VALIDATING THE QUALITY OF CROWDSOURCED DATA FOR FLOOD MODELING OF HURRICANE HARVEY IN HOUSTON, TEXAS

by

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ABSTRACT

Flood is one of the most widespread natural hazards in the world. Hurricane Harvey, a 1000-year flood event, hit Texas in 2017 and resulted in significant property damage, bodily injury, and casualty. As one of the most impacted areas, Houston is chosen to be the study area of this study. For future flood risk prediction and mitigation, it is important to find out the flood dynamics of Hurricane Harvey and generate flood inundation maps.

In these years, Volunteered Geographic Information (VGI) data such as social media and crowdsourced data arise as an alternative and supplementary data source to enhance the exercise of flood inundation mapping. However, compared to authoritative data acquired by government agencies (i.e. stream gage data, remote sensing), the quality of crowdsourced data often exists uncertainty due to lack of clear data standard and quality assurance/quality control (QA/QC) procedure. Therefore, the primary objective of this study was to examine the quality of crowdsourced data for flood mapping of Hurricane Harvey in the Houston area. As a free and innovative crowdsourced platform, the U-Flood project (map.u-flood.com), which reported and mapped flooded streets in the Houston metro area, is the target crowdsourced data to be examined in this study. The research questions of this study include (1) Are there any significant differences in the water depth among the H&H model (i.e. HEC-RAS), authorized reference (i.e. FEMA) and crowdsourced data (i.e. U-Flood data)? (2) Are there any significant differences in the inundated areas between the HEC-RAS modeled floodplain and U-Flood data observations? To answer these research questions, this study used HEC-RAS to simulate flood inundation maps in the Houston study area during Hurricane Harvey and validate

the result maps by comparing with Harvey High Water Marks (HWM) points using Wilcoxon sign rank test, and comparing with FEMA modeled floodplain using paired-samples t-test. Next, the crowdsourced U-Flood dataset was validated by comparing with HEC-RAS modeled result and the authorized reference (i.e. FEMA modeled flood map for Hurricane Harvey and USGS stream gages) in terms of a) water depth (WD) using Friedman test and b) the percentage of U-Flood street's count and length inside / outside of HEC-RAS modeled floodplain. In addition, the U-Flood dataset is compared with HEC-RAS and FEMA separately using the Wilcoxon Sign Rank test. The statistical results showed that there was a statistically significant difference among all comparison sets in terms of WD. In addition, the results showed that there was a statistically significant difference between the HEC-RAS modeled floodplain and U-Flood data in terms of U-Flood count and length inside/outside of HEC-RAS modeled floodplain. The results showed that a less consistent decreasing trend between U-Flood data and the modeled floodplain over time. Moreover, the U-Flood data distribution map with the WD difference level also visually displays spatial distribution.

Overall, this study provides a preliminary evaluation of data quality of VGI by comparing the WD among crowdsourced data, authoritative data, and HEC-RAS modeled output. Furthermore, the theoretical significance of this study as the first study in empirically comparing crowdsourced data with observed and modeled data in flood monitoring. Findings from this study also fill gaps in the literature of improving and assessing the uncertainty of crowdsourced data quality, and crowdsourcing data supplements in flood mapping research.

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I. INTRODUCTION

As one of the world's most common natural hazards, floods caused more than 500,000 deaths between 1980 and 2009 (Doocy et al. 2013). In the U.S. alone, 4,586 deaths could be attributed to the same cause from 1959 to 2005 (Ashley, 2008). Besides casualties, flooding is a natural disaster that causes serious economic loss. The average property loss is nearly 8 billion U.S. dollars a year from 1981 to 2011 in the U.S. (National Oceanic and Atmospheric Administration, 2013). In the hope of flood mitigation to minimize human casualties and economic loss, many flood studies explore plausible causes (e.g. anthropogenic; Ozkan, 2016) to mitigate future flood disasters. As urbanization and population density intensify in urban areas, it is important to understand the impacts of flooding on human settlements and populations vulnerable to floods. The need for flood management in urban areas has become obvious.

For example, Hurricane Harvey made landfall in Texas during late-August to early-September 2017 and affected Houston and other developed areas, which resulted in significant property damage, bodily injury, and casualty. Flood mapping through computer simulation is a common approach to model the affected areas inundated by floods. The conventional approach combines the Geographic Information System (GIS) and a Hydrologic and Hydraulic (H&H) model such as Hydrologic Engineering Center's River Analysis System (HEC-RAS) (USACE, 2016) to model flood inundation by delineating floodplains and estimating the water depth. Moreover, flood inundation maps can model the impact of stormwater during a flood. It is important to understand the flood dynamics of Hurricane Harvey, a 1000-year flood event (The Washington Post, 2017), and produce flood inundation maps for future flood risk prediction and mitigation in Houston.

Recently, social media and crowdsourced data emerged as an alternative and supplementary data source to augment the exercise of flood inundation mapping. For example, the inundation extent and water depth data could be extracted from social media to support rapid flood inundation mapping (Fohringer et al., 2015). Schnebele et al. (2014) also utilized the multi-sources of non-authoritative data, which includes crowdsourced aerial photos to map the potential road damage of Hurricane Sandy. In particular, crowdsourced data is unique because it provides observations at high temporal resolution in near-real-time (comparing to conventional data) and centered around a specific theme (comparing to social media) like flood mapping. Crowdsourced data is often in-situ data collected by a large number of volunteers equipped with mobile devices during the progress of an event (e.g. flood). While some crowdsourced data can be encoded in GIS format and published on map platforms via the internet to be shared quickly and simultaneously, some can be in any format (e.g. pictures or videos) (Douvinet et al., 2017). For crowdsourcing images of flood inundation, geotagged images with fine spatial reference may be used to infer the water depth at varying locations in near real-time. Comparing to authoritative data acquired by government agencies, however, crowdsourced data often lack clear data standard and quality assurance/quality control (QA/QC) procedure to ensure data quality (Kutija et al., 2014). Therefore, it is necessary to validate the quality of crowdsourced data to explore its possible use in flood modeling beyond gathering discrete observations about the flood extent and road damage.

As a free and innovative crowdsourced platform, the U-Flood project (map.u-flood.com) reported and mapped flooded streets in the Houston metro area as well as other cities such as Galveston, Baton Rouge, and New Orleans which were affected by Hurricane Harvey (Figure 1). The U-Flood project was developed by consultants at the environmental firm, Marine Weather and Climate, and the tech company, Tailwind Labs. Based on more than 1,500 reports of voluntary observations updated by the community, there were 991 roads inundated in Houston as a result of Hurricane Harvey (CNET, 2017). Hence, the U-Flood project was excellent as the target crowdsourced data to be examined in this study. This study compared the U-Flood data against the authorized reference such as the FEMA modeled flood map for Hurricane Harvey and USGS stream gages.

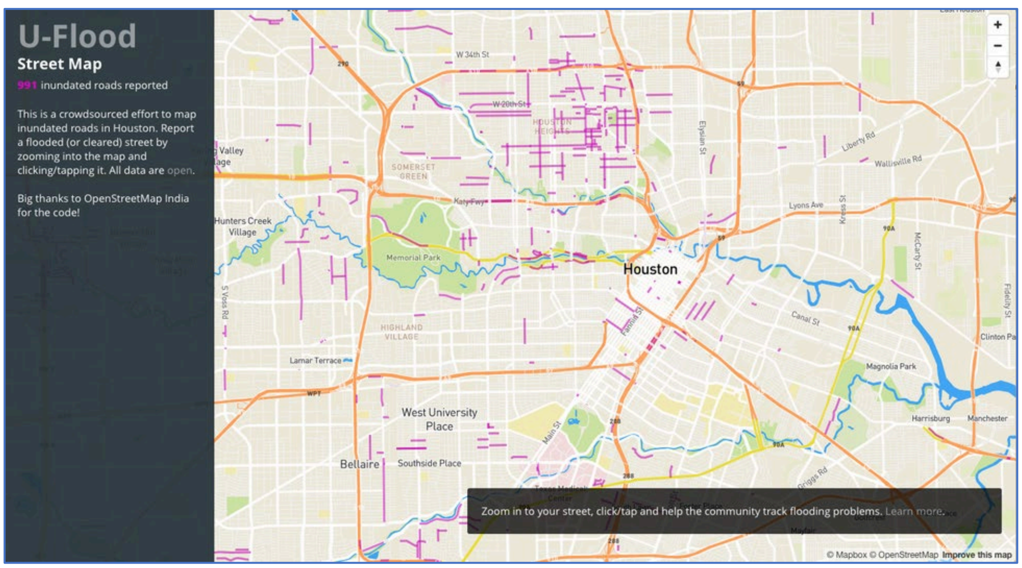

Figure 1. Near real-time flood mapping of inundated streets from U-flood street map (U-Flood Project, 2017)

The primary objective of this study was to examine the quality of crowdsourced data for flood mapping of Hurricane Harvey in the Houston area. This study used HEC-RAS to model flood inundation maps in the Houston study area during Hurricane Harvey and compare the result maps with crowdsourced U-Flood dataset. The high temporal resolution of U-Flood data also offered a unique lens to ascertain the impacts of dam release from Addick Reservoir and Barker Reservoir during the floods. By simulating the flood extent of Hurricane Harvey (which includes dam release water from the Addick Reservoir and Barker Reservoir during the floods), this study provided useful references for disaster management in urban areas for future risk assessment and mitigation.

The research questions of this study include:

(1) Are there any significant differences in the water depth among the H&H model (i.e. HEC-RAS), authorized reference (i.e. FEMA) and crowdsourced data (i.e. U-Flood data)?

(2) Are there any significant differences in the inundated areas between the HEC-RAS modeled floodplain and U-Flood data observations?

To answer these research questions, this study validated the crowdsourced data with modeled floodplain to examine its effectiveness in supporting the flood inundation map of the HEC-RAS model. This study also discussed possible ways of using crowdsourced data to improve model prediction.

To examine the quality of U-Flood data and its potential to improve the HEC-RAS model prediction, the null hypothesis (H_{A0}) states that there are no significant differences in Water Depth (WD) among HEC-RAS, FEMA and U-Flood data (i.e. $WD_{HEC\text{-}RAS} = WD_{FEMA} = WD_{U\text{-}Flood}$). The alternative hypothesis (H_{A1}) is that there would be significant differences between these three data sources. To examine the agreement between HEC-RAS model and U-Flood data, the null hypothesis (H_{B0}) states that there are no significant differences in the covered area between the HEC-RAS modeled floodplain and U-Flood data observations (i.e. Covered Area $_{HEC-RAS}$ = Covered Area $_{U-Flood}$). The alternative hypothesis (H_{B1}) is that there would be significant differences between these two data results.

II. LITERATURE REVIEW

Flood modeling could be different based on the data type, approach, and data quality. This section will review flood modeling studies relevant to this study's research questions. First, this section will review flood modeling calibration with conventional data, such as remote sensing (RS) data, to model the water surface elevation. Second, this section will review flood modeling calibration with unconventional data, such as Volunteered Geographic Information (VGI) data (e.g. social media data and crowdsourced data), to augment flood modeling accuracy and examine the modeled water surface elevation compared to conventional data in H&H modeling. Finally, this section will review the data quality validation of VGI data by various approaches in light of the research questions of this study.

2.1 Flood model calibration with conventional data

Many studies integrated the GIS and H&H model to simulate flood inundation and its impacts on hazard mitigation. Conventional data, including remote sensing (e.g. aerial photographs), lidar (Light Detection and Ranging), and in-situ field data (e.g. stream gauge, channel transects) are used as data inputs to calibrate the H&H models. In remote sensing, radar images portray the spatial distribution of precipitation useful for rainfall-runoff transformation and could be integrated with GIS and HEC-RAS for floodplain mapping. Moreover, extraction of water bodies from post-flood satellite imageries (e.g. Landsat TM) can be used to delineate and validate the floodplain boundary (Renschler and Wang, 2017). Combined with empirical flow data (e.g. USGS stream gauges), these data could be used to calibrate and validate the H&H model output in order to evaluate the model's ability to reproduce the flood.

Although conventional data is often regarded as “credible” since it is from the authoritative data source or in compliance with established data standards (e.g. Federal Geographic Data Committee), the modeled output does not necessarily present an accurate situation. Conventional data, such as satellite image or lidar, are limited for emergency response because they have fixed temporal resolution or require careful planning. Hence, the available products may not reflect the post-event landscape immediately after the impact. Besides, the discrepancy between the collection time of remote sensing image and storm period may cause model errors such as under- or over-estimation of flooding (Knebl et al. 2005).

2.2 Flood model calibration with unconventional data

In addition to using conventional data, VGI, such as crowdsourced and social media data, are good alternatives to assist with flood modeling. Crowdsourced data usually has a specific and well-defined scope of the project (e.g. type of data to be collected) and some two-way communication channels for volunteers to actively engage. The types of data (i.e. geometry, attributes) are usually more structured. Social media, on the other hand, uses a web/mobile platform to allow broadcasting of memes or microblogs. The topics of social media, however, are very diverse and general. Even on the same topic (i.e. hashtags), the relevant messages may cover feelings, opinions, observations, and comments. Social media data are often unstructured with different kinds of data types (e.g. text, picture, video). In some specific events, social media can be mobilized as a platform to crowdsource observations (e.g. civil movements like #metoo). Wang et al. (2018) used this method to filter and extract flood information (e.g. water depth) via Twitter Application Programming Interface (API) or collect geotagged flood photos from a crowdsourcing app/platform (e.g. MyCoast). Common concerns about unconventional data and their use are data quality, including spatial accuracy, temporal currency and attribute correctness of those observations (Schnebele et al., 2014; Jérôme et al., 2017; Eilander et al., 2016). For example, while data collected by mobile devices with GPS-enabled should be accurate to several meters, data without GPS may use the place or city name mentioned in the user's profile for geocoding. Similarly, diverse content and topics common in social media create significant noise and would require data cleaning before analysis. Therefore, it is important to validate the quality of unconventional data. For example, water-related information crowdsourced or extracted from social media has been compared with authoritative data such as remote sensing data (e.g. satellite images), precipitation data, and road closure reports in order to improve the accuracy of flood modeling (Wang et al., 2018).

