# **Evaluation of Multi-Radar Multi-Sensor (MRMS) and Stage IV Quantitative Precipitation Estimates (QPE) during Hurricane Harvey**

Shang Gao1, Jiaqi Zhang 2, Dongfeng Li 3, Han Jiang4, and Zheng Fang5

## ABSTRACT

Radar-based quantitative precipitation estimate (QPE) serves as input for flood forecasting, and its importance gets magnified during catastrophic storms, like Hurricane Harvey in 2017. The record-breaking rainfall from Hurricane Harvey covered vast spatial extents and lasted for a 5-day period, providing a unique chance for evaluating the radar errors, especially their spatiotemporal dependence. Using the rainfall data of Hurricane Harvey, the authors utilize a new method for sampling ground-based rainfall measurements over radar pixels (i.e. spatial reference rainfall) based on sub-pixel rainfall variability. The new method aims to enlarge sample size and allow for compressively evaluating the QPE. Two hourly QPE products, the Next Generation Weather Radar (NEXRAD) Stage IV and Multi-Radar Multi-Sensor (MRMS), are chosen for the evaluation due to their roles in major flood forecasting activities; and a dense rain gauge network covering the whole Harris County, Texas provides the spatial reference rainfall in this analysis. Comparative analyses are conducted based on Hurricane Harvey and other two flood-inducing storms occurring in 2015 and 2016 over Harris County. The results imply that the Stage IV and MRMS respectively overestimate and underestimate the total rainfall by a small factor, while both QPEs tend to overestimate very light precipitation. In addition, the study suggests that spatial correlation of radar error from both QPEs be described as powered exponential functions of inter-pixel distance. This study also includes hydrologic simulations for an urban watershed, which demonstrates the importance of both accuracy and spatial resolution of QPE in representing mean areal precipitation (MAP) over catchments. The insight gained from this study provides guidance for further improving the QPE performance, and the new sampling approach for spatial reference rainfall can be applied to comprehensively evaluate long-term radar rainfall data.

## KEY TERMS

Stage IV Radar Rainfall; Multi-Radar Multi-Sensor (MRMS) Radar Rainfall; Radar QPE Evaluation; Spatial Reference Rainfall; Hurricane Harvey

## INTRODUCTION

Hurricane Harvey made landfall as a Category 4 hurricane along the middle Texas coast on August 25th, 2017. The storm then stalled with its center near the Houston-Galveston area for four days, generating historic amounts of rainfall (more than 60 inches) over southeastern Texas (Blake and Zelinsky, 2018). The extreme precipitation of Hurricane Harvey caused catastrophic flooding, which inundated more than 300,000 structures and over 500,000 cars, and necessitated 120,000 rescues (Blake and Zelinsky, 2018; FEMA, 2017). During such chaos, the emergency management entities were overwhelmed and in urgent need of assistance. Accurate and timely flood forecasting could help emergency responders to prioritize the limited resources at hand and make the most effective decision at crisis. As the driving input for hydrological simulations, good-quality precipitation measurements play a crucial role in flood prediction. For instance, the rain gauge network has been conventionally used for flood warning. But due to the lack of spatial density of rain gauge network, its role in various forecasting activities has been gradually replaced by quantitative precipitation estimate (QPE) from weather radar systems.

In the early to middle 1990s, the National Weather Service (NWS) installed the Next Generation Weather Radar (NEXRAD) system which currently comprises of 160 WSR-88D radars across the United States (NCEI, 2018). Over almost two decades, the NEXRAD precipitation products have undergone a series of improvements and are currently in the fourth stage. NEXRAD precipitation products (Stages I, II, III, and IV) from the River Forecast Centers (RFCs) have been applied to hydrometeorology (Smith et al., 2001, 2002; Zhang and Smith, 2003); hydrologic analyses (Vieux and Bedient, 1998; Bedient et al., 2000; Fang et al, 2008; Fang et al, 2011; Juan et al., 2015; Torres et al., 2015; Bass et al., 2016; Gao and Fang, 2018); remote sensing validation (Krajewski and Smith,2002; Habib and Krajewski, 2002). The Stage IV product is a national mosaic of regional multi-sensor (combination of quality-controlled WSR-88D, satellite, and rain gauge data) precipitation estimates that are produced hourly at the NWS RFCs for operational hydrologic forecasting at the Hydrologic Rainfall Analysis Project (HRAP) grid of approximately 4 × 4 km2 spatial resolution (Lin and Mitchell, 2005; Habib et al, 2009).

As another emerging radar-based weather sensing/monitoring system, Multi-Radar Multi-Sensor (MRMS) system has become operational at the National Centers for Environmental Protection (NCEP) since September 2014 (Zhang et al. 2014, 2016). By integrating over 180 radars, 7,000 hourly rain gauges, and numerical weather prediction outputs across the continental United States, MRMS has four types of quantitative precipitation estimation (QPE) products including 1) radar-only QPE, 2) gauge-only QPE, 3) local gauge bias-corrected radar QPE (Q3gc), and 4) gauge and precipitation climatology merged QPE (Zhang et al, 2016). The hourly rain gauge data used for bias-correction in MRMS are quality-controlled from the Hydrometeorological Automated Data System (HADS; [www.nws.noaa.gov/oh/hads/](http://www.nws.noaa.gov/oh/hads/)). The new National Water Model (NWM) that has been operational since August 2016 (NOAA, 2016) utilizes hourly precipitation forcing in real time from the MRMS system to improve “street level” water information services over the continental U.S.

Precipitation measurements should be taken at a sufficiently high spatial and temporal resolution to represent the dynamic characteristics of storms. However, due to the indirect nature of radar measurement, radar-based rainfall products are subject to uncertainties, which will be inevitably propagated through further hydrologic simulations (Krajewski and Smith, 2002). Therefore, previous studies were conducted to evaluate the radar rainfall products, especially for the NEXRAD radar products. Habib et al. (2008) utilized a dense rain gauge network in Mississippi to evaluate various aspects of the errors in the Stage III products and the associated implications on streamflow simulation and concluded that bias adjustment can improve runoff prediction significantly. Wang et al. (2008) compared the Stage IV product with rain gauge measurements for a watershed in Texas and found that Stage IV products were better at rain detection than rain gauge network for a studied watershed. Habib et al (2009) used a dense rain gauge network in Louisiana to validate the Stage IV product and demonstrated its improved performance mainly due to the continuous algorithm update. These research efforts were motivated by a common focal point: how point measurements of rainfall (rain gauge data) can be used to represent the surface rainfall over an HRAP pixel (4 x 4 km2) over a small temporal scale (say an hour), or simply how to provide accurate hourly surface reference rainfall? Filtering criteria has been applied in these previous studies to select qualified radar pixels for evaluation, which might have resulted in the exclusion of useful data samples. In this study, the authors intend to simultaneously acquire the accuracy and the size of spatial reference rainfall data samples based on a new method, and to demonstrate this approach with Hurricane Harvey (2017).

