Assessing Dual-Polarization Radar Estimates of Extreme Rainfall during Hurricane Harvey

DAVID B. WOLFF

Wallops Flight Facility, NASA Goddard Space Flight Center, Wallops Island, Virginia

WALTER A. PETERSEN

NASA Marshall Space Flight Center, Huntsville, Alabama

ALI TOKAY

Joint Center for Earth Systems Technology, University of Maryland, Baltimore County, Baltimore, and NASA Goddard Space Flight Center, Greenbelt, Maryland

DAVID A. MARKS

Science Systems and Applications, Inc., Lanham, Maryland, and Wallops Flight Facility, NASA Goddard Space Flight Center, Wallops Island, Virginia

JASON L. PIPPITT

Science Systems and Applications, Inc., Lanham, and NASA Goddard Space Flight Center, Greenbelt, Maryland

(Manuscript received 13 May 2019, in final form 8 October 2019)

ABSTRACT

Hurricane Harvey hit the Texas Gulf Coast as a major hurricane on 25 August 2017 before exiting the state as a tropical storm on 29 August 2017. Left in its wake was historic flooding, with some locations measuring more than 60 in. (150 cm) of rain over a 5-day period. The WSR-88D radar (KHGX) maintained operations for the entirety of the event. Rain gauge data from the Harris County Flood Warning System (HCFWS) was used for validation with the full radar dataset to retrieve daily and event-total precipitation estimates for the period 25–29 August 2017. The KHGX precipitation estimates were then compared with the HCFWS gauges. Three different hybrid polarimetric rainfall retrievals were used, along with attenuation-based retrieval that employs the radar-observed differential propagation. An advantage of using an attenuation-based retrieval is its immunity to partial beam blockage and calibration errors in reflectivity and differential reflectivity. All of the retrievals are susceptible to changes in the observed drop size distribution (DSD). No in situ DSD data were available over the study area, so changes in the DSD were interpreted by examining the observed radar data. We examined the parameter space of two key values in the attenuation retrieval to test the sensitivity of the rain retrieval. Selecting a value of $\alpha = 0.015$ and $\beta = 0.600$ provided the best overall results, relative to the gauges, but more work needs to be done to develop an automated technique to account for changes in the ambient DSD.

1. Introduction

The hazards of hurricanes include strong winds, associated tornadoes, heavy rains, and storm surge. However,

Denotes content that is immediately available upon publication as open access.

according to [Blake and Zelinsky \(2018\)](#) and others, about 90% of hurricane-related fatalities are caused by coastal and inland floodwaters, and Hurricane Harvey (2017) was no exception. At least 103 people died in Harvey-related incidents, 68 of them from direct impacts, including flooding throughout Texas. [Blake and Zelinsky \(2018\)](#) also reported that more than 17 000 people had been rescued and an estimated 30 000 were displaced across the state. Hurricane Harvey tied with Hurricane

Corresponding author: David B. Wolff, david.b.wolff@nasa.gov

DOI: 10.1175/JTECH-D-19-0081.1

© 2019 American Meteorological Society. For information regarding reuse of this content and general copyright information, consult the [AMS Copyright Policy](#) (www.ametsoc.org/PUBSReuseLicenses).

FIG. 1. Hurricane Harvey track generated using National Hurricane Center “best track” data.

Katrina (2005) as the costliest tropical cyclone on record, inflicting \$125 billion in damage, primarily from catastrophic rainfall-triggered flooding in the Houston, Texas, metropolitan area.

Harvey started as a weak tropical storm near the Lesser Antilles on 17 August 2017 and then dissipated over the central Caribbean Sea (Blake and Zelinsky 2018). However, after crossing the Yucatan Peninsula on 24 August 2017, it reformed over the Bay of Campeche and rapidly developed into a category 4 hurricane before making landfall on the middle Texas coast on 0300 UTC 25 August 2017. The eye made landfall on the northern end of San Jose Island, near Rockport, Texas, with maximum sustained winds of 115 kt (59 m s^{-1}) and minimum central pressure of 937 hPa. The storm then made a second landfall 3 h later on the Texas mainland (on the northeast coast of Copano Bay) with maximum sustained winds of 105 kt (54 m s^{-1}) and minimum central pressure of 948 hPa. By 0600 UTC 25 August 2017, Harvey had weakened over land to a tropical storm and maintained a 35-kt (18 m s^{-1}) intensity for the next two days. The storm then stalled southeast of San Antonio, Texas, for several days, dropping copious amounts of rain over southeast Texas, before finally reemerging over the Gulf of Mexico on 28 August 2017. The storm then made a third and final landfall near Cameron, Louisiana, on 29 August 2017 and headed rapidly northeastward across Louisiana, Mississippi, Tennessee, and Kentucky. Figure 1 provides the track of Harvey using the National Hurricane Center (<https://www.nhc.noaa.gov>) best-track data (HURDAT2). Given such extreme rainfall over this period, it is important to determine how well conventional and unconventional rain estimates perform.

The National Weather Service dual-polarimetric radar (KHGX), located southeast of Houston, maintained

operations for the entirety of the event. The Harris County Flood Warning System (HCFWS) had over 200 rain gauges deployed in its network, concentrated in a relatively compact area of roughly 200 km^2 . Figure 2 is a map of southeastern Texas with the KHGX radar in the middle. Range rings of 25, 50, and 75 km are provided. The rectangle to the northwest represents the area over which many of the radar statistics are calculated throughout the paper. The selected gauge locations are shown as blue triangles. The polygon within the rectangle is a rough outline of Harris County, Texas.

With the advent of dual-polarimetric radars by the National Weather Service, the ability to accurately retrieve rain rates in a variety of precipitation types is now possible (Ryzhkov and Zrnić 1995; Brandes et al. 2002; Bringi et al. 2004; Giangrande and Ryzhkov 2008; Wang et al. 2013, 2019; Chen et al. 2017; Cocks et al. 2019). To properly quantify rainfall, a dense rain gauge network and dual-polarization weather radar are currently the best resources available. During Harvey, both data sources were available. Unfortunately, no disdrometer data that could be used to validate the evolving DSD were available. In this study, we used the full radar dataset to retrieve daily and event-total precipitation estimates within 75 km of the KHGX radar for the period 25–29 August 2017. These estimates were then compared with the selected HCFWS gauges. Four different rain retrievals were used: three polarimetric “hybrid” rainfall algorithms, which utilize observed values of horizontal reflectivity Z_H , differential reflectivity Z_{DR} , and differential propagation phase Φ_{DP} , from which the specific differential phase K_{DP} is calculated (Wang and Chandrasekar 2009), and an attenuation-based retrieval that uses observed values of Z_H and Φ_{DP} . The hybrid estimators and associated methods used were from

FIG. 2. Map of the HCFWS network of rain gauges. The rectangle to the top left is the averaging area used for computing means and profiles. The polygon within the rectangle is a rough outline of Harris County. Of the 120 gauges within the area, 21 were removed because of known blockage between 298° and 306° from the radar (the area between the dashed lines). The red diamonds represent locations at which National Weather Service Automated Surface Observations System (ASOS) sites are located and local wind data are analyzed.

