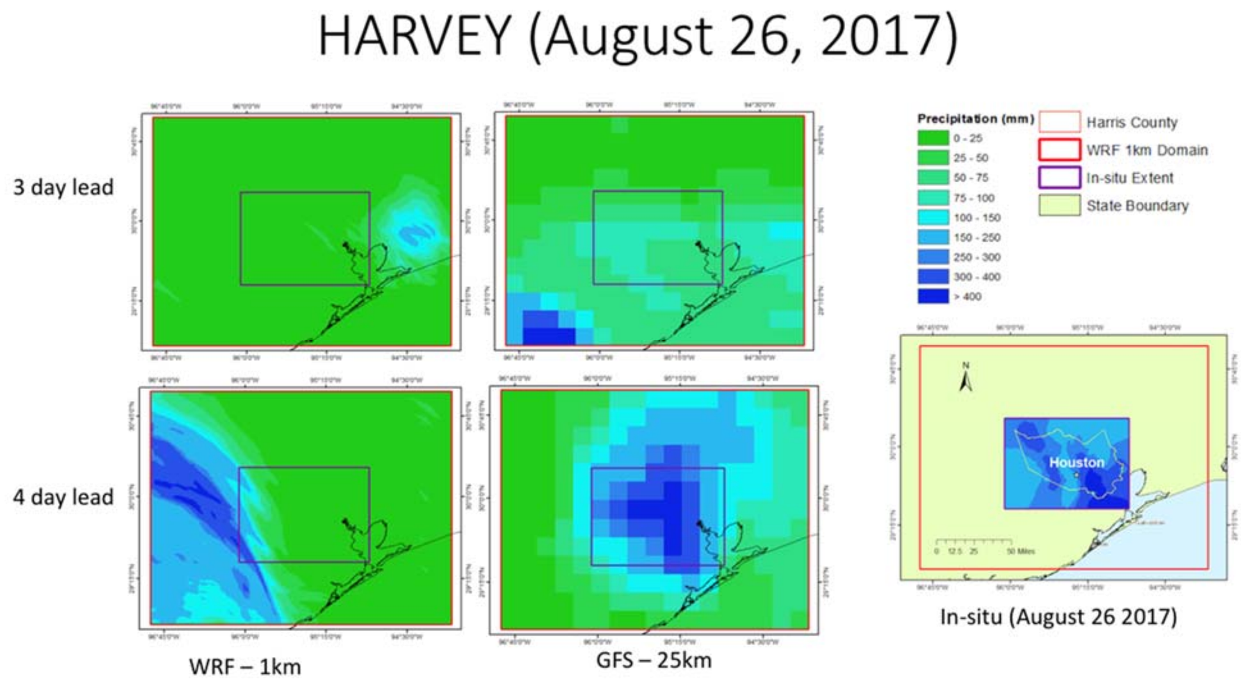

Fig. 3. Rainfall forecast for Hurricane Harvey on August 26, 2017; Left panel is the downscaled forecast using WRF at 1 km while right panel is the 25 km scale GFS forecast. The in-situ rainfall map is shown on the rightmost side and is based on all the gauges of HCFCD.

Table 2. Skill metrics for rainfall forecast of Hurricane Harvey on August 26, 2017. The metrics were calculated over the inner domain of WRF that included all 139 gauges. The % is the RMSE normalized by total precipitation and expressed as a percentage.

Lead time (hrs)	**RMSE (mm)**		**Correlation**		**Rainfall Total (mm)**		
	WRF	**GFS**	**WRF**	**GFS**	**WRF**	**GFS**	**In-situ Total**
24	96.84 (35%)	172.01 (63%)	-0.012	-0.346	269.50	140.42	276.00
48	222.14 (79%)	178.62 (64%)	-0.282	-0.364	75.58	126.18	276.00
72	275.74 (100%)	222.91 (80%)	0.264	-0.005	8.41	64.46	276.00
96	262.20 (95%)	114.80 (42%)	-0.302	0.112	35.52	274.98	276.00

5.2 NON-HARVEY STORM (FEBRUARY 2018)

Figure 4 with Table 3 show the rainfall forecast and skill metrics, respectively for a non-Harvey type storm that registered peak rainfall on February 21, 2018. It is clear that non-Hurricane (that are less intense and more frequent) storms have better skill in forecasting using the WRF set up ‘as is’ from Chen et al. 2017a. Furthermore, dynamic downscaling using WRF clearly adds value to GFS forecast. Strong correlation, acceptable percentage RMSE and Probability of Detection at 72 hours lead-time appear to indicate the 72-hour lead-time is an ideal time horizon for forecasting for HCFCD. With further calibration of WRF model similar to Chen and Hossain 2016 or Chen et al. 2017b by selecting appropriate parameterizations for winter precipitation, the WRF setup for Houston should yield skill improvement.

