Testing Passive Microwave-Based Hail Retrievals Using GPM DPR Ku-Band Radar

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ABSTRACT: Several studies in the literature have developed approaches to diagnose hail storms from satellite-borne passive microwave imagery and build nearly global climatologies of hail. This paper uses spaceborne Ku-band radar measurements from the Global Precipitation Measurement (GPM) mission Dual-Frequency Precipitation Radar (DPR) to validate several passive microwave approaches. We assess the retrievals on the basis of how tightly they constrain the radar reflectivity at -20°C and how this measured radar reflectivity aloft varies geographically. The algorithm that combines minimum 19-GHz polarization corrected temperature (PCT) with a 37-GHz PCT depression normalized by tropopause height constrains the radar reflectivity most tightly and gives the least appearance of regional biases. A retrieval that is based on a 19-GHz PCT threshold of 261K also produces tightly clustered profiles of radar reflectivity, with little regional bias. An approach using regionally adjusted minimum 37-GHz PCT performs relatively well, but our results indicate it may overestimate hail in some subtropical and midlatitude regions. A threshold applied to the minimum 37-GHz PCT ($\leq 230\text{ K}$), without any scaling by region or probability of hail, overestimates hail in the tropics and underestimates beyond the tropics. For all retrieval approaches, storms identified as having hail tended to have radar reflectivity profiles that are consistent with general expectations for hailstorms (reflectivity $> 50\text{ dBZ}$ below the 0°C level, and $> 40\text{ dBZ}$ extending far above 0°C). Profiles from oceanic regions tended to have more rapidly decreasing reflectivity with height than profiles from other regions. Subtropical, high-latitude, and high-terrain land profiles had the slowest decreases of reflectivity with height.

KEYWORDS: Hail; Severe storms; Climatology; Microwave observations; Remote sensing; Satellite observations

1. Introduction

When constructing global hail climatologies, there is difficulty in applying a uniform approach to regions with different hail reporting standards and capabilities. This drives the motivation to use spaceborne platforms. The remote sensing community has leveraged the scattering of upwelling microwave radiation by large ice particles to study distributions of convective systems (Spencer and Santek 1985; Mohr and Zipser 1996; Zipser et al. 2006). Empirical relationships between passive microwave brightness temperature T_b and the

likelihood of severe weather and hail have been used to estimate global distributions of hailstorms (Spencer et al. 1987; Cecil and Blankenship 2012; Ferraro et al. 2015; Mroz et al. 2017; Ni et al. 2017; Bang and Cecil 2019). Decreasing T_b s trend with higher percentages of hailing storms (Cecil 2009). These relationships are constructed mostly using the 37-GHz and higher-frequency channels on spaceborne microwave radiometers. In this paper, we evaluate several passive microwave hail-retrieval approaches from the literature, with an emphasis on testing them for consistency across regions. We use spaceborne Ku-band radar to assess these retrievals, as a globally uniform dataset avoids the inconsistencies and potential biases from nonmeteorological factors that arise in ground-based hail report datasets (Allen and Tippett 2015).

Some of the appeal of using spaceborne passive microwave measurements lies in the near-global coverage from multiple satellites in low-Earth orbit. A series of related instruments now provides a long record of intercalibrated measurements, dating back to the first Special Sensor Microwave/Imager (SSM/I) launched in 1987 (Berg 2016). Using passive microwave proxies for hail, many throughout the literature have constructed global or nearly global climatologies of hail using satellite platforms. Spencer et al. (1987) first noted the relationship between low 37-GHz passive microwave T_b and severe weather (including hail), and Cecil (2009) proposed

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the concept of using a series of minimum passive microwave T_b thresholds to build a climatology (70 K for 85 GHz, 180 K for 37 GHz, and 230 K for 19 GHz) using Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI) data.

Note that microwave T_b s are not unique to distinct profiles of hydrometeors (Toracinta et al. 2002). For example, a thick layer or high concentration of graupel may register the same T_b as a shallower depth of larger hail (Leppert and Cecil 2019). Therefore, the relationship between columns of scatterers and their associated T_b s may change between meteorological and geographical regimes (Cecil 2011; Cecil and Blankenship 2012; Ni et al. 2017).

Passive microwave instruments essentially measure the integrated effects of the surface, the overlying atmosphere, and hydrometeors. Active sensors like radar, on the other hand, contain information mapped to specific altitudes. Satellite-borne precipitation radars have flown onboard the Global Precipitation Measurement (GPM) mission *Core Observatory* [the Dual-Frequency Precipitation Radar (DPR)], and on its predecessor, the TRMM Precipitation Radar (PR). Using TRMM PR, Ni et al. (2017) created a radar-based climatology, setting a threshold value for hail wherein the 44-dBZ echo top temperature $\leq -22^\circ\text{C}$.

Because of the well-documented relationship between hail and radar reflectivity (Donaldson 1959; Waldvogel et al. 1979), particularly above 0°C , radar provides an excellent tool for evaluating passive microwave hail retrievals. The TRMM and GPM platforms provide nearly simultaneous and collocated passive microwave and radar datasets, allowing us to examine the variability in relationships between T_b and radar reflectivity. We focus here specifically on the relationships between T_b and radar reflectivity values associated with hail.

Cecil (2011) evaluated the differences in vertical profiles of TRMM PR Ku-band radar reflectivity with different threshold 37-GHz polarization corrected (brightness) temperature (PCT). Cecil (2011) found that the relationship between PCT thresholds and Ku-band vertical radar profiles is dependent on geographical regime. Cecil examined TRMM precipitation features (Nesbitt et al. 2000; Cecil et al. 2005; Liu et al. 2008) in four geographical categories: tropical land, tropical ocean, subtropical land, and subtropical ocean. Despite having the same minimum 37-GHz PCT (220 ± 2 K), profiles from each of these four categories differed in the slope of reflectivity above 0°C , indicating significant microphysical differences between profiles.

Several refinements to hail retrievals from passive microwave data have been made in the wake of the T_b thresholding put forward by Cecil (2009). Ni et al. (2017), in their passive-microwave-only hail retrieval, suggest a 37-GHz PCT threshold of 230 K so as to maximize the Heidke skill score and critical success index when validated against surface hail reports. Ferraro et al. (2015) apply T_b thresholds to both the 89- and 166-GHz channels of the Advanced Microwave Sounding Unit (AMSU-A and AMSU-B) instrument. Cecil and Blankenship (2012) employ a method similar to a lookup table, assigning a probability of hail based on 37-GHz PCT values. Using the probability of hail gives more weight to

storms with more strongly depressed 37-GHz PCTs, instead of equally counting all storms that satisfy a simple threshold. Mroz et al. (2017), in addition to constructing hail-detection algorithms based on the GPM Ku-band radar, propose a 19-GHz PCT threshold of 261 K. Laviola et al. (2020) developed hail probabilities for the 150- and 190-GHz channels from AMSU.