Many studies focused on the integration of crowdsourced data and social media data for flood modeling in order to provide additional flood information for calibration (Jérôme et al. 2017; Eilander et al. 2016). Crowdsourced and social media data could provide valuable flood information, such as damage reports, flood extent and depth, flow velocity and discharge by text, video, and photo (Jérôme et al., 2017). For example, Schnebele et al. (2014) fused specific crowdsourced data (Civil Air Patrol photos) and social media data (YouTube videos, Tweets) together by kriging interpolation to identify damaged areas. The resulting damage assessment could augment existing information (e.g. FEMA maps) and provide additional information to evaluate the condition of transportation infrastructure. Similarly, Eilander et al. (2016) used the Twitter streaming API to derive flood depth and location reference from substantial amounts of Twitter data (text and photo). By combining with Digital Elevation Model (DEM) and H&H modeling, they created a flood map in near real-time. In their flood model validation, about two-thirds of maximum water depth observations identified from Twitter matched the estimated depth in H&H modeling (Eilander et al., 2016). Jérôme et al. (2017) examined the crowdsourced methodology of three citizen science projects, including Flood Chasers (in Argentina), FloodScale (in France) and RiskScape (in New Zealand), launched by research organizations collecting flood-related crowdsourced data from the public. By deriving quantitative data from digital photos and videos, they found that the calculated surface velocity based on the Large Scale Particle Image Velocimetry technique (LSPIV) can be used to calibrate the H&H modeling roughness and to simulate the flow conditions of the analyzed event. Besides, time-series photos from the public at the same water gate can be used to track flood levels and help pinpoint the maximum flooding time during the event. Moreover, water surface elevations could be derived from public photos by referencing lidar-derived DEM of the city (Jérôme et al., 2017).

In order to warrant data quality, the crowdsourcing projects usually provide tutorial and guideline for public users without hydrology knowledge to contribute flood information (Jérôme et al., 2017). For the purpose of better H&H modeling, the users are required to upload flood-related videos and photos as well as the metadata, such as information about the date, time, and location, etc. (Jérôme et al., 2017). In another case, Starbird (2011) proposed Tweak the Tweet (TtT), a data protocol to ask Twitter users to crowdsource disaster-related tweets with specific hashtags (e.g. #need, #name, #location, and #contact tags) to translate these tweets into machine-readable information. Such information can be reformatted by adding the right tags and structures in place. Thus, these structured tweets could be utilized by computers to filter, classify, sort and map. Besides, Starbird (2011) also discussed some incentives and strategies to motivate crowdsourcing for providing information on crisis-related platforms. In TtT, users felt motivated by satisfying the social needs of individuals facing tragedy, as well as social capital and support from others during the event. Such efforts could be considered as crowdsourcing despite the platform is social media; since it had specific calling and data collection protocol for users to follow. However, even if crowdsourced texts, videos, and photos appear as valuable supplemental data to traditional post-flood discharge estimation, they still require further survey (topography survey, fieldwork, etc.) to collect data and assure quality (Jérôme et al., 2017). Data quality could vary if crowdsourced photos were captured at night or the objects of interest were unable to be seen from the shadow. Other data quality issues, such as incorrect information, imprecise location, and sampling bias, can also add to the uncertainty of crowdsourced data (Schnebele et al., 2014).

In light of data quality, Eilander et al. (2016) considered the uncertainty of crowdsourced data and generated flood probability maps based on water depth observation from tweeted photos. The likelihood of flooding was determined by the number of tweeted photos at the same place during the flood event. In this case, the higher likelihood of flooding indicates better reliability of data sources. However, insufficient observations could possibly become a limitation to the near real-time application of this method, especially in places where social media platform was rarely used. To address this issue, user interactions on the social media platform could confirm the presented information. Collecting data from multiple platforms (e.g. Instagram, Snapchat, Weibo and Facebook, etc.) could gain more observation samples as well as reliability (Eilander et al., 2016).

2.3 Validation of VGI data

VGI can provide value-added information at low cost; it can be used to enrich crisis management models (e.g. H&H modeling) or to refine its output results (Schade et al., 2013). However, the uncertainty and lack of credibility of data sources significantly obstruct its utilization. The quality of VGI data is highly variable and undocumented since it doesn't necessarily comply with the scientific principles of sampling design, and its coverage is incomplete (Goodchild and Li, 2012).

To extract reliable information from vast amounts of VGI with uncertainty, Schade et al. (2013) proposed a way to combine various sources of social media by applying cross-validation mechanisms. It might improve the accuracy and increase the potential utility of VGI in H&H modeling since it would provide more relevant results. In addition, random noises in social media could be reduced by filtering the picture tags, such as deleting pictures that are most likely not relevant to flood event or evaluate the probability that an event may confuse with another type of flood (Schade et al., 2013). These finding of social media could also be extrapolated to crowdsourced data. Several approaches are used to examine the quality of VGI data. Goodchild and Li (2012) described three approaches: crowd-sourcing, social, and geographic approaches. Among them, the crowd-sourcing approach uses the wisdom of the crowd to converge on the truth and to validate and correct the errors. For example, a single observation is reinforced by additional observations from the same or nearby points. The social approach relies on a hierarchy of reliable individuals who serve as gate-keepers to assure the quality of voluntary contributions, and such hierarchies of trust emulate the structure of traditional authoritative mapping agencies. Both approaches are good for assessment of the accuracy and credibility of VGI data. Compared to the previous two approaches, the geographic approach needs more research to fill the lack of conceptual or theoretical framework (Goodchild and Li, 2012).

Due to the uncertainties of VGI data, it is important to examine the spatiotemporal credibility of VGI and its potential to offer high-quality information to H&H modeling and calibration. Hung et al. (2016) assessed the geo-location credibility of the VGI flood instances based on locations and spatial distribution of two geo-referenced VGI dataset from the crisis mapping platforms (Ushahidi projects) in Brisbane, Australia. Approximately 2,000 VGI flood reports were extracted as single-point features and validated by authoritative data including physical road network, recreation areas, and statistical local area boundary released from the Department of Natural Resources and Mines (DNRM) to exclude data of inaccurate position (e.g. 150 m from the reference feature). Among them, 1200 reports were regarded as flood incidents in different tags, such as “flooded areas”, “evacuations”, “property damage”, “roads affected”, “hazards”, or “closed roads”. After data cleaning and classification, Hung et al. (2016) built a binary logistic regression model and performed a spatial pattern analysis, mean nearest neighbor analysis, for credibility assessment on the VGI dataset of the 2011 flood. Based on the feedback provided by Ushahidi platform managers, two labels of “high-credibility” and “low-credibility” were used to verify the flood extent and affected streets. If a flood incident was validated by a platform manager, the report would be labeled as “high-credibility”. This finding was consistent with Goodchild and Li (2012) which support the gate-keepers to assure the data credibility. To analyze the relationship between spatial distribution and credibility, Hung et al. (2016) overlaid the VGI incidents with flood risk zones and DEM data. The results demonstrated that highly credible incidents were not randomly distributed; in contrast, they were densely clustered and statistically significant (z-score = -22.8; p < 0.01). The following geographic factors were assumed to influence credibility: (x1) distance to flood risk zones, (x2) DEM value of VGI point, and (x3) distance to nearest VGI, and (x4): Distance to water resource areas. Excluding DEM values, all the other three predictors were positively significant. Thus, the final probability model of credibility assessment could be written as:

$$P = \frac{1}{1+e^{-(3.778933-0.00021x_1-0.00049x_3-0.00038x_4)}}$$

This probability model developed based on the VGI dataset of the 2011 flood was applied as a credibility classifier on the testing VGI dataset for the 2013 flood with 80.4% accuracy (Hung et al., 2016). By validating the VGI data quality, it is more reliable and more accurate for subsequent hydraulic modeling. Thus, higher quality of VGI could better describe flooding events and support disaster monitoring, disaster responses, model validation, and decision making.

2.4 Gaps of the Literature

The literature explored possible integration of VGI, such as social media and crowdsourced data, with hydraulic model simulation and its usage in calibration. Furthermore, the literature discussed the limitations of VGI data and ways of data quality improvement. However, most studies in the literature used social media data rather than crowdsourced data in H&H modeling. Thus, there is insufficient information to support the benefits by using crowdsourced data in H&H model calibration. Besides, most crowdsourced data used in previous studies were either an official project held by the government or official research institutes. In light of previous findings, this study will evaluate the data quality of the U-Flood crowdsourced project which is developed by consultants at the environmental firm. Moreover, most of the flood information such as timestamps and water depth are extracted from social media and crowdsourced data in the format of text, image, and video. This study tries to examine the use of an innovative U-Flood data, which crowdsourced and encoded flooded roads directly as GIS polyline format. Thus, the U-Flood data are very spatially explicit and unique in portraying the evolving inundation, especially after the release of stormwater from the reservoirs.

As discussed previously, different sources of uncertainties could be introduced in the process of VGI utilization (e.g. extraction, interpolation). Instead of examining the quality of water-related information inferred from crowdsourced data in previous studies, this study is unique in examining the data quality of crowdsourced input directly for H&H modeling.

III. METHODOLOGY

3.1 Study area

Houston is a high-risk area of flooding due to its flat topography, intensive urbanization, and constant influx of moisture from the Gulf of Mexico. Recently, recurring hurricanes and thunderstorms have left record-breaking precipitation that swelled the rivers and inundated many roads. Given the geography of Houston, it is only a matter of time when the city would suffer from flooding again.

The study area lies within the Buffalo Bayou watershed, which is primarily located in west-central Harris County, downstream of the Addicks reservoir and Barker reservoir in the Houston area (Figure 2). The drainage area of Buffalo Bayou watershed is 264.2km^2 (102 square miles). Buffalo Bayou is the primary stream which runs approximately 170.59 km (106 miles) through the high-density residential area with around 444,602 population in Harris County. The major tributaries include Rummel Creek, Soldiers Creek, Spring Branch and Turkey Creek (Harris County Flood Control District, 2017). In response to the intensive and continual rainfall throughout Harris County during Hurricane Harvey, the reservoirs were approaching the full capacity and released stormwater which caused flooding downstream. To examine the flood extent during Hurricane Harvey, four USGS stream gages located in the study area (Table 1) were used in the HEC-RAS model from upstream to downstream: gage 08073500 (inflow of dam release from Addicks Reservoir and Barker Reservoir), gage 08073600, gage 08073700, and gage 08074000 (outflow near Houston downtown).

Table 1. Four USGS stream gages in study area

USGS Gage Number	USGS Gage Name

08073500	Buffalo Bayou near Addicks, TX
08073600	Buffalo Bayou at W Belt Dr, Houston, TX
08073700	Buffalo Bayou at Piney Point, TX
08074000	Buffalo Bayou at Houston, TX

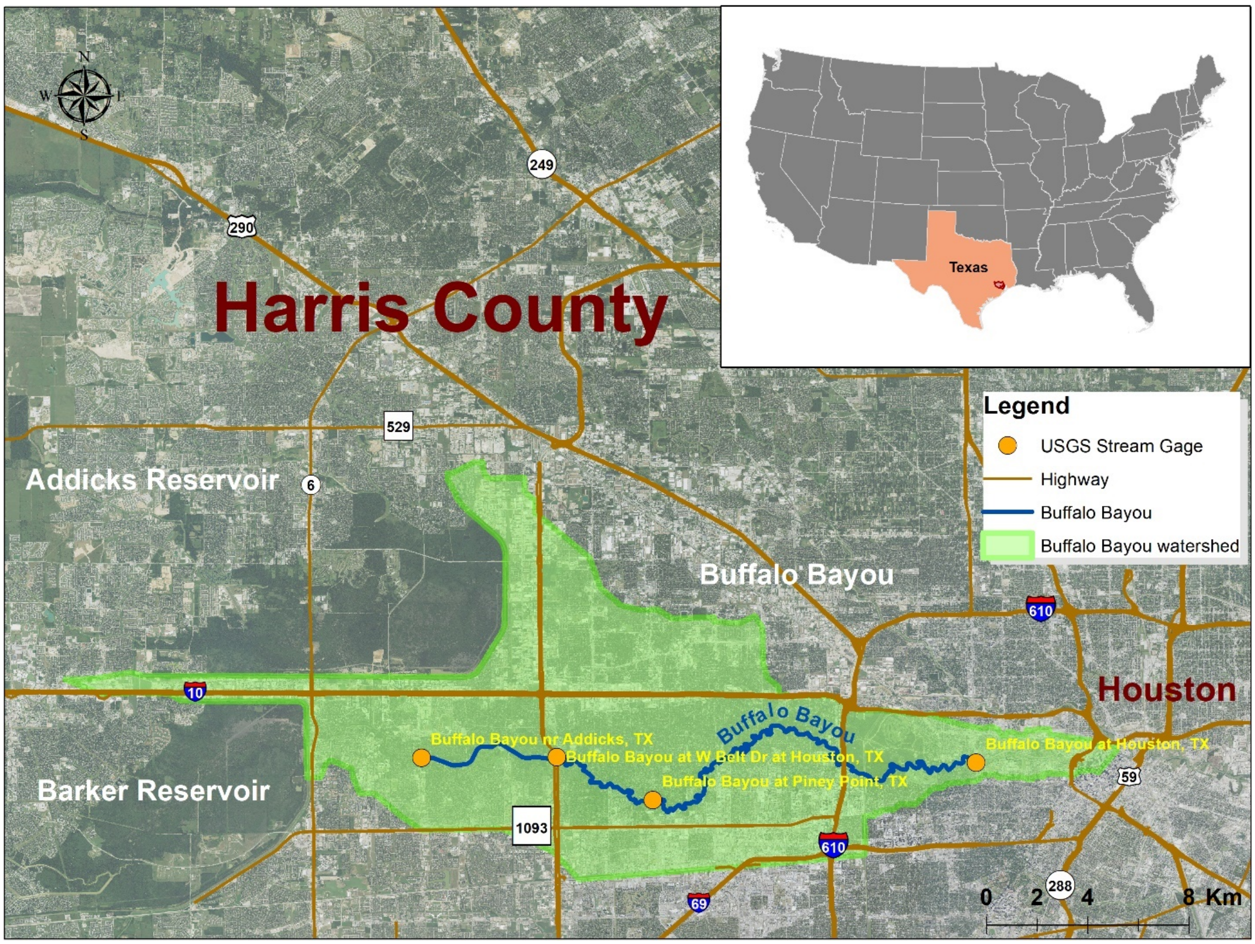

Figure 2. The USGS stream gauges in the study area in Buffalo Bayou watershed

3.2 Data collection

In this study, the input data for the flood model are acquired from the authoritative GIS database such as Texas Natural Resources Information System (TNRIS), U.S. Geological Survey (USGS), and Federal Emergency Management Agency (FEMA).