Cifelli et al. (2011) (hereinafter called method RC), Bringi et al. (2004) (method RP), and Chen et al. (2017) (method RR). We note that these hybrid estimators are currently used by NASA's Global Precipitation Measurement (GPM) (Hou et al. 2014) ground validation (GV) team for routine validation of GPM satellite estimates. The radar observed differential phase Φ_{DP} was also used to employ an attenuation-based retrieval (method RA), following Ryzhkov et al. (2014, hereinafter R14). One advantage of using the RA approach is that the phase measurement it relies on is relatively immune to blockage and calibration errors of both the reflectivity and differential reflectivity.

Section 2 of this paper discusses the data used in this study and describes the quality control procedures utilized. Section 2 also provides details of the rain-rate retrievals used. Section 3 will present comparisons between the several radar retrievals and rain gauges. Section 4 will discuss the sensitivity of the RA retrievals to changes in α and β . Section 5 will discuss changes in DSD over the Harvey

event and how they relate to changes in the radar retrievals. Section 6 will provide our summary and conclusions.

2. Data

a. Gauge data

The gauge data used for this study were obtained online from the HCFWS. According to the HCFWS website, data-collecting sensors at each tipping-bucket gauge station transmit rainfall amounts via radio frequency after 0.04 in. (~ 1 mm) of rain is measured by a sensor. Shortly after the Harvey event, we downloaded data from 244 gauges; however, more than half of those that were outside of the box shown in Fig. 2 were removed. We further eliminated another 21 gauges because they were located along radar azimuths with known radar beam blockages. The dashed lines in Fig. 2 show the blocked area (298° – 306°). According to M. Moore (2019, personal communication), who is a hydrologic specialist with the Harris County Flood Control District

* All fields are modified in each step to remove non-precipitating echo. Threshold values are default for WSR-88D radars.

FIG. 3. Flowchart of the DPQC stream used by the GPM GV group. The algorithm is adapted from Ryzhkov and Zrnić (1998), and this figure is taken from Pippitt et al. (2013).

(HCFCD), all of the rain gauges are checked every 6 months to assure that they meet the specifications of the manufacturer. For the tipping buckets they use, this represents an accuracy of $\pm 3\%$ at rainfall rates up to 2 in. h^{-1} ($\sim 50 \text{ mm h}^{-1}$). Any tipping buckets that do not meet this standard are rejected. Given the inherent uncertainty of these types of gauges resulting from rainfall rate errors and other environmental factors, HCFCD estimates a total uncertainty of approximately $\pm 10\%$ – 15% .

b. Radar data

The radar data used in this study were obtained from the KGHX WSR-88D instrument located in League City, Texas, which is southeast of Houston. Fortunately,

the radar operated continuously throughout the 5-day event. Because of frequent use of these radar data and comparisons with spaceborne reflectivities (Schwaller and Morris 2011) from NASA's GPM mission (Hou et al. 2014), the radar reflectivity and differential reflectivity were both well calibrated. The data consisted of full volume scans taken roughly every 5–6 min. We note that the specific differential phase used in this study was obtained from the Dual-Polarization Radar Operational Processing System, version 2 (DROPS2.0), algorithm (Wang and Chandrasekar 2009; Chen et al. 2017).

To provide quality control of the KGHX data, we employed the same dual-polarimetric quality control

FIG. 4. Flowchart of the hybrid dual-polarization rain retrieval developed by Cifelli et al. (2011).

(DPQC) procedures applied to radar data as those routinely generated by the GPM mission GV program (Ryzhkov and Zrnić 1998; Zrnić and Ryzhkov 1999; Cifelli et al. 2002). Specifically, GPM GV adapted a series of algorithms based on Ryzhkov and Zrnić (1998) for conducting DPQC. The DPQC algorithms are successful in identifying and removing nonprecipitating echoes (Ryzhkov and Zrnić 1998; Zrnić and Ryzhkov 1999; Ryzhkov et al. 2005; Cifelli et al. 2002) and unfolding of Φ_{DP} .

c. Radar data quality control

The DPQC algorithm initially uses its default thresholds, which produce a mostly clean radar product. The default data were then reviewed and additional manual adjustments were made to produce the highest-quality radar product. These manual adjustments are subjective tweaks that are applied by GPM GV radar specialists. See Marks et al. (2011) for a more detailed description of the DPQC method. The DPQC threshold modules are dependent on the observed values associated with many of the observed radar fields. When the value of a gate fell outside one of the thresholds, a missing data mask was applied to that specific gate for all fields. Each threshold module has utility for removing nonprecipitating echoes. Primary fields for quality-control threshold modules

include measured reflectivity DZ, differential reflectivity DR, cross-polar correlation RH, signal quality index SQ, differential phase PH, and specific differential phase KD. The output or “corrected” reflectivity field is given by CZ. Once the CZ map has been generated, the pixels with nonprecipitating echoes are used to mask all the other fields. A flowchart of the DPQC algorithm is presented in Fig. 3.

d. Radar rain retrievals

Once the data were properly quality controlled, several additional routines were executed to calculate K_{DP} (Chen et al. 2017), hybrid dual-polarization rain estimates (RC, RP, and RR), DSD retrievals of mass-weighted mean diameter DM and normalized slope parameter NW (Tokay et al. 2019), and the attenuation-based rain estimate RA that is based on R14. The quality-controlled radar data were gridded using the National Center for Atmospheric Research RadX software. The horizontal and vertical resolutions of the gridded data were 1 km, extending 100 km horizontally and 15 km vertically from the KHGX radar. From here onward, the quality-controlled and calibrated field reflectivity will be called CZ, differential reflectivity will be referred to as DR, and specific differential phase will be called KD.

FIG. 5. As in Fig. 4, but adapted from Bringi et al. (2004).

As previously mentioned, we generated three hybrid dual-polarization rain estimates following RC, RP, and RR. We refer these as hybrid estimates because, unlike conventional reflectivity–rainfall (Z – R) relationships that rely solely on CZ, these estimates consider different values of CZ, DR, and KD to determine the associated rain rate. We refer the reader to these references for a full description of these retrievals but provide a general overview here.

Although the RC method was originally developed for application to Colorado precipitation, the GPM GV team has found it to be an excellent approach in other regions

as well (e.g., the “Delmarva” Peninsula; Melbourne, Florida; and Kwajalein, Marshall Islands). A flowchart of the RC method is provided in Fig. 4. The full implementation of the RC algorithm makes a distinction between rain and ice (Seo et al. 2018); however, given the tropical nature of this event, we limit the analysis in this study to rain only.

The RP method uses the respective values of CZ, DR, and KD to first retrieve DSD parameters D_0 , N_W , and μ , which are the median drop diameter, normalized intercept parameter, and shape function, respectively. These parameters are retrieved by examining the values of CZ,

DR, and KD by assuming that a gamma distribution (Atlas and Ulbrich 1977) properly describes the DSD. The algorithm then derives a dynamically changing coefficient to a standard Z - R equation. The default Z - R equation proposed by Bringi et al. (2004) is given by $Z = aR^b$, where a and b are 219 and 1.45, R is in millimeters per hour, and Z is in $\text{mm}^6 \text{m}^{-3}$. From the values of the CZ, DR, and KD, the coefficient a is replaced with a' on a pixel-by-pixel basis. We follow the same logic as Bringi et al. (2004) but chose our default a and b values to be 300 and 1.4, respectively. A flowchart of this algorithm is provided in Fig. 5.