The sensitivity to scattering of any given passive microwave channel is dependent upon the size of the scatterers within the column relative to the channel's wavelength. The 89-GHz channel (85 for TRMM), while an effective proxy for the existence of precipitation and convection in general, is not a good discriminator of hail because the smaller wavelength can also be scattered to extremely low T_b s by deep columns of graupel (Cecil 2014; Leppert and Cecil 2019). Lower frequencies like 10 GHz (longer wavelengths) are less sensitive to scattering by most ice particles that are smaller than hail, and that sensitivity decreases with decreasing diameter of the scatterers (Mroz et al. 2017). Large horizontal footprint sizes for low-frequency channels [~ 600 km² and larger for 10-GHz channels on current satellites; see Table 2 in Cecil and Chronis (2018)] further reduce their sensitivity to most ice particles.

Severe hail, as defined by the U.S. National Weather Service, is 1 in. (25.4 mm) or greater in diameter. Because extinction coefficients decrease with decreasing frequency, Mroz et al. (2017) hypothesized that the 19-GHz microwave frequency might be a better discriminator of hail than is the 37-GHz frequency, which is also sensitive to scattering by graupel (<5 mm in diameter). Mroz et al. (2017) found that, of all of the GPM Microwave Imager (GMI) passive microwave frequencies taken alone, the 19-GHz channel was the most successful for detecting hail, as determined by hydrometeor identification from collocated dual-polarization ground radars.

Bang and Cecil (2019) constructed a hail retrieval that follows from the logic put forth by Cecil (2009), Cecil and Blankenship (2012), and Mroz et al. (2017). Training their retrieval on 16+ years of TMI data paired with surface reports of severe (>2.5 cm) hail, Bang and Cecil (2019) calculated the estimated probability of hail from two passive microwave variables: the minimum 19-GHz PCT, and the 37-GHz PCT depression normalized by the depth of the troposphere. Most of the retrieval approaches we assess (Cecil and Blankenship 2012; Ni et al. 2017; Bang and Cecil 2019) target identification of large hail reaching the surface, as they were trained using reports of large hail at the surface in the United States. The measurements used in these retrievals are more directly related to the presence of hail aloft, however, and cannot distinguish the actual vertical location or depth of a hail signature.

In this paper, we assess the performance of the passive microwave hail-retrieval approaches put forth by Bang and Cecil (2019) (combination of normalized 37-GHz PCT depression and minimum 19-GHz PCT), Ni et al. (2017) (37-GHz PCT ≤ 230 K), Mroz et al. (2017) (19-GHz PCT ≤ 261 K), and the Cecil and Blankenship (2012) retrieval (regionally adjusted lookup table using 37-GHz PCT). We use the terminology Ni17, Mroz17, CB12, and BC19 hereinafter to refer to the passive microwave retrieval algorithms from papers by Ni et al. (2017), Mroz et al. (2017), Cecil and Blankenship (2012), and

TABLE 1. Criteria for hail retrievals examined in this study. For the bottom three retrievals, probability of hail P_{hail} for each variable is parameterized by the logistic equation.

Ni17	Min 37-GHz PCT ≤ 230 K
Mroz17	Min 19-GHz PCT ≤ 261 K
CB12	Based on min 37-GHz PCT, adjusted for regional differences
BC19	$[P_{\text{hail}}(\text{normalized 37-GHz PCT depression}) \times P_{\text{hail}}(\text{min 19-GHz PCT})]^{1/2}$
Min 37-GHz PCT	$P_{\text{hail}}(x) = 1/[1 + \exp\{0.0723(x - 196)\}]$
Normalized 37-GHz depression [(max 37-GHz PCT – min 37-GHz PCT)/LRT]	$P_{\text{hail}}(x) = 1/[1 + \exp\{-0.762(x - 5.09)\}]$
Min 19-GHz PCT	$P_{\text{hail}}(x) = 1/[1 + \exp\{0.137(x - 257)\}]$

Bang and Cecil (2019). The full citations are used when referring to results or other aspects of those papers, as distinct from the retrieval algorithms themselves.

For this assessment, we use concurrent GPM DPR Ku-band radar data. We examine the accuracy and regional variability in radar reflectivity space of these retrievals. We particularly investigate to what extent each approach may lead to regional biases in the derived hail climatologies. After assessing those four approaches from the literature, we examine the performance of the individual components of the BC19 retrieval.

2. Data and methods

a. Datasets used

This analysis uses 4 years of GPM *Core Observatory* satellite data (April 2014–March 2018). Using 1C GMI T_b s (Berg 2016), we select contiguous areas of GMI 89-GHz PCT below 200 K that lie within the 245-km-wide domain of the GPM DPR Ku-band swath (Iguchi and Meneghini 2016). These areas are used to define polarization corrected temperature features (PCTFs) (in the manner of precipitation features, see Nesbitt et al. 2000; Cecil et al. 2005; Liu et al. 2008). The same treatment is applied to 1C TRMM TMI (GPM Science Team 2017) and PR (TRMM1Z 2014) data.

For each PCTF, the maximum Ku-band radar reflectivity is recorded in 500-m vertical increments between the surface and 20-km altitude. The GPM DPR attenuation corrected reflectivity product (Iguchi et al. 2010) is used. ECMWF interim reanalysis (ERA-Interim; Dee et al. 2011; Berrisford et al. 2011; ECMWF 2018) data (0.75° resolution) are interpolated in time and space to the geometric centroid of each PCTF. We then interpolate the vertical profile of DPR Ku-band maximum radar reflectivity to temperature coordinates in 2°C increments using ERA-Interim reanalysis heights and the radar height vector. Lapse-rate tropopause (LRT) height is also computed from ERA-Interim data using a method employed by Liu and Liu (2018), who have provided the LRTs used throughout this paper.

b. Hail-retrieval criteria

The hail-detection criteria examined in this paper (Table 1) ultimately depend on the minimum 37-GHz PCT and/or the minimum 19-GHz PCT within a PCTF. The Ni17 procedure treats any precipitation feature with minimum 37-GHz PCT ≤ 230 K as a hailstorm. Mroz17 treats any GMI pixel with 19-GHz PCT ≤ 261 K as having hail. We conduct this analysis

from a feature-based perspective, and here we treat any PCTF with minimum 19-GHz PCT ≤ 261 K as a hail detection for the Mroz17 procedure. The CB12 retrieval scales the minimum 37-GHz PCT by regionally dependent factors to account for observed differences in radar reflectivity profiles [see Figs. 2 and 3 of Cecil and Blankenship (2012) and Table 1 of Cecil (2011)]. CB12 then assigns a probability of hail P_{hail} on the basis of that scaled minimum 37-GHz PCT. All P_{hail} (CB12) is then accumulated for storms with a scaled 37-GHz PCT at or below 200 K.