Harvey High Water Marks from USGS was used for model validation. The source of crowdsourced data was from the U-Flood project. To examine the quality of crowdsourced data and its potential on inundation mapping, this study employed three types of data as stated below (Table 2).

Table 2. The summary of data type, name, sources and the year of acquisition

Data type	**Data name**	**Sources**	**Year of acquisition**
GIS	County and city boundaries	TNRIS, TxDOT, TPWD	2015
	Roadways	TNRIS, TxDOT	2015
	Watershed boundaries	TNRIS, USGS	2009
	Rivers, Streams, and Waterbodies	TNRIS, USGS, EPA	2009-2014
	Real-time Streamflow Stations and Discharges	USGS	2017
	National Flood Hazard Layer (NFHL)	FEMA	2015
	National Land Cover Database	TNRIS, USGS	2011
	USGS - Harvey High Water Marks	USGS	2018
	CIP Storm Sewer	City of Houston's open data portal	2018
Remote sensing	National Agriculture Imagery Program (NAIP) 1m NC\CIR Orthoimagery	TNRIS, USDA	2016

	Houston-Galveston Area Council (H-GAC) Lidar DEM	TNRIS	2008
Crowdsourced	U-Flood flooded streets layer	U-Flood project	2017

The crowdsourced data used in this study is the U-Flood data (i.e. crowdsourcing to map flooded streets in Houston). The flooded streets layers were contributed by the public and were acquired via the script from the U-Flood project (map.u-flood.com) as GeoJSON format, which converted into shapefile by this study for ArcGIS. The U-Flood data were segregated at hourly from August 31 to September 6, 2017. The resulting polyline shapefile was visualized in GIS with a recorded timestamp, road types and flood types in the attribute table. Figure 3 shows the maps of U-Flood by date.

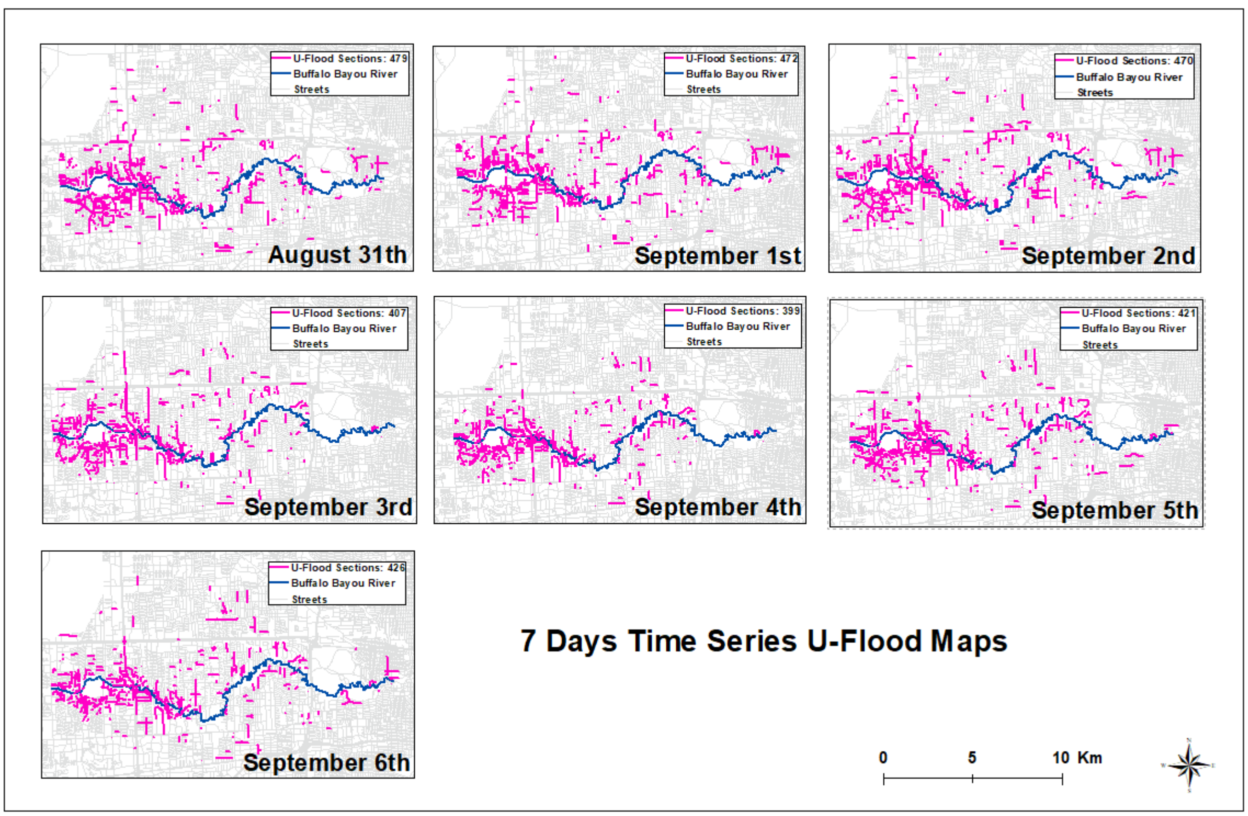

Figure 3. The time series of 7 days U-flood maps

3.3 Processing Geometry data

All GIS shapefiles and raster data used the coordinate system projection of the state plate coordinate system of Texas in zone 4204 for spatial reference. The roads, streams, and the USGS stream gauge shapefiles were clipped within the Buffalo Bayou watershed of Harris County. The lidar-derived Digital Elevation Model (DEM) data acquired from TNRIS was clipped, mosaicked and converted to a TIN file within the Buffalo Bayou watershed for further geometric data processing. The stream centerline, bank lines, flow path centerline, and cross-section cut lines were digitized by HEC-GeoRAS extension (a set of tools for processing geospatial data in ArcGIS) to prepare the RAS layers needed for HEC-RAS (Figure 4).

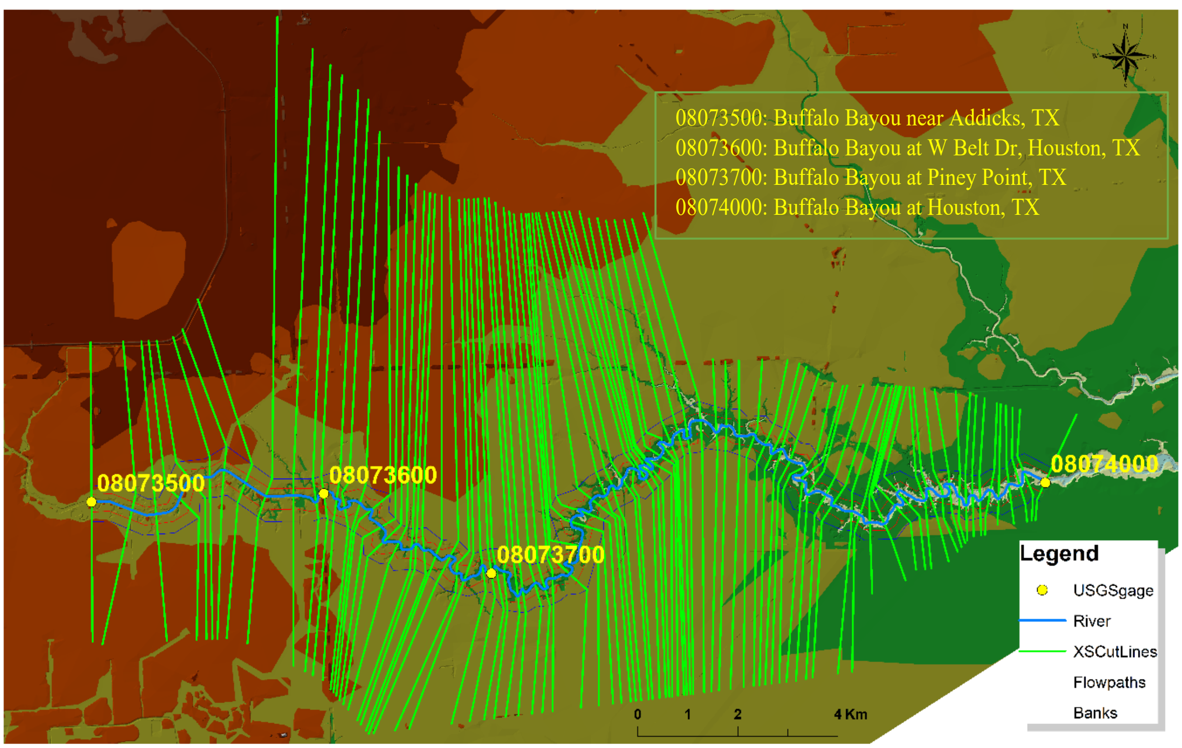

Figure 4. RAS Layers: river centerline, banks, flow path centerline, cross-sections

Editing the geometric data and flow data acceptable to HEC-RAS was a tedious and trivial process. The processes to ensure the geometric integrity of cross-sections data include cleaning intersected lines; recreating the TIN terrain file without unnatural fractures; and capturing representative cross-sections of critical turns along the winding stream of the watershed. For example, each cross-section line needs to be perpendicular to the stream centerline and non-intersecting to each other. However, it was indeed challenging to fully capture the channel geometry of this long and meandering Buffalo Bayou. Therefore, it needs to resolve those errors dealing with geometric data and flow profiles in order to run the HEC-RAS simulation successfully.

This study digitized 80 cross-section lines across the Buffalo Bayou watershed to capture the places of hydraulic interest (e.g. change in geomorphological landforms) as well as USGS gages along the Buffalo Bayou stream. In addition to adding attributes to the cross-sections, there was also a need to assign Manning's n value to cross-sections based on land use and land cover (Table 3). Manning's n value is assigned to three classes based on the existing lookup values "Open-Channel Hydraulics" (Chow, 1959) and HEC-RAS River Analysis System 2D Modeling User's Manual Version 5.0, Figure 3-19 (2016): channel 0.04, developed 0.06, and vegetation 0.08. The Manning's n value extracted from the National Land Cover Database 2011 (NLCD 2011) dataset for each cross-section. All RAS layers were prepared and exported from HEC-geoRAS and then imported into the HEC-RAS model for flood simulation.

Table 3. Manning's n value assigned to land use land cover dataset

LULC	Manning's n value
Open water	0.04
Dev, open space	0.06
Dev, low intensity	0.06

Dev, medium intensity	0.06
Dev, high intensity	0.06
Barren land	0.08
Deciduous forest	0.08
Evergreen forest	0.08
Mixed forest	0.08
Shrub/scrub	0.08
Grassland/herbaceous	0.08
Pasture/hays	0.04
Cultivated crops	0.04
Woody wetlands	0.04
Herbaceous wetlands	0.04

3.4 Data analysis

The workflow of the methodology involves the following steps: (1) flood simulation and inundation mapping using HEC-RAS; (2) model validation against authoritative data of FEMA flood inundated map, 3) compare the extent and WD among modeled flood inundation maps and U-Flood (Figure 5).