Hurricane Harvey was regarded as one of the most severe tropical cyclones in the United States history, according to spatial coverage and peak rainfall amount. The highest total rainfall recorded by a rain gauge during Hurricane Harvey was 154 cm (60.58 inches) in Nederland, northeast of Houston, which was nearly 9 inches higher than the previous record of 132 cm (52 inches) from Hurricane Hiki, in August 1950 (Blake and Zelinsky, 2018). **Figure 1** shows a comparison of the total precipitation over the Harris County generated by Hurricane Harvey and other two flood-inducing storms in Houston (2015 Memorial Day storm on May 25th, 2015 and 2016 Tax Day storm on April 17th, 2016) based on the MRMS gauge-corrected rainfall (Q3gc product). The comparison highlights the exceptional total rainfall amount of Hurricane Harvey due to its intensity and, more importantly, its five-day duration. In addition, the areal extent of heavy rainfall from Hurricane Harvey was truly overwhelming, with almost the entire Harris county receiving over 70 cm (about 2.3 ft) of rainfall. From the perspective of QPE evaluation, any rainfall events with large areal coverages and long durations tend to generate a large quantity of data samples. Therefore, Hurricane Harvey provides an opportunity for the authors to investigate spatial and temporal structures of radar errors, which would otherwise be hindered using small-scale short-duration storms.

**[INSERT FIGURE 1 HERE] Figure 1: Cumulative rainfall based on the MRMS data of A) 2015 Memorial Day storm on May 25th, 2015, B) 2016 Tax Day storm on April 17th, 2016 and C) Hurricane Harvey on August 25th, 2017, respectively.**

Despite its importance, accurate QPE doesn’t necessarily guarantee the optimal representation of precipitation as an input to hydrologic models. This is because the mean areal precipitation (MAP) is the actual input to catchments or grid boxes that make up watershed or model domain in hydrologic models. Given that the true MAP can’t be measured easily, comparison between the simulated flow/stage from hydrologic models and the observed values can indirectly reflect the uncertainty associated with MAP. Previous research efforts have been invested in examining the uncertainty within streamflow simulation induced by radar error (e.g. Yilmaz et al., 2005; Habib et al., 2008; Gourley et al., 2011). These studies were conducted upon the premise that MAP is the primary, if not the only, contributor to the uncertainty in model output. In other words, uncertainties from other sources (e.g., model structure, model parameters and state variables) need to be minimized. For instance, if a hydrologic model is well calibrated for a highly urbanized watershed with saturated soil, the uncertainty in simulated streamflow can then be linked to that in MAP, instead of in infiltration process. During Hurricane Harvey, an urban watershed - Brays Bayou in Harris County was considered a sufficient study area, as heavy rainfall rendered the soil fully saturated. Therefore in this study, the Brays Bayou watershed during Hurricane Harvey is selected to investigate the implication of MAP estimation on hydrologic simulation.

Given the importance of Stage IV and MRMS hourly QPEs in operational flood forecasting, the authors are motivated to evaluate their performance during Hurricane Harvey, to achieve better preparedness and decision making for future floods. Hurricane Harvey, as an unprecedented tropical rainfall event, presented a unique research opportunity for the authors to demonstrate the new sampling method in terms of increasing sample size and better understanding of the spatiotemporal structure of radar error via the following objectives:

1. To construct the spatial reference rainfall datasets over the scale of the radar pixels from a dense rain gauge network during 2015 Memorial Day storm, 2016 Tax Day storm and 2017 Hurricane Harvey in Harris County, Texas;
2. To examine the radar errors in terms of bias, conditional dependence on rainfall intensities and spatiotemporal structure;
3. To investigate the implication of radar errors for the accuracy of hydrologic simulation and prediction by analyzing runoff behaviors simulated by hydrologic models of Brays Bayou in Harris County.

## STUDY AREA AND DATA

Harris County is the third-most populous county in the United States and includes the largest city in Texas – Houston. **Figure 2** shows the area of this study, which is Harris County with 4,602 km2 located in the State of Texas. **Figure 3** shows the Brays Bayou watershed, where the hydrologic simulation is examined in this study. As one of the flood-prone urban watersheds, Brays Bayou is 95% developed with a population of more than 722,000 people, making it one of the most urbanized watersheds in Harris County, Texas (Harris County Flood Control District, 2017). The high tendency of flooding in this watershed is due to flat slopes, impermeable land surface and clay soils, and the explosive rainfall (Bedient et al., 2003; Bedient et al., 2007; Fang et al., 2008; Fang et al, 2011; Fang et al., 2014; Bass et al., 2016; Gao and Fang; 2018). There are four junctions with reliable streamflow observation during Hurricane Harvey from United States Geological Survey (USGS) gauges (**Junction 1**/USGS8074760@Belle Park Dr., **Junction 2**/USGS8074810@S. Gessner Rd., **Junction 3**/USGS8075000@Main St., and **Junction 4**/USGS8075110@MLK Blvd.).

**[INSERT FIGURE 2 HERE] Figure 2: Study area and the rain gauge network.**

**[INSERT FIGURE 3 HERE] Figure 3: The Brays Bayou watershed, Houston, Texas.**

The rain gauge observations were collected from the website of Harris County Flood Warning System (Retrieved on Sep 1, 2017, https://www.harriscountyfws.org). This Flood Warning System, which measures rainfall amounts and monitors water levels in bayous and major streams on a real-time basis, is operated and maintained by the Harris County Flood Control District (HCFCD). The system relies on 154 gauge stations strategically placed throughout Harris County bayous and their tributaries. For QPE evaluation, the surface reference rainfall needs to be independent from the QPE products (Habib et al, 2009). In other words, the rain gauges serving as “truth” should not overlap with those used by NWS in developing or adjusting the bias of QPE estimates. Therefore, the HADS rain gauges (white dots in **Figure 2**) are not utilized for evaluating the radar QPE, as they are already incorporated in processing the Stage IV and MRMS hourly gauge-corrected products.

The radar rainfall data used in this study are the Stage IV product and the MRMS Q3gc product, which are later referred to as Stage IV and MRMS, respectively. The Stage IV data is provided by the West Gulf River Forecast Center (WGRFC), whose service boundary fully encompasses the study area, Harris County. The MRMS are radar-only estimates locally adjusted by hourly HADS gauge data using an inverse distance weighting (IDW) scheme (Zhang et al, 2016; Cocks et al. 2017). As aforementioned, the Stage IV and MRMS have the same temporal resolution of one hour, but different spatial resolutions of 4 × 4 km2 and 1 × 1 km2, respectively. From the available period of both Stage IV and MRMS, three severe storm events, 2015 Memorial Day storm, 2016 Tax Day storm and Hurricane Harvey were selected for analysis, with their starting and ending times summarized in **Table 1**.