Similar to the CB12 retrieval, BC19 assigns P_{hail} to each PCTF and accumulates the probability for all storms that satisfy a threshold of at least 20% P_{hail} (BC19). BC19 individually computes P_{hail} using the minimum 37-GHz PCT, a normalized 37-GHz depression (divided by the height of the lapse-rate tropopause), and the minimum 19-GHz PCT. P_{hail} (BC19) is calculated as the square root of the product of the individual hail probabilities from the normalized 37-GHz depression and the minimum 19-GHz PCT. The hail probabilities based on minimum 37-GHz PCT are not ultimately used in the BC19 retrieval, but we do use minimum 37-GHz PCT in sections 3a and 3b for comparison with Ni17 and CB12, which both use minimum 37-GHz PCT, and for comparison with P_{hail} , which is based on minimum 19-GHz PCT.

c. Histogram adjustment of PCT distributions

The CB12, Ni17, and BC19 retrievals were created using TMI data paired with surface hail reports. Before applying those retrievals to GMI data, we histogram adjust the GMI data to account for differences from TMI data that are primarily related to footprint size. The procedure is described in the appendix. The minimum 10-, 19-, and 37-GHz PCTs, and the maximum 10- and 37-GHz PCTs are all adjusted using this method. Because of the similar footprint size of the 89-GHz GMI channel and the 85-GHz TMI channel, we do not adjust these PCTs. We tested the 89- and 85-GHz channels following the same procedures as used for the lower-frequency channels, confirming that no adjustment is needed. The Mroz17 retrieval was constructed using GMI data, so it is applied without any adjustment.

d. Surface snow and ice artifact filtering

Bang and Cecil (2019) also describe a snow screening method to account for snow- and ice-covered surfaces that produce very low T_b s. This snow screen entails subtracting the 89-GHz PCT (85) depression from double the 10-GHz PCT depression, $[2(\text{maximum 10-GHz PCT} - \text{minimum 10-GHz PCT})$

FIG. 1. (a) Scatterplot of minimum 89-GHz (85 for TRMM) PCT against $2\Delta 10 - \Delta 89$ (85 for TRMM) for all TRMM and GPM PCTFs. Color is DPR Ku-band maximum reflectivity at -20°C . (b) Percentage of PCTFs with maximum reflectivity $> 30\text{dBZ}$ at the -20°C temperature level (shaded) and two-dimensional histogram (white contours) of minimum 89-GHz (85 GHz) PCT vs $2\Delta 10 - \Delta 89$ (85) (see section 2). The surface snow and ice filter

TABLE 2. IQRs of maximum reflectivity at -20°C for PCTFs that meet the Ni17, Mroz17, CB12 ($\geq 20\%$), BC19 ($\geq 20\%$), minimum 37-GHz PCT ($\geq 20\%$), and minimum 19-GHz PCT ($\geq 20\%$) retrieval hail criteria. We also list total sample size (N) of PCTFs meeting the criterion for each retrieval, and the sample size weighted by $P_{\text{hail}}(N_w)$ for the probability-based retrievals, marked with an asterisk.

Retrieval	IQR (dB)	N	N_w
Ni17	5.46	5867	
Mroz17	4.51	4389	
CB12*	4.21	1894	618
BC19*	3.91	2297	994
Min 37-GHz PCT*	4.37	2762	1360
Min 19-GHz PCT*	3.91	2120	956

– (maximum 89-GHz PCT – minimum 89-GHz PCT)], which we call $2\Delta 10 - \Delta 89$ (85 for TRMM). The filter is reexamined here using TMI and histogram-adjusted GMI data combined, to create a slightly different method of thresholding $2\Delta 10 - \Delta 89$ and minimum 89-GHz PCT.

Figure 1a shows the maximum reflectivity at -20°C on a scatterplot of minimum 89-GHz PCT (85) against $2\Delta 10 - \Delta 89$ (85) for all TRMM and GPM PCTFs with an estimated $P_{\text{hail}}(\text{BC19}) \geq 20\%$. There is a sharp delineation between PCTFs with strong (over 30 dBZ) Ku-band echoes, and those with weak Ku-band reflectivities.

A two-dimensional histogram (Fig. 1b) depicts the percentage of PCTFs in each bin with Ku-band echoes over 30 dBZ at -20°C , as a function of minimum 89-GHz (85) PCT and $2\Delta 10 - \Delta 89$ (85). The Bang and Cecil (2019) paper applies threshold values of -30 K for $2\Delta 10 - \Delta 89$ and 120 K for minimum 89-GHz PCT, but, upon reexamination, the gradient in maximum reflectivity and in the concentration of high reflectivity at -20°C has a definable slope (Fig. 1b) in the parameter space of $2\Delta 10 - \Delta 89$ (85) and minimum 89-GHz (85) PCT. We define the threshold by fitting a line to the 50% concentration bins, shown by the black line in Fig. 1b, and lower threshold of 105 K for minimum 89-GHz (85) PCT. The threshold line is reproduced in Fig. 1a in pink.

To convey the dramatic shift from strong, deep convection on one side of the threshold line to weak reflectivities on the other side, Fig. 1c shows the percentage of PCTFs with 30- or 40-dBZ echo at the -20°C level as a function of distance to the right of the threshold line. Just to the left of the threshold line (negative distances in Fig. 1c), about 65% of PCTFs have at least 30 dBZ at -20°C , and the median is 45.3 dBZ at -20°C . Just to the right of the threshold line, only 33% of PCTFs have 30 dBZ at -20°C , and fewer than one-half of the PCTFs even have any detectable radar reflectivity at -20°C .

All figures henceforth have the snow/ice filter shown in Fig. 1 applied, even for retrievals based in the literature that did not employ this filter. Subjecting all retrievals to the same snow filter provides the fairest comparison.

e. Radar-based validation of hail retrievals

To assess the effectiveness of the passive microwave-based hail algorithms, we make the simplifying assumption that hailstorms identified by satellite should have broadly similar vertical profiles of radar reflectivity, without large geographical differences in their profiles. We recognize that this assumption is only an approximation of reality, as some hailstorms are stronger than others, and they can encompass a range of microphysical conditions and vertical profiles. However, the statistical properties of PCTFs identified as hailstorms are somewhat skewed toward those barely passing the hail-detection criteria, as those are by far the most common. That should bolster the expectation that such storms would have similar radar reflectivity profiles and mitigate concerns about some hailstorms being truly stronger than others.