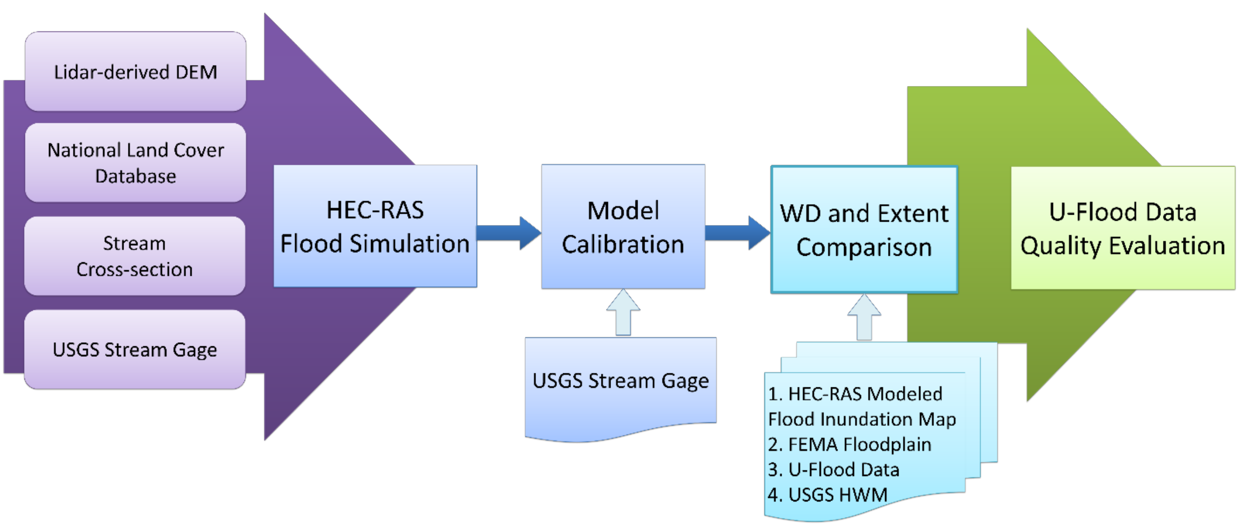

Figure 5. Flow chart of data input, model simulation, calibration, result comparison and data quality evaluation

3.4.1 Flood simulation

The flood simulation required several inputs and model parameters, including the inflow discharges from the stream gages, cross-sectional profiles of channel geometry extracted from lidar-derived DEM, and geometric data such as flow paths and river. The USGS stream gage peak inflow discharges were used as the inflow data. The resulting flood from Hurricane Harvey routed through the Buffalo Bayou river within the section downstream from the reservoirs to downtown Houston. In general, this study used the HEC-RAS model to simulate 7 days scenario of flood inundation maps from 2017/8/31 – 2017/9/6, which matches the date of U-Flood data retrieved from the U-Flood project.

It is also important to note that each cross-section of the stream can only allow up to 500 elevation points in HEC-RAS, so a cross-section point filter was used to remove any redundant and excessive elevation points. Another limitation of HEC-RAS cross-section processing is to verify and simplify over 100 Manning's n value to 20 for each cross-section line. In this study, the goal is to diversify the selection of appropriate Manning's n value to represent the heterogeneity of land use land cover (LULC) over channel and floodplain.

In this study, steady flow analysis was run to simulate the flood inundation maps along Buffalo Bayou mainstream. The flow change locations between upstream and downstream which corresponding to the specified cross-section line were added and entered the flow discharges inputs from four USGS gage with "Known W.S.". At first, the water surface (WS) seemed unnatural and looked like there was a 10-foot height drop in the main channel. Therefore, this study set internal changes in WS to modify water surface elevation by evenly distribute the height value between the drops and then added to each cross-section in the table. The modified result seemed smooth and natural. After setting up the correct geometric data and steady flow data, flood modeling is executed.

Table 4 lists the input parameters of the four selected USGS stream gages along Buffalo Bayou mainstream, which include gage number, gage name, date, time, discharge (cms), and gage height (m). In this research, the peak discharge of the USGS stream gage 08074000 happened on any given day during August 31 to September 6 was used as the threshold to calibrate the model, because it holds the largest flow discharge value compared to the other gages, which represents the worst flood scenario. Therefore, the same time/date when the peak discharge occurred at gage 08074000 was applied in the other 3 gages to simulate the worst flood situation.

Table 4. Flow data input parameters of four USGS stream gages from August 31, 2017 to September 6, 2017

Gage Number	Gage Name	Date	Time	cms	m
08074000	Buffalo Bayou at Houston, TX	8/31/2017	13:30	441.74	7.84
08073700	Buffalo Bayou at Piney Point, TX	8/31/2017	13:30	413.43	19.12
08073600	Buffalo Bayou at W Belt Dr, Houston, TX	8/31/2017	13:30	410.59	21.70
08073500	Buffalo Bayou near Addicks, TX	8/31/2017	13:30	368.12	23.55

Gage Number	Gage Name	Date	Time	cms	m
08074000	Buffalo Bayou at Houston, TX	9/1/2017	1:00	438.91	7.79
08073700	Buffalo Bayou at Piney Point, TX	9/1/2017	1:00	416.26	19.05
08073600	Buffalo Bayou at W Belt Dr, Houston, TX	9/1/2017	1:00	399.27	21.56
08073500	Buffalo Bayou near Addicks, TX	9/1/2017	1:00	353.96	23.44

Gage Number	Gage Name	Date	Time	cms	m
08074000	Buffalo Bayou at Houston, TX	9/2/2017	1:15	421.92	7.62
08073700	Buffalo Bayou at Piney Point, TX	9/2/2017	1:15	379.45	18.71
08073600	Buffalo Bayou at W Belt Dr, Houston, TX	9/2/2017	1:15	373.78	21.36
08073500	Buffalo Bayou near Addicks, TX	9/2/2017	1:15	345.47	23.30

Gage Number	Gage Name	Date	Time	cms	m

08074000	Buffalo Bayou at Houston, TX	9/3/2017	0:00	407.76	7.46
08073700	Buffalo Bayou at Piney Point, TX	9/3/2017	0:00	359.62	18.45
08073600	Buffalo Bayou at W Belt Dr, Houston, TX	9/3/2017	0:00	362.46	21.21
08073500	Buffalo Bayou near Addicks, TX	9/3/2017	0:00	342.63	23.23

Gage Number	**Gage Name**	**Date**	**Time**	**cms**	**m**
08074000	Buffalo Bayou at Houston, TX	9/4/2017	0:00	393.60	7.32
08073700	Buffalo Bayou at Piney Point, TX	9/4/2017	0:00	356.79	18.28
08073600	Buffalo Bayou at W Belt Dr, Houston, TX	9/4/2017	0:00	362.46	21.11
08073500	Buffalo Bayou near Addicks, TX	9/4/2017	0:00	336.97	23.15

Gage Number	**Gage Name**	**Date**	**Time**	**cms**	**m**
08074000	Buffalo Bayou at Houston, TX	9/5/2017	0:15	382.28	7.20
08073700	Buffalo Bayou at Piney Point, TX	9/5/2017	0:15	348.30	18.06
08073600	Buffalo Bayou at W Belt Dr, Houston, TX	9/5/2017	0:15	342.63	20.90
08073500	Buffalo Bayou near Addicks, TX	9/5/2017	0:15	331.31	23.03

Gage Number	**Gage Name**	**Date**	**Time**	**cms**	**m**
08074000	Buffalo Bayou at Houston, TX	9/6/2017	0:00	365.29	7.02
08073700	Buffalo Bayou at Piney Point, TX	9/6/2017	0:00	328.48	17.78
08073600	Buffalo Bayou at W Belt Dr, Houston, TX	9/6/2017	0:00	322.81	20.64
08073500	Buffalo Bayou near Addicks, TX	9/6/2017	0:00	317.15	22.87

Afterward, this study examined the hypotheses based on the water surface elevation layer from modeled output to delineate the flood extent and water depth. The layers could be visualized and overlaid in GIS and presented as the results.

3.4.2 Experiment of U-Flood data quality examination

Based on the above procedures of flood simulation, the quality of crowdsourced U-Flood data was examined by comparing a) the WD among the HEC-RAS modeled floodplain, FEMA flood map and U-Flood data (RQ1) and b) the extent of the modeled floodplain (RQ2).

To answer the research questions, this study compared various flood datasets and the corresponding attributes (Table 5).

Table 5. Comparison set among HEC-RAS model, FEMA flood map and U-Flood data

	Comparison set	Statistics method	Variable	Sample size	Date
1	HEC-RAS and FEMA	Paired-Samples t-test	WD	1,000	9/1
2	HEC-RAS and HWMs	Wilcoxon sign rank test	WD	29	8/31
3.1	U-Flood, HEC-RAS and FEMA	Friedman test	WD	184	9/1
3.2	U-Flood and HEC-RAS	Wilcoxon Sign Rank test	WD	303	8/31
				284	9/1
				259	9/2
				234	9/3
				230	9/4
				218	9/5
				188	9/6
3.3	U-Flood and FEMA	Wilcoxon Sign Rank test	WD	190	9/1
4	U-Flood and HEC-RAS	% Comparison	Count & Length	479	8/31
				472	9/1
				470	9/2
				407	9/3
				399	9/4
				421	9/5
				426	9/6

In order to verify the quality of the HEC-RAS model, the first comparison set examines the significant difference of WD between HEC-RAS modeled floodplain and FEMA floodplain. This research used HEC-RAS to simulate floodplain when U-Flood data was available, i.e. from August 31, 2017, to September 6, 2017, whereas FEMA floodplain depth data is only available from August 27, 2017, to September 1, 2017 (but without August 31). Thus, this study compared the modeled floodplain of HEC-RAS against the FEMA floodplain on September 1, 2017, the only matched date between the two datasets of FEMA and U-Flood. This study examined the agreement of WD between baseline HEC-RAS and FEMA floodplain at 1,000 random points. Assuming the water level changes gradually, WSE was extracted from the lidar-derived DEM at random points within the union of modeled floodplains modeled by HEC-RAS and FEMA. The union floodplain serves as the constraining extent to generate 1,000 random points and extracts water depth from both FEMA and HEC-RAS floodplains (Figure 6). The results of paired-samples t-test will be shown in section 4.2.

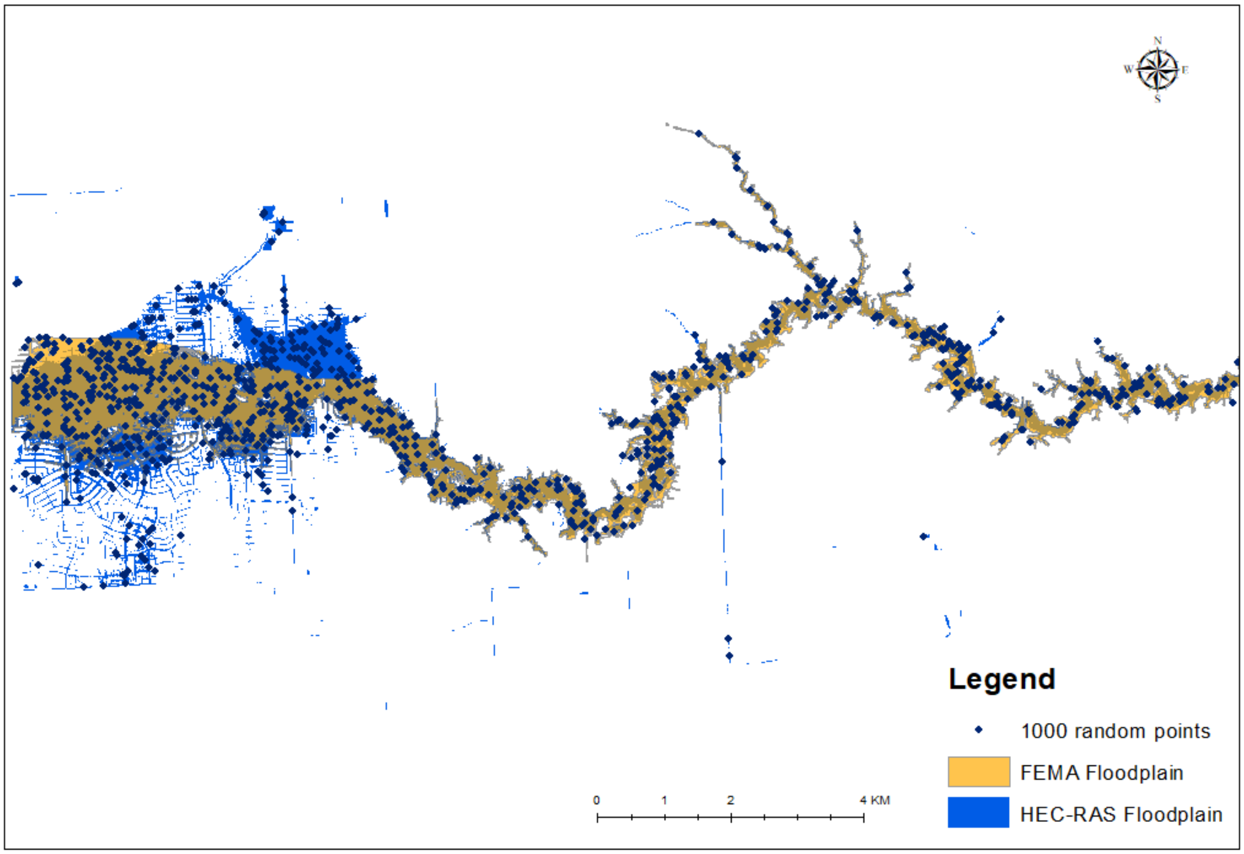

Figure 6. 1,000 random points in constrained floodplain extent

In addition to verifying the quality of the HEC-RAS model against FEMA floodplain, the second comparison set examines any significant difference of WD between HEC-RAS modeled floodplain and USGS Harvey High Water Marks (HWM) points. These HWM points are measured at 1258 sites after Hurricane Harvey, recording visual clues of peak stream height reached by floodwaters during the storm. The advantage of using HWM is to ensure that this study was comparing WD where there is a flood with an authoritative data source. There were 29 points available to be used in the statistical comparison. The 29 HWM points with WSE which was subtracted from the base DEM to estimate the water depth along with these HWM points. Then, these 29 points were used to extract WD from the HEC-RAS floodplain raster file on August 31, 2017, to compare with HWM WD. However, the HWM data doesn't reveal the date of the highest watermark and hence there is uncertainty about its timing to be compared with flood simulated on August 31. Nevertheless, this is one of the valid authoritative data available for WD comparison. A normality test was performed in advance to ensure that the sample is normally distributed. Based on the statistical results that were not in a normal distribution, this study run a nonparametric test as a statistical method. The statistical analyzation of the Wilcoxon sign rank test was shown in section 4.3.

