IMPACT OF RAIN GAUGE LOCATION ERRORS ON VERIFICATION OF RADAR-BASED PRECIPITATION ESTIMATES

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ABSTRACT

Flash flooding can cause hundreds of deaths and billions of dollars worth of damage each year. In 2015, there were 176 fatalities in the United States, Puerto Rico, Guam and Virgin Islands, which is roughly five times higher compared to those caused by tornadoes. The Multi-Radar Multi-Sensor (MRMS) system, which generates a 1-km grid of quantitative precipitation estimates (QPE), can provide insight to forecasters when issuing flash flood warnings. The most accurate data are needed for the high spatial resolution of MRMS. Rain gauges are treated as ground truth and can provide the most accurate verification of QPE. The most well-known gauge network is the 838 rain gauges from Automated Surface Observing System (ASOS) stations. It is a standard to accept that QPE values can vary from collocated observed gauge values; however, location errors of the rain gauge can have an impact on the verification of MRMS QPE. Using Google Earth, it is determined that ASOS location errors varied from less than 3 m to 80,163 m. The locations errors resulted in 79.31% of ASOS stations in the CONUS to be in a different MRMS QPE grid box. Of those stations, 19.44% were found more than 1 km away from the expected locations. QPE values for the new and old locations were compared to observed precipitation data with the correlation increasing from 0.777 to 0.810. This comparison highlights the need to update rain gauge metadata to improve the verification of radar-based QPE and other hydrometeorological products.

1. INTRODUCTION

Surface observations are critical for quick basic analysis of low-level weather phenomena. There are several combinations of surface instrumentation, including the Automated Surface Observing System (ASOS) stations, that collect surface observation data. There are thousands of these stations in the continental United States (CONUS). ASOS stations include a wide variety of instrumentation that collect measurements of variables crucial for verification of forecasts and meteorological numerical models. One of these instruments at the ASOS station is the rain gauge. The accuracy and importance of this data is beneficial for a wide range of meteorological and hydrologic applications, including detection of flash flood-producing rainfall.

The National Weather Service (NWS) recorded 176 flood fatalities in the United States, Puerto Rico, Guam and Virgin Islands in 2015 (http://www.nws.noaa.gov/os/hazstats.shtml). Weather fatalities related to flooding were nearly

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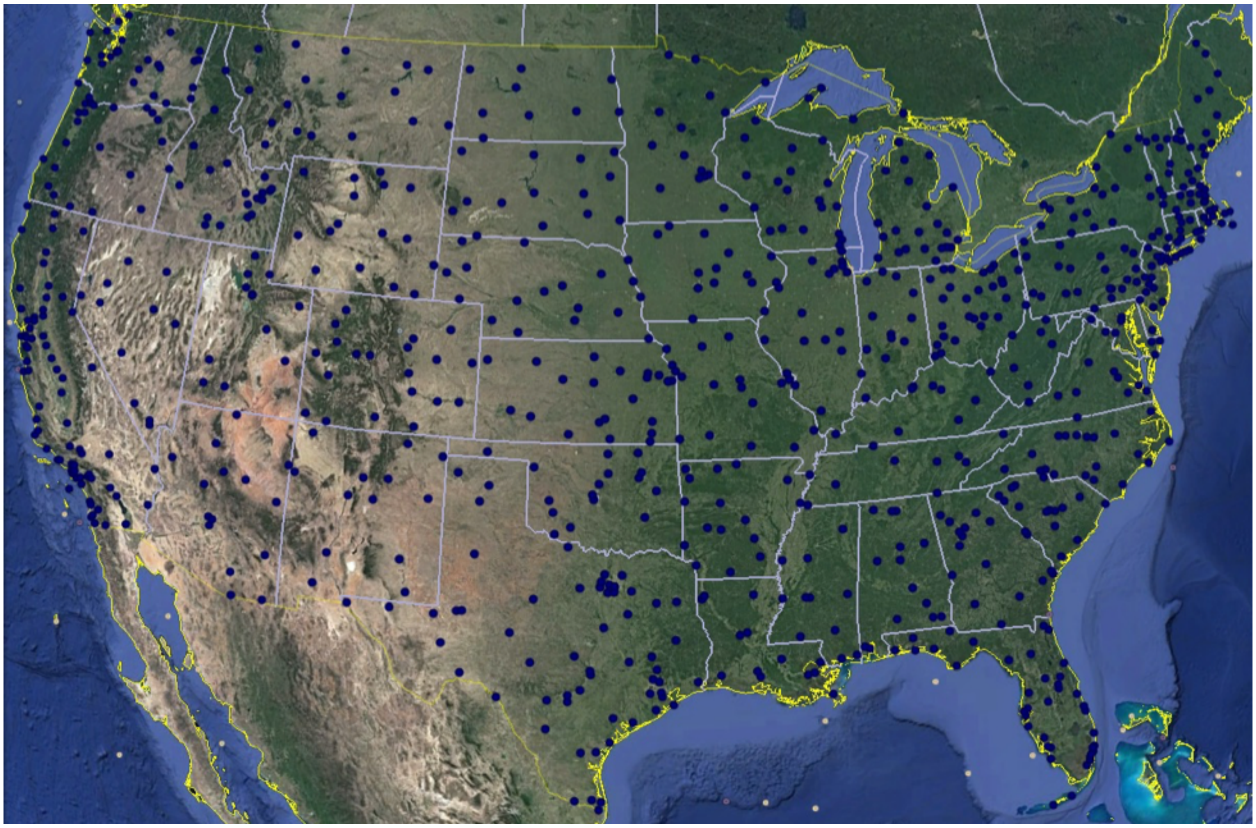