Throughout this paper, we target two specific aspects of the passive microwave hail retrieval to test: the accuracy of the retrieval, and the regional variability of the retrieval throughout the GPM domain. When testing with radar data, an accurate retrieval would yield a narrow range of radar reflectivities at a given temperature level for a given P_{hail} . A less accurate retrieval would yield a wide range of radar reflectivities for a given P_{hail} . Ni et al. (2017) found a statistically optimal threshold for hail detection from TRMM PR, with skill scores maximized for PFs whose maximum height of the 44 dBZ echo was at temperatures colder than -22°C . In this paper, we focus on reflectivities at the -20°C level. Without defining a particular value as representing “truth” for hail detections, we generally expect reflectivities greater than $\sim 45\text{ dBZ}$ for hailstorms.

We would also expect an effective hail retrieval to have consistent performance throughout the geographic domain of the satellite, and not show substantial regional bias in the reflectivities it associates with hail, regardless of latitude or differences in terrain. A poorly performing retrieval would show widely differing radar characteristics for storms assigned the same P_{hail} . If the retrieved hailstorms tend to have systematically lower reflectivities in one region than in another, this suggests the retrieval algorithm is triggered too easily and has a higher false alarm rate (overestimating hail) in the region with lower reflectivities. A region with systematically higher reflectivities for the retrieved hailstorms may suffer from missed detections, leading to underestimates of hailstorm occurrence.

←

threshold line is overlaid in pink in (a) and black in (b). (c) The fraction of PCTFs with 30 dBZ (black line) and 40 dBZ (blue line) with respect to distance to the right of the threshold line, shown in (a) and (b). The red dashed line is the median reflectivity (dBZ) of PCTFs with respect to distance to the right of the screening threshold line (right y axis).

FIG. 2. Number of PCTFs meeting the (a) minimum 37-GHz PCT ≤ 230 K (Ni17), (b) minimum 19-GHz PCT ≤ 261 K (Mroz17), (c) $P_{\text{hail}}(\text{CB12}) \geq 20\%$, (d) $P_{\text{hail}}(\text{BC19}) \geq 20\%$, (e) $P_{\text{hail}}(\text{minimum 37-GHz PCT}) \geq 20\%$, and (f) $P_{\text{hail}}(\text{minimum 19-GHz PCT}) \geq 20\%$ retrieval hail criteria in $15^\circ \times 15^\circ$ grid boxes (see Table 1 for probability curve parameters). Total sample size and total weighted sample size for these retrievals are listed in Table 2.

3. Results

a. Accuracy and regional variability

First, we examine how closely the hail retrievals constrain the radar reflectivity aloft. We use the interquartile range (IQR) of maximum radar reflectivity at -20°C as a simple but effective metric to quantify the range of radar reflectivities associated with hail by each retrieval. For all PCTFs surviving our snow filter from section 2, regardless of whether or not a retrieval algorithm identifies the PCTF as likely to have hail, the IQR is 8.25 dB. This can be thought of as a value for the hail-retrieval algorithms to “beat” by producing lower IQR. In Table 2, each hail retrieval easily beats this IQR, with values ranging from 3.91 dB (BC19 and the minimum 19-GHz PCT algorithm) to 5.46 dB (Ni17).

The probability-based retrieval approaches (marked with an asterisk in Table 2) all have the lowest IQR values, presumably because they do not assign equal weights to all PCTFs that satisfy a threshold, regardless of how easily they satisfy that threshold. In the most directly comparable approaches, Mroz17’s use of the 19-GHz channel outperforms Ni17’s use of the 37-GHz channel, and the probability-based approach using minimum 19-GHz PCT outperforms that using minimum 37-GHz PCT. As expected on the basis of Mroz et al.’s (2017) test of skill scores using several GPM inputs, and our physical

expectations based on the responsiveness of different frequencies to hail and graupel, the 19-GHz channel clearly shows improved performance over the 37-GHz channel. Although BC19 is an attempt to produce an improved retrieval by combining information from both these channels, the IQR in Table 2 suggests their approach only matched the effectiveness of a simpler approach relying on the 19-GHz channel alone.

Figure 2 maps the number of PCTFs retrieved as likely hailstorms from GMI data for April 2014–March 2018, using the six retrieval methods under consideration. A coarse (15°) grid size is used here to allow sample sizes suitable for analysis of radar reflectivity profiles within those grid boxes. Finer-resolution maps can be found in Ni et al. (2017), Cecil and Blankenship (2012), and Bang and Cecil (2019). There is a general similarity in the spatial patterns mapped by each retrieval approach. They agree on the same basic hot spots for hailstorm activity, with the most noticeable differences being the magnitudes of those hot spots in the tropics versus subtropics and midlatitudes. The radar-based approaches published by Mroz et al. (2017) and Ni et al. (2017) also agree on the same basic hot spots, with the radar-based approaches tending to favor the subtropics and midlatitudes more than some of the passive microwave approaches [cf. Fig. 7 in Mroz et al. (2017) and Fig. 8 in Ni et al. (2017)].

FIG. 3. Regional bias of the GPM DPR Ku-band radar reflectivity at -20°C relative to each retrieval's global median maximum value for all likely hailing PCTFs that pass the snow screen (Fig. 1), showing hail identification based on (a) minimum 37-GHz PCT $\leq 230\text{ K}$ (Ni17), (b) minimum 19-GHz PCT $\leq 261\text{ K}$ (Mroz17), (c) $P_{\text{hail}}(\text{CB12}) \geq 20\%$, (d) $P_{\text{hail}}(\text{BC19}) \geq 20\%$, (e) $P_{\text{hail}}(\text{minimum 37-GHz PCT}) \geq 20\%$, and (f) $P_{\text{hail}}(\text{minimum 19-GHz PCT}) \geq 20\%$ (see Table 1 for probability curve parameters). Panels (c)–(f) (also marked with an asterisk) are for mean deviations weighted by P_{hail} , whereas (a) and (b) weight all features satisfying the threshold equally.

The total sample size for each retrieval method is listed in Table 2. The threshold-based approaches Ni17 and Mroz17 yield far greater sample sizes than the probabilistic approaches CB12 and BC19, because CB12 and BC19 value low false alarm rates and assign low weights to PCTFs with low P_{hail} , whereas the Ni17 and Mroz17 approaches fully count any PCTF that satisfies the threshold associated with the maximum skill score.

These comparisons rest on an assumption that storms identified as having hail have similar radar reflectivities aloft. In reality, some hailstorms do appear stronger than others. Some range of measured radar reflectivities is expected, just as there is a range of T_{ps} that satisfy the criteria for the hail retrievals. We would expect the subset of storms that barely satisfy the hail-retrieval criteria to have a smaller range of reflectivities than the entire sample. Therefore, we computed IQR for the 20% of the sample with the highest 37-GHz PCT below 230 K (barely satisfying the Ni17 criterion) and the 20% of the sample with the highest 19-GHz PCT below 261 K (barely satisfying the Mroz17 criterion). This reduces the Ni17 IQR from 5.46 to 4.9 and reduces the Mroz17 IQR from 4.51 to 4.08. These values may be considered more fair comparisons to the probabilistic-based approaches. Using these IQR values,

the Mroz17 retrievals are slightly more accurate than any of the 37-GHz-based retrievals and almost on par with BC19 and the probabilistic minimum 19-GHz PCT retrieval.