The third hybrid approach is referred to as DROPS2.0 and is fully discussed in Chen et al. (2017). DROPS2.0 is very similar to DROPS1.0, which was derived from RC, but has been improved via better quality control and K_{DP} estimation, region-based hydrometeor classification, and rainfall estimation. Note the K_{DP} derived from the KHGX data used in this study was obtained from the DROPS2.0 program output.

Following R14, we also constructed an attenuation-based rain-rate retrieval. A flowchart showing our implementation of the RA method is given in Fig. 6. It is important to note that we made several modifications to the R14 approach. These changes were necessary to assure that we used data only of the highest quality. For clarity, we provide the equations discussed by R14 and intermediate steps taken to address quality-control issues of the differential phase data Φ_{DP} . The first step was to set the default rain rate as that provided by the RC estimator. Then for each ray in each sweep, all “speckle” or isolated pixels were removed. To prevent noisy edge effects, the beginning and ending of each segment were averaged over three 250-m range gates. Once this was completed, the $\Delta\Phi_{DP}$ across each rain segment in a ray was calculated. If $\Delta\Phi_{DP} > 3^\circ$ along the entire ray, then the ray was processed. If not, then the RC rain rates for that ray were used.

If the $\Delta\Phi_{DP}$ threshold was satisfied then the following was performed. The path-integrated attenuation (PIA; Meneghini and Nakamura 1990; Iguchi and Meneghini 1994; Testud et al. 2000; Bringi et al. 1990) is calculated:

$$\text{PIA} = \alpha \times \Delta\Phi_{DP}, \quad (1)$$

where PIA is along the ray and the factor α is the net ratio of A [defined below in Eq. (6)] and K_{DP} along the path and is a function of the DSD (Wang et al. 2019). The PIA is then used to calculate C in Eq. (7) below. Next we calculate

$$I(r_1, r_2) = 0.46\beta \sum (Z)^\beta, \quad (2)$$

FIG. 6. Flowchart of the attenuation-based dual-polarization rain retrieval by R14. The reflectivity Z is in units of $\text{mm}^6 \text{mm}^{-3}$. The temperature T corresponds to the temperature at the height of the beam at a given radar gate and was retrieved from hourly Rapid Update Cycle (RUC) model output (<https://rucsoundings.noaa.gov>).

where $I(r_1, r_2)$ is the integrated reflectivity along each rain segment in a ray using the linear reflectivity Z ($\text{mm}^6 \text{m}^{-3}$), β is a constant between 0.6 and 0.9 at microwave frequencies (R14), and r_1 and r_2 are the

FIG. 7. Scatterplot of radar vs gauge daily and total rain accumulations (mm) using $\alpha = 0.015$ and $\beta = 0.620$. The different rain estimates are color coded, as denoted in the top-left of each panel: RA is green, RC is blue, RP is red, and RR is golden. The corresponding colored lines are linear regression lines between the gauge accumulations and each estimator.

first and last valid gates of the each rain segment, respectively.

Then for each gate along the ray with a valid Φ_{DP} value, the reflectivity was integrated from the given gate to the last valid gate, given by

$$I(r, r_2) = 0.46\beta \sum (Z)^\beta, \quad (3)$$

where $I(r, r_2)$ is the integrated reflectivity from the current gate r to the last valid gate r_2 . According to R14, the RA method is only valid in nonfrozen precipitation; therefore, the height of each gate was checked and compared with the current sounding to assure that the current radar gate was below the freezing level. If the temperature T at the height of a given gate was $> 0^\circ\text{C}$, then the following parameters are calculated:

$$C_1 = (2.23 + 0.078T + 0.00085T^2) \times 10^3 \quad \text{and} \quad (4)$$

$$C_2 = 1 - 0.25(11 - \lambda), \quad (5)$$

where T is the ambient temperature at the height of the given radar gate, and λ is the radar wavelength. The total attenuation was given by

$$A = [C(Z^\beta)]/[I(r_1, r_2) + CI(r, r_2)], \quad (6)$$

where

$$C = \exp(0.23\beta \times \text{PIA}) - 1. \quad (7)$$

The rain rate at a given gate was then given by a power law of the attenuation:

$$\text{RA} = C_1 C_2 A^{1.03}. \quad (8)$$

According to R14, their approach is relatively immune to radar reflectivity Z biases and differential reflectivity calibration, as well as wet radome effects, partial beam blockage, and inadequate correction for attenuation. Also, rain-rate fields estimated from RA have the same spatial resolution and structure as $R(Z)$, whereas the shapes of rain cells retrieved by $R(K_{DP})$ can be slightly distorted and the fields of $R(K_{DP})$ are much noisier, particularly at lower rain rates.

There are two critical parameters utilized in the RA method. The first is α , defined as the net ratio of attenuation A and K_{DP} along the path, and it is sensitive

FIG. 8. Time series of 15-min rainfall accumulations from gauges and radar estimators. The light-gray series show 15-min rain accumulations from individual gauges, and the thick black line represents the 15-min mean from all gauges. The radar estimators are color coded according to the legend (RA is blue, RC is green, RP is red, and RR is golden). The dot-dashed lines indicate accumulated precipitation. As is evident, the RA estimator ($\alpha = 0.015$ and $\beta = 0.620$) greatly outperformed the hybrid estimators over the entirety of the event.

to the DSD, temperature, and radar wavelength (R14; Wang et al. 2019). Hence, it requires optimization for a particular rain regime. R14 suggested a value of $\alpha = 0.015$ at S band (Wang et al. 2019), which we also utilize for our first retrieval. According to Wang et al. (2019), α , which is the ratio of A/K_{DP} , depends on differential reflectivity Z_{DR} and monotonically decreases with increasing Z_{DR} at S band. Further, they state “Because rain rate estimated from the $R(A)$ relation is roughly proportional to α , the algorithm inevitably tends to underestimate tropical rain or light rain in general which are [sic] characterized by low values of Z_{DR} if a default value of α typical for continental rain is utilized.”

The second parameter is β , which according to R14 is “usually within 0.6–0.9 at microwave frequencies.” Wang et al. (2019) suggested a value of 0.62 for S-band radar, which we implemented for our first set of retrievals. To better understand how changes in α and β effect the retrievals during Harvey, we will explore the effects of different values of α and β on daily and total rainfall retrievals.

3. Comparison between gauge-observed and radar-estimated rainfall (mm) during Harvey

Figure 7 provides scatterplots of radar versus daily gauge accumulations for 25–29 August and for event total

precipitation (Fig. 7, bottom-right panel). The radar estimates include the three hybrid techniques (i.e., RC, RP, and RR) and the attenuation-based method RA using $\alpha = 0.015$ and $\beta = 0.620$, as suggested by Wang et al. (2019) and Cocks et al. (2019). The different radar/gauge pairs are denoted by their color, as marked.

The scatterplot for 25 August (Fig. 7, top-left panel), which was prior to the arrival of the bulk of the Harvey’s tropical precipitation and was dominated mostly by continental convection, shows that all of the retrievals provide good results, with the scatter roughly along the 1:1 line for the observed rain accumulations of less than 50 mm. As the regime evolved over the 26–29 August period, the hybrid retrievals remained very similar but were noticeably less than both the RA and gauge accumulations. On 27 August 2017, where the gauge-averaged rainfall exceeded 400 mm, all of the hybrid retrievals significantly underestimated the gauges while the RA retrievals agreed very well. On 28 August 2017, where gauge-averaged rainfall still exceeded 250 mm, all of the retrievals underestimated the gauge values, but RA accumulations were generally still higher than the hybrid accumulations.

