

Direct comparisons between GPM-DPR and CloudSat snowfall retrievals

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ABSTRACT

Two spaceborne radars currently in orbit enable the sampling of snowfall near the surface and throughout the atmospheric column, namely CloudSat’s Cloud Profiling Radar (CPR) and the Global Precipitation Measurement mission’s Dual-Frequency Precipitation Radar (GPM-DPR). In this paper a direct comparison of the CPR’s 2C-SNOW-PROFILE (2CSP), the operational GPM-DPR algorithm (2ADPR) and a neural network (NN) retrieval applied to the GPM-DPR data is performed using coincident observations between both radars. Examination of over 3500 retrieved profiles within moderate to strong precipitation (Ka-band ≥ 18 dBZ) show that the NN retrieval provides the closest retrieval of liquid equivalent precipitation rate (R) immediately above the melting level to the R retrieved just below the melting layer, agreeing within 5%. Meanwhile, 2CSP retrieves a maximum value of R at -15°C , decreases by 35% just above the melting layer, and is about 50% smaller than the GPM-DPR retrieved R below the melting layer. CPR measured reflectivity shows median reduction of 2-3 dB from -15°C to -2.5°C , likely the reason for the 2CSP retrieval reduction of R . Two case studies from NASA field campaigns (i.e., OLYMPEX and IMPACTS) provide analogues to the type of precipitating systems found in the comparison between retrieval products. For the snowfall events that GPM-DPR can observe, this work suggests that the 2CSP retrieval is likely underestimating the unattenuated reflectivity, resulting in a potential low bias in R . Future work should investigate how frequently the underestimated reflectivity profiles occur within the CPR record and quantify its potential effects on global snowfall accumulation estimation.

36 **1. Introduction**

37 Most of the world's precipitation falls as rain, but more than half can be related to ice processes
38 found aloft (Field and Heymsfield 2015; Heymsfield et al. 2020). Thus, any attempt to fully
39 quantify the hydrological cycle must include solid phase hydrometeor processes and measurements.
40 Furthermore, the amount of snow that falls to the surface is vital in mountainous regions where
41 humanity relies on the melted runoff as their main freshwater resource (e.g., Viviroli et al. 2003).
42 One method of quantifying characteristics of solid phase hydrometeors is the use of radar. Currently
43 there are two satellites in orbit carrying meteorological radars capable of quantifying global
44 precipitation characteristics, CloudSat and the Global Precipitation Measurement (GPM) mission
45 core observatory.

46 CloudSat was launched in 2006 carrying the Cloud Profiling Radar (CPR), a non-scanning 94
47 GHz radar in a 98° sun synchronous orbit (Stephens et al. 2002; Tanelli et al. 2008). The operating
48 frequency, high sensitivity and relatively small instantaneous field of view (IFOV) allows successful
49 detection of most clouds found in the troposphere. Since 2006, CPR has been used for numerous
50 global snowfall studies (Liu 2009; Kulie and Bennartz 2009; Palerme et al. 2014; Kulie et al.
51 2016; Palerme et al. 2017; Milani et al. 2018; Kulie and Milani 2018; Kulie et al. 2020), and after
52 evaluation against several ground-based methods (e.g., Cao et al. 2014; Norin et al. 2015; Chen
53 et al. 2016; Souverijns et al. 2018; Matrosov 2019), CPR has become commonly used as a global
54 snowfall reference (e.g., Palerme et al. 2017; Milani et al. 2018; Skofronick-Jackson et al. 2019;
55 Cabaj et al. 2020; Edel et al. 2020).

56 The GPM core observatory was launched in 2014 into a 65° non-sun synchronous orbit carrying
57 the scanning Dual-frequency Precipitation Radar (DPR) operating at 13.5 and 35.5 GHz (Hou
58 et al. 2014). Contrary to CloudSat, GPM-DPR has a relatively large IFOV and a more limited

sensitivity, thus GPM-DPR is generally more useful for moderate to intense precipitation. Despite GPM-DPR's limitations, the radar has been used for global snowfall studies (Adhikari et al. 2018; Adhikari and Liu 2019).

The comparison of CPR, GPM-DPR and their operational retrieval products, namely the 2C-SNOW-PROFILE from CloudSat (Wood and L'Ecuyer 2018, 2021) and the 2ADPR from GPM-DPR (Iguchi et al. 2018), show that the 2ADPR near surface snowfall retrieval product is low biased (Casella et al. 2017; Tang et al. 2017; Skofronick-Jackson et al. 2019). Casella et al. (2017) used a coincident database of CPR and GPM-DPR observations (Turk 2016; Turk et al. 2021) and found that more than 90% of near-surface snowfall events by number are missed by GPM-DPR, attributing this to GPM-DPR's lack of sensitivity. However, Casella et al. (2017) state that while GPM-DPR is missing a large fraction of events by number, the fraction of the snowfall accumulation captured by GPM-DPR is estimated to be around 30% of the total global snowfall accumulation. Skofronick-Jackson et al. (2019) compared three years of CPR and GPM-DPR measurements statistically, accounting for hardware, retrieval algorithm and operating frequency differences. After careful quality control, it was found that on a global average GPM-DPR near surface snowfall accumulation was about 43% lower than CPR, but the disparity can be larger at specific locations by up to 800 mm/yr (Skofronick-Jackson et al. 2019). Motivated by the work of Casella et al. (2017) and Skofronick-Jackson et al. (2019), Chase et al. (2020) investigated the microphysical assumptions within the 2ADPR retrieval algorithm and found that the assumed empirical parameterization between the liquid equivalent mass flux (R) and the liquid equivalent mass weighted mean diameter (D_m) does not characterize surface snowfall observations well and contributes to the low bias reported in Skofronick-Jackson et al. (2019). Following the work of Chase et al. (2020), Chase et al. (2021) developed an alternative dual-frequency retrieval for GPM-DPR that shows initially good performance against in-situ observations, with a median bias

83 of 13%, 120% and 10% for D_m , the liquid equivalent normalized intercept parameter (N_w) and ice
84 water content (IWC), respectively. Chase et al. (2021) also showed that their retrieval implemented
85 on the GPM-DPR measurements removes along track ray-to-ray instabilities found in the current
86 2ADPR method (c.f., Figure 15 in Chase et al. 2021).

87 The primary goal of this paper is to evaluate the new retrieval method developed for GPM-DPR by
88 Chase et al. (2021) directly against CPR's 2C-SNOW-PROFILE retrieval. Secondary goals of this
89 paper are to quantify and discuss the potential limitations of W-band single frequency retrievals
90 in context of moderate to intense snowfall events as well as evaluate the operational 2A.DPR
91 snowfall retrieval against the 2C-SNOW-PROFILE. Although CPR's 2C-SNOW-PROFILE has
92 shown generally good agreement with ground-based sensors (e.g., Cao et al. 2014; Norin et al.
93 2015; Chen et al. 2016; Souverijns et al. 2018; Matrosov 2019) there have been indications that the
94 2C-SNOW-PROFILE retrieval is low biased compared to other snow accumulation measurements.
95 For example, Ryan et al. (2020) showed 2C-SNOW-PROFILE is low compared to ice core estimates
96 over Greenland. Further Cao et al. (2014) and Mroz et al. (2021) showed for moderate to intense
97 snowfall rates ($> 1 \text{ mm hr}^{-1}$) 2C-SNOW-PROFILE underestimates the S-band radar snowfall.
98 The rest of this manuscript is structured as follows: Section 2 discusses the retrieval methods,
99 the coincident dataset between GPM-DPR and CPR, the quality control methods used to ensure a
100 consistent comparison of GPM-DPR and CPR, and information on the field campaign datasets used.
101 Section 3 contains the results, starting with the statistical comparison between snowfall products
102 on the coincident dataset, and then discussing the snowfall product comparison in context of two
103 cases studies from NASA field campaigns. Section 4 summarizes the main results, conclusions
104 and future directions of research.