To examine the regional bias of a passive microwave retrieval relative to the DPR Ku-band radar reflectivity further, we analyze the regional mean deviations from that retrieval's global median reflectivity at -20°C for $15^{\circ} \times 15^{\circ}$ boxes in the GPM domain in Fig. 3. For each passive microwave retrieval, we calculate the global median of all the PCTFs' maximum reflectivity values at -20°C . Then we calculate the deviation from that median for each PCTF and take the mean deviation in each grid box. Because the CB12, BC19, and minimum 37- and 19-GHz PCT retrievals (Figs. 3c–f, respectively) are all probability-based hail likelihoods, their median reflectivities are calculated as a function of P_{hail} and the means are P_{hail} weighted. The Ni17 and Mroz17 retrievals are threshold-based retrievals, and therefore there is no weighting. We calculate the deviation from the global median for the PCTFs in each $15^{\circ} \times 15^{\circ}$ box and plot the mean of the deviation in the color fill in Fig. 3.

In Fig. 3, a positive deviation (red value) signifies that the reflectivities at -20°C for PCTFs in that box tend to be higher than the retrieval's global median. This means the storms

FIG. 4. Profiles of the median maximum DPR Ku-band reflectivity for all PCTFs meeting the P_{hail} criterion for each retrieval (black), oceanic regions (blue), tropical land regions (green), subtropical land (red), and high-latitude land or regions with high terrain (orange). Panels (c)–(f) (also marked with an asterisk) present the P_{hail} -weighted medians for each profile. Hail identification is based on PCTFs with (a) minimum 37-GHz PCT ≤ 230 K (Ni17), (b) minimum 19-GHz PCT ≤ 261 K (Mroz17), (c) $P_{\text{hail}}(\text{CB12}) \geq 20\%$, (d) $P_{\text{hail}}(\text{BC19}) \geq 20\%$, (e) $P_{\text{hail}}(\text{minimum 37-GHz PCT}) \geq 20\%$, and (f) $P_{\text{hail}}(\text{minimum 19-GHz PCT}) \geq 20\%$.

triggering the retrieval in the red-shaded regions appear stronger to the radar than those in other locations. The retrieval is likely underestimating hail occurrence in the red-shaded regions, and overestimating hail in the blue-shaded regions. The retrievals based on the minimum 37-GHz PCT alone (Figs. 3a,c,e) have deeper colors than those using minimum 19-GHz PCT (Figs. 3b,d,f), suggesting larger regional deviations from those retrievals' global median value. We also note a strong

systematic latitudinal relationship from the 37-GHz-based retrievals, with values in the tropics being overrepresented (blue). At higher latitudes, a shift to positive values (red) signifies these retrievals are suppressing the signal from likely hailstorms. Ni et al. (2017) also noted that their minimum 37-GHz PCT retrievals indicated more hailstorms in the tropics than their retrievals that were based on radar reflectivity aloft.

While the CB12 retrieval's regional adjustment addresses much of the latitudinal bias seen in the other minimum 37-GHz PCT-based retrievals, it still exhibits some systematic latitudinal deviations, as seen in Fig. 3c. Its regional adjustments were designed without any data from poleward of 36° latitude, which makes its application to midlatitudes and high latitudes tenuous.

All three panels on the right side of Fig. 3 are based, at least in part, on the minimum 19-GHz PCT. The panels on the right have fewer grid boxes with large deviations than do those on the left. This suggests that using the 19-GHz signature yields more regional consistency than using the higher-frequency 37-GHz channel alone.

The Mroz17 panel shows moderate deviations but there is no systematic pattern to them compared to the panels on the left, besides a consistent underestimation relative to the radar over the Himalayas and China. There are several Southern Hemisphere oceanic grid boxes with moderate and large deviations from the global median maximum radar value at -20°C .

The BC19 panel (Fig. 3d) shows minimized bias over the entire GPM domain, though it shows a lack of any oceanic cases relative to the panels around it. There is a moderate positive deviation (passive microwave underestimation relative to radar) over eastern China. This pattern appears in the panels of BC19's components: minimum 37-GHz (Fig. 3e) and, to a lesser extent, minimum 19-GHz (Fig. 3f).

b. Geographical variability of reflectivity profiles

Following the example of Cecil (2011), we examine the vertical distributions of Ku-band maximum reflectivity for each hail retrieval in different geographical regions. Each panel in Fig. 4 has a series of five median maximum reflectivity profiles plotted, one for all PCTFs meeting the retrieval's hail criteria (black), and one for each geographical regime: oceans, tropical land, subtropical land, and high-latitude/high-terrain land. The profiles are median values of maximum reflectivity for the Ni17 and Mroz17 retrievals and weighted medians for the probability-based retrieval values.

Ideally, a retrieval would produce a series of tightly grouped median maximum reflectivity profiles with similar slopes of reflectivity with temperature, regardless of the type of regime plotted, as discussed in section 2e. Considering Fig. 4a (Ni17), the median maximum reflectivity at the -20°C level in oceanic regimes is 43.5 dBZ. For high latitude/high terrain, this value is 47.0 dBZ, yielding a spread of 3.5 dB between the median maximum reflectivity at -20°C for both regimes. The largest spreads at -20°C for all six retrievals are 3.5 dB (Ni17) (Fig. 4a), 1.4 dB (Mroz17) (Fig. 4b), 0.6 dB (CB12) (Fig. 4c), 1.5 dB (BC19) (Fig. 4d), 1.9 dB (Min. 37 PCT) (Fig. 4e), and 1.1 dB (Min. 19 PCT) (Fig. 4f).

All of the metrics exhibit the steepest drop-off of reflectivity with height in oceanic regimes, which is to be expected, as Cecil (2011) showed oceanic profiles have more precipitous drops in reflectivity above 0°C than do profiles over land, for a given value of 37-GHz PCT. In most of the panels of Fig. 4, the subtropical land profiles exhibit the mildest drop-off of reflectivity with height above 0°C , with the exception of Fig. 4a (Ni17), in which the high-latitude/high-terrain profile has the mildest slope.