Fig. 1: Map of CONUS provided by Google Earth with blue dots indicating the metadata ASOS station locations.

five times higher compared to those attributed to tornadoes in 2015. From 1969 to 1981, 93% of flash flood deaths were due to drowning, and of those, 42% were vehicle related (French et al. 1983). The 30-year average number of fatalities attributed to flooding are second only to those attributed to heat from 1986-2015. Flash flooding can also have wide repercussions when associated with property damage. The NWS estimated that the average 30-year flood loss is almost $8 billion per year (http://www.nws.noaa.gov/hic/index.shtml).

One of the primary observation tools for precipitation used in the CONUS is the Next-Generation Radar (NEXRAD) network. The upgrade of this system to dual-polarization (dual pol) has significantly improved our ability to monitor hydrometeors and weather. Dual pol allows the NEXRAD network to emit and receive signals using horizontal and vertical polarization, thus allowing more precise measurements of hydrometeors in the atmosphere compared to traditional radar technology (Li and Mecikalski 2012).

The primary mission of the NWS is to protect life and property from weather-related hazards. In some respects, this can be dependent on data accuracy. One tool available to NWS forecasters is the Multi-Radar Multi-Sensor (MRMS) system, which provides quantitative precipitation estimates (QPE) in real time. MRMS has been operational since September 2014 and has been running real time at the National Severe Storms Laboratory (NSSL) since June 2006 (Qi et al. 2016). MRMS processes data from nearly 180 operational radars to create a three-dimensional seamless radar mosaic at a high temporal (2 min) and spatial (1 km) resolution (Zhang et al. 2016). QPE is determined by dynamically varying reflectivity-rain rate (Z-R) relationships that are applied to each grid box in MRMS (Qi et al. 2016).

Errors in the QPE could alter how a forecaster issues flash flood warnings and in turn affects how the general public perceives the threat. The high resolution of MRMS has superior coverage in areas with sparse surface observation data and more frequent updates; however, this fine spatial resolution can also be problematic. The data that goes into the process of creating the QPE needs to be accurate and reliable.

Thousands of gauge sites are ingested and processed by MRMS. The vast majority located in the eastern CONUS and along the West Coast; the distribution of these gauges are sparse in the mountainous regions of the western CONUS

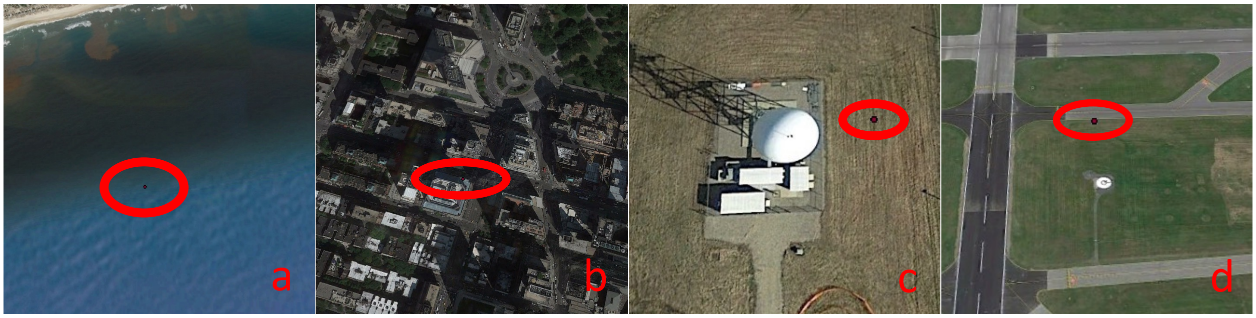

Fig. 2: (a) Depiction the metadata location for the HSE ASOS station off the coast of Frisco, North Carolina. (b) Depicts the metadata location of the NYC ASOS station in a building in Manhattan, New York. Pictures (a) and (b) are what the authors considered as atypical. (c) Depicts the metadata location of the GRR ASOS station at the NWS WFO in Grand Rapids, Michigan. (d) Depicts the metadata location of the ALB ASOS station at the Albany International Airport in Albany, New York. Pictures (c) and (d) are what the authors considered as typical.