**[INSERT TABLE 1 HERE] Table 1: Starting and ending times for the three selected historical storms**

## APPROACH AND METHODS

### Surface Reference Rainfall

MRMS has high spatial resolution of 1 × 1 km2, thus are directly compared with rain gauge measurements in this study. However for Stage IV, it is recognized that rain gauges at hourly or smaller scales may be limited by their near-point sampling and may not provide acceptable approximation of surface rainfall over the 4 × 4 km2 cell (Habib et al., 2009). Therefore, the critical issue in evaluating hourly Stage IV QPE has been how to get a measurement representing the areal average rainfall over a HRAP cell (Kitchen and Blackall, 1992). In previous studies, high-density rain gauge network (4 -10 gauges within each HRAP cell) has been used (Ciach and Krajewski, 1999; Habib and Krajewski, 2002; Ciach et al., 2003; Habib et al., 2004), which is however limited in spatial coverage and costly to implement and maintain. Wang et al (2008) utilized a method to select Stage III hourly radar estimates (also with 4 × 4 km2 resolution) only during uniform rainfall for evaluation. Although Wang et al (2008) managed to utilize even sparse rain gauge network (e.g., one gauge per HRAP cell), their definition for “uniform rainfall” is not based on the spatial variability of rainfall within the target radar cell (sub-pixel variability) but that among the target radar cell and its eight neighboring cells (inter-pixel variability).

In order to make improvements, the authors investigate sub-pixel spatial variability of hourly rainfall within a HRAP cell and further determine if the gauge(s) within the HRAP cell can sufficiently represent its areal average rainfall intensity. This new method features evaluating one type of radar QPE of coarser spatial resolution (i.e. Stage IV) using another kind of radar QPE of finer spatial resolution (i.e. MRMS). The MRMS QPE values at the gauge(s) and those encompassed by the HRAP cell boundary are compared to determine whether the rainfall values inside the HRAP cell are uniform enough such that their mean can be approximated by the gauge values. **Figure 4** illustrates the selection scheme for spatial reference rainfall data. The black square in bold is an HRAP cell of interest; the grey cells are the MRMS cells encompassed by the HRAP cell based on cell centroid location; and the three shaded grey cells represent MRMS cells with rain gauges inside. At a given hour, if the averaged MRMS rainfall of the grey cells (including the shaded ones) is sufficiently close to (90% to 110% of) the averaged MRMS rainfall of the shaded grey cells, it will be determined that the averaged rain gauge measurements can represent the mean areal precipitation (MAP) of the HRAP cell. Here, the authors employ a 10% threshold to determine if the mean of the rain gauge measurements could approximate the MAP of the HRAP cell. It is worth noticing that this method does not necessarily assume that MRMS QPE in the HRAP cell is true or unbiased, but that the MRMS QPE can adequately preserve the spatial variability of rainfall within the 4 km × 4 km scale. By applying the selection scheme to all the HRAP cells containing at least one rain gauge and for all the hours during storm events, the authors can then make the best use of data to comprehensively evaluate the QPEs via statistical metrics introduced in the following section. In comparison, the new method can generate a spatial reference rainfall sample three times the size of that from the traditional method in which only the HRAP cells with two or more gauges are selected.

**[INSERT FIGURE 4 HERE] Figure 4: Selection scheme for hourly spatial reference rainfall**

### Statistical Metrics

### Error

Error is defined as the deviation of radar rainfall estimates from the rain gauge observations, as shown by **Equation 1**.

(1)

where *Re* and *Ro* are hourly rainfall intensities from radar QPEs and rain gauges, respectively. Due to **Equation 1**, error that is greater (smaller) than 1 means overestimation (underestimation).

### Overall Bias

In order to investigate the systematic performance of the QPEs, overall bias (OB) is used to measure the averaged deviation of the rainfall estimates (*Re*) from observations (*Ro*), as represented by **Equation 2**.

(2)

In this study, *OB* is calculated with respect to individual storms, which means expectation (*E[]*) is calculated by temporally averaging the estimates or observations over the duration of a storm event. To examine the spatial variability of OB, the authors calculate OBs for each radar pixel separately. In addition, for radar pixels that encompass multiple rain gauges, the *Ro* is the arithmetic mean of the values from corresponding gauges.

### Conditional Bias

It has been found by previous researchers that radar rainfall bias can depend on the magnitude of estimated rainfall intensity (Ciach et al., 2000). Using moving average windows, the authors calculate the conditional bias (*CB*) using the following **Equation 3**.

(3)

where *a* and *b* are lower and upper limits of moving average window.

### Spatial and Temporal Autocorrelations of Error

In addition to bias analysis, spatial and temporal dependence of error needs to be assessed to infer the adequacy of bias adjustment in improving radar QPEs. The authors estimate the spatial autocorrelations of *ɛ* from marginal samples of *ɛ* at each time step, while the temporal autocorrelations are based on marginal samples of *ɛ* at all selected pixels. **Equation 4** below is the Moran’s I (Moran, 1950), as a measure of the spatial autocorrelation.

(4)

where *I (d)* is the Moran’s I as a function of distance *d*; *ɛi* and *ɛj* are errors at location *i* and *j*; *wij* is a weight of 0 or 1, 1 meaning that *ɛi* and *ɛj* are within a given distance class and 0 being all the other cases; and *W* is the sum of all *wij*; and *n* is the sample size. The temporal autocorrelation (Box and Jenkins, 1976) is defined as **Equation 5** below:

(5)

Where *r(τ)* is the autocorrelation of lag *τ*; *ɛi* and *ɛi+τ* are errors at *i*th hour and (*i+τ*) th hour; and *m* is the sample size. It should be noted that only the marginal samples with sufficient size (>= 200) are included in the analysis. This is the very reason why Hurricane Harvey provided an opportunity for investigating spatiotemporal structure of radar error, as the storm covered vast areas and lasted for a total of 5 days generating large samples of radar error information. In previous researches (Kessler and Neas, 1994; Habib et al., 2001b), sample size has been a limitation for estimating correlations at large spatial and temporal lags. However, the authors take advantage of Hurricane Harvey and present a more complete spatiotemporal structure of radar error during this event.