Figure 8 shows a time series of 15-min rain rates and accumulations for gauges and radar estimates. Individual 15-min gauge accumulations are shown in

FIG. 9. Maps showing total accumulation from Hurricane Harvey over the period 25–29 Aug 2017: (top left) RA ($A = \alpha = 0.015$; $B = \beta = 0.620$), (top right), RC, (bottom left) RP, and (bottom right) RR. Of particular note is the lack of blockage in the RA estimates, relative to all of the hybrid estimates.

the thin gray lines and indicate a large variance of rainfall over the domain. The black line is the all-gauge-averaged 15-min rainfall; the blue, green, red, and gold lines are the *area-averaged* rainfall for the radar estimates (RA, RC, RP and RR, respectively). The averaged area of these radar estimates is shown as the rectangle to the northeast of the radar location shown in Fig. 2 and is bounded from longitude -95.96° to -94.93° W and from latitude 29.50° to 30.18° N. As shown, the rainfall amounts are truly historic, with a gauge-observed event total of approximately 875 mm over 5 days. Also evident is the fact that the RA rainfall

retrievals track significantly closer to the gauge observations than do the hybrid estimators.

Figure 9 provides the areawide radar rainfall maps for RA, RC, RP, and RR. The top-left panel in Fig. 9 shows that the RA totals were in general higher than the hybrid estimators in areas of the heaviest rainfall. Further, the ability of the RA estimator to mitigate blockage is very evident as opposed to the hybrid estimators for which significant blockage occurred in the second, third, and fourth quadrants. As noted previously, we filtered gauges that were blocked in the averaging area (also shown in Fig. 2) to keep a “level playing field.” However, note that,

FIG. 10. Daily and total rainfall accumulations for gauges and all radar estimators, including the three hybrid estimators (RC, RP, and RR) as well as RA with $\alpha =$ (a) 0.015, (b) 0.025, and (c) 0.050 and $\beta = 0.600, 0.650, 0.700, 0.750, 0.800, 0.850$, and 0.900 [(a) also includes 0.620]. The horizontal dashed line represents the gauge-measured rainfall for each period and is provided as a visual reference. The large differences among the various RA estimates illustrate well the significant dependence of β on the attenuation-based rain retrieval.

in the absence of evidence of such blocking, use of the RA estimator does mitigate the problem.

4. Sensitivity of RA retrievals to changing values of α and β

From Eqs. (1)–(8), there are two critical parameters used in the RA approach: α and β . The parameter α is the net ratio of A and K_{DP} along the path (R14; Wang et al. 2019). The β parameter, which has been used in previous studies with values of $\beta = 0.6$ – 0.9 for microwave frequencies (R14), was shown to be highly sensitive to changes in environmental conditions and DSD characteristics. According to Wang et al. (2019), $\beta = 0.620$ is appropriate for S-band radars. To test the sensitivity of the RA estimates to the choice of specific α and β , we generated multiple datasets for combinations of $\alpha = 0.15, 0.25$, and 0.50 and $\beta = 0.600$ – 0.900 in increments of 0.050 , also including $\beta = 0.620$.

Figure 10a provides a bar chart of the daily and total event rainfall for gauges and radars using $\alpha = 0.015$. In this graph, the totals for the gauges, RC, RP, RR, and

the nine RA estimates (for $\beta = 0.600$ – 0.900 in increments of 0.050 , but also including $b = 0.620$) are shown. Figures 10b and 10c provide similar plots but are generated with $\alpha = 0.025$ and $\alpha = 0.050$, respectively. Note that for Figs. 10b and 10c, unlike for Fig. 10a, we did not calculate RA using $\beta = 0.620$. In all three panels, a dashed horizontal line is added above the daily/total gauge accumulations to enable quick visual comparison between the gauge-measured and radar-retrieved rainfall.

Examining these graphs, the following points can be made: 1) an increase in α , for a given β , results in an increased estimation of RA rainfall; 2) an increase in β , for a given α , results in a decreased estimation of RA rainfall; and 3) an increase in α creates a larger variance in rainfall for different β . Table 1 provides quantitative comparison of rainfall accumulations using different values of α and β . As an example, for $\beta = 0.600$, the total rainfall accumulated using $\alpha = 0.015$, $\alpha = 0.025$, and $\alpha = 0.050$ was 965.9, 1446.2 and 2243.7 mm, respectively. In other words, for $\beta = 0.600$, an increase from $\alpha = 0.015$ to $\alpha = 0.025$ resulted in an

TABLE 1. Daily and total rainfall radar/gauge accumulations over Harris County during Hurricane Harvey (25–29 Aug 2017). Gauge totals were obtained from the HCFWS. Shown are three hybrid polarimetric estimators (RC, RP, and RR) and the attenuation-based RA method using $\alpha = 0.015$, 0.025, and 0.050 while also varying parameter β from 0.6 to 0.9 in 0.05 increments. Here, Tot_acc indicates the total accumulation over the 5-day period.

Date	Gauge	RC	RP	RR	RA_0.600	RA_0.620	RA_0.650	RA_0.700	RA_0.750	RA_0.800	RA_0.850	RA_0.900
25 Aug 2017	18.3	21.6	24	20.7	22.3	21.4	19.1	16.6	14.7	13.3	12.1	11.3
26 Aug 2017	98.8	87.3	86.7	82.1	126.3	116	96.8	74.8	58.3	45.9	36.7	29.7
27 Aug 2017	430.9	339	326.6	328	515.6	475.4	397.6	303.7	212.1	178.3	137.1	106
28 Aug 2017	228.9	157	158.9	152.6	190.1	175.6	145.2	112	86.4	67.2	52.7	41.9
29 Aug 2017	124.6	86.2	85.5	83.2	111.9	114	85	65.2	50.7	40.1	32.1	26.3
Tot_acc	897.1	691.7	679	666.8	965.9	902.1	743.4	572.2	422.1	344.6	270.8	215
$\alpha = 0.025$												
25 Aug 2017	18.3	21.6	24	20.7	32.3		26.8	22.6	19.4	17	15.1	13.6
26 Aug 2017	98.8	87.3	86.7	82.1	183.6		147.8	116.7	91.5	71.6	56.7	45.4
27 Aug 2017	430.9	339	326.6	328	755.3		603.9	481.4	377.9	293	227.7	176.7
28 Aug 2017	228.9	157	158.9	152.6	292.6		229.2	179.3	139.9	108.6	85.3	66.9
29 Aug 2017	124.6	86.2	85.5	83.2	182.8		137.5	104.4	80	61.9	48.6	38.6
Tot_acc	897.1	691.7	679	666.8	1446.2		1144.9	904.1	708.5	552	433.2	341.2
$\alpha = 0.050$												
25 Aug 2017	18.3	21.6	24	20.7	59.9		48.2	39.1	32.5	27.1	23.3	20.1
26 Aug 2017	98.8	87.3	86.7	82.1	262.4		221.7	187.9	156.1	126.5	101.8	81.5
27 Aug 2017	430.9	339	326.6	328	1023.3		889.2	764.3	639.7	521.5	421.5	339.4
28 Aug 2017	228.9	157	158.9	152.6	495.4		403.3	325.5	263.2	209.1	166.8	131.3
29 Aug 2017	124.6	86.2	85.5	83.2	403.6		305.5	230.9	175.2	133.9	102.8	79.5
Tot_acc	897.1	691.7	679	666.8	2243.7		1867.3	1547.1	1266.2	1017.8	816	651.6