(Qi et al. 2016). Verification and data accuracy using gauges is only as good as the instrumentation and observations. Even with the advancement of technology, inaccuracies of rain gauges persist and are well documented. Three general sources of error have been identified for rain gauges: systematic spatial and altitudinal variations, systematic measurement error, and random measurement and sampling errors (Dreaver and Hutchnson 1974, Freimund 1992; Goodrich et al. 1995). The blockage of the orifice on the rain gauges can lead to precipitation underestimates, or more drastically, no measurable precipitation (Sevruk 2005; Sieck et al. 2007; Martinaitis et al. 2015). Another common data accuracy problem with rain gauges is undercatch; which is the process of losses induced by wind and is more prominent with snowfall (Chubb et al. 2015). The heated tipping bucket is the rain gauge used at the majority of ASOS stations and can cause enhanced evaporation with regards to frozen precipitation. These type of gauges record nearly 24% less precipitation due to enhanced evaporation (Savina et al. 2012). Tipping bucket rain gauges also have the tendency of splash out and loss of liquid during intense rainfall rates (Parsons 1941). Evaporation and/or sublimation on rain gauge siding and undercatch can cause underestimations. Groisman and Legates (1994) suggested that these errors can cause estimated bias that vary from 5% to 40% with higher bias in the winter. An additional difficulty with solid precipitation is timely measurements of liquid equivalency due to slow fall speeds between when radar beams aloft detects the precipitation and when it reaches the surface (Goodison et al. 1998; Savina et al. 2012).

To combat some of these problems, Qi et al. (2016) came up with a framework to categorize rain gauges with quality control (QC) flags with values ranging from -2 to 6 with each value corresponding to a specific designation (Table 1). The QC flag allows the user to filter potential suspect gauge measurements.

Radar-based QPE also has inherent sources of uncertainty. Hogan (1990) mentions that the location of a rain gauge can play a larger role compared to the overall number of rain gauges in reducing errors in precipitation estimation for multi-sensor QPE methods. In a case study, Rossa et al. (2010) demonstrated that the maximum radar-based QPE and the maximum observed rainfall locations did not coincide with each other. The standard is to assume that the gauge measurement is accurate (i.e., “ground truth”) while the QPE contains the error; however, errors in rain gauge locations could alter the verification process between rain gauges and radar-based QPE.

Prior to 2013, the verification of radar and satellite QPE in MRMS was based on the Hydrometeorological Automated Data System (HADS) list of rain gauge stations across the CONUS. The HADS list is maintained and distributed by the NWS Office of Hydrology. Numerous automated gauge networks were not included in HADS, but were available from other sources such as the National Operational Hydrologic Remote

QC flag	QC flag designation	Retained for MRMS use
−2	Out time window	No
−1	Unchecked	Yes
0	Pass	Yes
1	False precip	No
2	False zero	No
3	Outlier high	No
4	Outlier low	No
5	Frozen	No
6	Suspect	No

Table 1: QC flag for gauges used in MRMS. From Qi et al. 2016.

$$Distance = 6371000 * 2 * \arctan\left(\frac{\sqrt{a}}{\sqrt{1-a}}\right) \quad (1)$$

$$a = sin^2\left(\frac{Lat_n - Lat_o}{2}\right) + cos(Lat_o) * \cos(\mathrm{Lat}_n) * sin^2\left(\frac{Lon_n - Lon_o}{2}\right) \quad (2)$$

$$CC = \frac{\left[\frac{1}{n}\sum_{i=1}^{n}(ObsRain_i QPE_i)\right] - \left(\frac{1}{n}\sum_{i=1}^{n} ObsRain_i\right)\left(\frac{1}{n}\sum_{i=1}^{n} QPE_i\right)}{\left\{\left[\frac{1}{n}\sum_{i=1}^{n} ObsRain_i{}^2 - \left(\frac{1}{n}\sum_{i=1}^{n} ObsRain_i\right)^2\right]\left[\frac{1}{n}\sum_{i=1}^{n} QPE_i{}^2 - \left(\frac{1}{n}\sum_{i=1}^{n} QPE_i\right)^2\right]\right\}^{1/2}} \quad (3)$$

Sensing Center (NOHRSC). In 2013, MRMS developers attempted to produce a master gauge list by combining the HADS and NOHRSC lists. This process revealed metadata errors including: station ID mismatches, mismatches in latitude and longitude values, and numerous site duplications. An evaluation of rain gauge metadata locations would establish better verification for radar-based QPE in regards to current and future hydrometeorological products.