### Hydrologic Simulation

A hydrologic (Hydrologic Engineering Center Hydrologic Modeling System, HEC-HMS) model is used to simulate hydrologic response from Brays Bayou during Hurricane Harvey. The HEC-HMS model is part of the products from the Tropical Strom Allison Recovery Project (TSARP), which was initiated by the devastating impact from Tropical Storm Allison (2001). Calibration effort was invested to improve the hydrologic simulation of this model in several studies (Fang et al., 2011; Bass et al., 2016; Gao and Fang, 2018). Fang et al. (2011) conducted an analysis using storm events with accumulated rainfall ranging from 3.3 cm (1.3 inches) to 19.5 cm (7.8 inches) and found that the model had predicted floods with an average of 3.6% difference in peak flows and a R2 value of 0.90 for the overall performance from 2002 to 2010. Bass et al. (2016) updated soil/land use information in the model to best represent the actual land use conditions. Gao and Fang (2018) validated the model performances at all four USGS gauge locations during the 2015 Memorial Day storm and the 2016 Tax Day storm using the MRMS Q3gc product. With the well calibrated HEC-HMS model, the authors compare simulated hydrographs from three rainfall input data, i.e. Stage IV, MRMS and rain gauge. The two radar QPE products (Stage IV and MRMS) are processed into time series of MAP for each subbasin using the Hydrologic Engineering Center Meteorological Visualization Utility (HEC-MetVUE) program, while the rain gauge records are allocated into each subbasin using the Thiessen Polygon method (Brassel and Reif, 1979). Given the fact that infiltration of the study area plays very minor role in hydrologic simulations because Brays Bayou is 95% developed and the watershed is mostly impervious, the initial soil moisture is assumed to be fully saturated in the Green and Ampt method, meaning that all rainfall will be transformed to runoff in the HEC-HMS simulations. Four statistics are used to quantitatively evaluate model performance in runoff and streamflow, as shown in **Equations 6** to **9**.

Runoff volume error: (6)

Peak flow error: (7)

Root mean square error (RMSE): (8)

Nash–Sutcliffe model efficiency coefficient (NSE): (9)

where *n* is number of hours in the hydrographs, *Q* is runoff discharge, with the subscript ‘*max*’ denoting the peak value and the superscripts ‘*sim*’ and ‘*obs*’ denoting simulation and observation, respectively. The operator “”means arithmetic averaging.

## RESULTS AND DISCUSSION

As an overview of all data samples involved in this analysis**, Figure 5** shows scatter plots of Stage IV and MRMS hourly QPE against rain gauge data for the three investigated storm events (2015 Memorial Day storm, 2016 Tax Day storm, and 2017 Hurricane Harvey), along with coefficient of determination (R2), root square mean error (RMSE) and sample size (upper right table). The difference in sample size results from the Stage IV selection scheme that filters out about 50% of the data samples. It is found that both QPEs (Stage IV and MRMS) reached high R2 values (over 0.8), showing good overall performance during the storms. Given that there is no clear indication of biases for either QPE solely based on the scatter plot, the authors conduct the following analysis in overall bias.

**[INSERT FIGURE 5 HERE] Figure 5: Scatter plots of Stage IV and MRMS hourly QPE from the three storm events combined.**

### Overall Bias

Overall bias (OB) is quantified based on **Equation** **2** for each radar pixel and each storm to examine any spatial variability and inter-storm variability. **Figures** **6 and 7** show the maps for OB calculated at selected radar pixels of Stage IV and MRMS, for the 2015 Memorial Day storm (**6A** and **7A**), the 2016 Tax Day storm (**6B** and **7B**) and the 2017 Hurricane Harvey (**6C** and **7C**). It is found that there is no distinct spatial pattern of OB for either QPE or any storm event. The mean OB values from individual storm and all storms combined indicate overestimation by Stage IV and underestimation by MRMS, except for the case of Stage IV during the 2016 Tax Day storm. In the case of Stage IV, approximately 43%, 66%, and 30% of the data samples have OB values smaller than 1 (signified by the white dots) for the 2015 Memorial Day storm, the 2016 Tax Day storm and the 2017 Hurricane Harvey, respectively. In comparison, the majority of the OB values for MRMS are smaller than 1, with 95%, 90%, and 90% of the data samples represented by white dots for the three storms respectively. The statistics, including average, min, max, and total sample size of the OB values for each storm separately and for all storms combined are also summarized in **Table 2.** It is worth noticing that,for both QPEs, the distinctly large sample size from Hurricane Harvey (2017) is due to the vast spatial coverage and long duration of the storm. In summary, MRMS is found to carry the tendency of underestimating precipitation by a factor of 12% (OB = 0.88) for three storms combined, while Stage IV shows better performance in capturing the mean (temporally averaged) rainfall amount with an overestimation of 2% (OB = 1.02).

**[INSERT FIGURE 6 HERE] Figure 6: Overall bias of Stage IV for A) 2015 Memorial Day Storm, (B) 2016 Tax Day Storm, and (C) 2017 Hurricane Harvey, respectively.**

**[INSERT FIGURE 7 HERE] Figure 7: Overall bias of MRMS for A) 2015 Memorial Day Storm, (B) 2016 Tax Day Storm, and (C) 2017 Hurricane Harvey, respectively.**

**[INSERT TABLE 2 HERE] Table 2: OB summary table**

### Conditional Behavior of Radar Error

While overall bias represents the average behavior of radar error, the conditional behavior of radar error depending on the rainfall intensity has been demonstrated by previous researchers and thus needs to be investigated (Ciach et al., 2000; Ciach et al., 2007; Habib et al., 2008). Therefore in this study, the authors also examine the radar errors, conditioned on hourly rainfall intensity from rain gauges. Since this analysis is event-based and lacks large volume of data, it is important to consider the distribution of utilized data samples before investigating the conditional behavior of radar error. Therefore, the authors present a 2-D histogram of the combined data samples from all three storms plotted on log-scale radar error and log-scale hourly gauge rainfall intensity for Stage IV and MRMS in **Figures 8A** and **8B** respectively. The log-scale axes are used in plotting because both radar error and rainfall intensity are log-normally distributed. It is found that the two data samples (Stage IV and MRMS) share a similar distribution pattern along the X-axis, which means Stage IV data samples, though smaller in size, do capture the same distribution of rainfall intensities as the MRMS data samples. It is shown in both **Figures 8A** and **8B** that the sample population is divided by a gap located just above 1.5 mm/hr. This is due to the fact that readings from tipping bucket rain gauges are the number of tipping multiplied by the unit volume of each tip (in this case 0.04 inches or 1.016 mm). As for Stage IV (**Figure 8A**), these data samples mostly show overestimation with radar errors over one, while in the case of MRMS (**Figure 8B**) they seem to evenly distribute around one.