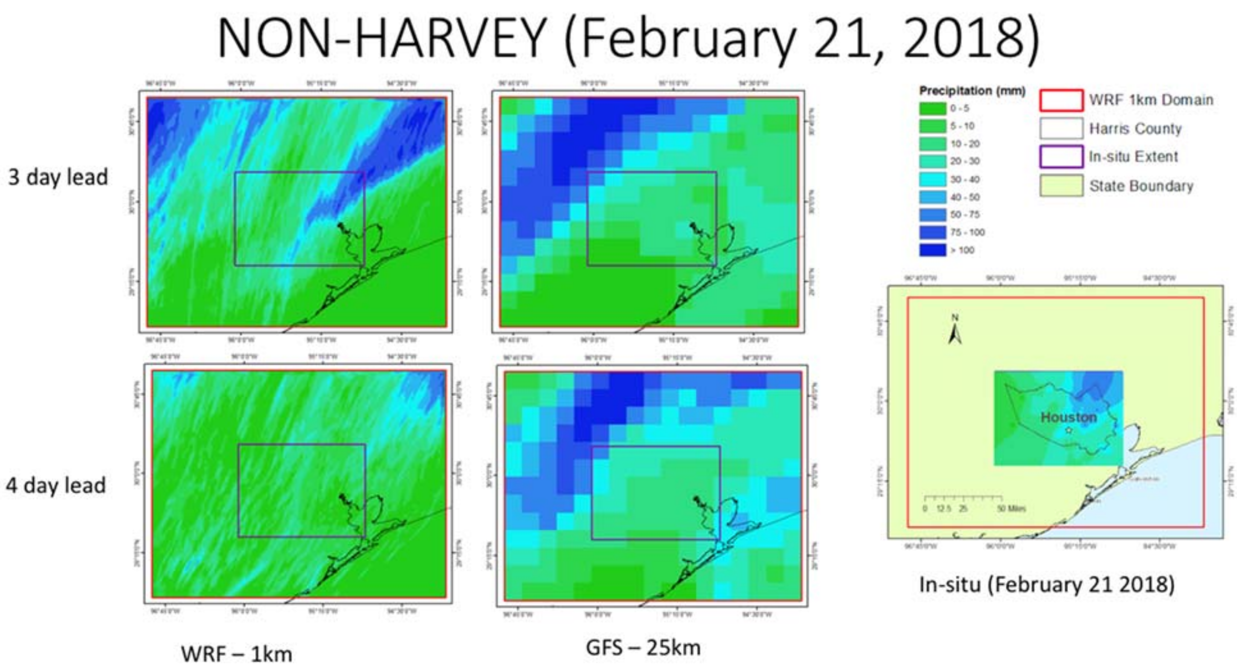

Fig. 4. Same as Figure 3, but for a non-hurricane storm that took place February 21, 2018.

Table 3. Skill metrics for rainfall forecast of non-Harvey storm date of February 21, 2018. The metrics were calculated over the inner domain of WRF that included all 139 gauges. The percentage for RMSE is the RMSE normalized by in-situ precipitation total and expressed as a percentage.

Lead time (hrs)	RMSE (mm)		Correlation		Rainfall Total (mm)		
	WRF	GFS	WRF	GFS	WRF	GFS	In-situ Total
24	14.95 (59%)	21.02 (84%)	0.38	0.66	26.74	43.24	25.00
48	19.75 (79%)	39.24 (150%)	-0.011	-0.34	17.28	34.84	25.00
72	15.62 (62%)	21.23 (84%)	0.62	-0.14	22.40	14.73	25.00
96	22.26 (89%)	17.78 (71%)	0.20	-0.19	7.59	20.57	25.00

6. RAPID FLOOD INUNDATON FORECASTING

Using the current WRF set up, water level forecasting based on rainfall forecast was explored. Since, each rainfall gauge also had a water level gauge, the response of water level to rainfall spells in the same region was studied. Assuming that almost all the rainfall transforms as urban runoff due to the highly impervious landscape and high rainfall rates, the water level should in principle be forecastable based on precipitation forecast alone. To explore this idea, two gauge locations were randomly selected to study the rainfall-water level change co-variability for nowcast and forecast rainfall (Figure 5; see figure 1 for location). The rainfall here is the accumulation over the specific WRF 1X1km grid cell and not the drainage area of the gauge location.