In comparing Fig. 4a with Fig. 4b, and Fig. 4e with Fig. 4f, it is seen that the 19-GHz channel appears to constrain the radar reflectivity profiles more tightly than the 37-GHz channel. This is likely due to the 19-GHz channel's longer wavelength being more responsive to large graupel and hail particles, and less responsive to smaller graupel. Comparing Fig. 4a against Fig. 4e, and Fig. 4b against Fig. 4f suggests that some of the spread in the threshold-based retrievals is due to equally weighting a broad range of storm intensities, regardless of whether a storm barely satisfies or easily exceeds the threshold. As previously mentioned, some hailstorms are stronger than others, and our comparisons here do not account for that. Cecil (2011) showed (in his Fig. 1) TRMM PR reflectivity profiles for storms with minimum 37-GHz PCT near 180, 220, and 260 K. The storms measuring 180 K at 37-GHz would easily exceed Ni17's 230-K threshold, and they produce much higher reflectivities and much slower decreases of reflectivity with height than the storms with higher 37-GHz PCTs. Those profiles also show substantial differences between land and ocean, and between tropics and subtropics, even when constrained to a narrow range of 37-GHz PCT, consistent with our Fig. 4. This may also be occurring, but to a much lesser extent, with the minimum 19-GHz PCT retrieval.

We hesitate to make any sweeping conclusions about the profiles at temperatures warmer than freezing, as the downward-looking Ku-band radar is susceptible to attenuation in a hailstorm. The DPR reflectivity algorithms impose path-integrated attenuation corrections to the data to account for this, but uncertainty remains about the accuracy of the reflectivity observations below heavily attenuating layers (Gingrey et al. 2018; Iguchi et al. 2018).

In terms of regional variability and range of Ku-band radar values at -10° and -20°C , which are common proxies for hail, we observe strong performance of probability-based hail retrievals like CB12, BC19, and the logistic-curve-based approximation using minimum 19-GHz PCT. They exhibit narrowly grouped median maximum reflectivities at these temperatures, regardless of geographical regime. The PCT thresholding method shows poor performance when applied to the 37-GHz channel, as in the microwave-only retrieval by Ni17. The Mroz17 19-GHz PCT thresholding retrieval shows an improved performance over the Ni17 retrieval in both regional variability and narrow ranges of reflectivities above the freezing level for different geographical regimes.

The 19-GHz channel shows promise as a good estimator for hail detection, as seen in the narrow reflectivity distributions and latitudinal independence we observe in Fig. 3 and the tight grouping of median reflectivity with height in Fig. 4. We find the best results when we combine both the 19- and 37-GHz channels, as in the BC19 retrieval. Compared to other retrievals from the literature, BC19 exhibits latitudinal independence, low regional bias, and tight grouping of reflectivity with height. We suspect the normalized 37-GHz depression component of this retrieval is filling in the gaps where features' hailing regions may be exhibiting nonuniform beam filling in the 19-GHz channel's large footprint.

FIG. 5. (a) Profiles of the median maximum DPR Ku-band reflectivity with temperature for all PCTFs meeting the 25% P_{hail} threshold $\pm 5\%$ as estimated using the BC19 retrieval (black), along with median profiles for oceanic regions (blue), tropical land regions (green), subtropical land (red), and high-latitude land or regions with terrain (orange). Also shown are the same categories of geographical regime but broken down into specific regions in each regime: (b) oceans, (c) tropical land, (d) subtropical land, and (e) high-latitude or high-terrain land.

c. Finescale regional variability of BC19 against its components

We now assess the BC19 retrieval against its individual components (normalized 37-GHz PCT depression and minimum 19-GHz PCT) to test the performance of each component individually and together. We examine the regional variability in further detail by breaking down the four overarching regional categories into more specific categories, in the same vein as Cecil (2011, see his Fig. 1). To examine the performance of the retrieval at the low end of the P_{hail} distribution, Fig. 5 shows median maximum reflectivity profiles for the 25% ($\pm 5\%$) P_{hail}

level from BC19. Figure 5a is similar to Fig. 4d, but this time the sample is restricted to a narrow range of P_{hail} and the profiles are not P_{hail} weighted. Figures 5b–e break these down into specific subregions classified as oceans (Fig. 5b), tropical land (Fig. 5c), subtropical land (Fig. 5d), and high latitude/high terrain (Fig. 5e). As before, we are examining the profiles for closeness of grouping and similarity of slope, indicating similar performance in radar space across a diverse set of regions.

The median maximum reflectivity profiles in each grouping of subregions generally follow the overall trend of the overarching regimes shown in Fig. 5a. Namely, oceanic profiles have high maximum reflectivities at low levels below the freezing level but

$$P_{\text{hail}}(\text{Normalized } 37 \text{ GHz PCT Depression}) = 25\% \pm 5\%$$

FIG. 6. As in Fig. 5, but as estimated using normalized 37-GHz PCT depression (black).

exhibit a steep drop-off of reflectivity with height. High-latitude profiles have lower maximum reflectivities at low levels relative to the oceanic profiles but the reflectivity change with height is milder than profiles from the other regimes. The tropical land and subtropical land regimes fall between the oceanic and high-latitude profile structures.

The maximum spreads of median maximum reflectivities at -20°C from these profiles are 0.8 dB (oceans), 1.1 dB (tropical land), 1.7 dB (subtropical land), and 3.4 dB (high latitude/high terrain). Other than at low levels where the attenuation correction may be dubious, the similarities between reflectivity profiles from a variety of tropical land regions in Fig. 5c is especially noteworthy.

Profiles from the ocean subregions are also very similar to each other (Fig. 5b), with the exception of the profile for the Mediterranean Sea, which follows a profile that is more similar

to those over land. We suspect this is due to the Mediterranean box including a higher fraction of island, peninsula, and coastal features that the other oceanic regions do not have. The high-latitude/high-terrain profiles exhibit the least amount of cohesion, which could be a product of the small sample sizes and the diversity of regions that constitute this regime.

Figure 6 similarly shows the regional differences in median maximum reflectivity profiles for normalized 37-GHz PCT depression at the 25% P_{hail} level $\pm 5\%$. There tend to be more features that meet the 25% normalized 37-GHz PCT depression threshold than meet the 25% BC19 threshold. The reflectivities decrease most rapidly with height for the ocean regions (Fig. 6b), and least rapidly for subtropical land (Fig. 6d) and high-latitude/high-terrain (Fig. 6e) regions. The pattern of weaker profiles for oceans and stronger profiles for subtropical land and high-latitude/high-terrain regions was also seen in

FIG. 7. As in Fig. 5, but as estimated using (histogram adjusted) minimum 19-GHz PCT (black).

Figs. 4 and 5. The reflectivity profiles for distinct regions shown by Cecil (2011) and constrained by minimum 37-GHz PCT also fit this pattern. Ni17 showed reflectivity profiles for selected tropical and subtropical land regions for cases with minimum 37-GHz PCT below 230 K and also found large reflectivity decreases with height for the tropical regions.