Keeping the data sample distribution in perspective, the authors further calculate the conditional bias for both QPEs using the same measures to divide sample population (equal interval in log scale) as in the 2-D histograms. **Figures 9A** and **9B** show the conditional bias (CB) against the hourly gauge rainfall intensity both plotted in log scale for Stage IV and MRMS, respectively. It can be found that Stage IV overestimates very light rainfall (< 1.5 mm/hr) and the overestimation decreases with increasing rainfall intensity; Stage IV exhibits steady and good performance with a slight overestimation when rainfall ranges from 3.5 mm/hr to 25 mm/hr. In comparison, MRMS shows small overestimation for rainfall lighter than 1.5 mm/hr and a steady but slight underestimation for rainfall from 3.5 mm/hr to 25 mm/hr. Despite the limited spatial and temporal extent of data in this analysis, the findings echo with those reported by previous researchers. For instance, Nelson at el. (2016) conducted a comprehensive assessment of Stage IV for the Continental United States (CONUS) over the period 2002-2012, and found that larger overestimation exists for light rainfall for all RFCs and all seasons. The overestimation of light rainfall by the MRMS was founded by Cocks et al. (2017) who evaluated the MRMS Q3gc (gauge corrected) products at east of the Rockies during 2014 warm seasons. For both Stage IV and MRMS, this common issue of overestimating light rainfall is probably due to precipitation evaporating before reaching the gauge and gauge wetting losses, as speculated by previous researchers (Catizone et al. 2014; Cocks et al. 2017).

**[INSERT FIGURE 8 HERE] Figure 8: 2-D histogram of radar error from the three storm events combined for (A) Stage IV and (B) MRMS.**

**[INSERT FIGURE 9 HERE] Figure 9: Conditional bias from the three storm events combined for (A) Stage IV and (B) MRMS.**

### Spatial and Temporal Structure of Radar Error

Although the conditional behavior of radar error is recognized in the prior section, it is unclear whether the radar errors have distinct spatial and temporal dependence. As shown in **Figures 6 and 7**, the maps of OB show no explicit spatial pattern in terms of the averaged deviation from the radar estimates to the gauge measurements. However, it is still possible that the radar errors can exhibit clustering pattern in space, therefore it is necessary to decipher the spatial dependence of the radar error using spatial autocorrelations. **Figures 10A and 10B** respectively show the spatial autocorrelation coefficients (Moran’s I) of Stage IV and MRMS radar errors (ɛ) calculated based on **Equation** **4** at intervals of radar pixel size (4 km for Stage IV and 1 km for MRMS) for the three storms. The sample size used for calculating each coefficient is also presented as the inverted bars in **Figures 10A and 10B**. It should be noted that the Moran’s I values are based on marginal samples collected at all time steps and only those with sample sizes larger than 200 are displayed; the remarkably larger sample size from Hurricane Harvey as shown in both **Figures 10A and 10B** is mainly caused by its 5-day duration. Due to the clear difference in sample size, Hurricane Harvey ought to yield the most representative result among the three storms. For Hurricane Harvey (2017), the Moran’s I values for both QPEs are relatively high at short spatial lag, with Stage IV yielding 0.68 at 4 km and MRMS yielding 0.7 at 2 km. In addition, the Moran’s I values, in all six cases (two QPEs and three storms), are fitted to powered exponential functions, meaning that the correlation of the radar error ɛ decays exponentially with increasing spatial spacing. This finding widely echoes with previous studies in radar error modeling where the spatial correlation function is parameterized by fitting a two-parameter power exponential function (Mandapaka et al., 2010; Dai et al., 2014; Ko et al., 2018).

**[INSERT FIGURE 10 HERE] Figure 10: Spatial autocorrelation coefficients of radar errors from the three storm events separately for (A) Stage IV and (B) MRMS.**

In the similar fashion as **Figures 10A and 10B**, the temporal autocorrelations of radar error are presented in **Figures** **11A** and **11B**, except that the only results from Stage IV during Hurricane Harvey and MRMS during 2016 Tax Day storm and Hurricane Harvey are displayed because of the sample size limit (>200). Due to its vast spatial coverage, Hurricane Harvey generates the most marginal samples collected at the selected radar pixels, as indicated by the inverted bars. It is found that no significant autocorrelation exists at any temporal lag for the storms or for either QPE, meaning that no persistence is observed in the temporal variation of radar error. Previous studies seemed to diverge regarding the temporal structure of radar errors: some found insignificant temporal correlations as this study does (e.g., Habib et al. 2008); while other studies on radar error modeling utilized autoregressive lag-one model assuming positive correlation at small time step (e.g., Ko et al., 2018). In spite of the differences among the previous studies, most of them lacked sufficient observations to firmly support any conclusion or assumption on the temporal structure of radar errors. More research is thereby needed to understand the spatiotemporal correlations of radar errors for various types of rainfall and radar data (Peleg et al., 2013). Herein, the authors intend to emphasize that sample size is vital for estimating the correlation coefficients and thus should be maximized (Kessler and Neas, 1994; Habib et al, 2001a). Therefore, to augment and verify the findings from this study, the authors will apply the new sampling approach to long-term radar and rain gauge data in a future study.

**[INSERT FIGURE 11 HERE] Figure 11: Temporal autocorrelation coefficients of radar errors from the three storm events separately for (A) Stage IV and (B) MRMS.**

### Hydrologic Simulation

The calibrated HEC-HMS model was used to simulate runoff during Hurricane Harvey with three types of rainfall inputs, i.e. Stage IV, MRMS, and rain gauge. Comparisons are made between simulated stream flow and the observed at four junctions along Bray Bayou (**Junction 1**/USGS8074760@Belle Park Dr.; **Junction 2**/USGS8074810@S. Gessner Rd.; **Junction 3**/USGS8075000@Main St.; and **Junction 4**/USGS8075110@MLK Blvd.) (see Figure 3). Differences between simulated and observed hydrographs are summarized statistically (**Table** **3)** using the **Equations 6** to **9** and presented visually in **Figure** **12**:

**[INSERT TABLE 3 HERE] Table 3: Summary of hydrograph comparison** **[INSERT FIGURE 12 HERE] Figure 12: Simulated and observed hydrographs for Hurricane Harvey in Brays Bayou at (A) Junction 1/USGS8074760@Belle Park Dr., (B) Junction 2/USGS8074810@S. Gessner Rd., (C) Junction 3/USGS8075000@Main St., and (D) Junction 4/USGS8075110@MLK Blvd..**