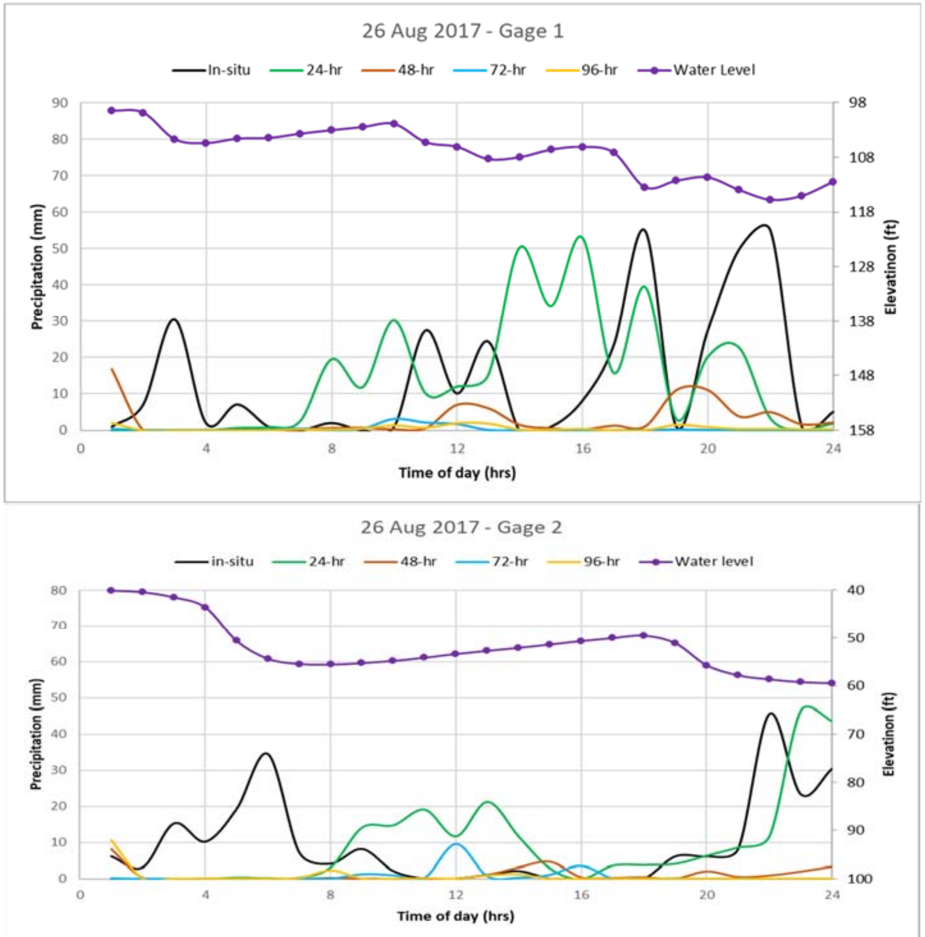

Fig. 5. Water level (right axis) variation against precipitation spells (in-situ and forecast for August 26 2017 (Hurricane Harvey). Locations of gages 1 and 2 can be found in Figure 1.

It is clear from Figure 5 that water level rise at a point in a stream is triggered strongly by the short precipitation spells at that location, and it is most likely due to most of the rainfall transforming as urban runoff. To explore this phenomenon further for the entire city of Houston, the rainfall and water level changes were analyzed at all the locations over multiple storms. Figure 6 shows a map of correlation between in-situ rainfall and in-situ water level increase in water level for the 139 locations in Houston. Figure 7 shows empirical rainfall versus water level increase response at select locations of Figure 6 shown as red triangles.