2. Methodology

a. Retrieval Methodologies

2C-SNOW-PROFILE, hereafter 2CSP, uses optimal estimation (Rodgers 2000) to retrieve profiles of the two parameters of the exponential particle size distribution based on a state vector containing the gaseous attenuation corrected W-band reflectivity profile supplemented with coincident environmental conditions from ECMWF High Resolution Forecast simulations and a priori characteristics of snow (Wood and L’Ecuyer 2018, 2021). From the two parameters of the size distribution and a few assumptions, snowfall properties such as IWC and R can be calculated. For the 2CSP retrieval, the terminal fall velocity relation used is pressure adjusted, while the 2ADPR (Seto et al. 2013) and the Chase et al. (2021) retrieval using the GPM-DPR data assume that the retrieval is made with a pressure of 1013 hPa. Since the fall speeds of particles, and thus their precipitation rate, is proportional to air pressure (i.e., more air pressure, more drag, lower precipitation rate), the 2CSP retrieval is converted to a retrieval that is assumed to be at 1013 hPa. To convert the 2CSP retrieval a scale factor is applied to the 2CSP product using the following relation (Brandes et al. 2008),

$$R_{msl} = R_i \left(\frac{P_i}{1013 \text{ hPa}} \right)^{0.5} \quad (1)$$

where R_{msl} is the liquid equivalent precipitation rate at mean sea level (1013 hPa), R_i is the precipitation rate at the retrieval level and P_i is the pressure at the retrieval level. For the rest of the analysis in this paper, the R_{msl} is compared between all retrievals (hereafter written as R).

The latest version for the GPM-DPR retrieval, version 6 (Iguchi et al. 2018), uses a prescribed relation between R and D_m to simultaneously retrieve R and D_m for a given measured radar reflectivity factor (Z_e). The retrieval is done iteratively, varying an adjustment parameter ϵ in the column to minimize the error between the retrieved and estimated path integrated attenuation and

the measured Ka-band Z_e . More details are found in the algorithm theoretical basis document (Iguchi et al. 2018). Overall, the algorithm shows good performance on the retrieval of R and D_m in rain compared to data collected during NASA’s Ground Validation field campaigns, satisfying GPM’s level 1 mission requirement of an error of less than 50% and 0.5 mm for R and D_m respectively (Petersen et al. 2020; Gatlin et al. 2020). Note that the $R - D_m$ retrieval framework is used in all GPM-DPR gates, regardless of hydrometeor phase despite being derived from surface rainfall measurements. Version 6 of the 2ADPR algorithm does make adjustments to some of the assumptions in the scattering tables and the underlying particle size distribution when being used for solid phase designated radar gates, but the underlying $R - D_m$ relation is exactly the same. The use of the $R - D_m$ parameterization has contributed to the low bias within snowfall retrievals (e.g., Skofronick-Jackson et al. 2019; Chase et al. 2020), but the 2ADPR retrieval for snowfall is included for comparison in Section 3.1.

As an alternative to the $R - D_m$ retrieval in snowfall using GPM-DPR, a dual-frequency radar neural network retrieval of snowfall parameters formulated by Chase et al. (2021) is also evaluated. The retrieval was built using state-of-the-art particle scattering models (e.g., Discrete Dipole Approximation; Yurkin and Hoekstra 2011) and measured particle size distributions from multiple NASA field campaigns (e.g., Jensen et al. 2016; Skofronick-Jackson et al. 2017; Houze et al. 2017) to inform the weights and biases of a neural network. The Chase et al. (2021) retrieval, hereafter NN, is performed on a gate-by-gate basis and takes inputs of the measured Z_e at Ku-band, measured dual-frequency ratio between Ku- and Ka- band, and the temperature of the radar gate. The retrieval passes the inputs through trained weights and biases, and outputs estimates of D_m and N_w . From D_m and N_w IWC can be calculated following Delanoë et al. (2014),

$$\text{IWC} = \left(\frac{N_w D_m^4 \rho_l \pi}{4^4} \right) \quad (2)$$

151 where ρ_l is the density of liquid water.

152 Since the goal of this study is to compare R , some assumptions have to be made to convert the
153 IWC to R within the NN retrieval. To do so, a linear regression between $\log(R)$ and $\log(\text{IWC})$ is fit
154 using ground-based precipitation imaging package (PIP) measurements acquired at the University
155 of Helsinki Hyytiälä Forestry Field Station in Finland (von Lerber et al. 2017; Chase et al. 2020)
156 and the National Weather Service office in Marquette, Michigan USA (Pettersen et al. 2020). The
157 PIP data are used because the mass of particles are retrieved from their respective observed fall
158 velocities (c.f., von Lerber et al. 2017), thus giving a more constrained estimate of R and IWC from
159 measured particle size distributions. The fit to the empirical relation is given by

$$160 \quad R = 3.64(\text{IWC})^{1.06} \quad (3)$$

161 and is shown graphically in Fig. 1. The units for the coefficient of 3.64 in Equation 3 are
162 $(\text{m}^3 \text{ g}^{-1})^{1.06} \text{ mm hr}^{-1}$. The total PIP dataset includes about 600 hours of snowfall measurements,
163 comprised of 5 min individual observations. The mean estimated error (i.e., regression R –
164 observed R) from using a linear regression to calculate R from IWC is 0.04 mm hr^{-1} . While an
165 empirical relationship, such as the one presented in Equation 3, can introduce a bias in the NN
166 retrieval, there is added confidence in the fact that deriving the relationship with the two sites
167 independently only changes the fitted parameters by less than 10%. Furthermore, since GPM-DPR
168 can only observe echoes with $K_a > 18 \text{ dBZ}$, echoes likely contain precipitation sized particles like
169 the ones observed by the surfaced based probes.

170 *b. Coincident Dataset and Quality Control:*

171 The primary dataset used here is the coincident CloudSat-GPM archive (2B.CSATGPM; Turk
172 2016; Turk et al. 2021). This dataset consists of all GPM overpasses from 04/2014 to 08/2016

that have a CloudSat track passing through the GPM swath separated by less than 15 min in time. While any time offset can lead to errors, more strict time difference requirements (i.e., 5 mins) did not change the general conclusions of this manuscript. The closest GPM-DPR footprint to each CloudSat along track footprint is deemed coincident and used for the comparison. These data have already been used successfully in informing the current status of the operational GPM-DPR retrieval of snowfall (Casella et al. 2017), determining the effectiveness of high frequency radiometers for snowfall retrievals (Panegrossi et al. 2017, 2018; Yin and Liu 2019), training of passive microwave radiometers to derive snowfall properties of the column (Rysman et al. 2018) and near surface (Rysman et al. 2019), as well as informing retrievals of ice water path within convective systems from passive microwave radiometers (Rysman et al. 2021).

Since the original goal of Turk (2016) was to include both coincidences of CloudSat with GPM-DPR, and coincidences with the much wider swath radiometer on GPM (GMI; Draper et al. 2015), there are many files with little to no meteorological signal from GPM-DPR. To remove files containing no valid GPM-DPR snowfall retrievals, a list of files was identified manually to contain GPM-DPR signal. Then from the shorter list of coincident orbits, each file was quality controlled to be used for analysis in Section 3 as discussed below.

First, echoes determined as convective by the GPM-DPR retrieval (i.e., no bright-band present) are removed. Convective profiles are removed because the NN retrieval is not expected to perform well in convection given the likely presence of large amounts of supercooled liquid water and riming, which are not included in the formulation of the NN retrieval (c.f., Chase et al. 2021). Then surface echoes are removed by using the included surface elevation with a buffer of 1 km for the CloudSat dataset and the GPM-DPR supplied lowest clutter free bin parameter for the GPM-DPR dataset. Subsequently, the noise above echo-top is eliminated by using the minimum sensitivity thresholds for each radar, which are -25, 18 and 12 dBZ for W-, Ka- and Ku- bands, respectively.

197 The result from the aforementioned steps are shown in Fig. 2a,b. In order to isolate solid phase
198 echoes, the melting layer was removed by removing gates with temperatures $> -2.5^{\circ}\text{C}$, where the
199 temperature is obtained by the closest ECMWF-AUX profile included within the matched dataset.
200 The threshold of -2.5°C was chosen to be conservative and to assure most of the melting layer
201 would be excluded from the analysis. The result of removing liquid phase echoes from the retrieved
202 R are found in Fig. 2c,d. Afterwards, the 2CSP retrieval is then constrained to where the NN
203 retrieval was successfully performed (i.e., where there is Ku and Ka signal). Profiles where at least
204 3 valid gates (i.e., meet the aforementioned conditions) within the ice layer are kept for the analysis
205 and all others are removed.