The third comparison set was to examine any significant differences of WD among the HEC-RAS modeled floodplain, FEMA flood map, and U-Flood data. While there is no water depth information directly encoded in the U-Flood data, this study derived WD from the inundated street segment of U-Flood data using a GIS approach. This study used a 25-feet (7.62 meters) buffer around the crowdsourced U-Flood centerline, based on the standard width of a lane is 12 ft (American Association of State Highway and Transportation Officials) and the typical width of a two-way road segment in the US is nearly 25 ft. Next, this study created random points and obtained zonal maximum elevation by overlaying the buffered inundated street segments with the lidar-derived DEM. There were 184 points available to be used in the statistical comparison. Assuming a constant water surface across the inundated street segment, the 184 points within the buffered street segment would assume to be the WSE, which was then subtracted from the base DEM to estimate the water depth along the U-Flood inundated street segment. Then, these 184 points were used to extract WD from FEMA and HEC-RAS floodplain raster file on September 1, 2017, to compare with the WD of U-Flood (Figure 7). A normality test was performed in advance to ensure that the sample is normally distributed. Based on the statistical results that were not in a normal distribution, this study run a nonparametric test as a statistical method. The result of the Friedman test was showed in section 4.4.1. In addition to comparing the WD of U-Flood, FEMA, and HEC-RAS, this study also compared the WD between U-Flood and HEC-RAS in 7 days (from August 31 to September 6, 2017) as well as the WD between U-Flood and FEMA on September 1, 2017. Thus, both comparisons set of extracted WD values from the corresponding data were analyzed by the Wilcoxon sign rank test and were shown in section 4.4.2 and 4.4.3.

Figure 7. Sample points for extracting WD from U-Flood Buffered Zones

Besides WD, the fourth comparison in Table 4 was to examine any significant differences of flood extent between the HEC-RAS modeled floodplain and U-Flood data in terms of the U-Flood count and length from August 31 to September 6, 2017. This study assessed them based on count % and length % of U-Flood inside and outside of the HEC-RAS modeled floodplain. All U-Flood data were intersected and constrained in the Buffalo Bayou bounding polygon (which was generated based on the cross-sections covered zone in HEC-RAS). The first assessment was to compute the percentage of the U-Flood data counts inundated in the HEC-RAS modeled floodplain over the total number of U-Flood data. In this study, the street segments from U-Flood that intersected with the HEC-RAS floodplain were selected to illustrate the inundated roads reported by the crowd. The second assessment method was to compare the length of inundated street segments reported in U-Flood and the HEC-RAS modeled floodplain to the total length of U-Flood data. The inundated length of the U-Flood road was then clipped within the HEC-RAS modeled floodplain. Afterward, this study calculated the length of each U-Flood street segment. The statistical analyzation of the Wilcoxon sign rank test was shown in section 4.5.

IV. RESULTS

This section presents the results from flood simulation in HEC-RAS (section 4.1) as well as the statistical results of each comparison set. As documented in Table 4, the first WD comparison results of HEC-RAS and FEMA are stated in section 4.2. The second WD comparison results of HEC-RAS and HWMs are stated in section 4.3. The third WD comparison results of (1) U-Flood, HEC-RAS and FEMA, (2) U-Flood and HEC-RAS, and (3) U-Flood and FEMA are stated in section 4.4. Finally, the fourth % comparison results of U-Flood and HEC-RAS are stated in section 4.5.

4.1 Visualize flow data in flood inundation maps

All simulated flows were visualized in GIS to generate the flood inundation maps with water depth and bounding polygons. Based on the flow discharge and the gage height of the four USGS stream gages from August 31, 2017, to September 6, 2017, the 7 days flood maps were presented as Figure 8. The WSE got lower over time (i.e. water receded) and flood inundation extent gradually decreased from August 31, 2017, to September 6, 2017, as the flood maps showed. The biggest change in flood extent across 7 days happened in the upper stream along the Buffalo Bayou and the surrounding areas.

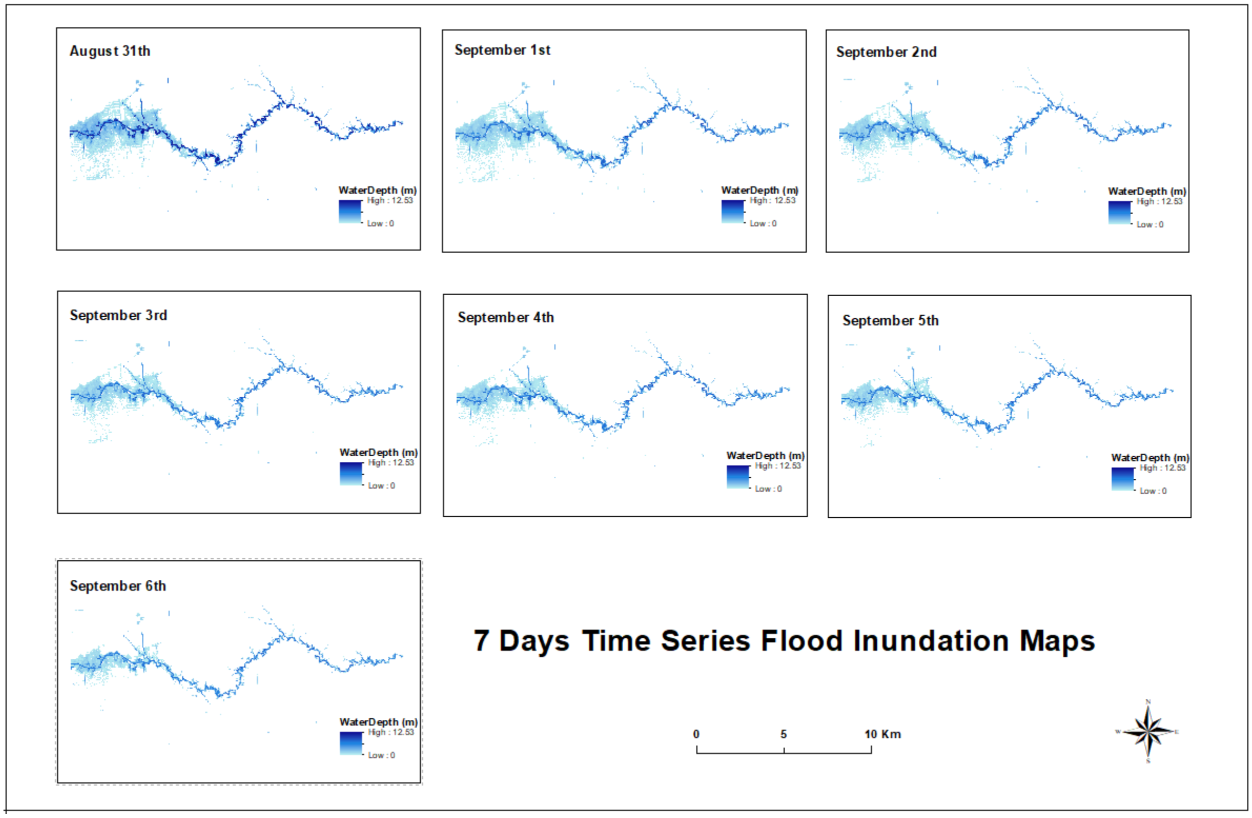

Figure 8. The time series of 7 days flood inundation maps

The WD difference distribution map of one subtracting from another (e.g. FEMA – HEC-RAS) over the random points are shown in Figure 9a) FEMA – HEC-RAS, b) HEC-RAS – U-flood (), c) FEMA – U-flood to visually represent the spatial comparing WD difference distribution. There are five different point types to represent WD difference (WDD) level between each pair of dataset comparison as follows: (1) ≤ -2 m, (2) -2 m < WDD ≤ -1 m, (3) -1 m < WDD ≤ 1 m, (4) 1 m < WDD ≤ 2 m, and (5) > 2 m. Take FEMA – HEC-RAS for example, the positive value means the overestimation of FEMA over HEC-RAS, while the negative value means the underestimation of FEMA over HEC-RAS. From these WD difference distribution maps, it is clear that where the HEC-RAS model underestimates or overestimates WD when compared to authoritative data (FEMA) or the crowdsourced U-Flood dataset.

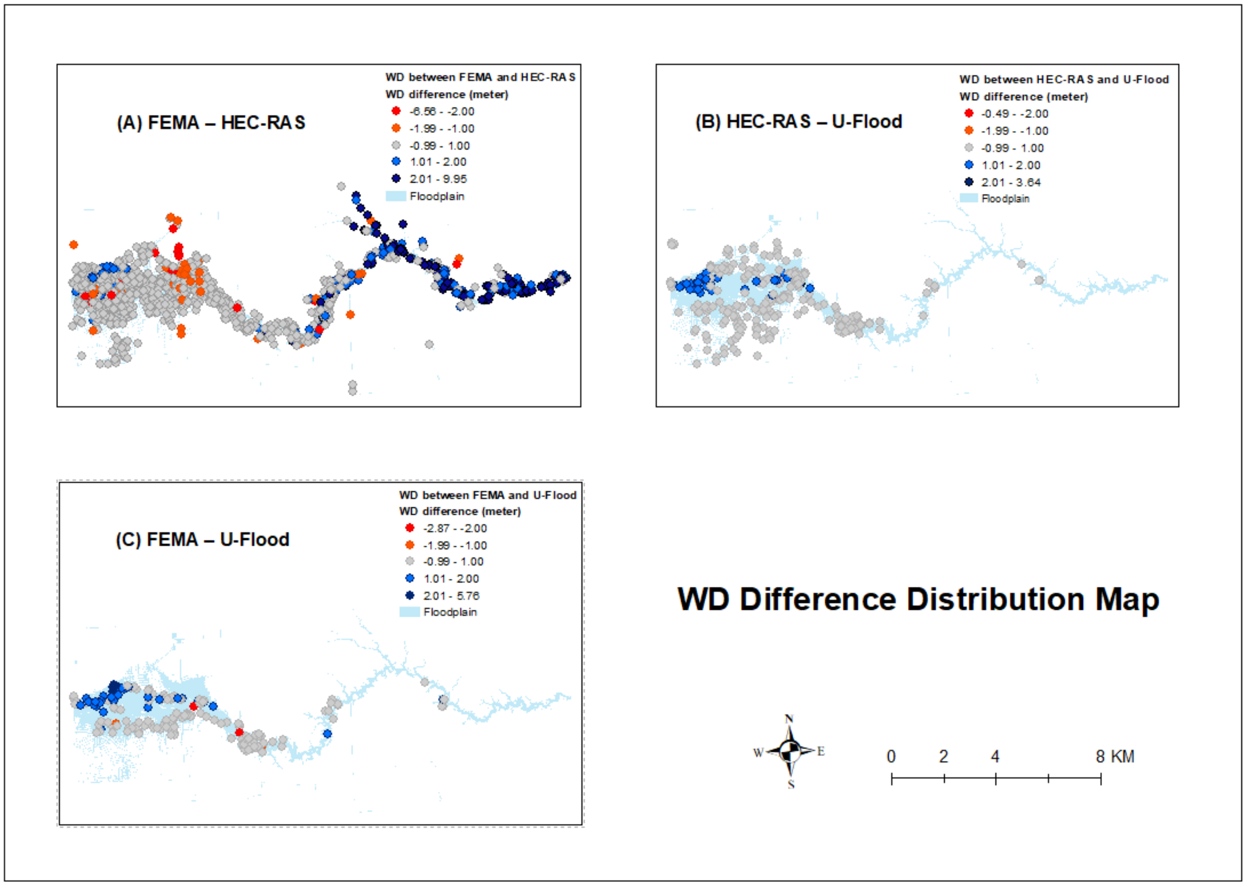

Figure 9. WD difference distribution maps between a) FEMA and HEC-RAS, b) HEC-RAS and U-Flood, and c) FEMA and U-Flood.

4.2 WD comparison between FEMA floodplain and HEC-RAS modeled floodplain

This study compared 1,000 water depth values between FEMA and HEC-RAS model using the paired sample t-test. The mean water depth from FEMA is 0.38 meters higher than the HEC-RAS counterpart. Despite the water depth of HEC-RAS modeled floodplain is highly correlated with FEMA water depth ($r = 0.878$), there was a significant difference between the water depth of HEC-RAS modeled floodplain and FEMA floodplain ($t = 8.239$; $p < 0.0001$; $n = 1,000$). Based on Figure 8 above, the most obvious difference in floodplain extent and WD occurred near the upstream of Buffalo Bayou.

Based on Figure 9A, mostly WD differences are in the range between -1m – 1m (grey points), which indicates that there is only a small WD difference between FEMA and HEC-RAS modeled floodplain. However, there is some obvious WD difference in the range between 1m – 2m (blue points) and above 2 m (dark blue points) cluster along the downstream and upstream of the Buffalo Bayou mainstream. The difference in both extent and WD between FEMA and HEC-RAS modeled floodplain may be caused by many reasons. One possible reason is that FEMA data doesn't indicate the time it used for flood simulation. Therefore, the result of FEMA may be different from HEC-RAS which was modeled with USGS gage peak flow discharge of September 1, 2017.

4.3 WD comparison between HEC-RAS modeled floodplain and HWMs

This study ran a normality test (e.g. Shapiro-Wilk W test) in advance to ensure whether the samples present normal distribution. The results of the Shapiro-Wilk W test of two groups showed that each group of the data is not normally distributed (p-value < 0.05). Therefore, the statistics used in comparing the water depth of HEC-RAS and HWMs on August 31, 2017, was the Wilcoxon Signed-Rank test. Based on HEC-RAS and HWMs water depth values in the 29 sample points, the result was a significant difference at the 0.05 level ($Z = -2.0001$, $p = 0.0455$). Due to the means of the two groups, it can be concluded that there was a statistically significant difference in the water depth between HEC-RAS and HWMs.