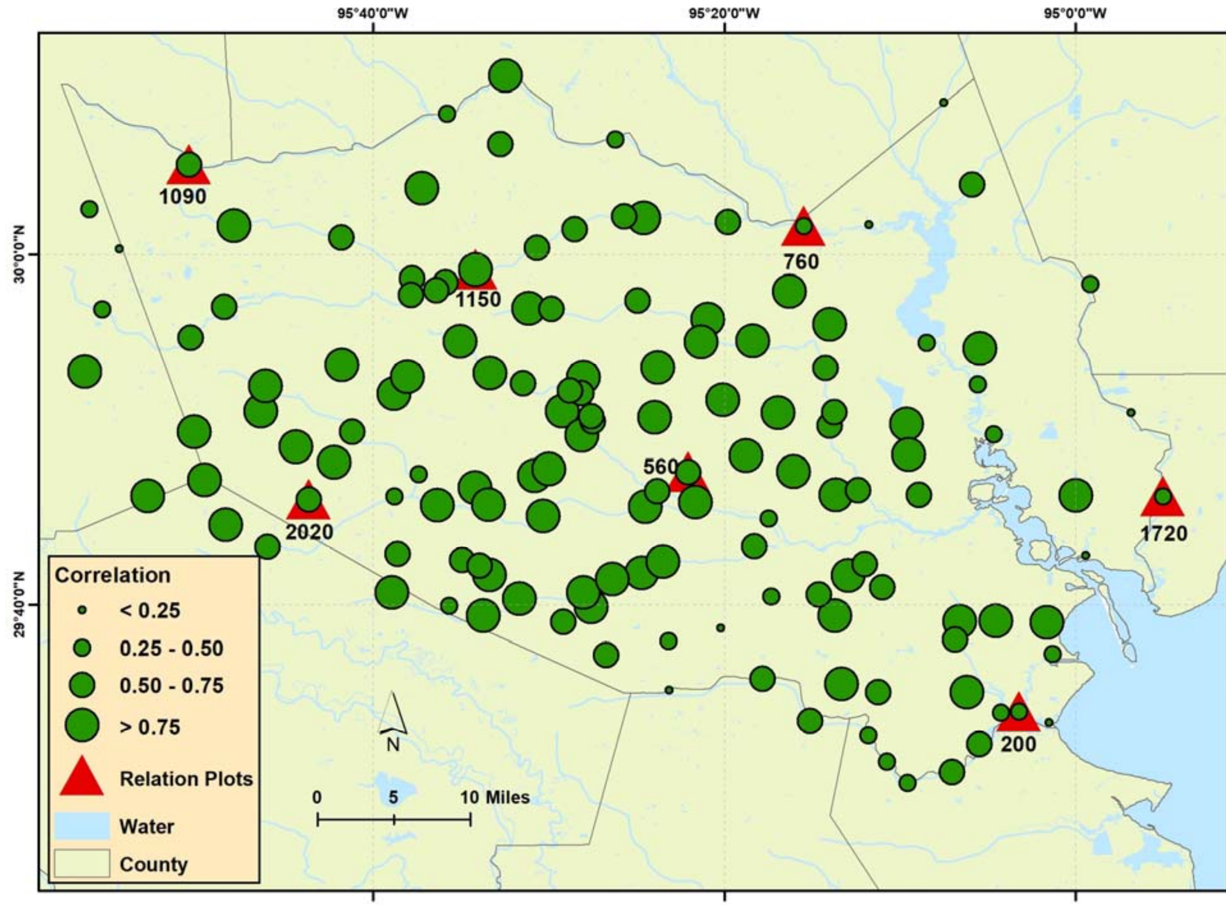

Fig. 6. Correlation between in-situ rainfall and water level increase (from in-situ gauges) at all the gauge locations of HCFCD over multiple storms. The size of the circle is proportional to the correlation. The empirical rainfall versus water level increase relationship are shown for locations shown as red triangles in Figure 7.

Since, almost every gauge location showed strong covariance between rainfall and runoff, rating curves were established for each location using in-situ record. This rating curve essentially predicted the water level increase for a given amount of rainfall. The initial investigation revealed that a non-linear regression model (such as the logistic or polynomial equation) was more robust than a linear rating curve in capturing the expected water level