FIG. 11. Daily and total rainfall bias between gauges and all radar estimators, including the three hybrid estimators (RC, RP, and RR) as well as RA with $\alpha = 0.015$, (b) 0.025, and (c) 0.050 and $\beta = 0.600, 0.650, 0.700, 0.750, 0.800, 0.850$, and 0.900 [(a) also includes 0.620]. The “DP methods” biases are shown as the black dotted lines.

increase in rainfall by 49.7% and an increase from $\alpha = 0.025$ to $\alpha = 0.050$ resulted in an increase in rainfall by 55%. Hence, rain accumulation is highly sensitive to the chosen α .

We also calculated the normalized radar/gauge bias:

$$\text{bias} = 100\% \times (R - G)/G. \quad (9)$$

Figure 11a provides the normalized daily and event total normalized biases between the gauge-measured and radar-retrieved accumulation using a set value $\alpha = 0.015$. In this figure, R is the mean radar accumulation (mm) and G is the mean gauge accumulation. It shows the biases for the three hybrid retrievals (the dual-polarization methods), as well

as multiple RA retrievals using $\beta = 0.600, 0.620, 0.650, 0.700, 0.750, 0.800, 0.850$, and 0.900 . In general, the hybrid methods tend to underestimate the gauges, except for 25 August 2017 for which they slightly overestimate them. The RA retrievals for $\beta = 0.600, 0.620$, and 0.650 all do very well, but for $\beta > 0.650$ the RA retrievals tend to underestimate the gauges. Similarly, Figs. 11b and 11c show the biases, with set values of $\alpha = 0.025$ and $\alpha = 0.050$, respectively. The dashed lines show that the three hybrid estimators all track very closely to one another. However, the RA totals are variable and become more so as α increases. For $\alpha = 0.015$ and $\alpha = 0.025$, the minimum biases are those with β between 0.600 and 0.750; however, for $\alpha = 0.050$, the lowest biases are those

TABLE 2. Daily and total rainfall radar/gauge biases over Harris County during Hurricane Harvey (25–29 August 2017). Gauge totals were obtained from the HCFWS. Shown are three hybrid polarimetric estimators (RC, RP, and RR) and the attenuation-based RA method using $\alpha = 0.015, 0.025$, and 0.050 while also varying the parameter β from 0.6 to 0.9 in 0.05 increments. The results show that the RA biases are highly sensitive to the chosen α and β parameters. All values are in percent.

Date	RC	RP	RR	RA_0.600	RA_0.620	RA_0.650	RA_0.700	RA_0.750	RA_0.800	RA_0.850	RA_0.900
$\alpha = 0.015$											
25 Aug 2017	18.1	31.3	13.5	22.2	17.1	4.4	−9.2	−19.5	−27.4	−33.5	−38.2
26 Aug 2017	−11.7	−12.3	−16.9	27.7	17.4	−2.1	−24.3	−41	−53.5	−62.9	−70
27 Aug 2017	−21.3	−24.2	−23.9	19.7	10.3	−7.7	−29.5	−50.8	−58.6	−68.2	−75.4
28 Aug 2017	−31.4	−30.6	−33.3	−17	−23.3	−36.6	−51.1	−62.2	−70.6	−77	−81.7
29 Aug 2017	−30.8	−31.4	−33.3	−10.2	−8.5	−31.8	−47.7	−59.3	−67.9	−74.2	−78.9
Tot_bias	−22.9	−24.3	−25.7	7.7	0.6	−17.1	−36.2	−52.9	−61.6	−69.8	−76
$\alpha = 0.025$											
25 Aug 2017	18.1	31.3	13.5	76.9		46.7	23.8	6.4	−7	−17.3	−25.3
26 Aug 2017	−11.7	−12.3	−16.9	85.8		49.6	18	−7.4	−27.6	−42.6	−54
27 Aug 2017	−21.3	−24.2	−23.9	75.3		40.1	11.7	−12.3	−32	−47.2	−59
28 Aug 2017	−31.4	−30.6	−33.3	27.8		0.2	−21.7	−38.9	−52.5	−62.7	−70.8
29 Aug 2017	−30.8	−31.4	−33.3	46.7		10.3	−16.2	−35.8	−50.3	−61	−69
Tot_bias	−22.9	−24.3	−25.7	61.2		27.6	0.8	−21	−38.5	−51.7	−62
$\alpha = 0.050$											
25 Aug 2017	18.1	31.3	13.5	228.3		164	114.3	78.1	48.7	27.7	10
26 Aug 2017	−11.7	−12.3	−16.9	165.5		124.3	90.1	57.9	27.9	3	−17.5
27 Aug 2017	−21.3	−24.2	−23.9	137.5		106.4	77.4	48.4	21	−2.2	−21.2
28 Aug 2017	−31.4	−30.6	−33.3	116.4		76.2	42.2	15	−8.6	−27.1	−42.6
29 Aug 2017	−30.8	−31.4	−33.3	223.8		145.2	85.3	40.6	7.4	−17.5	−36.2
Tot_bias	−22.9	−24.3	−25.7	150.1		108.2	72.5	41.2	13.5	−9	−27.4

using β between 0.800 and 0.900 . Table 2 provides the values of the radar-retrieved biases relative to the gauges for the three hybrid estimates as well as multiple RA accumulations using different values of α and β . We emphasize that the point of this study is not to find the best α, β pair for a given day but rather to understand how different values of α and β affect the accumulations in general.

5. Changes in the DSD over the Harvey event

Figure 12 shows probability density functions (PDF) of key radar observables, (CZ, DR, and PH, which was used to calculate KD), as well as three retrieved parameters (DM, NW, and RA). These PDF show how these fields changed from day to day over the event. For example, on 25 August 2017, the PDF of reflectivity (Fig. 12a) shows that CZ was substantially weaker than on other days, with a mode of about 27 dB, whereas for the reflectivities on 27 August 2017 (red curve) the reflectivity mode was closer to 30 – 35 dB. Also, on 27 August 2017, the PDFs indicate that larger DR, KD, and DM were observed relative to the other days.