Based on *RMSE*, *NSE* and hydrograph shape, simulations driven by MRMS and rain gauge generate equally better overall match with the observations than those from Stage IV at all junctions. The *Pe* and *Ve* values indicate that peak flow and runoff volume are overestimated in the Stage IV hydrographs at most junctions. Because of the model calibration effort, the saturated soil moisture, and the impervious land cover of Brays Bayou, the runoff simulation error herein is mainly attributed to the MAP estimation error instead of other modeling and parameter uncertainties. **Table** **4** summarizes two factors in the three rainfall inputs affecting MAP estimation: (1) being the averaged overall bias () of the rainfall measurements enclosed by the Bray Bayou boundary; (2) spatial resolution being the area of radar pixel in the cases of QPEs and the average area of Theissen polygons in the case of rain gauge. According to values, Stage IV and MRMS respectively overestimate ( = 1.11) and underestimate ( = 0.94) the rainfall in Brays Bayou, which corresponds to their *Ve*  values of 28% and -5% at Junction 4 (near the watershed outlet). Furthermore, it is worthwhile noticing the implication of spatial resolution on the accuracy of MAP estimation. Of all three rainfall inputs, MRMS has superior spatial resolution, while Stage IV and rain gauge are coarser. When combining and spatial resolution, one can find that Stage IV produces lesser MAP estimation, as it has the largest and coarsest spatial resolution. The difference in spatial resolution also explains why the hydrologic simulations driven by rain gauge and MRMS perform similarly despite that the rain gauge measurement is unbiased ( = 1).

**[INSERT TABLE 4 HERE] Table 4: Averaged overall bias and spatial resolution of rainfall inputs.**

Using one watershed (Brays Bayou) in the Harris County, the authors cannot simply determine the better QPE product (Stage IV or MRMS) for flow simulations during Hurricane Harvey, but would like to emphasize the significance of spatial resolution of QPE in MAP estimation. When rainfall estimates are unbiased, the uncertainty in MAP estimation can be analytically decomposed into two components: (1) the fractional coverage of rainfall over catchments and (2) the spatial variability of rainfall itself, or inner variability (Entekhabi and Eagleson, 1989; Barancourt et al., 1992; Seo and Smith, 1996; Zhang and Seo, 2017). Uncertainty in estimating the first component depends on the spatial resolution of QPE in a way that QPE with the higher resolution better represents the fractional coverage of rainfall over catchments.

## CONCLUSIONS AND FUTURE WORK

The authors investigate the performances of two hourly radar QPEs, the NEXRAD Stage IV and the MRMS Q3gc products, because of their important roles as precipitation input in major operational river forecasting activities. A new sampling approach for spatial reference rainfall is introduced in this study, which features resolving spatial variability of one QPE at sub-pixel level by using another QPE with finer spatial resolution. Due to the vast spatial coverage and long duration, Hurricane Harvey (2017) provides a unique opportunity to demonstrate this new methodology. In comparison to the other two flood-inducing storm events (2015 Memorial Day storm and 2016 Tax Day storm) occurring in Harris County, Texas, Hurricane Harvey shows not only its exceptional rainfall magnitude but also the importance of sample size in studying the spatiotemporal characteristics of radar error. Thanks to the excellent spatial scale and density of HCFCD rain gauge network, the authors manage to effectively collect sufficient spatial reference rainfall samples with the new approach and then evaluate the radar errors in terms of bias, conditional dependence on rainfall intensities and spatiotemporal structure. Several major findings from this study are summarized as below:

1. Serving as truth in QPE evaluation, sufficient spatial reference rainfall samples are vital for truthfully revealing the performance of QPE as well as various aspects of radar error. The collection of spatial reference rainfall should be based on spatial rainfall variability at sub-pixel level.
2. The Stage IV and MRMS QPEs perform fairly well during the three investigated storms: with Stage IV overestimating and MRMS underestimating the hourly rainfall by 2% and 12% respectively. Both QPEs tend to overestimate very light rainfall.
3. Spatial correlation of radar errors from both QPEs can be described as powered exponential functions of inter-pixel distance. No significant temporal correlation of radar errors is found in this study for either QPE at any temporal lags.
4. Spatial resolution of QPE determines the estimation of mean areal precipitation (MAP) as the inputs to hydrologic simulations.

The insight gained from investigating radar error will enable us to further improve QPE performance in two ways: (1) to improve the rainfall estimation algorithm accounting for conditional biases; (2) to model radar error as spatially and temporally correlated random process. In addition, the sampling approach of spatial reference rainfall is not limited to Stage IV and MRMS, as long as two utilized QPE products have different spatial resolutions and overlapping spatial and temporal extents. Therefore, this approach can be applied more broadly. For instance, provided available rain gauge records, 20 years of the multi-senor precipitation estimates (MPE, 4 × 4 km2) covering the CONUS can be evaluated by utilizing the corresponding reflectivity product (1 × 1 km2) converted to rainfall intensity using Radar Reflectivity-Rainfall Rate (Z-R) relationship. Such research will be presented in a forthcoming paper.

## ACKNOWLEDGMENT

The authors would like to thank the West Gulf River Forecast Center (WGRFC) for providing radar rainfall data, and the Harris County Flood Control District (HCFCD) for providing the rain gauge data.

## REFERENCES

Bass, B., Juan, A., Avantika, G., Fang, Z., and Bedient, P.B. (2016). “2015 Memorial Day Flood Impacts for Changing Watershed Conditions in Houston, TX”. ASCE *Journal of Natural Hazards Review*, [10.1061/(ASCE)NH.1527-6996.0000241](http://ascelibrary.org/doi/abs/10.1061/%28ASCE%29NH.1527-6996.0000241), 05016007.

Barancourt, C., Creutin, J. D., & Rivoirard, J. (1992). A method for delineating and estimating rainfall fields. *Water Resources Research*, 28(4), 1133-1144.

Bedient, P.B., Hoblit, B.C., Gladwell, D.C., and Vieux, B.E. (2000). NEXRAD Radar for Flood Prediction in Houston. *Journal of Hydrologic Engineering* 5, 269-277.

Bedient, P. B., Holder, A., Benavides, J. A., and Vieux, B. E. (2003). Radar-based flood warning system applied to Tropical Storm Allison. *Journal of Hydrologic Engineering* 8(6), 308–318.

Bedient, P. B., Holder, A., and Thompson, J. F., and Fang, Z. (2007). “Modeling of Stormwater Response under Large Tailwater Conditions – Case Study for the Texas Medical Center”. ASCE *Journal of Hydrologic Engineering*, Vol. 12, No. 3, May 1, 2007, ISSN 1084-0699/2007/3-256-266.

Blake E. S., & Zelinsky D. A. (2018). Hurricane Harvey - National Hurricane Center - NOAA. <https://www.nhc.noaa.gov/data/tcr/AL092017_Harvey.pdf>

Brassel, K. E., & Reif, D. (1979). “A procedure to generate Thiessen polygons”. *Geographical Analysis*, 11(3), 289-303.

Catizone, P. A., Zell, S. E., Arrington, C. R., Newman, M. B., Weber, S. F., and White, R. J. (2014). Comparative Statistical Study of Hourly Precipitation Determined by Radar-Based Stage IV and Ground-Based Methods in the North Central United States. *Journal of the Air and Waste Management Association* 64(3), 291-308.