The objective of this study is to investigate and evaluate the impact of rain gauge metadata location errors on the perceived skill of MRMS QPE and to determine the current state of metadata accuracy.

2. DATA AND METHODOLOGY

The hourly MRMS QPE dataset that is used in this study covers 0000 UTC 1 January 2015 to 2300 UTC 31 December 2015 and is obtained from the National Centers for Environmental Prediction (NCEP). The MRMS domain extends from -130° to -65° longitude and from 55° to 20° latitude. The 838 rain gauges were evaluated in this study are from the ASOS station network (Fig. 1). The original ASOS station metadata for these 838 sites came primarily from NOHRSC; however, some may be based on the NWS Location Identifiers (NWSLI) database if they were not included in the original NOHRSC list. While most metadata ASOS station locations can be considered reasonably accurate, there are several metadata station locations that can be considered erroneous (e.g., Fig. 2). The coordinate system used in Google Earth and to record the ASOS station locations is the World Geodetic System of 1984 datum.

In order to compute the approximate location errors in the ASOS station metadata, the actual locations of the 838 ASOS stations needed to be determined and recorded. The ASOS station IDs, latitudes, and longitudes were encoded into a KMZ file that was imported into Google Earth. The Google Earth satellite imagery was then used to locate the true location of each ASOS station, and the new latitude and longitude values were recorded. As the quality of the satellite imagery varied per location, the coordinates for the actual location of the ASOS station were based on the power supply box for the ASOS station.

The distance difference between the actual location and metadata location was determined by the Haversine Formula (1) and (2) since it provides the great circle distance between two coordinate points on a sphere in meters. In (2), Lat_n, Lat_o, Lon_n, and Lon_o are the new latitude, old latitude, new longitude, and old longitude, respectively. Statistical analysis was done on the distance data and include minimum, first quartile, median, third quartile, and maximum values for the distance to demonstrate the variability between the old and new ASOS locations.

Before any statistical analysis was performed on the new dataset, the authors set criteria that all data points must meet. For example, one such requirement is, if both the old and new QPE value both equaled zero, that data point would be ignored. The second requirement is that the gauge QC flag must be either -1 or 0 for the data point to be considered in any further analysis. The third and final requirement that had to be met was if the old and new ASOS location were situated within the same QPE grid box that station would be ignored. From here, two separate datasets were created that included both above criteria with the third requirement being absent in one of the two

$$Mean\ Bias = \frac{\frac{1}{n}\sum_{i=1}^{n} ObsRain}{\frac{1}{n}\sum_{i=1}^{n} QPE} \quad (4)$$

$$Mean\ Error = \frac{1}{n}\sum_{i=1}^{n}(QPE_n - QPE_o) \quad (5)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|QPE_n - QPE_o| \quad (6)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(QPE_n - QPE_o)^2 \quad (7)$$

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}(QPE_n - QPE_o)^2\right]^{1/2} \quad (8)$$

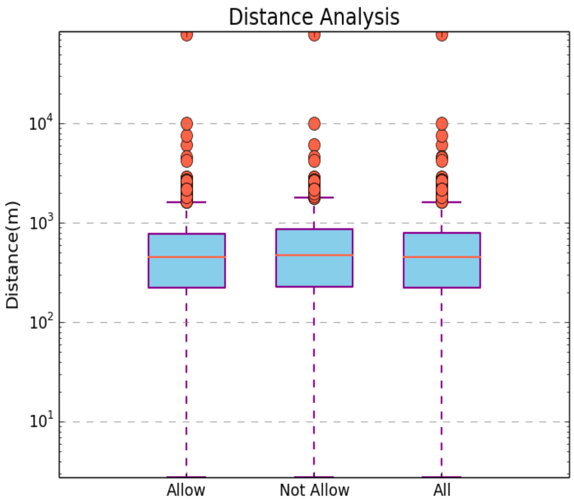

Fig. 3: Box and whisker plots comparing the distances of the two datasets: allowing and not allowing same QPE grid point stations with the box and whisker plot with all the distances.

Allows Same QPE Grid Point	Min	Q1	Median	Q3	Max
Yes	2.8	223.6	455.4	783.1	80162.6
No	2.8	229.8	475.2	861.0	80162.6
All	2.8	223.3	455.3	789.2	80162.6

Table 2: Distance statistics in meters for the ASOS stations in CONUS shown in Fig. 3.

datasets. The notion of creating two different datasets using only the first two requirements and only incorporating the third requirement in one of the datasets is to compare how the stations that remain in the same QPE grid box influence the overall statistical analysis of the research.