Figure 13 [following Carr et al. (2017)] shows a density plot comparing reflectivity (ordinate) and differential reflectivity (abscissa). Figures 13 shows the daily extraction of CZ and DR pairs over the area of interest (i.e., the rectangle above the gauges shown in Fig. 1) for 25–

29 August 2017. The contours represent the relative percent of observed pairs over each day. To minimize noise in the data, the pairs were selected only if $1 < CZ < 60$ dBZ, binned by 1 dB, and $0 < DR < 4$ dB, binned by 0.25 dB. Together Figs. 12 and 13 can be used to better understand the evolving DSD from day to day, and Table 3 summarizes these characteristics. On 25 August 2017, the precipitation was relatively light (average gauge rainfall of only 16.4 mm) and was associated with small CZ, DR, KD, DM, and NW. Using DM as a proxy for drop size and NW as a proxy for drop counts, 25 August 2017 was dominated by a small number of small drops and thus the rain rates were relatively low. On the other hand, the precipitation on 27 August 2017 was characterized by moderate ZH and NW and large CZ, KD, and DM. Hence, this day was dominated by a moderate-to-large number of large drops, resulting in very large rain rates: average gauge rainfall was in excess of 400 mm. By 28 August 2017, the precipitation was dominated by a large number of moderate-sized drops, resulting in another very heavy rain event with average gauge rainfall in excess of 200 mm.

Figure 14 illustrates how the hybrid retrievals (here proxied by the RC retrieval) were affected by the changing CZ, DR, and KD environments by providing a time series of the specific method invoked on a scan-to-scan basis. In the RC method, there are four methods invoked to

FIG. 12. PDF of key radar observables and retrieved parameters by day, showing the observed (a) reflectivity CZ, (b) differential reflectivity DR, and (c) specific differential phase KD as well as the retrieved (d) mass-weighted mean diameter DM, (e) normalized intercept parameter NW, and (f) rain rate RA.

retrieve the rain rate from a set of observations of CZ, DR, and KD. See Fig. 4 for the specific values needed to trigger a given method. Figure 14 then gives the percentage of pixels in each scan for which a particular method was invoked. On 25 August 2017, for which the prestorm precipitation was mostly continental convection, the Z_H -only (brown) method was invoked about 60% of the time and the remainder of the points used the $Z_H + Z_{DR}$ (gold) method. Between 1000 and 2000 UTC 26 August 2017, as the storm settled to the west of Houston, $Z_H + K_{DP}$ was utilized up to about 15% of the time, and $Z_H + Z_{DR}$ and Z_H were invoked approximately 60% and 25% of the time, respectively. On 27 August 2017, which is the period during which the bulk of the event rainfall fell, the $Z_{DR} + K_{DP}$ was utilized as much as 30% of the time and the $Z_H + Z_{DR}$ method was used as much as 75% of the time. This is indicative of large Z_H , Z_{DR} , and K_{DP} . In other words, this was probably the result of the presence of a large number of large drops in the DSD resulting in extremely heavy rainfall. By 28 August 2017, the regime seems to have changed such that a large number of

small drops were present, typical of tropical cyclone DSD characteristics (Tokay et al. 2008). This change may be due to drop sorting by the stronger winds that were present on this day. Recent research has shown that wind effects can affect the DSD. Testik and Pei (2017) found that increasing wind speeds modified the DSD by increasing the number of small drops and decreasing the number of large drops via collisional drop breakup. Figure 15 provides the series of wind speeds and directions observed at Houston Intercontinental Airport (KIAH in Fig. 2). Although the center of Harvey was located well west of Harris County for much of the time, wind speeds were on the order of 15–20 kt (~ 8 – 10 m s^{-1}) during 25–26 August 2017 but did increase some during 28–29 August. To be sure, this DSD regime still provided significant rainfall, but not as high as that on 27 August 2017. On 25 August 2017, on which Z_H , Z_{DR} , and K_{DP} were in general relatively small, the lowest accumulations occurred. On 27 August 2017 Z_H was moderate while Z_{DR} and K_{DP} were large, resulting in a large number of large drops and intense rainfall. By 29 August 2017, Z_H was

FIG. 13. Daily probability density plots of differential reflectivity as a function of reflectivity. The contours show the relative contribution of CZ and DR pairs that contributed to the total observations. The colors shown represent normalized contributions to the distribution of paired values, with red indicating values that dominated the observed values (i.e., the modal values) and the remaining colors contributing to a lesser number of observed pairs.

moderate while Z_{DR} and K_{DP} were small, resulting in only moderate (in relative terms) rainfall.

6. Summary and conclusions

A comparison of several dual-polarization radar retrievals versus rain gauges was performed over Houston during the 5-day Hurricane Harvey flooding event (25–29 August 2017). The radar data used in this study were obtained from the KGHX WSR-88D located in League City, which is southeast of Houston. The radar operated

continuously throughout the 5-day event. To provide quality control of the KHGX data, we employed the DPQC procedures applied to radar data because those are routinely generated by the GPM mission GV program [Petersen et al. 2020; cf. details for DPQC in Pippitt et al. (2013) and Marks et al. (2011)]. Specifically, GPM GV adapted a series of algorithms based on Ryzhkov and Zrnić (1998) for conducting DPQC. The DPQC algorithms are successful in identifying and removing non-precipitating echoes (Ryzhkov and Zrnić 1998; Zrnić and Ryzhkov 1999; Cifelli et al. 2002).

TABLE 3. Summary of bulk statistics of key observed (ZH, DR, and KD) and retrieved (DM and NW) variables derived from PDFs of the variables averaged over the gauge network (outlined rectangle in Fig. 1) and how they relate to observed precipitation. Units for the CZ and DR modes are in reflectivity decibels (dBZ) and decibels, respectively, and rainfall is in millimeters.

Date	CZ	DR	CZ mode	DR mode	KDP	DM	NW	Gauge rainfall
25 Aug 2017	Small	Small	26.8	0.26	Small	Small	Small	16.36
26 Aug 2017	Moderate	Small	28	0.26	Moderate	Moderate	Moderate	102.59
27 Aug 2017	Moderate	Large	31.4	0.5	Large	Large	Moderate	422.36
28 Aug 2017	Large	Moderate	34.9	0.3	Small	Small	Large	214.11
29 Aug 2017	Moderate	Small	31	0.26	Small	Small	Moderate	118.47

FIG. 14. Percentage of points that utilize one of four methods ($Z_H + K_{DP}$, K_{DP} , $Z_H + Z_{DR}$, or Z_H) in the RC algorithm by day. Each point represents a single volume scan from the KHGX radar. The solid and dashed lines shows the hourly accumulation estimated by the RC and RP retrieval algorithms, respectively.

The reference dataset utilized 120 rain gauges that are part of the HCFWS; however, because of some limited radar blockage over the network, an additional 21 of the 120 gauges were removed from the analysis. The radar rain retrievals were from three common hybrid techniques: [Cifelli et al. \(2011\)](#) (RC), [Bringi et al. \(2004\)](#) (RP), [Chen et al. \(2017\)](#) (RR), and a fourth estimator that utilizes an attenuation-base method provided by [R14](#) was also used (RA).

There are two key parameters introduced utilized by the RA method: α , which is the coefficient of the PIA described by others ([Meneghini and Nakamura 1990](#); [Iguchi and Meneghini 1994](#); [Testud et al. 2000](#); [Bringi et al. 1990](#)), and β , which has been used in previous studies with values of $\beta = 0.6$ – 0.9 for microwave frequencies ([R14](#)). It was shown that both α and β are highly sensitive to the DSD of the precipitation. According to [Wang et al. \(2019\)](#), $\beta = 0.620$ is appropriate for S-band radars. To test the sensitivity of the RA estimates to the choice of specific α and β , we generated multiple datasets for combinations of $\alpha = 0.15, 0.25$, and 0.50 and $\beta = 0.600$ – 0.900 in increments of 0.050 . As an example, for $\beta = 0.600$, the total rainfall accumulated using $\alpha = 0.015$,

$\alpha = 0.025$, and $\alpha = 0.050$ was 965.9, 1446.2, and 2243.7 mm, respectively. In other words, for $\beta = 0.600$, an increase from $\alpha = 0.015$ to $\alpha = 0.025$ resulted in an increase in rainfall by 49.7% and an increase from $\alpha = 0.025$ to $\alpha = 0.050$, resulted in an increase in rainfall by 55%. Hence, rain accumulation is highly sensitive to the chosen α .