Ciach, G. J., & Krajewski, W. F. (1999). Radar–rain gauge comparisons under observational uncertainties. *Journal of Applied Meteorology*, 38(10), 1519-1525.

Ciach, G. J., Morrissey, M. L., & Krajewski, W. F. (2000). Conditional bias in radar rainfall estimation. *Journal of Applied Meteorology*, 39(11), 1941-1946.

Ciach, G. J., Habib, E., & Krajewski, W. F. (2003). Zero-covariance hypothesis in the error variance separation method of radar rainfall verification. *Advances in Water Resources*, 26(5), 573-580.

Ciach, G. J., Krajewski, W. F., & Villarini, G. (2007). Product-error-driven uncertainty model for probabilistic quantitative precipitation estimation with NEXRAD data. *Journal of Hydrometeorology*, 8(6), 1325-1347.

Cocks, S. B., Zhang, J., Martinaitis, S. M., Qi, Y., Kaney, B., and Howard, K. (2017). MRMS QPE Performance East of the Rockies during the 2014 Warm Season. *Journal of Hydrometeorology*,18(3), 761-775.

Dai, Q., Han, D., Rico-Ramirez, M., and Srivastava, P. K. (2014). Multivariate Distributed Ensemble Generator: a New Scheme for Ensemble Radar Precipitation Estimation over Temperate Maritime Climate. *Journal of Hydrology*,511, 17-27.

Entekhabi, D., & Eagleson, P. S. (1989). Land surface hydrology parameterization for atmospheric general circulation models including subgrid scale spatial variability. *Journal of Climate*, 2(8), 816-831.

Fang, Z., Bedient, P. B., Benavidas J.A, and Zimmer A. L. (2008). “Enhanced Radar-based Flood Alert System and Floodplain Map Library”. ASCE *Journal of Hydrologic Engineering*, Vol. 13, No. 10, October 1, 2008, ISSN 1084-0699/2008/10-926-938.

Fang, Z., Bedient, P. B., and Buzcu-Guven, B. (2011). “Long-Term Performance of a Flood Alert System and Upgrade to FAS3: A Houston Texas Case Study”. ASCE *Journal of Hydrologic Engineering*, Vol. 16, No. 10, October 1, 2011, ISSN 1084-0699/2011/10-818-828.

Fang, Z., Dolan, G., Sebastian A., and Bedient, P.B. (2014). “Case Study: Flood Mitigation and Hazard Management at the Texas Medical Center in the Wake of Tropical Storm Allison (2001)”. ASCE *Journal of Natural Hazards Review*, ISSN 1527-6988/05014001(11), 15(3).

FEMA (2017). Historic Disaster Response to Hurricane Harvey in Texas. https://www.fema.gov/news-release/2017/09/22/historic-disaster-response-hurricane-harvey-texas

Gao, S., and Fang, Z. (2018). “Using Storm Transposition to Investigate the Relationships between Hydrologic Responses and Spatial Moments of Catchment Rainfall”. ASCE *Journal of Natural Hazards Review*, ASCE 2018 19(4):04018015 DOI:10.1061/(ASCE)NH.1527-6996.0000304

Gourley, J.J., Vieux, B.E. (2005). Evaluating the Accuracy of Quantitative Precipitation Estimates from a Hydrologic Modeling Perspective. *Journal of Hydrometeorolog,* 2, 115–133.

Habib, E., Krajewski, W. F., and Ciach, G. J. (2001a). Estimation of Rainfall Interstation Correlation. *Journal of Hydrometeorology* 2(6), 621-629.

Habib, E., Krajewski, W. F., & Kruger, A. (2001b). Sampling errors of tipping-bucket rain gauge measurements. *Journal of Hydrologic Engineering*, 6(2), 159-166.

Habib, E. and Krajewski, W.F. (2002). Uncertainty Analysis of the TRMM Ground-Validation Radar-Rainfall Products: Application to the TEFLUN-B Field Campaign. *Journal of Applied Meteorology,* 41, 558-572.

Habib, E., Ciach, G. J., & Krajewski, W. F. (2004). A method for filtering out raingauge representativeness errors from the verification distributions of radar and raingauge rainfall. *Advances in Water Resources*, 27(10), 967-980.

Habib, E., Aduvala, A., and Meselhe, E.A. (2008). Analysis of Radar-Rainfall Error Characteristics and Implications for Streamflow Simulations Uncertainty. *Hydrological Sciences Journal*, 53(3), 568–587.

Habib, E., Larson, B. F. and Graschel, J. (2009). Validation of NEXRAD Multisensor Precipitation Estimates using an Experimental Dense Rain Gauge Network in South Louisiana. *Journal of Hydrology*, 373(3), 463-478.

Harris County Flood Control District (HCFCD). (2017). Projects and studies, Brays Bayou overview. (https://www.hcfcd.org/projects-studies/brays-bayou/) (Jun. 2017).

Juan, A., Fang, Z., and Bedient, P. B. (2015). Developing a Radar-based Flood Alert System for Sugar Land, Texas, ASCE *Journal of Hydrologic Engineering*, [10.1061/(ASCE)HE.1943-5584.0001194](http://ascelibrary.org/doi/abs/10.1061/%28ASCE%29HE.1943-5584.0001194) , E5015001.

Kessler, E., and Neas, B. (1994). On Correlation, with Applications to the Radar and Raingage Measurement of Rainfall. *Atmospheric Research* 34(1-4), 217-229.

Kitchen, M., & Blackall, R. M. (1992). Representativeness errors in comparisons between radar and gauge measurements of rainfall. *Journal of Hydrology*, 134(1-4), 13-33.

Ko, D., Lee, T., and Lee, D. (2018). Spatio-Temporal-Dependent Errors of Radar Rainfall Estimates in Flood Forecasting for the Nam River Dam Basin. *Meteorological Applications* 25(2), 322 – 336.

Krajewski, W.F. and Smith, J.A. (2002). Radar Hydrology: Rainfall Estimation. *Advances in Water Resources* 25, 1387-1394.

Lin, Y., and Mitchell, K. E. (2005). 1.2 The NCEP stage II/IV hourly precipitation analyses: Development and applications. In 19th Conf. Hydrology, *American Meteorological Society*, San Diego, CA, USA.

Mandapaka, P. V., Villarini, G., Seo, B. C., and Krajewski, W. F. (2010). Effect of Radar-Rainfall Uncertainties on the Spatial Characterization of Rainfall Events. *Journal of Geophysical Research: Atmospheres* 115(D17).

Moran, P. A. (1950). “Notes on continuous stochastic phenomena.” *Biometrika*, 37(1/2), 17-23.