For the first requirement, the authors wanted to see the difference in QPE values based on the location error; the statistical weight of zero values for both old and new QPE will be much greater compared to nonzero QPE values due to the naturally sparse nature of hourly precipitation data. For the second requirement, according to Qi et al. (2016), a QC flag with a value of -1 and 0 are retained in MRMS, which represent gauges either passing all QC checks or being located in areas where the QC check could not be performed; thus gauge measurements flagged as suspect for any reason were excluded. The third requirement is designed to alleviate the dataset of stations that did not have location errors large enough to move them to a different QPE grid box.

Two datasets were formed that resulted in 648 and 798 ASOS stations. The dataset containing 798 ASOS stations represents the rain gauges that resulted from running Python script without any additional requirement; while, the dataset that contains 648 stations represents the same dataset with the additional requirement of ignoring the rain gauges that remain in the same QPE grid box. The datasets included 246,504 and 305,725 data points respectively. From the two datasets, the same statistical analysis is done to determine the impact of ASOS location error on radar-based QPE

Using a Python script, values of MRMS QPE were determined for both the metadata and newly found ASOS locations. Each of the two datasets were exported into separate text files to streamline the statistical analysis. The statistical analysis included basic statistics for both new and old QPE: mean, minimum, maximum, etc. The authors also ran analysis to compare the old and new radar-based QPE values to those observed by the rain gauge. The gauge versus QPE error analysis includes: mean bias, mean error, mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), and correlation coefficient (CC). Equations (3) through (8) were used to compare the observed precipitation by the rain gauge and the new and old QPE, where ObsRain, QPE, QPE_n, and QPE_o are observed gauge precipitation, QPE at the new gauge location, and QPE at the old gauge location, respectively.

3. RESULTS

3.1 Distance Error Analysis

817 of the 838 ASOS stations were located and recorded. The remaining 21 stations were not recovered due to poor satellite imagery quality and uncertainty. Due to the removal of missing or non-reporting observations from the original hourly gauge data prior to analysis, the overall number ASOS stations for not allowing same QPE grid box stations and allowing same QPE grid box stations dropped to 648 and 798 respectively. This represented 79.31% and 97.67% of the ASOS stations recovered using Google Earth or 77.33% and 95.23% of the total ASOS stations in CONUS. From the Haversine Formula (1) and (2), the authors determined that the distance between the listed locations in the metadata and actual ASOS locations for both datasets varied from 2.8 m to 80,162.6 m (Table 2). The ASOS identification that corresponds to the 2.8 m error is ICT and is located at the Wichita Mid-Continent Airport in Wichita, Kansas. The minimum distance of 2.8 m in both datasets represents the ideal for data accuracy. Over the CONUS, 2.8 m is practically insignificant; however, this distance could be significant

on the 1-km QPE grid spacing given the possibility that a small distance change could displace it out of the original QPE grid box. The ASOS identification that corresponds to the approximately 80 km error is OTM. The metadata location for OTM is Newton Municipal Airport in Newton, Iowa; however, the actual location of OTM is Ottumwa Regional Airport in Ottumwa, Iowa.

The two datasets are statistically different when considering that one of the datasets has the different cell requirement and the other does not (Fig. 3). When including the different cell requirement, the first quartile, median, and third quartile all increased (Table 2). The box and whisker plots are displayed on a logarithmic scale due to the high outliers.

3.2 QPE Analysis

There were 246,504 data points in the dataset that included the different cell requirement and 305,725 data points in the dataset that did not include the difference grid cell requirement. The difference in statistics for these two datasets indicates that the different cell requirement had some effect on both new and old QPE values (Table 3). The standard deviation increased for both new and old QPE values when the different cell requirement is in place. The maximum new QPE value decreased, suggesting that the original maximum occurred in the same QPE grid box and thus was ignored when those points were excluded from analysis. The mean values also decreased with the old QPE decreasing .017 mm compared to a .007 mm decrease in new QPE; thus showing that rain gauge location can have an impact on verification of radar-based QPE (Fig. 4). The overall number of observations along the one-to-one line decreased with the exclusion of data points from the different cell requirement, and thus, decreased the linearity between new and old QPE values.