4.4 WD comparison among U-Flood, HEC-RAS and FEMA

4.4.1 U-Flood, HEC-RAS and FEMA

Similarly, the normality test revealed that the WD of U-Flood, HEC-RAS, and FEMA are not normally distributed (p-value < 0.05). Therefore, the Friedman Test was run to examine the null hypothesis. The water depth of September 1, 2017 was selected because it is the only date when these three data sources are available. The Friedman (X^2_r) statistics result rejected the research hypothesis, which indicated that there was a significant difference among the three groups at the $\alpha = 0.01$ significance level (p-value < 0.01) (Table 6). Therefore, the null hypothesis (H_{A0}) was rejected.

Table 6. The statistics table of Friedman Test

Source	Size Number	Mean	Std Error	P-value	X^2_r
FEMA	184	1.222	0.096	< 0.0001	72.1168
HEC-RAS	184	1.223	0.095		
U-Flood	184	0.762	0.087		

4.4.2 U-Flood and HEC-RAS

Again, the results of the Shapiro-Wilk W test rejected the assumption of normal distribution in WD of both datasets (p-value < 0.05). Therefore, the statistics used in comparing the water depth of U-Flood and HEC-RAS from August 31 to September 6, 2017 was the Wilcoxon Signed-Rank test. Based on the U-Flood and HEC-RAS water depth values in the different sample points on each date, the result was a significant difference at 0.01 level ($Z = 10.732$ to 15.087, $p = 0.0000$) (Table 7). Based on the means of the two groups, it can conclude that there was a statistically significant difference in the water depth between U-Flood and HEC-RAS. Based on Figure 9b, mostly WD differences are in the range between -1m – 1m (grey points), which indicates that there is only a small WD difference between HEC-RAS modeled floodplain and U-Flood. However, there is some scattered WD difference in the range between 1m – 2m (blue points) cluster near the upstream of the Buffalo Bayou mainstream.

Table 7. The statistics table of Wilcoxon Signed-Rank Test

Date	Size Number	Z-value	P-Value

8/31	303	15.087	0.0000
9/1	284	13.573	0.0000
9/2	259	13.632	0.0000
9/3	234	13.016	0.0000
9/4	230	11.977	0.0000
9/5	218	11.703	0.0000
9/6	188	10.732	0.0000

4.4.3 U-Flood and FEMA

This study run the normality test (e.g. Shapiro-Wilk W Test) in advance to ensure whether the samples present normal distribution. The result of the Shapiro-Wilk W Test of three groups showed that each group of the data is not normally distributed (p-value < 0.05). Therefore, the statistics used in comparing the water depth of U-Flood and HEC-RAS on September 1, 2017 was the Wilcoxon Signed-Rank test. Based on the U-Flood and FEMA water depth values in the 190 sample points, the result was a significant difference at 0.05 level ($Z = -2.4217$, $p = 0.01552$). Due to the means of the two groups, it can conclude that there was a statistically significant difference in the water depth between U-Flood and FEMA. Based on Figure 9c, mostly WD differences are in the range between -1m – 1m (grey points), which indicates that there is only a small WD difference between FEMA and U-Flood. However, there is some obvious WD difference in the range between 1m – 2m (blue points) cluster near the upstream of the Buffalo Bayou mainstream. Besides, there is only few WD difference in the range above 2m (red points) locate in the center of the floodplain.

4.5 U-Flood data and HEC-RAS modeled flood inundation map comparison

Figure 10 shows the extent comparison between U-Flood data and the HEC-RAS modeled floodplain in the study area on September 1, 2017. This figure also shows the spatial distribution of the WD difference of U-Flood data. The red line presents U-Flood street data outside of HEC-RAS floodplain, while there are three different line types to present different WD level of U-Flood street data inside of HEC-RAS floodplain as the follows (1) WD difference < 1 m; (2) WD difference ≥ 1 m and < 2 m; and (3) WD difference ≥ 2 m. There are 85.9% of WD difference below1 meter, 8.8% of WD difference between 1 to 2 meters, and 5.3% of WD difference from 2 to 8 meters. From Figure 12, it is clear that those U-Flood segments with significant WD difference (2 - 8 meters) represented by black bold lines are totally inside of the floodplain. The reason will be discussed and stated in section 5.1.

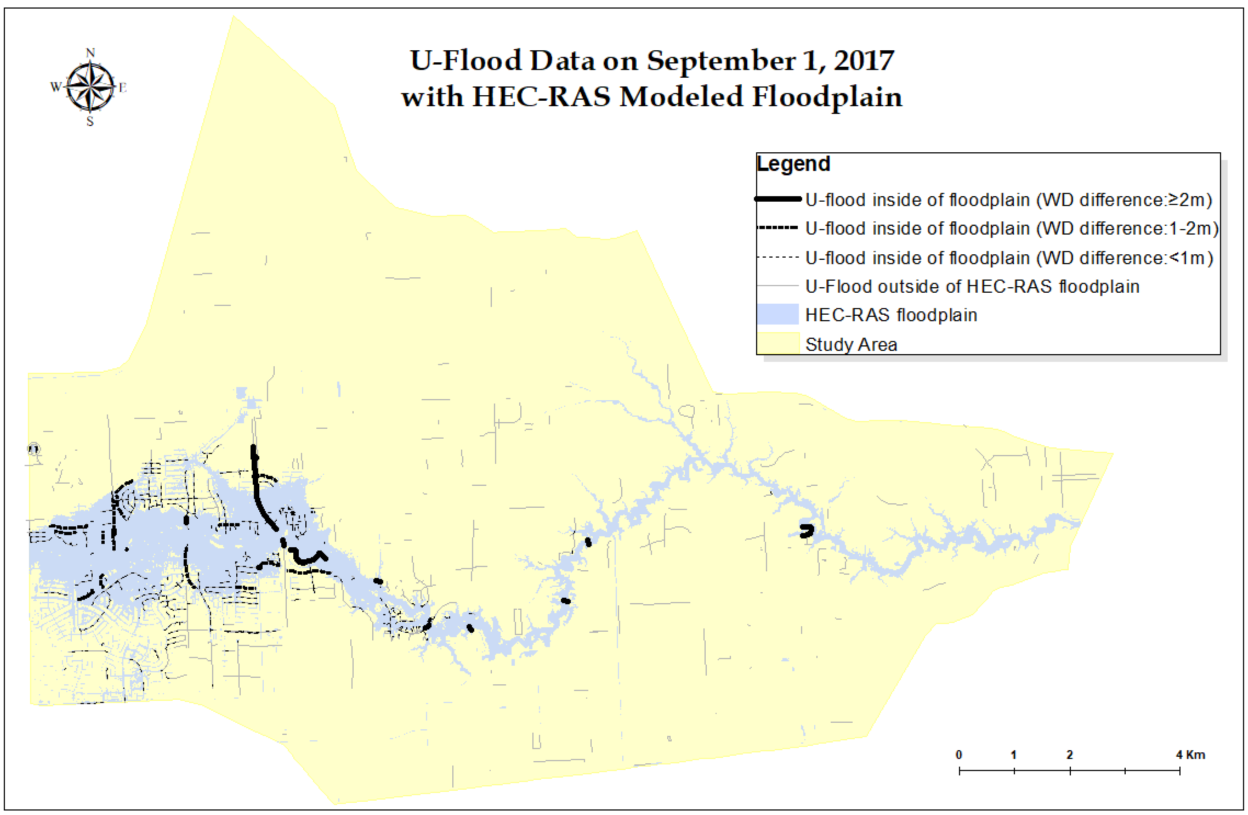

Figure 10. U-Flood Data on September 1, 2017 with HEC-RAS Modeled Floodplain

4.5.1 The comparison of the count of U-Flood data observation

The total number of U-Flood data per day during August 31, 2017, to September 6, 2017 ranges between 399 – 479, while the number of U-Flood data within the modeled floodplain per day during the same period ranges from 188 – 295 (i.e. 44.13% – 61.59% of all U-Flood data). The reported count of U-Flood data inside modeled floodplain is consistently decreasing, whereas the total U-Flood observations from August 31, 2017, to September 6 change at a slower rate and often rebound especially after September 4 (Figure 11). It looked like both the modeled floodplain and U-flood data is shrinking in extent (i.e. receding flood), but there are relatively less U-flood reporting inside the modeled floodplain over time (i.e. more U-Flood data outside the floodplain). There is a decreasing trend of the percentage as time progresses, which means fewer U-Flood data were in line as the decreasing trend goes. A possible reason could be the HEC-RAS model only accounts for riverine flooding in the main channel, whereas U-Flood observations may account for tributary flooding and other storm surges (e.g. overland flow, stormwater backlash). In general, most of the intersected U-Flood data clustered near the reservoir discharge outlet and the upstream of the Buffalo Bayou.

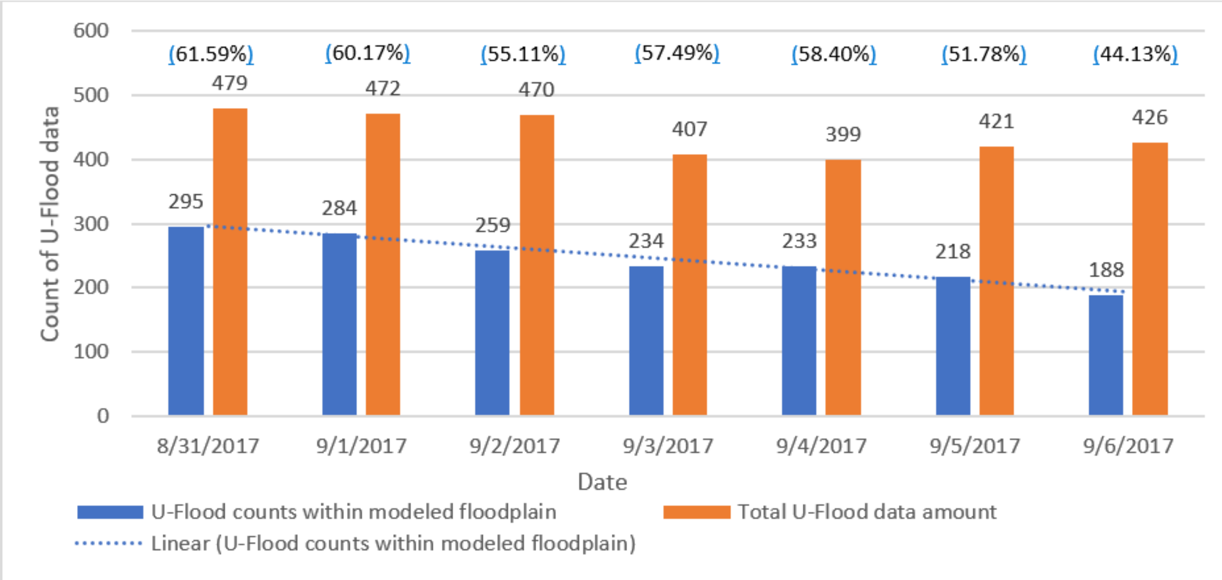

Figure 11. Summary of U-Flood counts in HEC-RAS modeled floodplain compared to total U-Flood amount on a daily basis

4.5.2 The comparison of the length of U-Flood data observation

The total length of U-Flood data in the study area for August 31, 2017, to September 6 is about 107.83 – 132.87 km, and the length of U-Flood data within the floodplain is about 34.81 – 63.00 km, which indicates 29.06% – 47.43% of the total length of U-Flood data. There is also a decreasing trend of the length of reported U-Flood data inside floodplain from August 31, 2017, to September 6 (Figure 12). The more days passed, the less U-Flood data in line with HEC-RAS modeled floodplain.

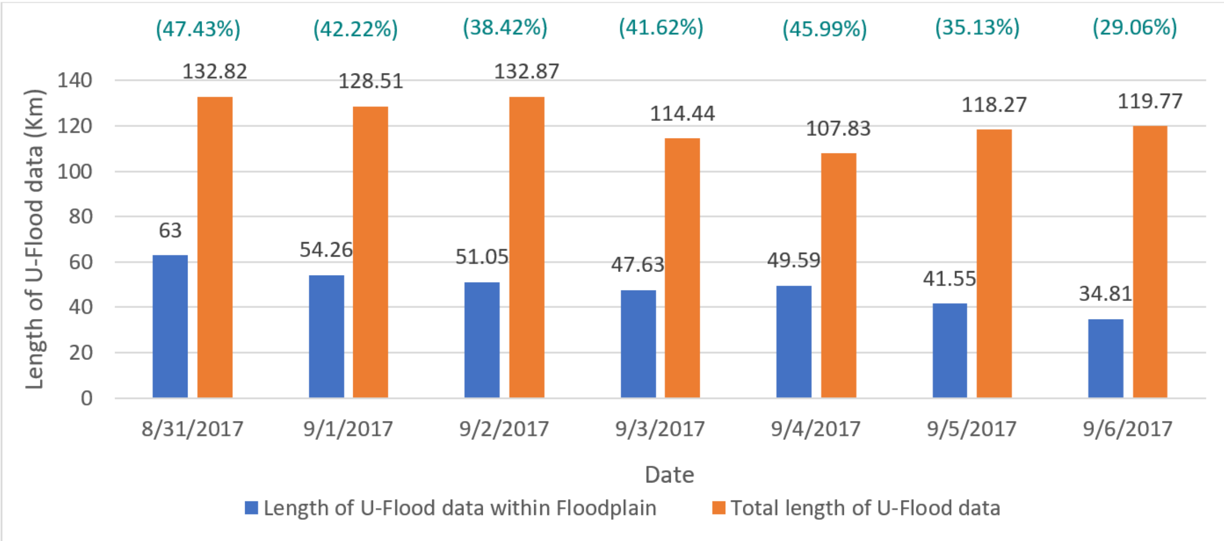

Figure 12. Summary of U-Flood length in HEC-RAS modeled floodplain compared to total U-Flood length on a daily basis

4.5.3 The conclusions of the statistics of two comparisons

Based on the results, the statistical comparison of count agreement between U-Flood and the HEC-RAS model from 44.13% – 61.59% while the length agreement from 29.06% – 47.43%. The average agreement of the count is 55.52%, while the average agreement of the length is 39.98%. Therefore, the length percentage agreement is relatively low to indicate much agreement between the U-Flood data and HEC-RAS model results. As explained earlier, such difference could be attributed to the fact that HEC-RAS only predicts riverine flooding in the main channel, whereas the U-Flood data still has the potential to be the supplementary data to bring up the HEC-RAS model or FEMA to full strength, based on its real-time characteristic.