National Center for Environmental Information (NCEI, 2018). “NEXRAD”. Retrieved from https://www.ncdc.noaa.gov/data-access/radar-data/nexrad.

Nelson, B., Prat, O., Seo, D., and Habib, E. (2016). Assessment and Implications of NCEP Stage IV Quantitative Precipitation Estimates for Product Comparisons. *Weather Forecasting* 31, 371–394, doi:10.1175/WAF-D-14-00112.1.

NOAA (National Oceanic and Atmospheric Administration). (2016). National Water Model: Improving NOAA’s Water Prediction Services. http://water.noaa.gov/documents/wrn-national-water-model.pdf.

Reed, S. M., and Maidment, D. R. (1999) Coordinate Transformations for using NEXRAD Data in GIS-based Hydrologic Modeling. *Journal of Hydrologic Engineering* 4, 174–183.

Seo, D. J., & Smith, J. A. (1996). Characterization of the climatological variability of mean areal rainfall through fractional coverage. *Water resources research*, 32(7), 2087-2095.

Smith, J.A., Baeck, M.L., Zhang, Y., and Doswell, C.A. (2001). Extreme Rainfall and Flooding From Supercell Thunderstorms. *Journal of Hydrometeorology* 2, 469-489.

Smith, J.A., Baeck, M.L., Morrison, J.E., and Sturdevant-Rees, P. (2002). The Regional Hydrology of Extreme Floods in an Urbanizing Drainage Basin. *Journal of Hydrometeorology* 3, 267-282.

Torres, J., Bass, B., Irza, N., Fang, Z., Proft, J., Dawson, C., Kiani, M., and Bedient, P.B. (2015). “Characterizing the Hydraulic Interactions of Hurricane Storm Surge and Rainfall-Runoff for the Houston-Galveston Region”. *Journal of Coastal Engineering*, Elsevier (2015) 7-9/0378-3839 <http://dx.doi.org/10.1016/j.coastaleng.2015.09.004>.

Vieux, B.E. and Bedient, P.B. (1998). Estimation of Rainfall for Flood Prediction from WSR-88D Reflectivity: A Case Study. *Weather and Forecasting* 13(2), 407-415.

Wang, X., Xie, H., Sharif, H., Zeitler, J., (2008). Validating NEXRAD MPE and Stage III Precipitation Products for Uniform Rainfall on the Upper Guadalupe River Basin of the Texas Hill Country. *Journal of Hydrology* 348, 73–86. doi:10.1016/j.jhydrol.2007.09.057.

Yilmaz, K., Hogue, T., Hsu, K.L., Sorooshian, S., Gupta, H., Wagener, T., (2005). Intercomparison of Rain Gauge, Radar, and Satellite-Based Precipitation Estimates with Emphasis on Hydrologic Forecasting. *Journal of Hydrometeorology* 6, 497–517.

Zhang, Y., & Seo, D. J. (2017). Recursive estimators of mean-areal and local bias in precipitation products that account for conditional bias. *Advances in Water Resources*, 101, 49-59.

Zhang, Y. and Smith, J.A. (2003). Space-Time Variability of Rainfall and Extreme Flood Response in the Menomonee River Basin, Wisconsin. *Journal of Hydrometeorology* 4, 506-517.

Zhang, J., and Coauthors, (2014). Initial operating capabilities of quantitative precipitation estimation in the Multi-Radar Multi-Sensory system. 28th Conference of Hydrology, Atlanta, GA. [Available online at https://ams.confex.com/ams/94Annual/webprogram/Paper240487.html.]

Zhang, J., Howard, K., Langston, C., Kaney, B., Qi, Y., Tang, L., Grams, H., Wang, Y., Cocks, S., Martinaitis, S. and Arthur, A. (2016). Multi-Radar Multi-Sensor (MRMS) Quantitative Precipitation Estimation: Initial Operating Capabilities. *Bulletin of the American Meteorological Society* 97(4), 621-638.

Table 1: Starting and Ending Times for the Three Selected Historical Storms

|  |  |  |  |
| --- | --- | --- | --- |
| **Storm** | **Start Time (CDT)** | **End Time (CDT)** | **Duration (hours)** |
| 2015 Memorial Day Storm | 5/25/2015 19:00 | 5/27/2015 7:00 | 36 |
| 2016 Tax Day Storm | 4/17/2016 13:00 | 4/19/2016 6:00 | 41 |
| 2017 Hurricane Harvey | 8/25/2017 00:00 | 8/30/2017 00:00 | 120 |

Table 2: OB Summary Table

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Rainfall Product** | **Storm Event** | **Average OB** | **Minimum OB** | **Maximum OB** | **Total Sample Size** |
| MRMS | 2015 Memorial Day | 0.85 | 0.63 | 1.20 | 952 |
| 2016 Tax Day | 0.78 | 0.43 | 1.07 | 1377 |
| 2017 Hurricane Harvey | 0.92 | 0.67 | 1.14 | 7607 |
| All | 0.88 | 0.43 | 1.20 | 9936 |
| Stage IV | 2015 Memorial Day | 1.12 | 0.62 | 3.70 | 417 |
| 2016 Tax Day | 0.93 | 0.49 | 2.08 | 520 |
| 2017 Hurricane Harvey | 1.06 | 0.77 | 1.28 | 3677 |
| All | 1.02 | 0.49 | 3.70 | 4614 |

Table 3: Summary of Hydrograph Comparison

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Statistic Measures** | **Junction #** | **Stage IV** | **MRMS** | **Rain Gauge** |
| *Ve* | 1 | 16% | -18% | -10% |
| 2 | 38% | 0% | 9% |
| 3 | 23% | -8% | 0% |
| 4 | 28% | -5% | 3% |
| *Pe* | 1 | 30% | -5% | 3% |
| 2 | 74% | 40% | 53% |
| 3 | 2% | -8% | -7% |
| 4 | 21% | 10% | 11% |
| *RMSE (m3/s)* | 1 | 33 | 19 | 17 |
| 2 | 141 | 61 | 82 |
| 3 | 164 | 71 | 91 |
| 4 | 220 | 90 | 82 |
| *NSE* | 1 | 0.68 | 0.89 | 0.91 |
| 2 | 0.15 | 0.84 | 0.71 |
| 3 | 0.78 | 0.96 | 0.93 |
| 4 | 0.63 | 0.94 | 0.95 |

Table 4: Averaged Overall Bias and Spatial Resolution of Rainfall Inputs

|  |  |  |
| --- | --- | --- |
| **Rainfall Input** |  | **Spatial Resolution** |
| Stage IV | 1.11 | ~16 km2 |
| MRMS | 0.94 | ~1 km2 |
| Rain Gauge | 1 | 13 km2 |