Allows Same QPE Grid Point	QPE	Min	Q1	Median	Q3	Max	Std Dev	Var	Mean
Yes	New	0.1	0.5	1.1	2.2	105.8	3.644	13.280	2.102
Yes	Old	0.0	0.5	1.1	2.2	116.5	3.662	13.408	2.056
No	New	0.1	0.5	1.1	2.2	103.1	3.635	13.213	2.095
No	Old	0.0	0.4	1.0	2.2	116.5	3.657	13.371	2.039

Table 3: Basic statistical analysis comparing the new and old QPE values (mm) for the two datasets.

Allows Same QPE Grid Point	Obs vs.	Mean Bias	Mean Error	MAE	MSE	RMSE	CC
Yes	New	0.892	0.227	1.042	4.958	2.227	0.810
Yes	Old	0.912	0.182	1.083	5.652	2.377	0.784
No	New	0.892	0.226	1.043	4.953	2.225	0.810
No	Old	0.917	0.170	1.093	5.814	2.411	0.777

Table 4: Error statistical analysis comparing the new and old QPE values to observed precipitation (mm) for the two datasets.

The comparison between observed precipitation to new and old QPE values are more significant to understanding whether rain gauge location error can have an impact on radar-based QPE verification. For both datasets, the error analysis shows that the new rain gauge locations lead to statistically better QPE verification compared to the metadata locations (Table 4).

The correlation coefficient increased by 0.026, without the different cell requirement, and 0.033 with the different cell requirement. The different cell requirement had a greater effect on the observed precipitation versus old QPE in both datasets compared to the observed precipitation versus new QPE (Table 4). For both datasets,

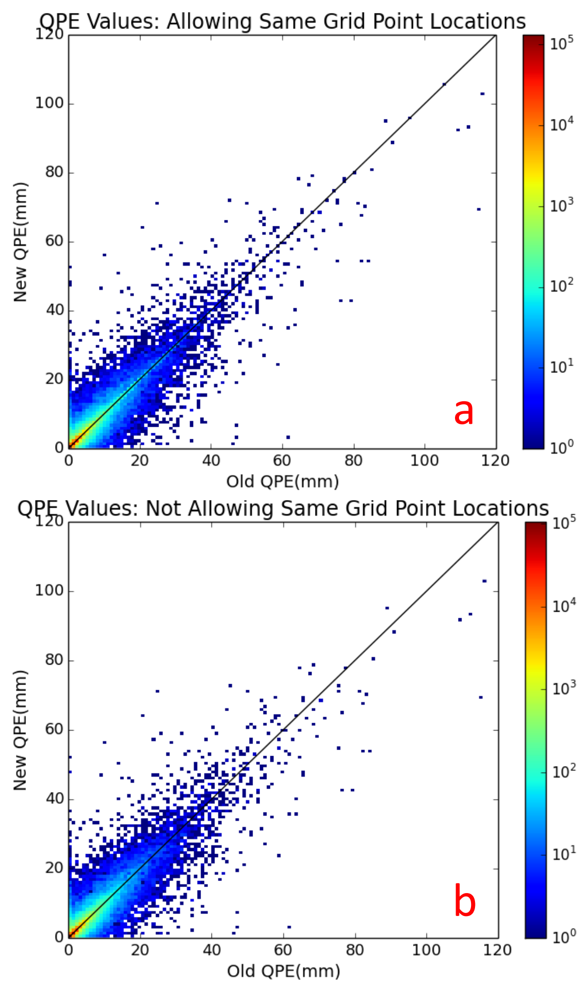

Fig. 4: Density scatter plots comparing: (a) the new and old QPE in the dataset that allows same QPE grid point stations and (b) the new and old QPE in the dataset that does not allow same QPE grid point stations.