V. DISCUSSION

5.1 Research Questions

To answer the research question of whether there are any significant differences in the water depth among the H&H model (i.e. HEC-RAS), authorized reference (i.e. FEMA) and crowdsourced data (i.e. U-Flood data), the statistics comparison results of Table 5 indicates that there was a statistically significant difference among HEC-RAS, FEMA, and U-Flood data. Furthermore, there was a statistically significant difference in the water depth between U-Flood and HEC-RAS comparison as well as U-Flood and FEMA comparison. Therefore, the null hypothesis (H_{A0}) (i.e. $WD_{\text{HEC-RAS}} = WD_{\text{FEMA}} = WD_{\text{U-Flood}}$) was rejected.

Moreover, the geographic pattern of WD among U-Flood, FEMA, and HEC-RAS displayed high similarity at the edge of the floodplain; while there were some WD significant difference occurred inside the floodplain (Figure 10). The zonal maximum method to extract WD tends to be overestimating especially when 1) the U-Flood road segment is long, 2) the slope along those segments is steep (i.e. large elevation change). Moreover, another possible reason is that the premise of the WD extraction method using by this study is to assume that all U-Flood segments have encountered floodplain boundary (where WD = 0). While the maximum DEM of this U-Flood segment occurred at the boundary of the floodplain, the derived WD at the sample point (max DEM subtract base DEM) would be close to the WD from HEC-RAS modeled floodplain. However, U-Flood segments that are "totally inside floodplain from start to the end" don't meet this assumption. In this scenario, since the U-Flood segment doesn't have at least one end touching the boundary of floodplain and the whole U-Flood segment may fall far below the water surface, it will not match the real water surface elevation no matter which DEM point collected from the U-flood segment. Thus, the WD of HEC-RAS and U-Flood would have a significant difference when using this method to get false WSE. Therefore, this study suggests that future studies could exclude U-Flood segments which is "totally inside floodplain from start to the end" to avoid this issue. Only the U-Flood segments near the floodplain edge can get reasonable WD when using this method.

According to Figure 9 in section 4.1, there is a geographic pattern of the WD difference in each comparison. There is an obvious WD difference between -2 m and 2 m when comparing the WD difference between HEC-RAS and FEMA. However, it seems there is not so much WD difference over 2 m when comparing U-Flood to FEMA or HEC-RAS. It could be due to the random sample amounts (i.e. there are 1,000 random sample points in FEMA and HEC-RAS comparison, but only 284 points in HEC-RAS and U-Flood comparison, and 190 points in HEC-RAS and U-Flood comparison). Overall, it required more data and information for further interpretation of the geographic pattern. This is also a worthy direction for future research.

To answer the research question of whether there are any significant differences in the inundated areas between the HEC-RAS modeled floodplain and U-Flood data observations, the statistics comparison results of Figure 11 and Figure 12 indicates that there was a statistically significant difference among HEC-RAS and U-Flood data. Therefore, the null hypothesis (H_{B0}) states that there are no significant differences of the covered area between HEC-RAS modeled floodplain and U-Flood data observations (i.e. Covered Area $_{\text{HEC-RAS}}$ = Covered Area $_{\text{U-Flood}}$) was rejected. With regards to the count and length comparisons of U-Flood and HEC-RAS modeled floodplain in Figure 11 and

Figure 12, the percentage accounted for those U-Flood data outside of the floodplain is 38.41 – 55.87 % and 52.57 – 70.94 % respectively.

There was a difference in the underlying geographic pattern among the HEC-RAS model, FEMA flood data and U-Flood data. First, the HEC-RAS and FEMA didn't model the tributaries. Instead, the HEC-RAS model deployed in this study only simulates the mainstream of the Buffalo Bayou watershed in the study area with only four targets USGS gage flow data. However, some U-Flood data may be observed near the tributaries or far from the mainstream. Second, the U-Flood data outside the floodplain may be caused by ineffective sewer drainage compounded with increased surface runoff from overland flow. This study overlaid the Houston storm sewer map with Kernel Line Density which produced from U-Flood distribution (Figure 13) for further analysis. From Figure 13, there is a high-density cluster of the U-Flood distribution near the upstream and two dams. On the other hand, there is only some U-Flood scattered away from the upstream. Excluding the sewers that are not connected to the FEMA floodplain in the Buffalo Bayou, there are 214 out of 472 (45.34 %) U-Flood data intersected with storm sewers on September 1, 2017. This might suggest areas with U-Flood data that did not intersect with the storm sewer lines (54.64 %) would suffer from flood inundation due to the absence of sewer lines to drain overflows during the Hurricane Harvey. Those areas without storm sewers may need to build more storm sewers to cope with future flooding during more than 500-year flood levels. These U-Flood data were observed in the urban area, so it was possible that the inundated streets were affected by the floodwater from multiple sources besides the riverine flooding (e.g. damaged pipelines).

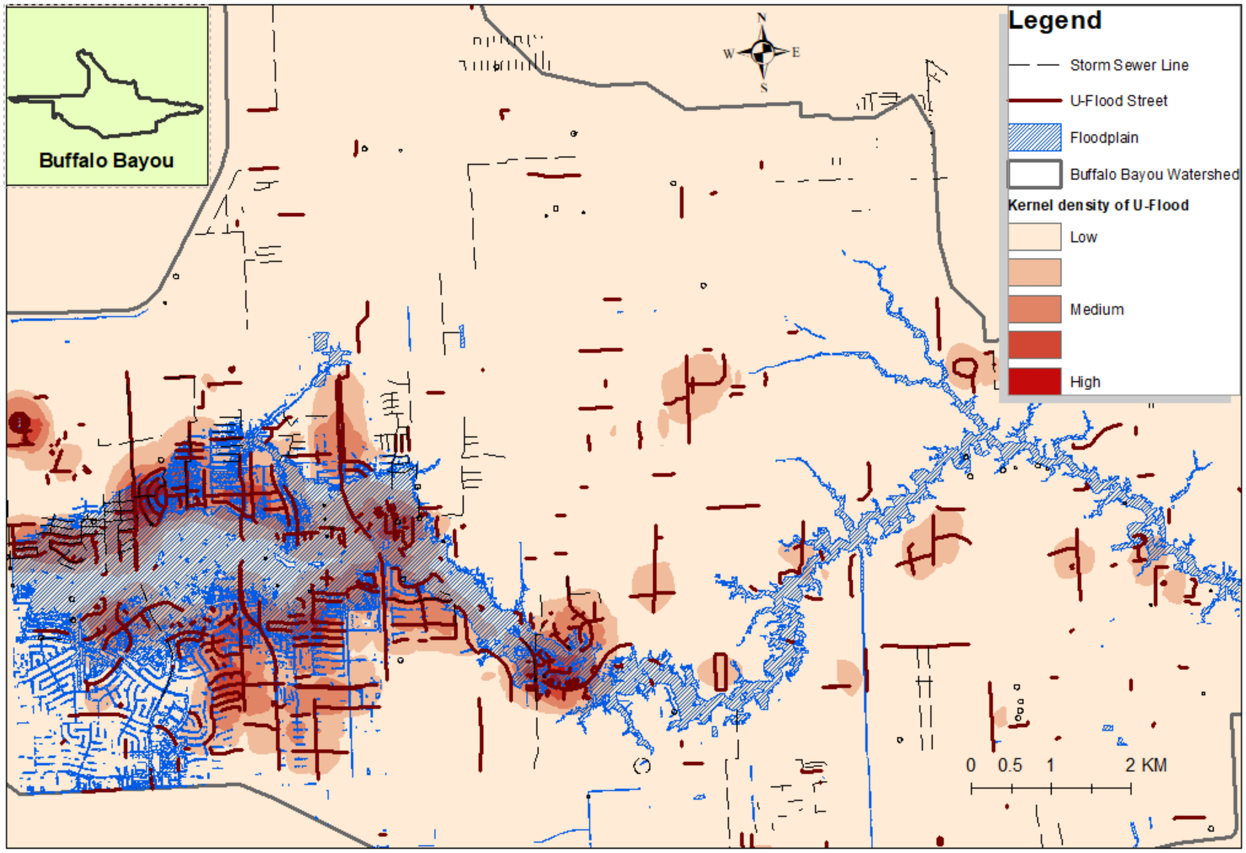

Figure 13. Storm Sewer map with U-Flood Distribution Map

Third, the absence of U-Flood data in some areas (e.g. HEC-RAS modeled floodplain or FEMA floodplain) could be attributed to no volunteers to observe or report the inundated streets. The results showed that a less consistent decreasing trend between U-Flood data and the modeled floodplain over time. It could be a result of a) fewer observations volunteered by the crowd or b) less flood across 7 days over a spatially heterogeneous inundation landscape. With regards to the former cause, people may not report flood information because they didn't have good signals or devices during or immediately after the flood, or some places where floods happened are sparsely populated. This phenomenon may be further compounded by the geographic disparity of digital divide. However, there was a decreasing reporting trend (about 11% reduction) in total number of U-Flood data observation during the study period from August 31, 2017, to September 6; and it was about 36 % reduction in the count of U-Flood data inside HEC-RAS modeled floodplain (Figure 11), which means less observation volunteered by the crowd might be a partial cause of the inconsistency. Besides, the modeled flood inundation maps (Figure 8) and the USGS gage records (Table 8) showed that the flood receded gradually over the 7-days period.

Table 8. The peak value (cms) of each date from USGS gage record

Date/Gage	**08073500**	**08073600**	**08073700**	**08074000**
25-Aug	5.58	15.38	19.77	***NoData**
26-Aug	134.79	170.18	163.96	*124.31
27-Aug	242.96	328.48	345.47	***NoData**
28-Aug	294.50	342.63	376.61	***923.13**
29-Aug	385.11	342.63	373.78	835.35
30-Aug	*390.77	407.76	410.59	487.05
31-Aug	370.95	413.43	424.75	441.74
1-Sep	356.79	402.10	*419.90	436.08
2-Sep	351.13	379.45	*385.11	421.92
3-Sep	345.47	368.12	362.46	407.76
4-Sep	342.63	362.46	356.79	393.60
5-Sep	331.31	342.63	348.30	379.45
6-Sep	317.15	325.64	328.48	365.29
				* Lost data on this day

Based on the statistics and the analysis above, the difference of WSE may be caused by the limitations of U-Flood crowdsourced data. Due to significant differences found among U-Flood data, HEC-RAS model and FEMA floodplain, it is recommended to exercise caution in interpreting U-Flood data and its potential use to calibrate the HEC-RAS model at this stage (to be discussed in the next section). However, U-Flood data still has the potential to supplement real-time observations especially outside of the floodway and immediate floodplain to the main channel even outside of the modeled floodplain area (Figure 11 and Figure 12). Floodplain modeling (e.g. HEC-RAS) is typically restricted to the main channel but not the tributaries and upstream floodplain due to the need and availability of USGS gage data for calibration, so such a modeling approach is only as good (or as comprehensive) as gage data can support it. Hence, non-riverine flooding in those remote areas would go unrecorded and their impacts on the local communities could be underestimated. At this time, U-Flood data could be potentially helpful as a supplementary data source for HEC-RAS modeling by offering valuable observations in regions without USGS stream gages or authoritative data.

Nevertheless, the quality of U-Flood is of vital importance to the accuracy and utility of flood monitoring. Furthermore, it might be possible to reduce the uncertainties of U-Flood data by setting the gatekeepers to review reported observations from the public. For example, Goodchild and Li (2012) described the social approach that imitates the structure of traditional authoritative mapping agencies with "experts" who serve as gatekeepers to reconcile any inconsistent observations and assure the quality of voluntary contributions. The crowd-sourcing approach (Goodchild and Li, 2012) leverages the power of the crowd to approximate the "ground truth" and to validate the errors that can potentially improve the credibility of U-Flood data. For example, a single observation can be examined by nearby observations to flag any sampling bias. Moreover, informing and educating the public to report scientific observations can improve the data quality as a long-term strategy. For example, empowering the public with clear instructions of data collection protocol along with a user-friendly web/mobile interface can enable effective citizen science of essential attributes for each observation to be recorded (i.e. GPS location, flood status, etc.). As a result, such instructions may reduce spatial and/or temporal uncertainties associated with such VGI.

In summary, this study provides some suggestions on "best practices" of crowdsourcing data in the digital platform (i.e. app or website) for future applications: a) provide a form with easy user interface designed to ease user input; b) users report data with GPS turned on for accurate location of flood; c) use existing media outlets (e.g. radio stations, social media) to promote the app before storm season to raise public awareness. Overall, the combination of the strategies stated above would improve the quality of U-Flood data.