206 Since there is no “ground truth” of retrieved snowfall within the Turk (2016) dataset, one way
207 to evaluate retrieval performance is to compare the liquid equivalent mass flux right above the
208 melting layer to the mass flux right below the melting layer. Heymsfield et al. (2018) used this
209 method, suggesting that on average the mass flux above and below the melting layer should be
210 quasi-conserved. While this may not be directly intuitive, given the fall velocity of melted particles
211 is much faster than their solid phase counterparts, the number concentration of particles scales
212 inversely with the fall velocity, thus the mass flux should be quasi-conserved. Additional evidence
213 for the quasi-balance of R across the melting layer is shown in a recent case study by Mróz et al.
214 (2020) using triple-frequency Doppler spectra measurements. It was shown that the mass flux just
215 above the melting layer is well preserved just below the melting layer outside of regions of intense
216 aggregation (e.g., where the dual-frequency ratio at X-Ka is > 10 dB). Lastly, since the retrieval
217 of rain from radars is generally more constrained (e.g., raindrops are quasi-spherical; constant
218 density) the rainfall retrieval, supplied from version 6 of the 2ADPR algorithm, just below the
219 melting layer is used as a benchmark for the snowfall retrievals just above the melting layer. Thus,
220 as a final constraint on the dataset, a rain echo with at least 3 gates had to be present for the profile

to be used in the analysis. The final result of all the quality control is found in Fig. 2e,f. A separate dataset of near-surface snowfall events (i.e., 0°C isotherm below the clutter echo) is also analyzed in the same manner, but the final constraint of the rain echo requirement is removed. While there is no baseline estimate to suggest which snowfall retrieval is performing better, the near-surface snowfall analysis is included to assess if trends from the snow over rainfall persist to snow only cases. After quality control there are a total of 3657 profiles of coincident retrievals of snowfall above rain and 1322 profiles of coincident retrievals of snowfall near the surface. A map of the location of all the profiles can be found in Fig. A1.

c. Field Campaign Data:

In order to supply discussion of the differences between 2CSP and the NN retrieval, two case studies using observations are shown. Specifically, a flight leg obtained as part of the Investigation of Microphysics and Precipitation for Atlantic Coast-Threatening Snowstorms (IMPACTS) and a flight leg from Olympic Mountains Experiment (OLYMPEX; Houze et al. 2017) are used. During both of the field campaigns, coordinated flights between a higher altitude aircraft carrying radars and a lower altitude aircraft carrying in-situ probes were frequently conducted in order to obtain coincident measurements of remotely sensed variables, like Z_e , and in-situ measurements. The specific radars used in this analysis are the Airborne Precipitation Radar (Sadowy et al. 2003) version 3 (APR3; Durden et al. 2019), the Cloud Radar System (CRS; Li et al. 2004), the High Altitude Imaging Wind and Rain Profiler (HIWRAP; Li et al. 2016) and the ER-2 Doppler Radar (EXRAD; Heymsfield et al. 1996).

The APR3 is a triple frequency scanning radar measuring co-located Z_e at Ku- (13.4 GHz), Ka- (35.6 GHz) and W-band (94 GHz) which was flown on NASA's DC-8 during the OLYMPEX field campaign. The APR3 measurements are estimated to have a calibration uncertainty of 1 to 1.5 dB

244 after being calibrated to the surface echo of the ocean surface in clear conditions and comparisons
245 of the dual-frequency ratio measured in low Z_e regions of cloud top (Tanelli et al. 2006). The
246 other 3 radars, CRS, HIWRAP, and EXRAD, are all nadir pointing doppler radars that measure at
247 W- (94 GHz), Ka- (35.6 GHz), Ku- (13.9 GHz), and X- (9.6 GHz) band. The CRS, HIWRAP and
248 EXRAD were flown together aboard the ER-2 aircraft for IMPACTS. Calibration of the radars was
249 performed in a similar way as the APR3 and are estimated to have a calibration uncertainty of 1
250 dB. All measured frequencies of Z_e are corrected for gaseous attenuation of O_2 and H_2O using a
251 dropsonde for OLYMPEX, a balloon borne radiosonde for IMPACTS, and the 2013 report from
252 the Radiocommunication Sector of International Telecommunication Union 2013 implemented in
253 pyLayers (<https://github.com/pylayers/pylayers>). Mean two-way attenuation correction
254 for gaseous extinction is 0.2, 0.4 and 0.6 dB for Ku-, Ka- and W- band respectively.

255 Simultaneous cloud in-situ data were collected during both field campaigns. For OLYMPEX, in-
256 situ observations were collected on board the University of North Dakota's Cessna Citation aircraft
257 (Delene et al. 2019), while for IMPACTS they were collected on NASA's P3 aircraft. Beyond
258 the common state parameters measured (e.g., pressure, temperature, relative humidity), the in-
259 situ aircraft carried the same optical array probes (OAP) to measure the particle size distribution
260 within clouds. Specifically, they had a 2-dimensional stereo (2DS) and a high-volume precipitation
261 spectrometer version 3 (HVPS3). The OAP data are quality controlled using the University of
262 Illinois-University of Oklahoma Optical array Probe Software (UIOOPS; McFarquhar et al. 2017;
263 Jackson et al. 2014) to correct images that are hollow, remove shattered artifacts and reconstruct
264 particles that have dimensions larger than the OAP diode array. The 2DS and HVPS data are
265 combined to give size distributions between $175 \mu\text{m}$ and 3 cm, with a transition between the probes
266 at 1 mm. Particles smaller than $175 \mu\text{m}$ are not included because of a small and uncertain depth
267 of field, and such small particles do not contribute significantly to calculated IWC.

Unfortunately, for the case from IMPACTS there was not good co-location between the radar carrying aircraft and the in-situ aircraft. Thus, to provide additional support for the hypotheses discussed in this paper the following three additional datasets are included in the discussion in Section 3b. The first one is the Multi-Radar Multi-Sensor (MRMS) radar only precipitation rate retrieval (Zhang et al. 2011). While the MRMS radar only precipitation rate is a static power-law between Z_e and R (i.e., a single Z-R relationship), it has been used before in evaluating various snowfall retrievals from space in the United States (Cao et al. 2014; Mroz et al. 2021). The second dataset is surfaced based measurements of R from three nearby stations. One of the three stations is a standard Automated Surface/Weather Observing Systems (ASOS) station located at the Syracuse, NY airport. The other two stations are a part of the New York State Mesonet (Brotzge et al. 2020).

3. Results and Discussion

a. Coincident Statistics between GPM-DPR and CPR:

Statistics of measured and retrieved variables from all coincident measurements between CPR and GPM-DPR after quality control are shown in Fig. 3. For surface rainfall events, the median profile of measured Z_e for GPM-DPR generally increases with temperature, from 19.7 dBZ and 21.6 dBZ to 21.5 dBZ and 25.6 dBZ for Ka- and Ku- band, respectively (red and blue lines; Fig 3a). Meanwhile, the CPR median measured Z_e decreases from 13.8 dBZ to 11.4 dBZ (yellow line; Fig. 3a). As a first order approximation, the retrieval of R just below the melting layer is compared to the retrieval of R just above the melting layer. Heymsfield et al. (2018) and Mróz et al. (2020) suggested that R should be approximately conserved through the melting layer. Thus if the assumptions of mass flux conservation are true on average, which implies relative humidity with respect to water (RH) is near 100%, then R is approximately conserved. Note that Heymsfield

et al. (2018) show that a modest decrease in RH (95%) can result in a non-negligible reduction in R across the melting layer (23%, c.f. Fig. 1 in Heymsfield et al. 2018), but if the RH is indeed less than 100% on average for the profiles studied here, then the rain retrieved R would be a lower bound to the snowfall retrieved R . In Fig. 3c the NN retrieval is closest to the rainfall retrieval, with a median value of 1.9 mm hr^{-1} and a percent difference from the rain retrieval of +2%. The next closest to the rain retrieval is the 2ADPR snowfall retrieval and then 2CSP, with median values of 1.01 mm hr^{-1} and 0.95 mm hr^{-1} and percent differences with respect to the rain retrieval of -48% and -51%, respectively. Considering the profiles over all temperatures, the smallest values of R in the snow layer are retrieved from 2ADPR, followed by the 2CSP and then the NN retrieval. The slopes of retrieved R for 2ADPR and 2CSP generally follow the shapes of the reflectivity that make up their retrieval (Fig 3a, while the NN retrieval is effectively constant for all temperatures, but does show an increase from 1.74 mm hr^{-1} at -10°C to 1.9 mm hr^{-1} at -2.5°C . Events where there is no rain retrieval available to be used as a reference (i.e., 0°C in or at lower altitudes than the ground clutter) are shown in Fig. 3b,d. The pattern overall is the same as the profiles with a coincident rain retrieval (Fig. 3a,c). The smallest retrieved R is produced by the 2ADPR algorithm followed by the 2CSP and the NN retrieval respectively.