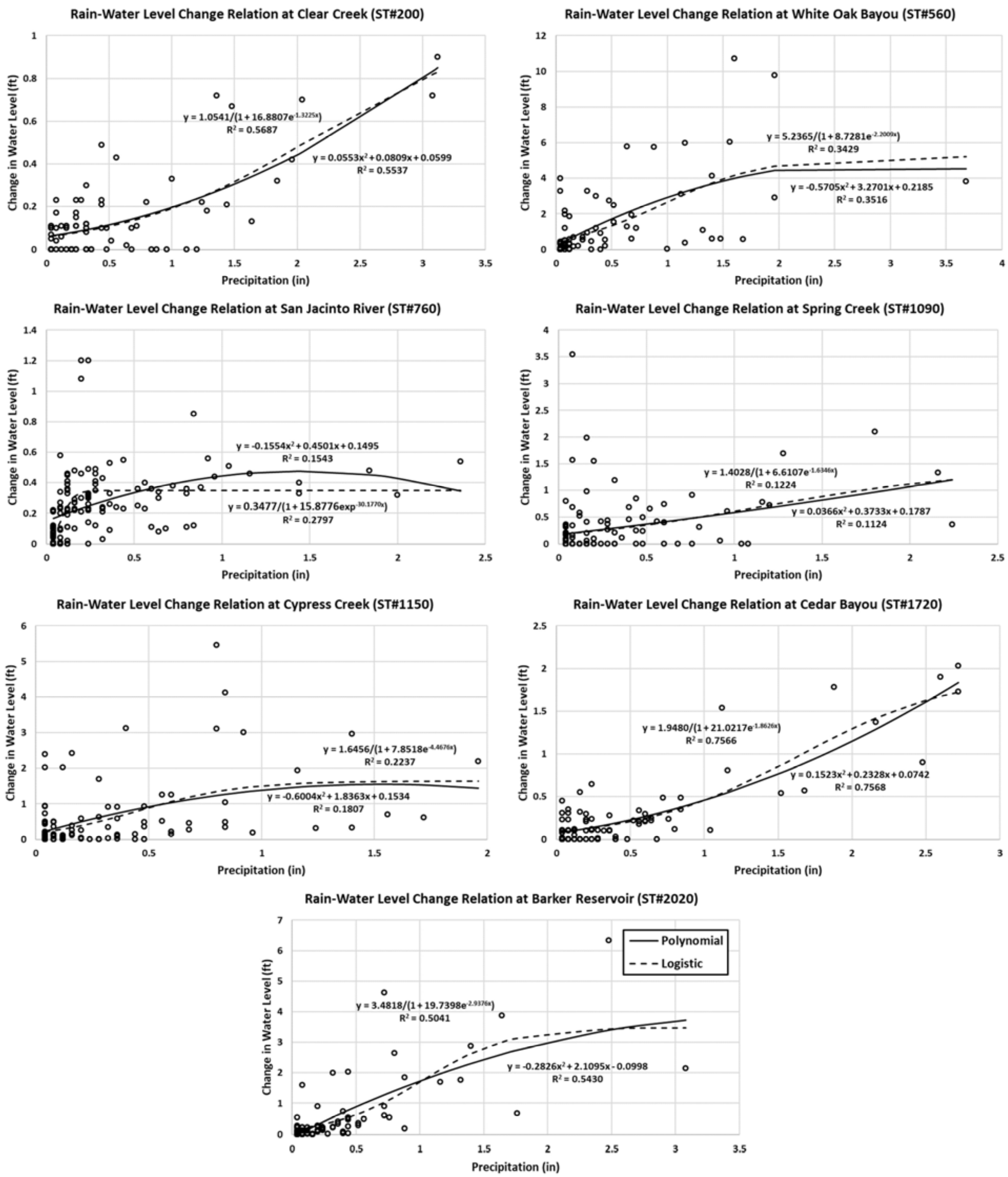

Fig. 7. Empirical relationship between in-situ rainfall and water level increase at in-situ gauges for selection locations in Houston.

increase at a location. Using these rating curve relationships developed for each of the 139 locations based on in-situ data, the forecasted rainfall was used to forecast corresponding water level increase (forecast) for Harvey and non-Harvey storms. The forecasted water level increase from the rating curves was added with the latest available in-situ water level to predict the water level at that location for different lead times (i.e., 1-4 day lead). The forecasted water levels were then assessed of its skill against in-situ water level. For example, to forecast the water level after 24 hours, the forecasted water level change within the next 24 hours was added to the in-situ nowcast water level at the beginning of 24 hours. Similarly, to forecast the water level after 48 hours, the forecasted water level change within the next 24-48 hours was added to the forecasted water level after 24 hours, and so on for 72 and 96 hours of lead-times. This approach of applying a rating curve to generate forecasted water level is summarized in Figure 8 as a flowchart. It was assumed that the water level will only increase in a location if there is any precipitation, otherwise the change in water level will be zero. Therefore, this approach is only valid of a storm event as the storm is intensifying and not when precipitation has already ended, since there is no decrease in water level.