The results of this analysis showed the following: 1) an increase in α , for a given β , results in an increased estimation of RA rainfall; 2) an increase in β , for a given α , results in a decreased estimation of RA rainfall; and 3) an increase in α creates a larger variance in rainfall for different β . [Wang et al. \(2019\)](#) and [Cocks et al. \(2019\)](#) suggest a method for determining an α on a scan-by-scan basis using $\beta = 0.620$. The differences in the ambient DSD characteristics made setting a constant value of α and β difficult. Also, there unfortunately were no in situ DSD data available for Harvey, and therefore we had to rely on the radar observables to deduce how the DSD changed over the course of the event. To do so, we utilized probability distributions of observed reflectivity, differential reflectivity, and the differential phase, which was used to calculate the specific differential phase. We also examined the PDFs of retrieved

FIG. 15. Wind speed (m s^{-1} , left axis scale; black curves) and wind direction ($^{\circ}$, right axis scale; red curves) as measured by the National Weather Service ASOS site located at KIAH, which is located approximately 65 km northwest of the KHGX radar. The three numbers in the top left of each panel show the mean, standard deviation, and maximum wind speed for the day from left to right.

DSD parameters, including mass weight mean diameter DM, the normalized intercept NW, and rain rate.

Density plots comparing reflectivity versus differential reflectivity showed the daily extraction of CZ and DR pairs over the area for 25–29 August 2017. The contours represent the relative percent of observed pairs over each day. To minimize noise in the data, the pairs were selected only if $1 < CZ < 60$ dBZ, binned by 1 dB, and $0 < DR < 4$ dB, binned by 0.25 dB. On 25 August 2017, the precipitation was relatively light (average gauge rainfall of only 16.4 mm) and was associated with small CZ, DR, KD, DM, and NW. Using DM as a proxy for drop size and NW as a proxy for drop counts, 25 August 2017 was dominated by a small number of small drops and thus the rain rates were relatively low. On the other hand, the precipitation on 27 August 2017 was characterized by moderate CZ and NW and large DR, KD, and DM. Hence, this day was dominated by a moderate-to-large number of large drops, resulting in very large rain rates: average gauge rainfall was in excess of 400 mm. By 28 August 2017, the precipitation was dominated by a large number of moderate sized drops, resulting in another very heavy rain event with average gauge rainfall in excess of 200 mm.

Each of the hybrid techniques base their point-by-point retrievals on observed values of CZ, DR, and KD. To illustrate each particular method, we developed time plots of the percentage of points for a given scan that is employed by a given method. We demonstrated how the hybrid retrievals (here proxied by the RC retrieval) were affected by the changing CZ, DR, and KD environments by providing a time series of the specific method invoked on a scan-to-scan basis. It was shown that CZ, ZD, and KD values affect the intensity of the rain rate and the associated DSD values.

These results suggest that there are large differences in the RA rain-rate retrievals that are highly influenced by changing the ambient DSD. Wang et al. (2019) and Cocks et al. (2019) suggest a method for specifying α on a scan-by-scan basis using $\beta = 0.620$. We did not invoke this procedure in this study because our emphasis was to examine the sensitivity of rain retrievals to changes in α and β . However, we do recognize that such techniques do need to be employed to make RA estimates more robust and will continue to investigate techniques to improve rain retrievals for GPM GV.

Acknowledgments. We thank Dr. Gail Skofronick-Jackson for her support as the previous GPM Project Scientist and current Program Scientist. This study was funded through the NASA Precipitation Measurement Mission and the GPM ground validation program.

REFERENCES

- Atlas, D., and C. W. Ulbrich, 1977: Path- and area-integrated rainfall measurement by microwave attenuation in the 1–3 cm band. *J. Appl. Meteor.*, **16**, 1322–1331, [https://doi.org/10.1175/1520-0450\(1977\)016<1322:PAIRM>2.0.CO;2](https://doi.org/10.1175/1520-0450(1977)016<1322:PAIRM>2.0.CO;2).
- Blake, E. S., and D. A. Zelinsky, 2018: National Hurricane Center tropical cyclone report: Hurricane Harvey (AL092017). NOAA Rep., 77 pp., https://www.nhc.noaa.gov/data/tcr/AL092017_Harvey.pdf.
- Brandes, E. A., G. Zhang, and J. Vivekanandan, 2002: Experiments in rainfall estimation with a polarimetric radar in a subtropical environment. *J. Appl. Meteor.*, **41**, 674–685, [https://doi.org/10.1175/1520-0450\(2002\)041<0674:EIREWA>2.0.CO;2](https://doi.org/10.1175/1520-0450(2002)041<0674:EIREWA>2.0.CO;2).
- Bringi, V. N., V. Chandrasekar, N. Balakrishnan, and D. S. Zrnić, 1990: An examination of propagation effects in rainfall on polarimetric variables at microwave frequencies. *J. Atmos. Oceanic Technol.*, **7**, 829–840, [https://doi.org/10.1175/1520-0426\(1990\)007<0829:AEOPFI>2.0.CO;2](https://doi.org/10.1175/1520-0426(1990)007<0829:AEOPFI>2.0.CO;2).
- , T. Tang, and V. Chandrasekar, 2004: Evaluation of a new polarimetrically based Z–R relation. *J. Atmos. Oceanic Technol.*, **21**, 612–623, [https://doi.org/10.1175/1520-0426\(2004\)021<0612:EOANPB>2.0.CO;2](https://doi.org/10.1175/1520-0426(2004)021<0612:EOANPB>2.0.CO;2).
- Carr, N., P. E. Kirstetter, J. J. Gourley, and Y. Hong, 2017: Polarimetric signatures of midlatitude warm-rain precipitation events. *J. Appl. Meteor. Climatol.*, **56**, 697–711, <https://doi.org/10.1175/JAMC-D-16-0164.1>.
- Chen, H., V. Chandrasekar, and R. Bechini, 2017: An improved dual-polarization radar rainfall algorithm (DROPS2.0): Application in NASA IFloodS field campaign. *J. Hydrometeorol.*, **18**, 917–937, <https://doi.org/10.1175/JHM-D-16-0124.1>.
- Cifelli, R., W. A. Petersen, L. D. Carey, S. A. Rutledge, and M. A. F. da Silva Dias, 2002: Radar observations of the kinematic, microphysical, and precipitation characteristics of two MCSs in TRMM LBA. *J. Geophys. Res.*, **107**, 8077, <https://doi.org/10.1029/2000JD000264>.
- , V. Chandrasekar, S. Lim, P. Kennedy, Y. Wang, and S. Rutledge, 2011: A new dual-polarization radar rainfall algorithm: Application in Colorado precipitation events. *J. Atmos. Oceanic Technol.*, **28**, 352–364, <https://doi.org/10.1175/2010JTECHA1488.1>.
- Cocks, S. B., L. Tang, P. Zhang, A. Ryzhkov, B. Kaney, K. L. Elmore, Y. Wang, J. Zhang, and K. Howard, 2019: A prototype quantitative precipitation estimation algorithm for operational S-Band polarimetric radar utilizing specific attenuation and specific differential phase. Part II: Performance verification and case study analysis. *J. Hydrometeorol.*, **20**, 999–1014, <https://doi.org/10.1175/JHM-D-18-0070.1>.
- Giangrande, S., and A. Ryzhkov, 2008: Estimation of rainfall based on the results of polarimetric echo classification. *J. Appl. Meteor.*, **47**, 2445–2462, <https://doi.org/10.1175/2008JAMC1753.1>.
- Hou, A. Y., and Coauthors, 2014: The Global Precipitation Measurement Mission. *Bull. Amer. Meteor. Soc.*, **95**, 701–722, <https://doi.org/10.1175/BAMS-D-13-00164.1>.
- Iguchi, T., and R. Meneghini, 1994: Intercomparison of single frequency methods for retrieving a vertical rain profile from airborne or spaceborne radar data. *J. Atmos. Oceanic Technol.*, **11**, 1507–1516, [https://doi.org/10.1175/1520-0426\(1994\)011<1507:IOSFMF>2.0.CO;2](https://doi.org/10.1175/1520-0426(1994)011<1507:IOSFMF>2.0.CO;2).
- Marks, D. A., D. B. Wolff, L. D. Carey, and A. Tokay, 2011: Quality control and calibration of the dual-polarization radar at Kwajalein, RMI. *J. Atmos. Oceanic Technol.*, **28**, 181–196, <https://doi.org/10.1175/2010JTECHA1462.1>.
- Meneghini, R., and K. Nakamura, 1990: Range profiling of the rain rate by an airborne weather radar. *Remote Sens. Environ.*, **31**, 193–209, [https://doi.org/10.1016/0034-4257\(90\)90089-5](https://doi.org/10.1016/0034-4257(90)90089-5).