While the comparison to the GPM-DPR rainfall retrieval was informative for gates near 0°C , unfortunately there are no reference data to compare the three snowfall retrievals to at temperatures lower than -2.5°C . Thus, it is impossible to provide an objective assessment of which retrieval is performing best at lower temperatures. Although, given there are measurements of reflectivity at Ku-, Ka- and W- band, some hypotheses can be postulated. The general increase of Z_e at Ku-, Ka- paired with a general decrease of W-band suggests a few possible scenarios that could result in the decrease of Z_e and subsequently a decrease of 2CSP R from -15°C to -2.5°C :

1. The 2CSP algorithm is underestimating the effects of attenuation at W-band.
2. The 2CSP is not correctly representing non-Rayleigh scattering effects at W-band.
3. The 2CSP algorithm is not correctly quantifying the amount of multiple scattering.

These three potential explanations are not mutually exclusive nor an exhaustive list of everything that can be going on. Furthermore, all of the listed scenarios could be affecting the 2CSP retrieval to some extent even though the 2CSP algorithm does attempt to account for these affects.

Discussing point (1), the decrease in W-band Z_e and the subsequent retrieval of R starting at -15°C coincides with temperatures that are more likely to contain supercooled liquid water and rimed particles (Kneifel and Moisseev 2020), which both have larger attenuation at W-band compared to that of aggregate-like particle models used in the 2CSP retrieval. For example, if the 2CSP assumed properties produce too little attenuation, the Z_e value used in the retrieval of R will be underestimated, and since Z_e and R are proportionally related, the retrieval of R will be underestimated. Meanwhile, since Ku- and Ka- band do not experience the same magnitude of attenuation from supercooled water and rimed particles, the retrievals using Ku and Ka have increasing (or constant) Z_e and R across the -15°C to -2.5°C layer.

As for point (2), there has been a lot of work conducted over the past decade that has shown larger snowfall particles at shorter wavelengths (e.g., Ka- and W-band) will have non-Rayleigh scattering characteristics which vary depending on the assumed particle type (e.g., Kneifel et al. 2011; Tyynelä et al. 2011; Leinonen and Szyrmer 2015). Since the reduction in Z_e from CloudSat in Fig. 3ab coincides with larger temperatures which are more likely to contain larger particles (i.e., aggregates; Hobbs et al. 1974), there is an increased likelihood of non-Rayleigh scattering. Since there is considerable uncertainty in the backscatter cross-section for these non-Rayleigh scattering particles (e.g., dendrite versus a bullet rosette; Kneifel et al. 2011), the 2CSP's assumed

particle type could be underestimating the backscattering cross-section, which in turn leads to the underestimate of R . Given the scattering of a particle is mainly determined by its relative size to the wavelength of the radar, W-band would be most affected by non-Rayleigh scattering which might explain why the 2CSP retrieval is most effected.

Coinciding with the likelihood of larger particles and radar gates at further range, multiple scattering for CloudSat is important (e.g., point (3)). The 2CSP retrieval assumes the result from Matrosov and Battaglia (2009), which is that multiple scattering in snowfall largely offsets the amount of attenuation (see more information about the 2CSP retrieval in Wood and L'Ecuyer 2018, 2021). More specifically, Matrosov and Battaglia (2009) show that on average the amount of total extinction expected (i.e., the attenuation loss plus the multiple scattering increase to Z_e) is a net reduction of 1-2 dB. However, Matrosov and Battaglia (2009) used T-matrix spheroidal particles to simulate the scattering properties of the snowfall, which have since been shown to be less accurate compared to discrete dipole approximation particles of large aggregates (e.g., Tyynelä et al. 2011; Kneifel et al. 2011). Thus, it is possible that for deep, moderate to intense snowfall like the profiles in Fig. 3, the assumed balance between multiple scattering and attenuation could be incorrect. In order to fully assess the impacts of multiple scattering and attenuation, new Monte Carlo simulations (i.e., like the ones done in Matrosov and Battaglia 2009) with more realistic particle shapes and rime fraction are required, which is beyond the scope of this manuscript.

b. Case Studies:

In this section, two case studies from NASA field campaigns assist in providing additional discussion on scenarios where W-band radar shows decreasing Z_e while Ku-, Ka- band show increasing Z_e at larger temperatures. Each case study was specifically chosen to exemplify potential analogue samples from Fig. 3, but with much higher resolution and better sensitivity radar systems.

Furthermore, both case studies provide some external in-situ observations as a reference for the different snowfall retrievals.

1) IMPACTS: 07 FEBRUARY 2020 15:08 UTC:

The first case study examined is from IMPACTS. This case is analogous to the profiles measured in Fig. 3b,d (i.e., surface snowfall events). On 07 February 2020, a deepening mid-latitude cyclone was moving eastward across the state of Pennsylvania, producing a large precipitation shield over central New York (Fig. 4). Snowfall accumulation at the surface for this event exceeded 233 mm (liquid equivalent 35 mm) at Syracuse, NY, USA. The IMPACTS field campaign targeted the northside of the cyclone flying a racetrack pattern from Syracuse, NY to Albany, NY and back. Data from one of the three coincident flight legs between both aircraft are shown in Fig. 5.

The cross-section of measured Z_e at W-band (Fig. 5a) and Ku-band (Fig. 5b) show different perspectives of the same cyclone. Median W-band Z_e grows to maximum 16.9 dBZ near 4 km, then reduces to 7.8 dBZ at 0.5 km (yellow, Fig. 5e). Meanwhile, X-, Ku- and Ka-band reflectivity are at a maximum near 1.5 km with values of 29.5, 28.7 and 23.8 dBZ, respectively (black, blue and red lines, Fig. 5e). Retrieved R from an optimal estimation retrieval using the exact assumptions as the 2CSP retrieval is shown in Fig. 6c, while the NN retrieved R is shown in Fig. 5d. As expected, both R retrievals generally follow the Z_e used within each respective retrieval. The two separate retrievals are relatively close in magnitude from 8 to 6 km, but then deviate from 6 km towards the surface (Fig 5). The 2CSP like retrieval shows a peak in median R near 5 km with a value of 1.88 mm hr⁻¹, then decreases to a value of 1.5 mm hr⁻¹ at 4 km (yellow line; Fig. 5f), then increases to about 2 mm hr⁻¹ at 0.5 km. Meanwhile the NN retrieved R increases with decreasing altitude, peaks around 2.5 km with a value of 2.93 mm hr⁻¹ (purple line, Fig. 5f) then reduces to 2.81 mm hr⁻¹ at 0.5 km. Unfortunately during this cross-section the in-situ aircraft was turning into the

ER-2 flight track after the ER-2 already sampled the region. Thus, the in-situ data are not matched well and could not be used for evaluation of the retrievals.