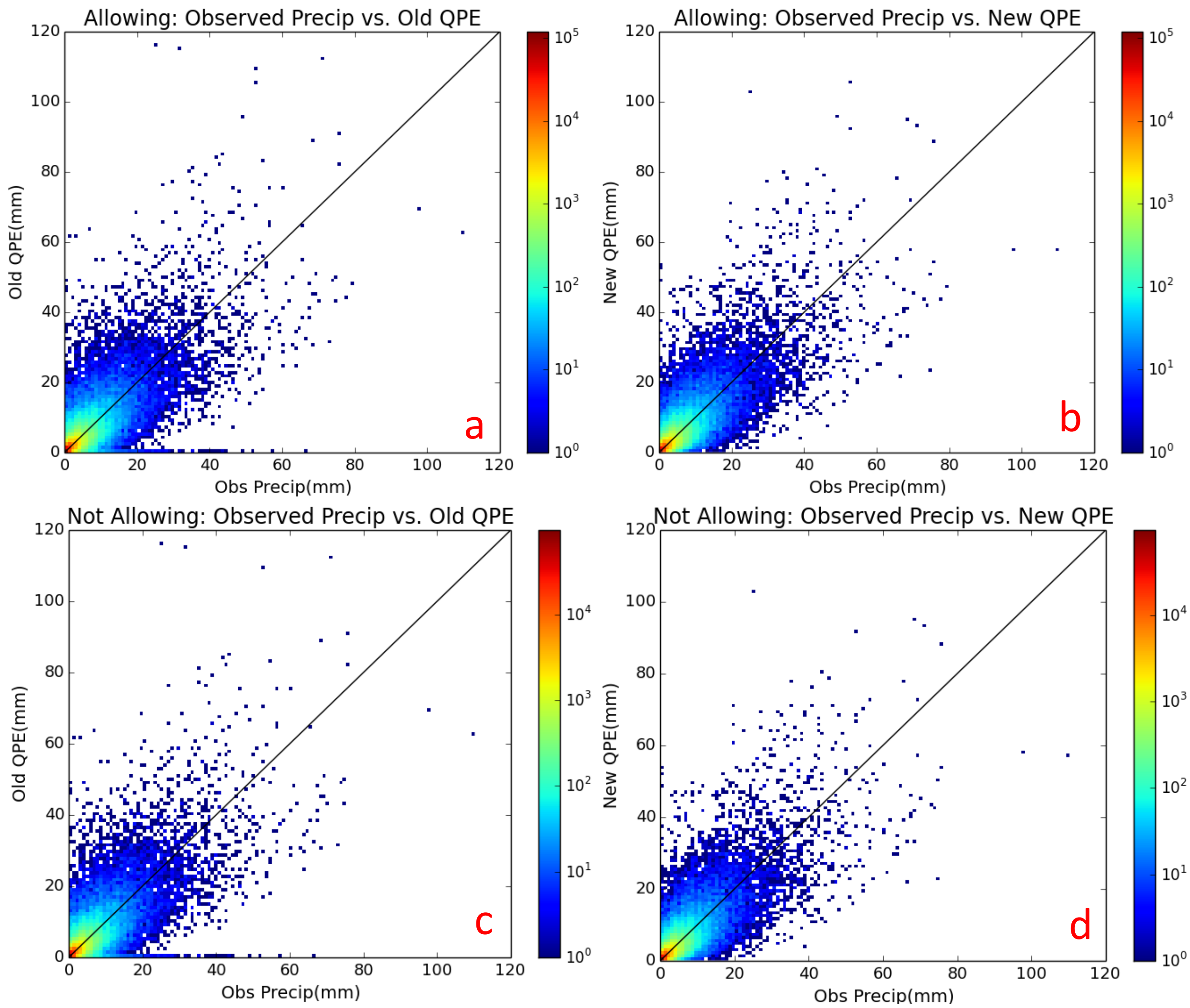

Fig. 5: Density scatter plots comparing observed precipitation and: (a) the old QPE value in the allowing dataset, (b) the new QPE value in the allowing dataset, (c) the old QPE value in the not allowing dataset, and (d) the new QPE value in the not allowing dataset.

the new rain gauge locations eliminated false zero precipitation estimates (Fig. 5). These values were denoted as points that are along the horizontal axis. The “False zero” classification states that the rain gauge observed measurable water and the radar-based QPE predicted no measurable precipitation. These false zero precipitation reports were eliminated when using the new QPE values based on the new, corrected rain gauge locations. The comparison between the two different datasets, allowing and not allowing same QPE grid box stations, showed an increase in linearity between both new and old QPE versus observed precipitation. The increased linearity between the datasets was more apparent in the new QPE comparison with observed precipitation (Table 4). The elimination of the data points along with the increase in correlation and linearity was in response to the different cell requirements that ignores ASOS stations that remain in same QPE grid box.

The comparison between distance and QPE error highlights the impact of excluding same QPE grid box locations (Fig. 6). The range and magnitude of errors were smaller when comparing the dataset that includes the different cell requirement than the dataset that does not include the different cell requirement. The comparison of new/old QPE to distance in the individual datasets also suggests that the actual ASOS locations provide less QPE error compared to the metadata locations.