- Petersen, W. A., P. E. Kirstetter, J. Wang, D. B. Wolff, and A. Tokay, 2020: The GPM Ground Validation Program. *Satellite Precipitation Measurement*, V. Levizzani et al., Eds., Springer Nature, in press.
- Pippitt, J. L., D. A. Marks, and D. B. Wolff, 2013: Dual-polarimetric quality control for NASAs Global Precipitation Measurement (GPM) mission ground validation program. *36th Conf. on Radar Meteorology*, Breckenridge, CO, Amer. Meteor. Soc., <https://ams.confex.com/ams/36Radar/webprogram/Handout/Paper228522/36radarposter.pdf>.
- Ryzhkov, A. V., and D. S. Zrnić, 1995: Comparison of dual-polarization radar estimators of rain. *J. Atmos. Oceanic Technol.*, **12**, 249–256, [https://doi.org/10.1175/1520-0426\(1995\)012<0249:CODPRE>2.0.CO;2](https://doi.org/10.1175/1520-0426(1995)012<0249:CODPRE>2.0.CO;2).
- , and —, 1998: Polarimetric rainfall estimation in the presence of anomalous propagation. *J. Atmos. Oceanic Technol.*, **15**, 1320–1330, [https://doi.org/10.1175/1520-0426\(1998\)015<1320:PREITP>2.0.CO;2](https://doi.org/10.1175/1520-0426(1998)015<1320:PREITP>2.0.CO;2).
- , S. E. Giangrande, and T. J. Shurr, 2005: Rainfall estimation with a polarimetric prototype of WSR-88D. *J. Appl. Meteor.*, **44**, 502–515, <https://doi.org/10.1175/JAM2213.1>.
- , M. Diederich, P. Zhang, and C. Simmer, 2014: Potential utilization of specific attenuation for rainfall estimation, mitigation of partial beam blockage, and radar networking. *J. Atmos. Oceanic Technol.*, **31**, 599–619, <https://doi.org/10.1175/JTECH-D-13-00038.1>.
- Schwaller, M. R., and K. R. Morris, 2011: A ground validation network for the Global Precipitation Measurement Mission. *J. Atmos. Oceanic Technol.*, **28**, 301–319, <https://doi.org/10.1175/2010JTECHA1403.1>.
- Seo, B.-C., and Coauthors, 2018: Comprehensive evaluation of the IFloodS radar rainfall products for hydrological applications. *J. Hydrometeorol.*, **19**, 1793–1812, <https://doi.org/10.1175/JHM-D-18-0080.1>.
- Testik, F. Y., and B. Pei, 2017: Wind effects on the shape of rain-drop size distribution. *J. Hydrometeorol.*, **18**, 1285–1303, <https://doi.org/10.1175/JHM-D-16-0211.1>.
- Testud, J., E. Le Bouar, E. Obligis, and M. Ali-Mehenni, 2000: The rain profiling algorithm applied to polarimetric weather radar. *J. Atmos. Oceanic Technol.*, **17**, 332–356, [https://doi.org/10.1175/1520-0426\(2000\)017<0332:TRPAAT>2.0.CO;2](https://doi.org/10.1175/1520-0426(2000)017<0332:TRPAAT>2.0.CO;2).
- Tokay, A., P. G. Bashor, E. Habib, and T. Kasparis, 2008: Rain-drop size distribution measurements in tropical cyclones. *Mon. Wea. Rev.*, **136**, 1669–1686, <https://doi.org/10.1175/2007MWR2122.1>.
- , L. P. D’Adderio, D. B. Wolff, and W. A. Petersen, 2019: Development and evaluation of the raindrop size distribution parameters for the NASA Global Precipitation Measurement Mission ground validation program. *J. Atmos. Oceanic Technol.*, <https://doi.org/10.1175/JTECH-D-18-0071.1>, in press.
- Wang, Y., and V. Chandrasekar, 2009: Algorithm for estimation of the specific differential phase. *J. Atmos. Oceanic Technol.*, **26**, 2565–2578, <https://doi.org/10.1175/2009JTECHA1358.1>.
- Wang, Y., J. Zhang, A. V. Ryzhkov, and L. Tang, 2013: C-band polarimetric radar QPEs based on specific differential propagation phase for extreme typhoon rainfall. *J. Atmos. Oceanic Technol.*, **30**, 1354–1370, <https://doi.org/10.1175/JTECH-D-12-00083.1>.
- , S. Cocks, L. Tang, A. Ruzhkov, P. Zhang, J. Zhang, and K. Howard, 2019: A prototype quantitative precipitation estimation algorithm for operational S-Band polarimetric radar utilizing specific attenuation and specific differential phase. Part I: Algorithm description. *J. Hydrometeorol.*, **20**, 985–997, <https://doi.org/10.1175/JHM-D-18-0071.1>.
- Zrnić, D. S., and A. V. Ryzhkov, 1999: Polarimetry for weather surveillance radars. *Bull. Amer. Meteor. Soc.*, **80**, 389–406, [https://doi.org/10.1175/1520-0477\(1999\)080<0389:PFWSR>2.0.CO;2](https://doi.org/10.1175/1520-0477(1999)080<0389:PFWSR>2.0.CO;2).