As an alternative evaluation method, the MRMS retrieved R and the measured R from three surfaced based gauges nearby the flight track are analyzed in Figure 5f and Figure 6. The median MRMS retrieved R over the distance of the flight track is 2.8 mm hr^{-1} , which is effectively the same as the NN retrieval. Meanwhile the minimum measured MRMS retrieved R along the flight track is 2.0 mm hr^{-1} (black circle Figure 5f), which is closest to the 2CSP median retrieved value. The surface based gauges at the time of the radar overpass (15:09 UTC) show R ranging from 1.5 mm hr^{-1} at Syracuse to 5.16 mm hr^{-1} measured at Westmoreland. Since tipping bucket gauges (Syracuse is a tipping bucket gauge) can have issues with measuring snowfall rates (e.g., Rasmussen et al. 2012), there is more confidence with the Fayetteville and Westmoreland stations which are Pluvio2 weighing bucket gauges in a fenced enclosure (Brotzge et al. 2020). Thus, all radar retrieved R are low biased at the time of the flight compared to Fayetteville, with percent differences of 127%, 63% and 62% for the 2CSP, MRMS and NN retrieval respectively.

While the aforementioned analysis is just one case study, given the results of the statistical comparison of Section 3a and this section in combination, there is empirical support showing that the 2CSP retrieval of R could be low biased in moderate to intense ($Ka > 18 \text{ dBZ}$) snowfall events. This case study also shows that the NN retrieval and the retrieval from MRMS could also be low biased compared to surface based gauges. Future field campaigns, such as IMPACTS year 2-3, should aim to collect more cases to help characterize these events by designing flight tracks to coincide directly with surface based measurements of snowfall and have better co-location with an in-situ aircraft.

2) OLYMPEX: 18 DECEMBER 2015 06:46 UTC:

The second case study examined is from OLYMPEX. This case is analogous to the profiles measured in Fig. 3a,c (i.e., surface rainfall events). On 18 December 2015 an occluded front was moving eastward from the Pacific Ocean towards the Olympic Peninsula in Washington State forcing widespread stratiform precipitation (Fig. 7). The OLYMPEX field campaign conducted three coincident flights between the NASA's DC-8 and the UND Citation over the same east-west track. One of the coincident flights from over the ocean is shown in Fig. 8.

As opposed to the previous case where surface snowfall was observed, Fig. 8b shows a clear melting level (i.e., bright-band) located at 1.6 km highlighting the phase transition from snow to rain. Thus, this case provides a potential example of the cases shown in Fig. 3a,c and closely resembles the structure in Fig. 2. As in the previous case, the W-band Z_e (Fig. 8a) and Ku-band Z_e (Fig. 8b) show different vertical variations for the same precipitation. W-band Z_e increases to a maximum at 4.1 km of 12.7 dBZ, then fluctuates down and back up to 12.7 dBZ at 2.9 km. From 2.9 km, the W-band Z_e decreases to 9.1 dBZ at 1.9 km (Fig. 8e). The other measured frequencies show increasing Z_e throughout most of the profile, reaching a maximum before melting of 20.9 and 27.4 dBZ for Ka- and Ku-band, respectively (Fig. 8e). Here, IWC is compared because there are fewer assumptions in the measurement of IWC from the in-situ aircraft. The retrieved IWC follows the general shape of the measured Z_e used in the respective retrievals (Fig. 8c,d). The 2CSP retrieval suggests a maximum IWC of 0.15 g m^{-3} at 4.1 km and then decreases to 0.08 g m^{-3} at 2 km (Fig. 8f). Meanwhile, the NN retrieved IWC agrees with the 2CSP routine from 8 km to around 4 km, but then is approximately six times larger at 2 km, with the maximum IWC of 0.51 g m^{-3} (Fig. 8f).

For this case, the in-situ aircraft was flying at an average altitude of 1.7 km (-0.5°C), right within the observed reduction of W-band Z_e . This location of reduced Z_e at W-band has been termed the radar ‘dark’ or ‘dim’ band in the literature (e.g., Sassen et al. 2005; Heymsfield et al. 2008; Kollias and Albrecht 2005; Sassen et al. 2007). The IWC calculated from the measured particle size distribution by assuming moderately rimed aggregates from Leinonen and Szyrmer (2015) ($\alpha=0.249 \text{ kg m}^{-\beta}$, $\beta=2.30$ for the mass-Dimension relation) shows the best agreement with the measured Ku- and Ka-band reflectivity (markers with error bars, Fig. 8e) and suggests median IWC values close to the NN retrieved IWC of 0.51 g m^{-3} . Thus, it is expected that the NN retrieval is more plausible given the 2CSP retrieval of IWC is six times smaller than the in-situ data and the in-situ data can reproduce the measured median Z_e to within 2 dB.

Fig. 9 shows the measured particle size distribution and some particle images from the in-situ aircraft. Large aggregates with dimensions exceeding 1 cm are observed, with particles greater than 2 cm observed near the end of the flight. Using the Cloud Droplet Probe and the Rosemount Icing Detector, there is limited or no supercooled liquid water present in the sampled layer (not shown). On average, larger mean particle sizes results in larger Z_e (c.f. Figure 4 in Kneifel et al. 2011). Since Ku- and Ka-band Z_e increase across this layer, and melting is not detected by the in-situ instruments (e.g., temperature less than 0°C , images are non-spherical, low CDP measurements) mean particle size should be increasing. Thus, the measured reduction in Z_e at W-band can only be explained by non-Rayleigh scattering effects and/or attenuation. While there is no method to disentangle the attenuation and non-Rayleigh effects, it is clear that the radar measured Z_e , which is ultimately used in the retrievals, is low compared to the PSD calculated Z_e (yellow marker and yellow line in Fig. 8e), resulting in a smaller retrieved IWC at the level of in-situ observations.

4. Conclusions

With the advent of spaceborne radars, the global estimation of precipitation and the quantification of the hydrologic cycle has been enhanced. Both CPR and GPM-DPR provide unique opportunities to study snowfall near the surface and snow properties throughout the atmospheric column. For the first time, a direct quantitative comparison of the 2C-SNOW-PROFILE (Wood and L'Ecuyer 2018, 2021), 2ADPR (Iguchi et al. 2018) and a neural network retrieval (Chase et al. 2021) on coincident measurements globally was conducted. The main conclusions from the comparison of over 3500 precipitating profiles collected globally are as follows:

1. The neural network (NN) snowfall retrieval just above the melting layer from Chase et al. (2021) provided the best agreement to the rain layer retrieved precipitation rate (R) from 2ADPR just below the melting layer.
2. CloudSat's 2C-SNOW-PROFILE (2CSP) retrieval showed decreasing R with temperatures greater than -15°C , decreasing by about 35% in magnitude from -15°C to -2.5°C and underestimating compared to the rain layer retrieved R from GPM-DPR.
3. GPM-DPR's 2ADPR snowfall retrievals for most temperatures showed the smallest retrieved R compared to the 2CSP and the NN retrieval.

It should be emphasized that the data that resulted in the conclusions above are from profiles that have at least 3 gates of 18 dBZ Ka-band Z_e within the ice layer. Thus, the profiles used in the analysis are likely in the upper tail of the distribution of intensity for stratiform precipitation, but it is expected that while these profiles are less frequent in terms of total number, they likely have a disproportionate effect on the total accumulation of precipitation. Initial investigations have shown the GPM-DPR is not well suited for capturing the entire distribution of snowfall accumulation (Casella et al. 2017; Skofronick-Jackson et al. 2019), but if the bias in the retrieved

471 R from 2CSP reported in Fig. 3 also exists at lower temperatures and occurs within a large
472 fraction of snowfall events within the CloudSat record, then there is opportunity for GPM-DPR
473 to assist in the quantification of the moderate to intense snowfall events since the 2CSP retrieval
474 is highly uncertain and likely biased low. Furthermore, for the profiles used in Fig. 3 some of
475 the assumptions made in the 2CSP optimal estimation retrieval, such as the particle model or the
476 quasi-balance between multiple scattering and attenuation, could be inappropriate and might be
477 what is leading to the reduction in R from -15°C to -2.5°C . Future work should investigate how
478 including new state-of-the-art particle scattering models (e.g., Kuo et al. 2016; Eriksson et al.
479 2018) impact the 2CSP retrieval and the expected multiple scattering with CloudSat geometries
480 within moderate to intense snowfall events.