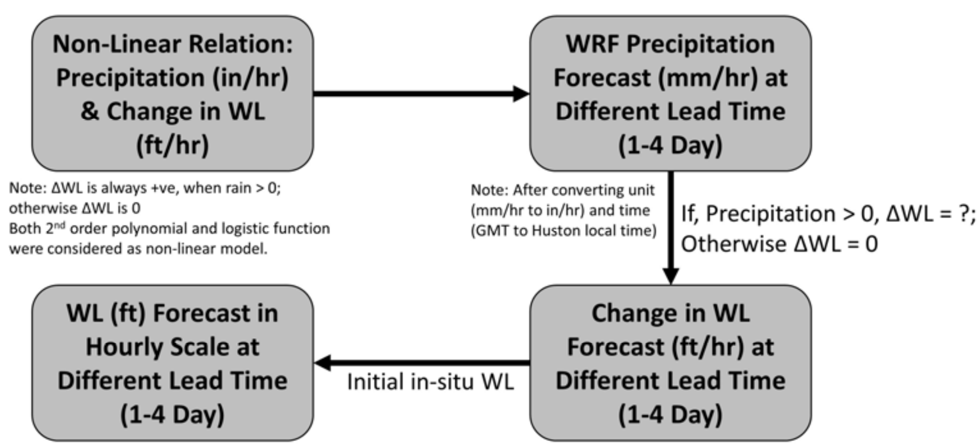

Fig. 8. Workflow for generating forecasted water level at each of the 139 locations using the pre-developed rating curves and QPF.

Figures 9 and 10 show the skill of water level forecast as a function of lead time and choice of equation for rating curve for Harvey and non-Harvey storms in terms of correlation and normalized RMSE, respectively. High skill at correlation (> 0.7) and low NRMSE (< 10%) is maintained even after lead-time of 96 hours (4 days) although the spread or variability across the 139 gauges is often wider. The fact that forecast water level is better than forecast rainfall even for hurricane type storms should not be entirely surprising. The contributing runoff leading to the water level at a location benefits from a highly urbanized drainage where almost all rainfall becomes runoff and likely cancels the errors in precipitation forecast. For a flood control district like HCFCD, this is a welcome finding as the proposed rating curve approach to forecasting inundation is rapid as it can be completed as soon as QPF runs are complete and converted into maps. Since, the application of a CPU-intensive two dimensional flood inundation model (like HEC RAS 2D) is not needed, an agency like HCFCD can generate such forecasted inundation maps as frequently as needed when new precipitation forecasts are available.

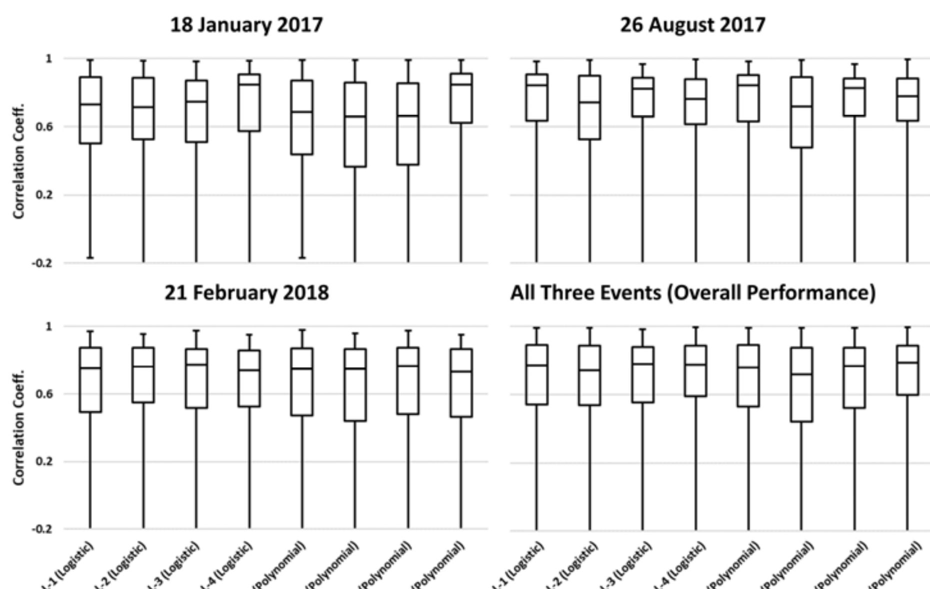

Fig. 9. Correlation of forecasted water level as a function of lead time and rating curve equation type (logistic and polynomial) for 3 storms. The correlation is aggregated over all the 139 gauge locations.