4. SUMMARY AND FUTURE WORK

Rain gauges verify the radar-based QPE and thus provide valuable insight and data for operational forecasters and researchers. The current

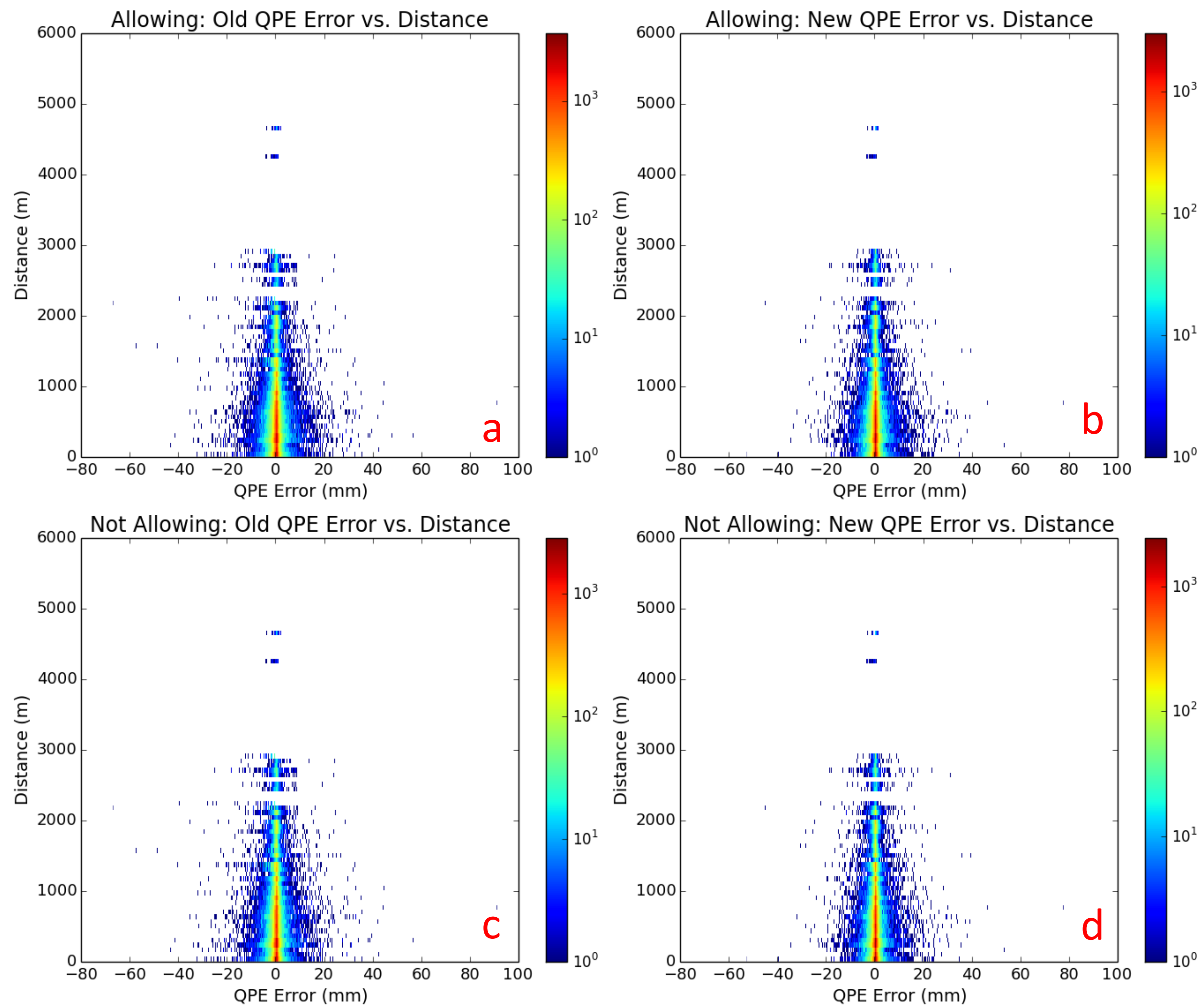

Fig. 6: Density scatter plots comparing distance to (a) the old QPE value in the allowing dataset, (b) the new QPE value in the allowing dataset, (c) the old QPE value in the not allowing dataset, and (d) the new QPE value in the not allowing dataset. ASOS stations ATT, SFO, TOI and OTM are excluded in graphs (a) and (b). ATT, TOI and OTM are excluded in graphs (c) and (d).

verification process of QPE assumes that the location of rain gauges are accurate; however, of the 838 ASOS stations, 21 of them were not identifiable and/or found on Google Earth. The actual locations varied from 2.8 m to 80,162.6 m away from the metadata locations. This location error impacts the verification of radar-based QPE. 79.31% of the 817 ASOS stations were found to be in a different QPE grid box. Of those stations, 19.44% were found more than 1 km away from the expected locations.

The two final gauge datasets, one that allows and the other that does not allow same QPE grid box stations in the statistical analysis, provided a difference in the verification and correlation between QPE and observed precipitation. The correlation for the dataset that allows same QPE grid box stations increased from 0.784 to 0.810; while the correlation for the dataset that does not allow same QPE grid box stations increased from 0.777 to 0.810. The implications of this shows that gauge location errors can impact the QPE verification.

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