481 In addition to the results from the coincident GPM-CloudSat dataset, two case studies from NASA
482 field campaigns highlight the apparent challenges of W-band only retrievals of snowfall. The main
483 conclusion from the two case-studies is as follows: Coincident W-, Ka- and Ku- band measurements
484 suggest that W-band only retrievals of IWC and R , are non-negligibly affected by attenuation and
485 non-Rayleigh scattering. While the overall amount of attenuation might initially seem small, 2-3
486 dB, its effect on the 2CSP retrieval is clearly not negligible. In both cases, the 2CSP retrieval peaks
487 near the dendritic growth zone (-15°C) and then decreases towards greater temperatures. The
488 analysis of the multifrequency radar measurements here further support the already documented
489 notion that multifrequency radar measurements improve snowfall retrievals (e.g., Kneifel et al.
490 2011, 2015; Grecu et al. 2018; Leinonen et al. 2018; Tridon et al. 2019; Battaglia et al. 2020). Thus,
491 it is advantageous for any future planned spaceborne missions, such as the planned international
492 mission named the Atmospheric Observing System (AOS; <https://aos.gsfc.nasa.gov>), to
493 include a longer wavelength radar (e.g., a Ka- or Ku-band system) in tandem with the W-band in
494 order to improve precipitation science and the associated scientific outcomes. The added longer

wavelength will provide valuable insight to when there is appreciable attenuation/non-Rayleigh scattering at W-band and hopefully inform the retrieval to rely on the longer wavelength in said regions.

Additional future work should explore the CloudSat record and consider the documented reduction in R with larger temperatures from this paper. For example, many studies (Liu 2009; Kulie and Bennartz 2009; Palerme et al. 2014; Kulie et al. 2016; Palerme et al. 2017; Milani et al. 2018; Kulie and Milani 2018; Skofronick-Jackson et al. 2019; Cabaj et al. 2020; Edel et al. 2020; Kulie et al. 2020) have adopted the near-surface gate as the source of data to analyze when calculating the distribution of global snowfall accumulation and its properties. Rather, the entire profile of measured Z_e should be considered in order to diagnose when unexpected reductions in W-band Z_e could be occurring, and thus the frequency and effect of these attenuated profiles on the global snowfall accumulation could be estimated. While stratiform profiles were mainly used in this paper, shallow convective clouds that make up a non-negligible fraction of total snowfall over the ocean (Kulie et al. 2016) also have considerable attenuation issues at W-band (Battaglia and Panegrossi 2020), and should be carefully considered as well. Finally, other future work should update the analysis presented here with the extended coincident dataset after August 2016, when the required products from CloudSat are available.

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524 *Data availability statement.* The coincident dataset between CloudSat and GPM-DPR can
 525 be found on NASA GPM's arthurhou ftps on each of their respective days after free regis-
 526 tration with NASA's PPS (register here: [https://registration.pps.eosdis.nasa.gov/](https://registration.pps.eosdis.nasa.gov/registration/)
 527 registration/). For example you can find a file at this address https://arthurhouhttps.pps.eosdis.nasa.gov/gpmdata/2014/05/05/radar/2B.CSATGPM.COIN.64S_157W_04420_000_250_866.20140505-S011851-E012159.001032.V04.nc4. Within the coinci-
 529 dent files are the 2CSP retrievals and the matched reanalysis data. In order to get the GPM-DPR
 530 2A.DPR data the 2ADPR files need to be downloaded from the same ftps location (DOI: <http://dx.doi.org/10.5067/GPM/DPR/GPM/2A/05>). The neural network retrieval from Chase et al.
 531 (2021) can be found with their paper's doi (https://doi.org/10.13012/B2IDB-0791318_V2).
 532 The IMPACTS (<http://dx.doi.org/10.5067/IMPACTS/DATA101>) and the OLYMPEX
 533 (<http://dx.doi.org/10.5067/GPMGV/OLYMPEX/DATA101>) data can be found on the GHRC.

536 APPENDIX

537 Map of profile locations

538 A map of all the profiles used in Fig. 3.

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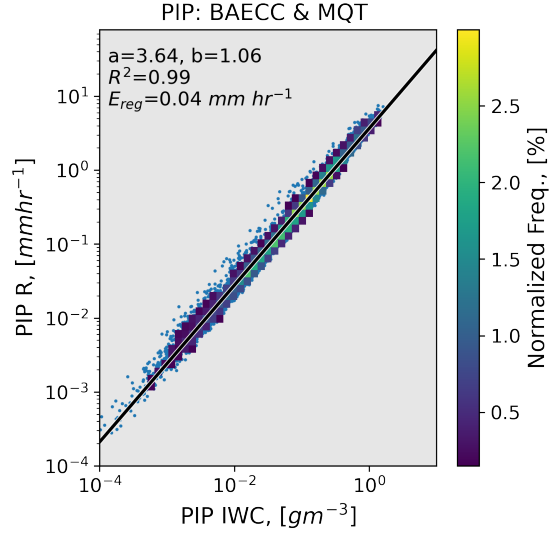


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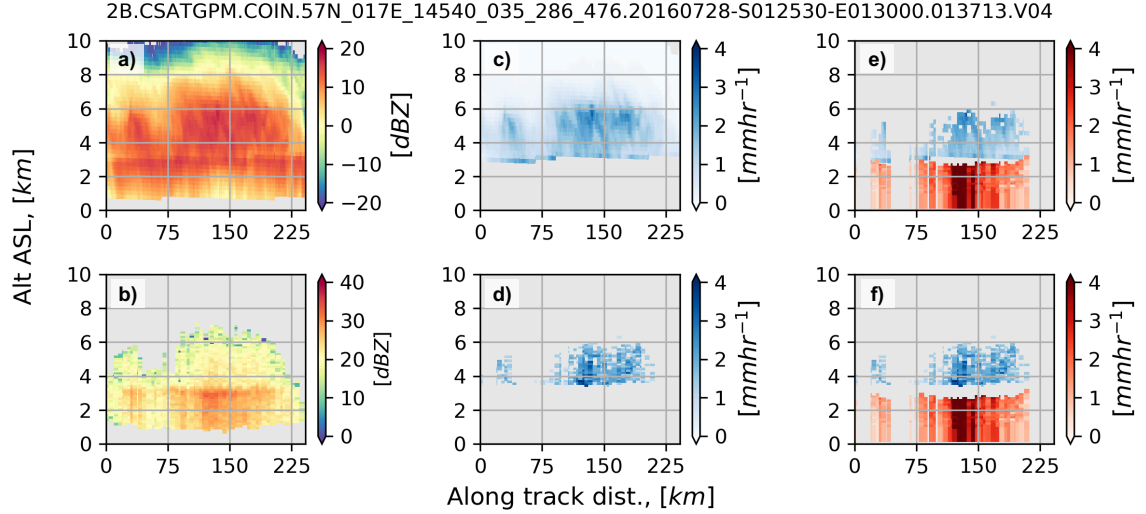


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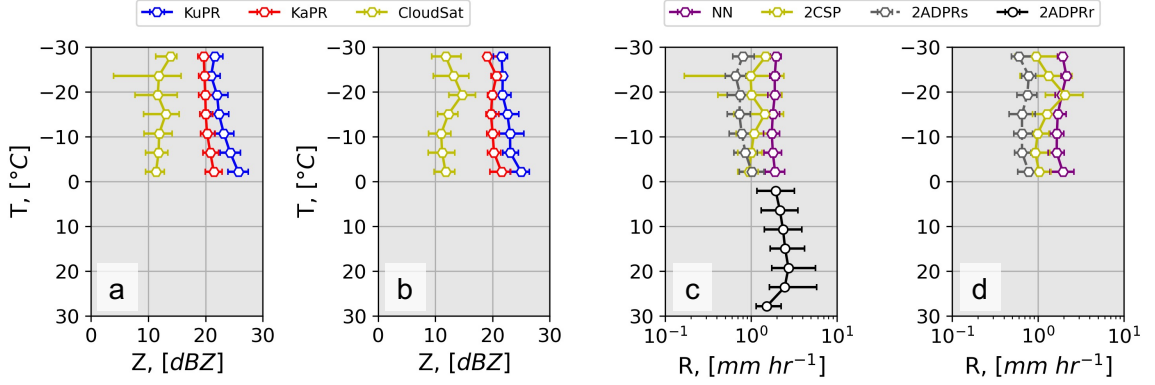