The profiles in Fig. 6 based on normalized 37-GHz PCT depression are less tightly grouped than those seen in Fig. 5, for most of the regimes. This is most notable over subtropical land and the oceans above -10°C . The maximum spreads of median reflectivities -20°C are 3.5 dB (oceans), 3.0 dB (tropical land), 2.2 dB (subtropical land), and 2.9 dB (high latitude/high terrain).

The 25% level for minimum 19-GHz PCT taken by itself (Fig. 7), reveals patterns and dichotomies that were not apparent in the weighted medians seen in Fig. 4f. The oceanic

profiles (Fig. 7b) and the subtropical land profiles (Fig. 7d) vary much more widely than the same groupings of profiles for BC19 (Figs. 5b,d). The maximum spread of median reflectivities at -20°C for the different regions is 2.1 dB (oceans), 2.2 dB (tropical land), 2.2 dB (subtropical land), and 2.7 dB (high latitudes/high terrain). Additionally, the sample sizes are smaller than those using BC19 at the same P_{hail} threshold (Fig. 5).

The pattern of reflectivity decreasing the most rapidly with height in the ocean regions and least rapidly in the subtropical and high-latitude/high-terrain regions is again repeated in Fig. 7, this time with reflectivity profiles constrained based on minimum 19-GHz PCT, though the difference is less pronounced. The reflectivity profiles from the ocean and tropical land regions do not decrease as rapidly with height as they do in Fig. 6. This suggests that the minimum 19-GHz PCT constrains

FIG. 8. Profiles of the weighted median maximum DPR Ku-band reflectivity for all PCTFs meeting the P_{hail} criterion for each retrieval (black), oceanic regions (blue), tropical land regions (green), subtropical land (red), and high-latitude land or regions with terrain (orange). Shown are PCTFs with a given hail probability of $50\% \pm 5\%$. Hail identification is based on (a) the BC19 retrieval and on its components: (b) normalized 37-GHz PCT depression and (c) minimum 19-GHz PCT.

the convective intensity slightly more than the normalized 37-GHz depression. In Fig. 7c, the Mediterranean profiles again stand slightly apart from the groupings of profiles in the oceanic regime. Both components of the BC19 algorithm contribute to this region being a slight outlier in Fig. 5.

Figure 8 shows median maximum reflectivity profiles from the $50\% \pm 5\%$ P_{hail} threshold, to test how the algorithm performs at a higher P_{hail} . The 50% P_{hail} reflectivity profiles tend to have ~ 2 dB greater reflectivity at -20°C than the 25% P_{hail} profiles, and the decrease of reflectivity

with height is not as rapid. Above -20°C , the BC19 profiles show tight grouping, which may also be attributable to the strong performance of the minimum 19-GHz PCT profiles above -20°C . All three retrievals show the oceanic profiles straying the furthest from the grouping of profiles from other regimes, but there are not many hailing cases retrieved over the oceans at this P_{hail} threshold.

4. Conclusions

Using well-known spaceborne radar-based hail proxies (such as reflectivity at -20°C), we test the effectiveness and regional bias of passive microwave-based hail retrievals: Ni et al. (2017), Cecil and Blankenship (2012), Mroz et al. (2017), and Bang and Cecil (2019), and the individual components of the Bang and Cecil (2019) algorithm. We used the terminology Ni17, CB12, Mroz17, and BC19 (respectively) throughout this paper to refer to the passive microwave retrieval algorithms from these papers.

The Ni17 approach (a threshold for minimum 37-GHz PCT ≤ 230 K) is particularly vulnerable to regionality bias. The Ni17 approach assigns “hail” to features with a wide range of radar reflectivities at -20°C , with a tendency for lower reflectivities in the tropics and higher reflectivities in the subtropics and midlatitudes. This suggests the minimum 37-GHz PCT threshold is easier to meet for storms in the tropics. We suspect that tropical features have deep columns of graupel-sized frozen hydrometeors (<5 mm), which would be able to depress the 37-GHz PCT significantly and trigger false alarms for the Ni17 retrieval. Ni et al. (2017) propose a similar explanation when comparing their own radar-based hail climatology. Frequencies higher than 37 GHz, such as 85 GHz (89 GHz for GPM) can exhibit extremely low T_b s in graupel (Mroz et al. 2017).

Mroz17 is a similar approach to Ni17, setting a 19-GHz PCT threshold ≤ 261 K. The 19-GHz channel has a longer wavelength than the 37-GHz one and is therefore not as susceptible to scattering by smaller-sized ice particles. The 19-GHz channel also has a relatively larger footprint size when compared with the 37-GHz channel (for GPM: 198 km^2 vs 135 km^2 , respectively), as compared with the average size of a hail core (on the order of a few square kilometers). Therefore the 19-GHz footprint often exhibits nonuniform beam filling, with the hail core scattering upwelling microwave radiation in only a small portion of the scene. A T_b threshold set upon 19-GHz data may miss legitimately hailing cases that do not occupy enough of the footprint to exhibit a sufficiently low T_b to meet the threshold. Nonetheless, the 19-GHz-based retrievals exhibited a narrow range of reflectivities at -20°C and appear somewhat resistant to regional bias.

The CB12 retrieval took a probability-based approach, applying a lookup table of hail probability to bins of minimum 37-GHz PCT. They mitigated regional biases by applying a regional scaling to the T_b s. Our analysis shows this regional scaling is effective, with reduced (but not wholly eliminated) biases compared to other 37-GHz-based approaches.

The BC19 retrieval, which estimates P_{hail} based on both normalized 37-GHz PCT depression and the minimum 19-GHz PCT, appears to combine the best of both retrievals. It exhibits little regional variability, even when examining

regional reflectivity profiles at a finescale. While Mroz17 also showed little regional bias due to its use of the 19-GHz channel, BC19 shows improved performance in oceanic regimes.

We present several hail retrievals from the literature as well as from our probabilistic P_{hail} estimation not only to validate these passive microwave retrievals against each other and against the coincident GPM DPR dataset, but also because we realize that the hail remote sensing community has diverse needs, and a wide range of available datasets. The BC19 algorithm is the most complex but also the best performing in our analysis. The Mroz17 19-GHz PCT threshold retrieval performed well in terms of discerning a narrow range of radar reflectivities above the freezing level. The Mroz17 retrieval combines effectiveness with simplicity; it is straightforward to use for GPM. The minimum 19-GHz PCT logistic-curve-based retrieval (Table 1) performed slightly better but is slightly more complicated to apply. In the absence of 19-GHz data, or if the footprint of a 19-GHz channel is prohibitively large (e.g., on the SSM/I), the probabilistic retrieval using normalized 37-GHz PCT depression was a good discriminator of hail proxies (high radar reflectivity above 0°C) and showed less regional bias than thresholding methods. In the absence of lapse-rate tropopause height data to normalize the 37-GHz PCT depression, the CB12 minimum 37-GHz PCT-based retrieval showed resistance to large regional biases, due to its regional T_b scaling. The CB12 retrieval still exhibited some widespread regional issues when examined over the entire GPM domain, as in Fig. 3. Future studies may need to balance considerations of algorithm complexity, available microwave channels, and ancillary datasets. We present these results in the hopes of helping users to assess the strengths and limitations of available approaches.