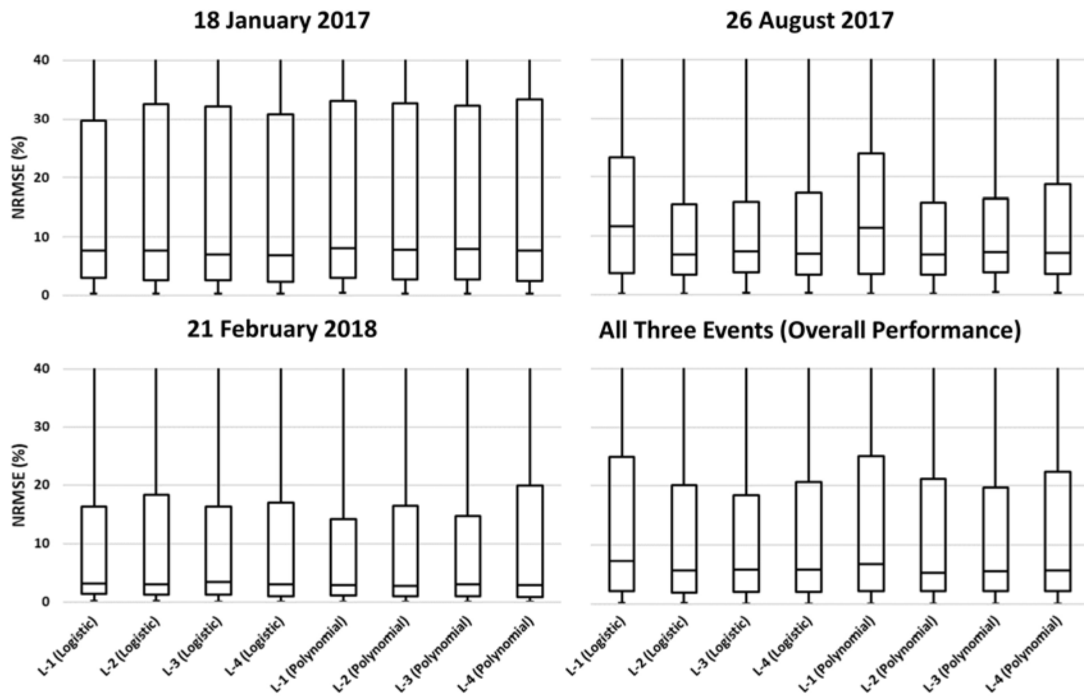

Fig. 10. Normalized RMSE of forecasted water level (normalized to actual water level) as a function of lead time and rating curve equation type (logistic and polynomial) for 3 storms. The correlation is aggregated over all the 139 gauge locations.

In Figure 11 the forecasted inundation map is compared with a satellite radar imagery from Sentinel-1 that overpassed Houston a day later. The same map is also compared with the map produced using in-situ water levels from HCFCD. The idea here is to explore the spatial consistency and value of the inundation that is being forecasted here while recognizing that the flood maps produced in this way are limited to the density of water level gauges. In general, the spatial consistency seems reasonable when compared with Sentinel-1 or in-situ mapping technique.