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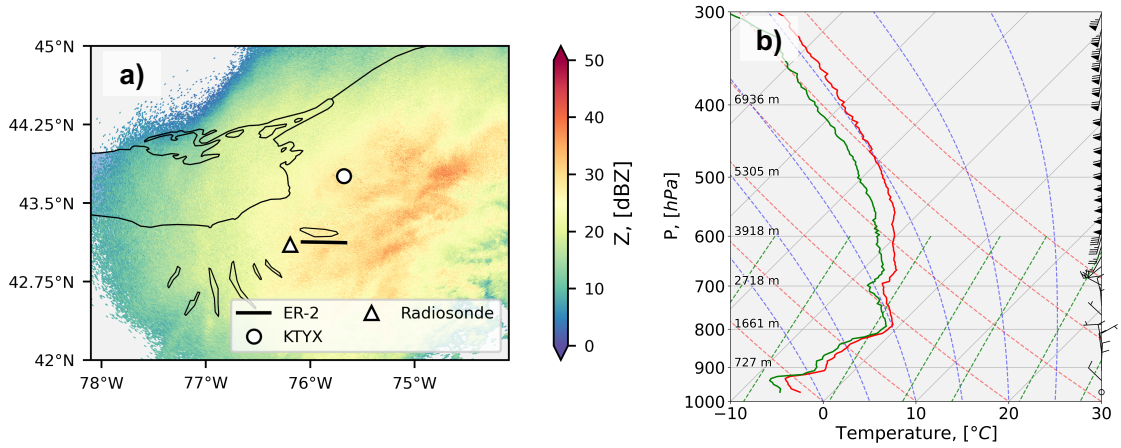


FIG. 4. Map and sounding from a case study from the IMPACTS field campaign 07 February 2020 from 15:08:25 – 15:10:50 UTC. (a) The radar scan is from the lowest elevation (0.5 degrees) from the KTYX NEXRAD (circle marker) radar at 15:07 UTC. The black line is the ground track of the airborne radars. The triangle is where a ground based radiosonde was launched at 14:14 UTC. (b) Skew-T diagram of the radiosonde. Wind barbs are in knots.

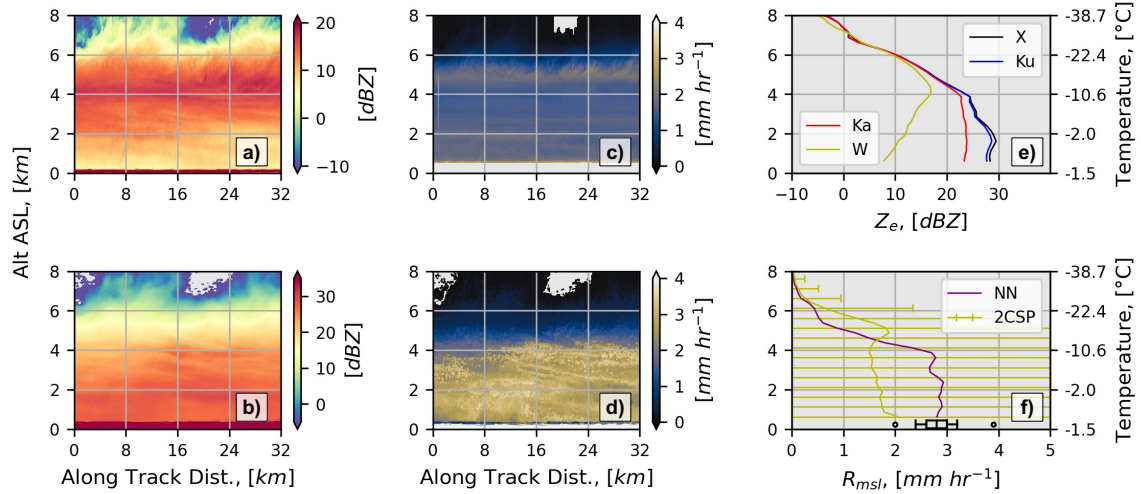


FIG. 5. A case study from the IMPACTS field campaign 07 February 2020 from 15:08:25 – 15:10:50 UTC. (a) Nadir W-band Z_e (in dBZ) corrected for gaseous attenuation of O_2 and H_2O . (b) As in (a) but for Ku-band. (c) Retrieval of liquid equivalent precipitation rate (R) from the W-band only CloudSat like retrieval (in $mm\ hr^{-1}$). (d) Calculation of R from the NN retrieval of D_m and N_w (in $mm\ hr^{-1}$). (e) Median profiles of X- (black), Ku- (blue), Ka- (red) and W-band (yellow) along the cross-section. The tick labels on the right are approximate temperatures for each height inferred from radiosonde measurements. (f) as in e, but now showing the median R from the CloudSat like retrieval (2CSP; yellow) and the NN retrieval (purple). The error bars on the 2CSP median is the median uncertainty estimated from the optimal estimation retrieval. The black boxplot located at 0.5 km is the 0th, 10th, 25th, 50th, 75th, 90th and 100th percentile of MRMS retrieved R along the flight track.

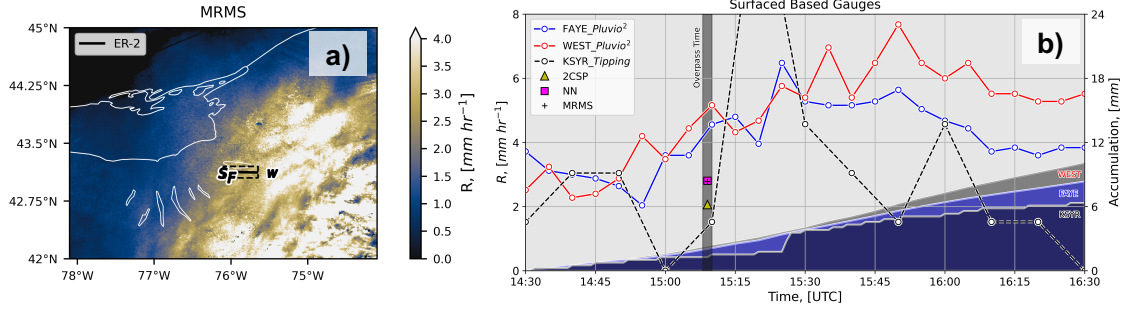


FIG. 6. Additional snowfall measurements for 07 February 2020. (a) Mean MRMS retrieved precipitation rate from 1506 - 1508 UTC for the same location as Fig. 4a. Letter markers are S, F and W which correspond to the named surface stations which are Syracuse, Fayetteville and Westmoreland respectively. Black solid line is the flight track in Figure 5, and the dashed black rectangle is the area over which the MRMS data tabulated for the statistics in Figure 5e and b. (b) Time series of the surfaced based gauges in a. Left y axis corresponds to the lines, while the right axis corresponds to the filled curves. The data for Syracuse, Fayetteville and Westmoreland are in black, blue and red respectively. The median retrieved value from Figure 5f is also shown at 1509 UTC for 2CSP (yellow triangle), the NN (purple square) and MRMS (black plus sign).

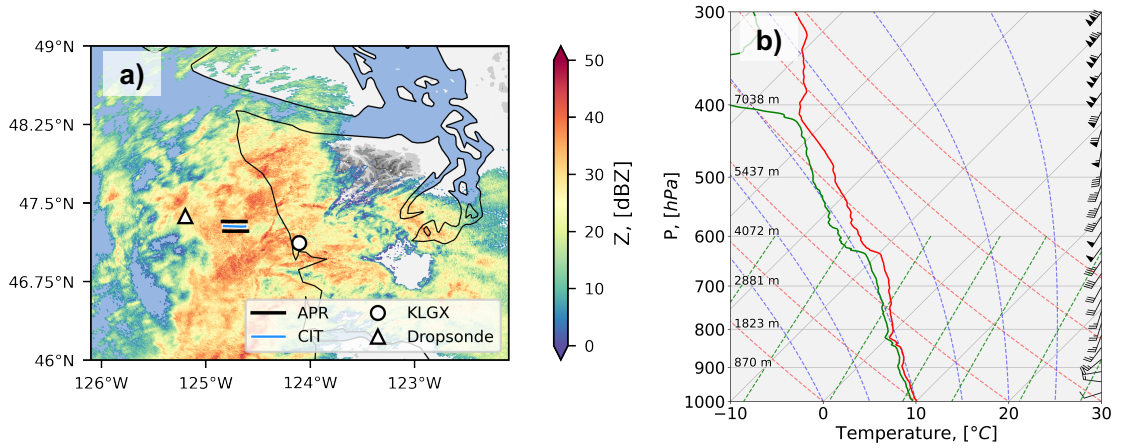


FIG. 7. As in Figure 4, but for a case study from the OLYMPEX field campaign 18 December 2015 from 06:47:48 – 06:49:17 UTC. (a) The ground-based radar used is the KLGX radar from 06:49 UTC. The black lines are the extent of the APR3 swath and the blue line is the in-situ aircraft. The triangle is a dropsonde, dropped from the APR3 aircraft at 05:57 UTC. (b) Skew-T diagram of the dropsonde data in (a).