5.2 Limitations

U-Flood data might not fully represent the peak discharge reflected by water depth because of several reasons. First, these crowdsourcing projects are often a response to an urgent need (e.g. a natural disaster) that would involve time lag. This indicates that we should learn from this and be proactive in the future. The data reported from the public only available from August 31, 2017, to September 6, which was already far away from the most severe flooding happened about August 25, 2017, to August 28. In fact, the daily peak flow discharge of USGS stream gage 08074000 was observed when the dam released floodwater on August 28, 2017. Second, there may be some data reported from the public not in the exact time and the location when and where the flood occurred. Some people reported inundated streets or roads hours or even days after they had access to the internet, while the flood might already fade or keep flowing rapidly elsewhere. Thus, the time lag in the crowdsourced report might not reflect the realistic flooding situation corresponding to the time stamp in U-Flood data. Third, U-Flood data has a lot of uncertainties. Some users might report a flood when they were walking or traveling in a boat, so the WSE was uncertain. Besides, U-Flood data doesn't provide attributes indicative of the context of local inundation, some of them may come from dam released flood water or direct stormwater runoff. Finally, the U-Flood data doesn't have water depth, and any water depth extraction of U-Flood would have some errors to be compared with other flood datasets used in this study.

Moreover, there were a lot of technical challenges in data processing which include the diversity of data source, map projection, data format, spatial resolution, and the missing flow data on some days. For example, if the multi-source data was not converted in the same projection, format, and resolution, the GIS data would cause many errors to interrupt the HEC-RAS model. In addition, the U-Flood data need to be transformed from JSON format to the shapefile in order to display and compare it to other GIS data. While the FEMA floodplain data was modeled from August 27, 2017, to September 1 (except August 31), the U-Flood data was only available from August 31, 2017, to September 6. This study simulated floodplains in line with specified date and time by HEC-RAS and then run several comparisons to examine the quality of U-Flood data.

Due to the limitation of data availability, this study used the lidar-derived DEM (2008) and land cover (2011) and assumes that there were no major topographic changes from the time of data collection to August 2017. Although both data might not fully account for the current situation, these dated datasets are the best available data. While the research hypotheses examined the quality of U-Flood data, this study did not fully address any error propagation due to the spatiotemporal uncertainties associated with the crowdsourced data despite the results indicate disparities of sampling bias. It is noted, however, that varying degrees of sampling bias would also occur in conventional and authoritative datasets (e.g. USGS) and any subsequent models that use them as well. Another limitation is the extraction of water surface elevation at random points by overlaying the U-Flood data with DEM. This study assumed the water flow to be steady and uniform flow (i.e. the WSE changes linearly and gradually over time and space).

As mentioned, the U-Flood data lacks water depth and has lots of uncertainties. Thus, the method to extract WSE from the U-Flood segments may not get the accurate water depth. Besides, the information for each U-Flood segment only specified flooded or not, but it does not mention whether it was flooded along the whole street or only part of the segment. This ambiguous information leads to uncertainty in the statistical comparison of WD. On the other hand, data shortage in damaged USGS gauge station also limits the HEC-RAS model in representing the “reality” in Hurricane Harvey.

5.3 Dam release influence

Besides, anthropogenic activities affect the flood landscape as well. As there have been fluxes of dam release from the Addicks and Barker Reservoirs, it was hard to distinguish whether the flood extent was affected by the dam release or directly from the stormwater. Moreover, the USGS gage (08074000) in the study area was damaged during Hurricane Harvey and thus missed some records during Hurricane Harvey. USGS announced that the discharge data for the period August 26, 2017, to August 28, 2017, were revised based on re-analysis of gage height, the timing of the event, and hydrologic comparison of upstream and downstream gages (USGS, 2018). Even if the data had been estimated by USGS, there were still some missed flow discharge data from August 25, 2017, to August 28, 2017. For example, there was no discharge data on August 27 before dam release (August 28) to simulate the flood as well as to compare the storm with or without dam release (Figure 14). The missed discharge data of the study period could be referred to Table 8 above. Overall, future studies could improve the results from this study by using precipitation data as the auxiliary data to derive missing USGS stream gage data and better evaluate the impacts of dam release on flood extent.

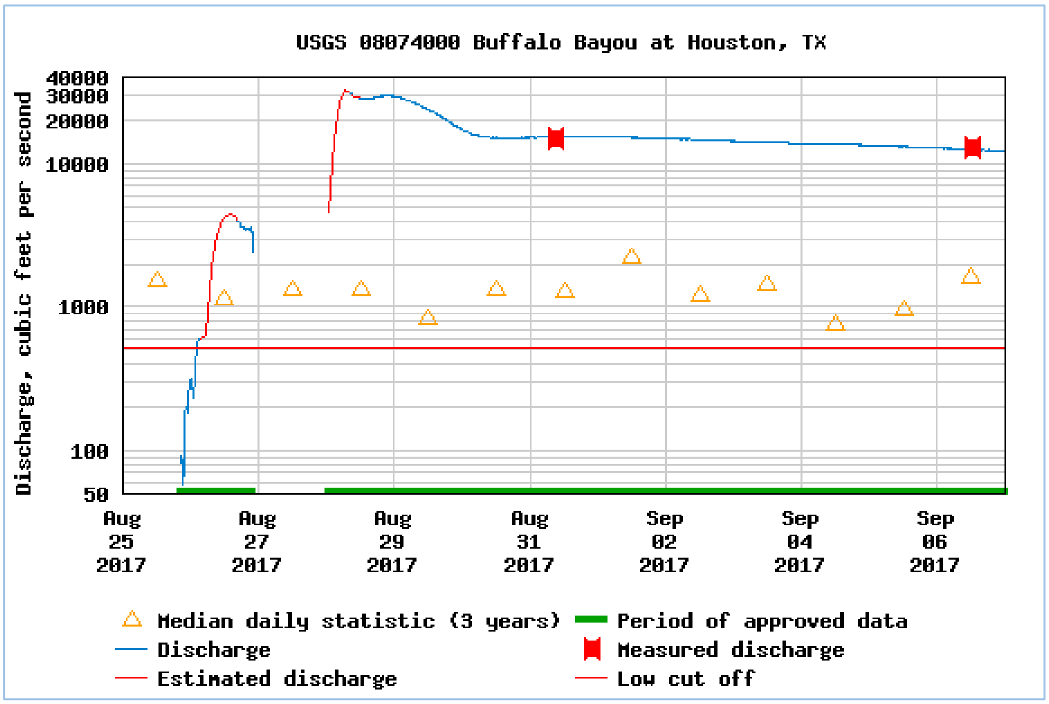

Figure 14. Missed data in USGS 08074000 record

According to the USGS hydrograph (Figure 15 and Figure 16), the normal flow discharge is about 0 – 100 cfs (2.83 cms) on July 25 and arise dramatically to the estimation about 10,000 cfs (283.17 cms) at USGS gage 08073500 (upstream) and 30,000 cfs (849.51 cms) at USGS gage 08074000 (downstream) around August 28 – August 29 when US Army announced the release of stormwater from Addicks and Barker Dams. The USGS stream gage 08073500 is located upstream which is nearest the outflow of two dam release while the USGS stream gage 08074000 is located downstream which is nearest the downtown of Houston. Thus, it could be estimated that about 10,000 – 30,000 cfs (283.17 – 849.51 cms) was distributed to various locations by the dam release, while Harris County Flood Control District estimated an amount of 16,000 cfs (453.07 cms) was released from Addicks and Barker Dams (HCFCD, 2017).

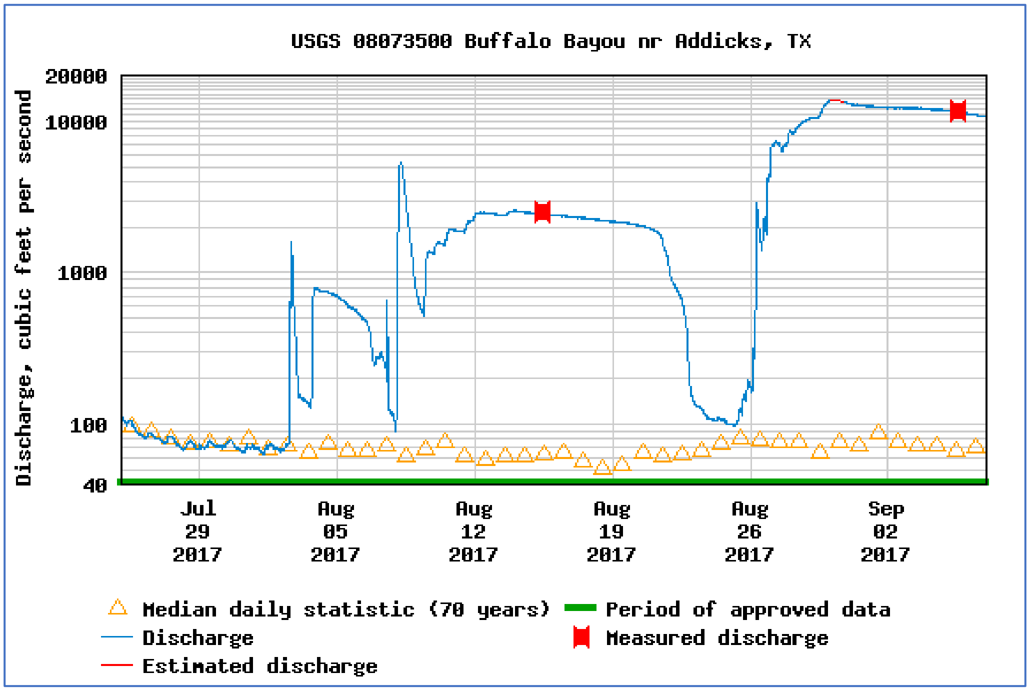

Figure 15. July 25 to September 6 USGS 08073500 hydrograph illustrates that about 10,000 cfs (283.17 cms) was brought from Hurricane Harvey

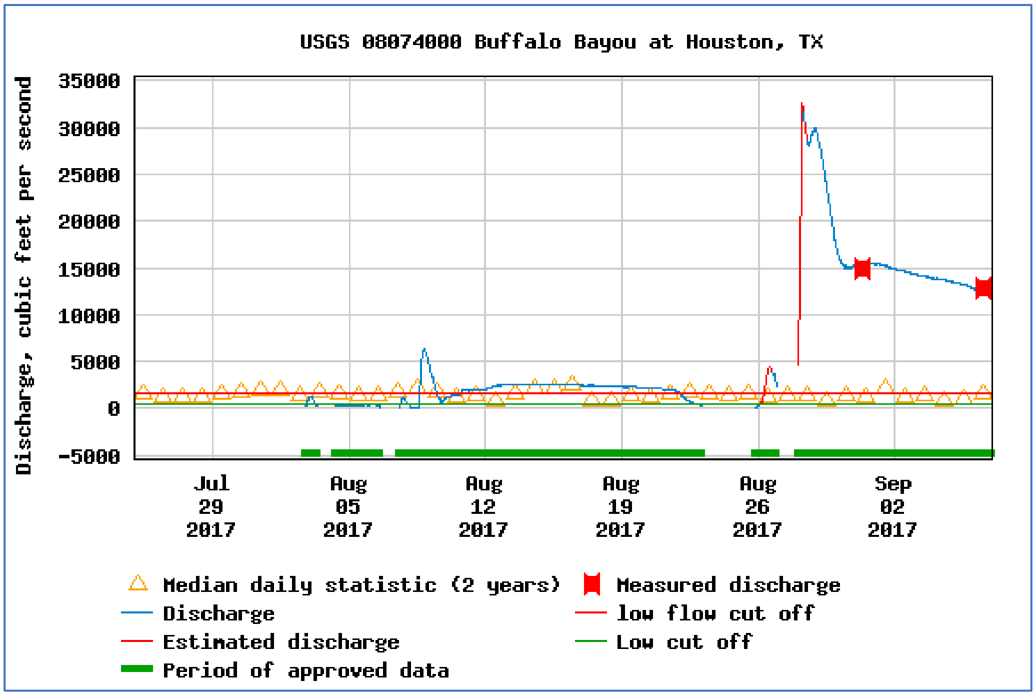

Figure 16. July 25 to September 6 USGS 08074000 hydrograph illustrates that about 30,000 cfs (849.51 cms) was brought from Hurricane Harvey

VI. CONCLUSION

The primary purpose of this study was to evaluate the quality of crowdsourced data for flood mapping of Hurricane Harvey in the Houston area. This study provides a preliminary assessment of data quality of VGI by comparing the WD among crowdsourced data, authoritative data, and modeled output. The theoretical significance of this study as the first study in empirically comparing crowdsourced data with observed and modeled data in flood monitoring. This fills a gap in the literature about the usefulness of crowdsourced data in flood, but also shed useful insights about their spatiotemporal uncertainties (despite there're lots of uncertainties). Being able to prove where and when these uncertainties are with empirical data and visualize them in this study is a good start to understanding the quality of big data analytics. In addition, a practical significance is to learn from this study to better plan crowdsourcing projects ahead of time from the disaster (so there would be less time lag) and be aware of any spatial sampling bias. Findings from this study also open new research agenda in improving and assessing the uncertainty of crowdsourced data quality, and crowdsourcing data supplements in flood mapping research.

The most notable contribution of this study is conducting a comparative assessment in terms of flood extent and WD to evaluate the data quality of the crowdsourced U-Flood dataset. From the comparison results, this study identified that there was a decreasing trend of U-flood observations in both within and outside the modeled floodplain over time in 7 days. The reasons causing these significant differences and geographic distribution are worthy to investigate in future studies and will be insightful to illustrate the appropriate caution to use crowdsourced data as supplementary data for flood mapping. It is noteworthy to pay more attention to evaluate the accuracy of crowdsourced data by checking their quality and improving the workflow to acquire such crowdsourced data. Despite the spatiotemporal uncertainties in the crowdsourced U-Flood dataset (e.g. the lack of water depth, lag reports from the public), it may present an opportunity to serve as supplementary observations to calibrate the hydrologic and hydraulic models, especially in areas without USGS stream gage or not covered by the FEMA floodplain maps. In particular, U-Flood available outside the modeled floodplain could present supplementary data available outside of observed USGS stream gauge and HEC-RAS model. The emergence of such crowdsourced data presents an opportunity to be cautiously capitalized in future citizen science projects.

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