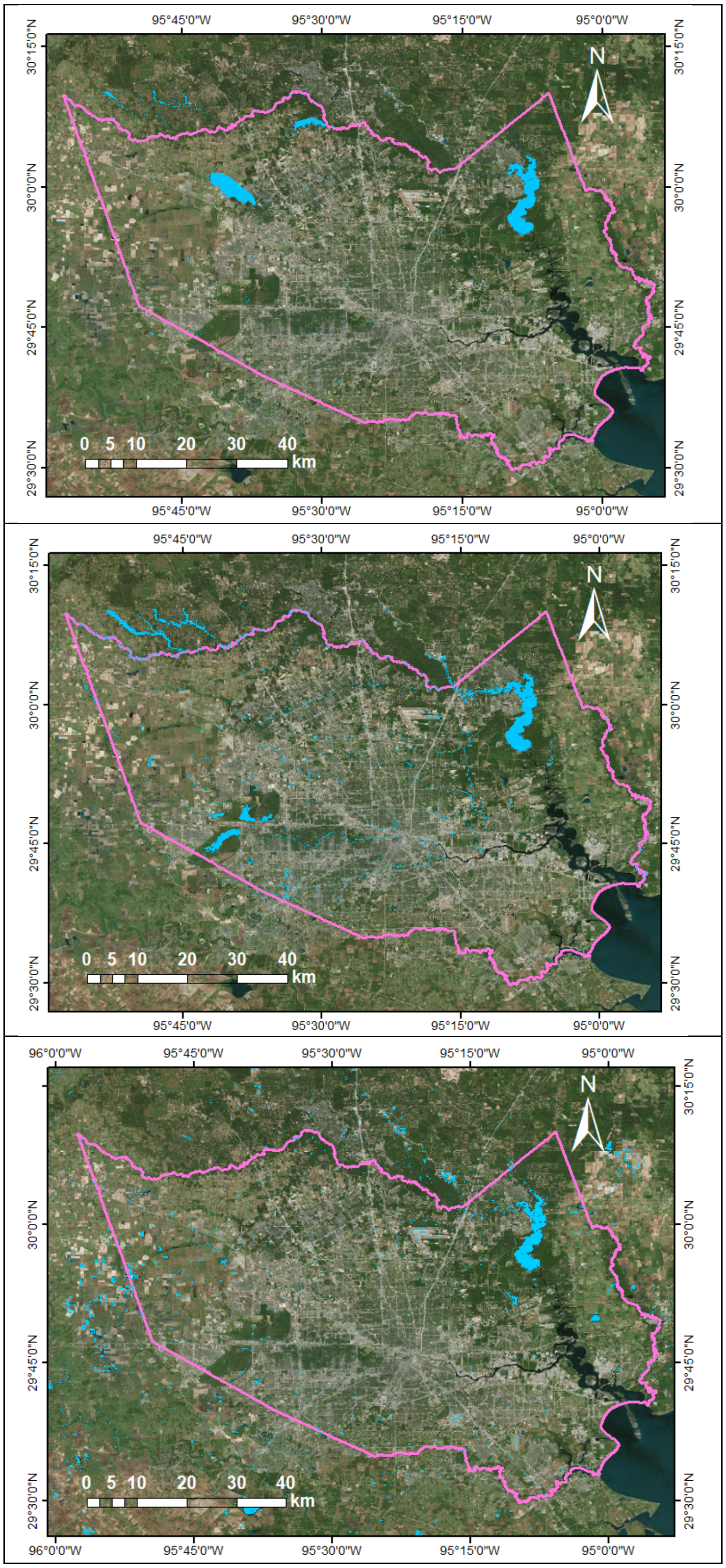

Fig. 11. Comparison of forecasted flood inundation map for Jan 18, 2017 at 1 day lead time (topmost pane) with observed in-situ gauge based inundation map (middle panel) and satellite radar imagery from Sentinel-1 (overpass on Jan 19, 2017)

7. CONCLUSIONS AND RECOMMENDATIONS FOR HCFCD

HCFCD has currently developed a system that predicts inundation extent of riverine flooding on real-time basis based on observed gage water surface elevation and effective HEC-RAS model products. This real-time prediction is available for public on Harris County Flood Warning System website (https://www.harriscountyfws.org) to notify the people about the extent of the flood during storm event. Therefore, having forecasted water surface elevation can improve decision making involving inundation-forecasting by HCFCD using the existing Flood Inundation Mapping System (FIMS), which is developed for the real-time inundation prediction based on now cast of water levels by gauges. The rating curve based approach yields acceptable skill at 1-4 day lead times and does not require CPU or time-intensive procedures. Thus, these inundation maps can be generated and continuously updated as soon as a new QPF run is complete and provide HCFCD an additional source of information for risk assessment and decision making.

In addition to the key finding on the feasibility of the rapid inundation forecasting technique, this research makes the following conclusions for urban flood forecasting:

1. Affordable CPU resources in the range of 3000-4000 USD should be invested as they are sufficient for quantitative precipitation forecasting up to 72 hours or more. An alternate option is to leverage the power of cloud computing services now being offered by various vendors such as Google Earth engine and Amazon web services at a low price.
2. Since, hurricane strength storm forecasting using GFS downscaling is challenging without adequate calibration and parameterizations, agencies like HCFCD should also look at rapid refresh cloud motion IR imagery with WRF/GFS forecast for storms while appropriate WRF set up is developed using HWRF.

3. Moderately intense storms can be forecast by GFS and WRF with much higher skill.
4. To further improve QPF skill, WRF set up should be calibrated with appropriate parameterization selection for Houston – and season (summer and winter) and hurricanes using HWRF. In other words, agencies like HCFCD should explore unique WRF setups at 1km resolution with differing choice of parameterizations for each flood season.
5. To further improve water level forecasting skill, unique rating curve between precipitation and water level change at a location should be developed for small, moderate and heavy storms that trigger differing runoff hydraulics.

The goal in this study was to explore the operational feasibility and skill of high-resolution QPF using NWP models for rapid (real-time) urban flood management for the Harris County Flood Control District. Based on a very systematic study using WRF over hurricane and non-hurricane storms using dense gauge network, a path forward for this operational sustainability for HCFCD has been identified. The authors believe that with continued work based on the key conclusions of the study, a flood management agency like HCFCD should be able to add forecast functionality to its inundation mapping capability in a sustainable manner. Consequently, this new functionality should considerably improve decision making to save lives and protect property without adding considerably to operational overhead of the agency.

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