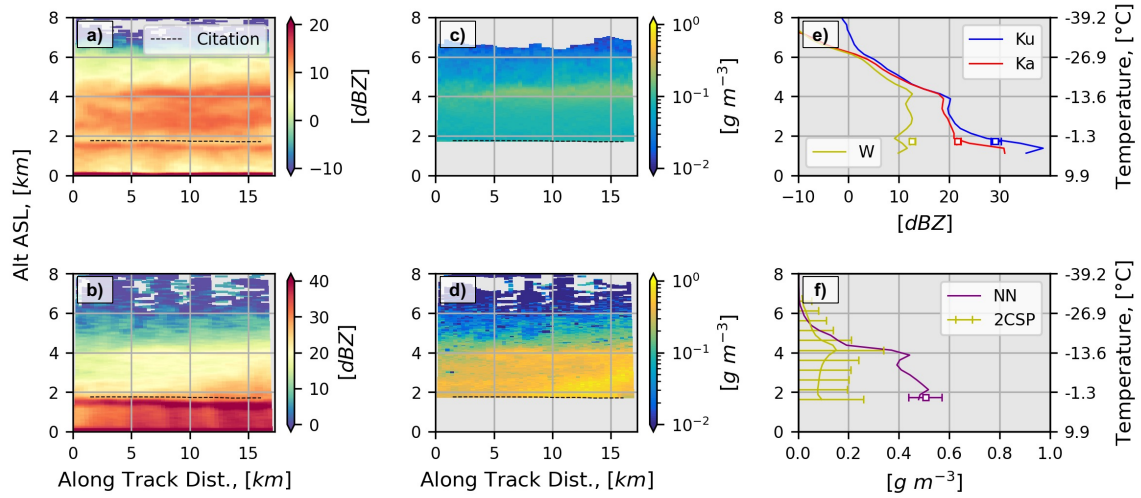


FIG. 8. Similar to Figure 5, but for a case study from the OLYMPEX field campaign 18 December 2015 from 06:47:48 – 06:49:17 UTC and now the retrieved parameter from the radars is ice water content (c,d,f). Furthermore, (e) and (f) now have markers with caps that indicate the 25th, 50th and 75th percentiles calculated from the in-situ measured PSD using Leinonen and Szyrmer (2015) backscatter cross-sections.

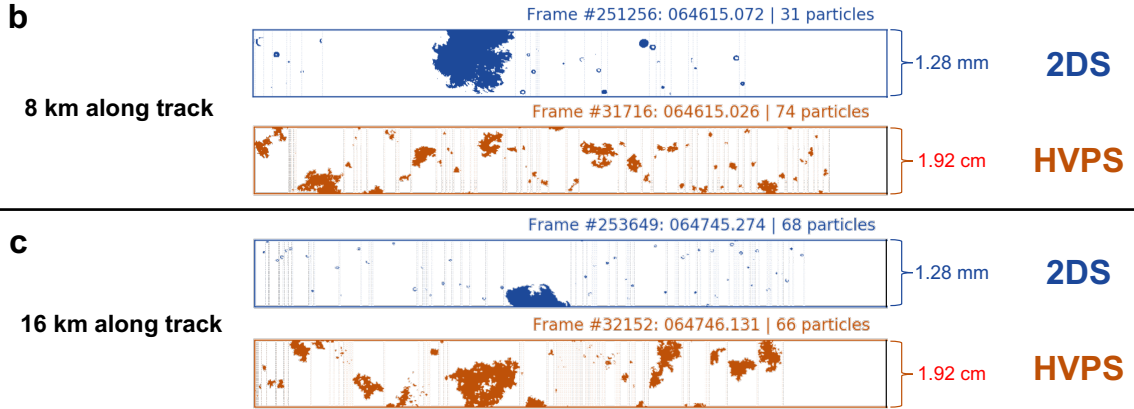
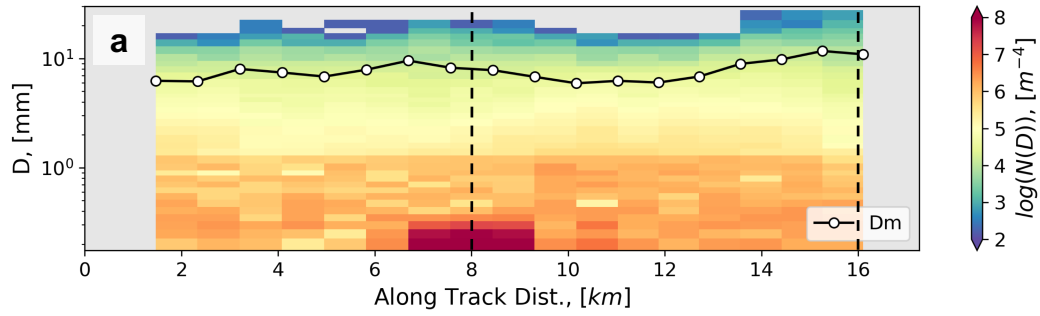


FIG. 9. In-situ observations from 18 December 2015. The in-situ aircraft is located by the dashed line in Figure 8. (a) Measured $N(D)$ with the same x-scale as Figure 8 (shading). The line with markers is the mass weighted mean diameter assuming the same m - D from Leinonen and Szyrmer (2015) that recreates the measured Z_e in Figure 8. (b) Example particle images from both the 2DS (blue) and the HVPS (orange). These are from the 8 km location on the x-axis. (c) same as b, but for 16 km on the x-axis.

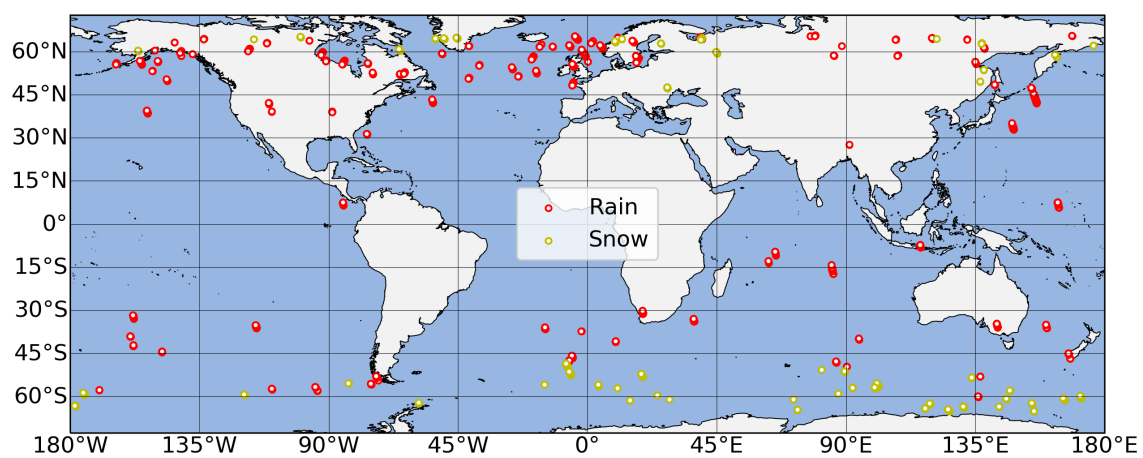


Fig. A1. Map of all footprints used in the comparison between the retrieval products.