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Data availability statement. The data used in this paper are publicly available for all, as cited in the references: GMI, Level 1C (Berg 2016; <https://doi.org/10.5067/GPM/TMI/TRMM/1C/05>); DPR Ku (Iguchi and Meneghini 2016; <https://doi.org/10.5067/GPM/DPR/Ku/2A/06>); and TMI, Level 1C (GPM Science Team 2017; <https://doi.org/10.5067/GPM/TMI/TRMM/1C/05>). The GMI 1C, TMI 1C, and GPM Ku data are available for download from the Precipitation Processing System (<https://earthdata.nasa.gov/earthdata/handbook/precipitation-processing-system>), after registering (<https://registration.pps.eosdis.nasa.gov/registration/>). TRMM PR (from level 1Z) can be obtained at http://atmos.tamucc.edu/trmm/data/trmm/level_1/ (TRMM1Z 2014). ERA-Interim

reanalysis data are at <https://apps.ecmwf.int/datasets/data/interim-full-daily> (ECMWF 2018). Adjustments made to GPM T_b s are presented in the appendix.

APPENDIX

Adjustment of GMI Brightness Temperatures to TMI Footprint

To apply retrievals trained using TRMM data to GPM data, we need to ensure that the brightness temperatures T_b are interchangeable. The channels onboard TRMM and GPM have different footprint sizes and slightly different frequencies (Table S1 in the online supplemental material). While the T_b s have been intercalibrated as part of the GPM Level 1C dataset (Berg et al. 2016), differences related to footprint size and frequency remain. In particular, the 10- and 19-GHz channels from TRMM have much larger footprints than those from GPM, and therefore they are susceptible to greater effects from nonuniform beam filling (NUBF). This appendix describes our histogram-matching approach aimed at eliminating those differences.

For applicability to the hail retrievals in this paper, we focus on TRMM and GPM PCTFs (areas with 85-GHz PCT (89 for GPM) ≤ 200 K within the swath of the TRMM PR/GPM DPR Ku-band radar) within 20°S–20°N. We restrict our distributions to the tropical latitudes to avoid sampling differences related to the two satellites' different inclinations (35° vs 65°).

The distributions of the PCTFs' minimum PCT and maximum PCT for a given frequency have different shapes from each other, and from the distributions of all PCTs. The PCTF's minimum PCT is measured where there is a convective core, and this is usually where NUBF effects are greatest. We therefore have separate adjustments for the minimum and maximum PCTs, each with its own table of adjustment factors.

We demonstrate our approach using the distributions of minimum 19-GHz PCT for all TRMM (red) and GPM (black) PCTFs (Fig. A1a). The TRMM distribution peaks at higher PCTs than does the GPM distribution. The goal of the histogram adjustment is to adjust the GPM PCTs such that the distributions would lie on top of each other. We select a series of cumulative frequency percentiles and find the corresponding TRMM and GPM minimum 19-GHz PCT for each percentile (Fig. A1b; Table S2 in the online supplemental material). The TRMM PCTs are categorically warmer than those of GPM for any given percentile. Dividing the TRMM PCT by the GPM PCT for each percentile results in a "scale factor" by which to multiply the GPM PCT in order to get a value scaled to the TRMM footprint (Fig. A1c; Table S2 in the online supplemental material). The scale factors above the 99.9% and below the 0.1% percentiles are kept at the 99.9% and 0.1% levels, because the sample sizes are extremely low above and below these levels (red line). The intercalibration performed by Berg et al. (2016) takes a similar flatline approach at the extremes of the T_b distribution.

To adjust a GPM PCT to the TRMM footprint, we use

$$\text{PCT}_{19_{\text{TMI}}} = \text{scale factor} \times \text{PCT}_{19_{\text{GMI}}} \quad (\text{A1})$$

The scaling factor is not a simple curve in Fig. A1c, and therefore we were not able to parameterize the adjustment for

FIG. A1. (a) Minimum 19-GHz PCT for all PCTFs from 20°S to 20°N. The cumulative distribution for each satellite is overlaid in the same colors in solid lines. (b) For a given set of percentiles for the cumulative distributions shown in (a), we show the minimum 19-GHz brightness temperature associated with each percentile for TRMM PCTFs (y axis) and GPM PCTFs (x axis). A 1:1 line is shown across the plot, and some demonstrative percentiles are demarcated in red to aid in comparison. The TRMM minimum 19-GHz PCTs are warmer than those from GPM at every percentile. (c) Scale factor for adjusting GPM minimum 19-GHz PCTs to the TRMM footprint. The values from the data are shown with black plus signs, and the adjustment factor as we applied it is shown by the red line. The adjustment we applied asymptotes at the values at 0.1 and 99.9 percentiles to mitigate noise. The scale factors can be found by dividing the TRMM PCT by the GPM PCT for each percentile in (b). To get an adjusted GPM PCT, multiply the GPM value by the scale factor, as shown in Eq. (A1).

this analysis. Instead, the following lookup tables in the online supplemental material are used for the passive microwave variables in the hail retrievals and snow filter discussed in this paper: minimum 19-GHz PCT (supplemental Table S2), minimum 37-GHz PCT (supplemental Table S3), maximum 37-GHz PCT (supplemental Table S4), minimum 10-GHz PCT (supplemental Table S5), and maximum 10-GHz PCT (supplemental Table S6). Scale factors are linearly interpolated between the entries in the lookup tables but not extrapolated beyond the range of each table. PCTs are then adjusted as in Eq. (A1) for the analysis in this paper, except where noted.

Our histogram adjustment method can be summarized as follows: 1) creating cumulative frequency distributions of relevant passive microwave variables from PCTFs within the

20°S–20°N domain, 2) finding the TRMM and GPM values for a given set of percentiles, 3) creating scale factors by dividing the TRMM value by the GPM value for each percentile, 4) asymptotically approaching the scale factors at and beyond the 99.9% and 0.1% percentiles, 5) interpolating the scale factor to each measured GPM value, and then 6) multiplying the GPM value by the scale factor to get a value that is consistent with the TRMM footprint size and frequency. This method was designed to be transferable to any passive microwave satellite instrument with similar frequencies as TRMM (such as AMSR-E and AMSR2). It therefore provides a pathway to applying the TRMM-based retrievals to other passive microwave datasets and thereby create passive microwave hail climatologies using the same method across multiple platforms.

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