

1 Evaluation of Several A-Train Ice Cloud Retrieval Products with in situ Measurements Collected
2 during the SPARTICus Campaign

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22 For publication in *Journal of Applied Meteorology and Climatology*

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38 **Abstract**

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40 In this study we evaluate several ice cloud retrieval products that utilize active and passive A-
41 Train measurements using in situ data collected during the Small Particles in Cirrus (SPartICus)
42 field campaign. The retrieval data sets include ice water content (IWC), effective radius (r_e) and
43 visible extinction (σ) from CloudSat 2C-ICE, CWC-RVOD, DARDAR, and σ from CALIPSO.
44 When the discrepancies between the radar reflectivity (dBZ_e) derived from 2D-S in situ
45 measurements and dBZ_e measured by the CloudSat radar are less than 10 dBZ_e , the flight mean
46 ratios of the retrieved IWC to the IWC estimated from in situ data are 1.12, 1.59, and 1.02,
47 respectively for 2C-ICE, DARDAR and CWC_RVOD. For r_e , the flight mean ratios are 1.05,
48 1.18, and 1.61, respectively. For σ , the flight mean ratios for 2C-ICE, DARDAR and CALIPSO
49 are 1.03, 1.42, and 0.97, respectively.

50 The CloudSat 2C-ICE and DARDAR retrieval products are typically in a close agreement.
51 However, the use of parameterized radar signals in ice cloud volumes that are below the detection
52 threshold of the CloudSat radar in the 2C-ICE algorithm provides an extra constraint that leads to
53 slightly better agreement with in situ data. The differences in assumed mass-size and area-size
54 relations between CloudSat 2C-ICE and DARDAR also contribute to some subtle difference
55 between the datasets. r_e from the CWC-RVOD dataset is biased larger than the other retrieval
56 products and in situ measurements by about 40%. A slight low bias in CALIPSO σ may be due to
57 5 km averaging in situations where the cirrus layers have significant horizontal gradients in σ .

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63 1. Introduction

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65 CloudSat is one of the five satellites in the A-Train constellation. A vertical profile of radar
66 reflectivity factor (dBZ_e) is measured by the 94 GHz Cloud profiling radar (CPR; Im et al., 2006)
67 at a vertical resolution of 240 m between the surface and 30 km altitude. The footprint size is
68 approximately 1.3 km across track by 1.7 km along track. The CPR has a minimum sensitivity of
69 $\sim -30 \text{ dBZ}_e$ (Stephens et al 2008). During the period of this study, CALIPSO followed CloudSat
70 by no more than 15 seconds. The CALIPSO lidar (Winker et al., 2008) measures parallel and
71 perpendicular attenuated backscatter (β) at 532 nm and total backscatter at 1064 nm at vertical and
72 along-track resolutions that are altitude dependent (60 m vertical resolution with footprints
73 averaged to ~ 1.0 km along track between 8.2 and 20.2 km and 30 m vertical and 0.333 km along
74 track resolution below 8.2 km). The data sets produced by these two active remote sensors, when
75 combined with the passive remote sensors of the A-Train constellation (Stephens, et al., 2008)
76 have provided an unprecedented global view of clouds (Sassen et al 2008, Mace et al 2009) and
77 precipitation (Stephens 2010) and also motivated development of a series of cloud property
78 retrieval algorithms using various combinations of radar, lidar and radiometer measurements
79 (Austin et al 2001; Hogan et al 2006; Young and Vaughan 2009; Delanoë and Hogan 2008, 2010;
80 and Deng et al 2010; Mace, 2010).

81 Because ice clouds are composed of nonspherical ice crystals with bulk microphysical
82 properties that cover a wide dynamic range that depend on their formation mechanism, history,
83 and dynamic and thermodynamics atmospheric states, many assumptions are often necessary to
84 reduce the inversion of the remote sensing data to a tractable problem. Therefore, uncertainties in
85 ice cloud property retrievals can be substantial. While algorithm developers often work to reduce
86 biases, it is difficult to determine quantitatively how accurate the algorithms are under specific

87 circumstances. While data collected in situ has its own set of problems, these problems are often
88 different and also often more manageable than those confronting remote sensing inversion
89 algorithms. Therefore, in situ data can be quite useful in identifying shortcomings in remote
90 sensing retrievals that arise due to assumptions in the inversion process. In this paper, we evaluate
91 several ice cloud retrieval products with data collected during a long term in situ measurement
92 campaign called Small Particles in Cirrus (SPartICus, January to June 2010, Mace 2009) funded
93 by the Department of Energy Atmospheric Radiation Measurement Program (DOE ARM;
94 Ackerman and Schwartz, 2004).

95 This paper is organized as follows. First, the retrieval datasets and in situ measurements are
96 introduced in Section 2 followed by the evaluation methodology in Section 3. Then we examine
97 several case studies to evaluate algorithm performance in different radar and lidar measurement
98 situations in Section 4 where the retrieval results are discussed within the context provided by the
99 in situ measurements. In Section 5, statistical comparisons are presented that show the
100 relationships among the algorithms. The relationships between the IWC, extinction coefficients, r_e
101 and radar reflectivity are investigated in comparison with the in situ measurement data set. In the
102 last section, we present our conclusions and summary.

103

104 **2 Satellite retrieval products and the SPartICus project**

105 *2.1 2C-ICE*

106 The CloudSat and CALIPSO ice cloud property product (2C-ICE; Deng et al., 2010) is a
107 standard operational CloudSat dataset that is publicly available through the CloudSat data
108 processing center at Colorado State University. 2C-ICE provides a vertically resolved retrieval of
109 ice cloud properties such as r_e , IWC and σ by synergistically combining CloudSat dBZ_e and

110 CALIPSO β at 532 nm at the CloudSat horizontal and vertical resolutions based on an optimal
111 estimation framework. Lidar multiple scattering is accounted for with a constant factor for a fast
112 lidar forward model calculation. Lidar ratio (extinction to backscattering ratio) is assumed to be
113 constant in the 2C-ICE version that is evaluated in this paper. The forward model assumes a first
114 order Gamma particle size distribution (PSD) of idealized non-spherical ice crystals (Yang et al
115 2000). The Mie scattering of radar reflectivity is calculated in the forward model look up table
116 according a discrete dipole approximation (DDA) by Hong 2007.

117 The characteristics of the instruments convolved on the physical properties of clouds in the
118 upper troposphere require us to consider that three distinct lidar-radar regions could exist in any
119 ice cloud layer. For the lidar-only region, where dBZ_e is below the CPR detection threshold, the
120 radar signal is parameterized using DOE ARM ground-based Millimeter Cloud Radar (MMCR)
121 observations so that the retrieval can still be loosely constrained with two inputs. When the lidar
122 signal is unavailable due to strong attenuation (i.e the radar-only region), the retrieval tends
123 towards an empirical relationship using the radar reflectivity factor and temperature (Hogan et al
124 2006, Liu and Illingworth 2000). Readers desiring a more in-depth description of the 2C-ICE
125 algorithm should refer to Deng et al., (2010) for details. The algorithm has been applied to
126 CloudSat/CALIPSO data as well as lidar and radar data collected by the ER2 during the TC⁴
127 (Tropical Composition, Cloud and Climate Coupling) mission (Toon et al 2010). The retrieved r_e ,
128 IWC and σ are shown to compare favorably with coincident in situ measurements collected by
129 instruments on the NASA DC-8. For example, we calculated the mean and median and standard
130 deviation of the CVI/2C-ICE and 2DS/2C-ICE IWC ratios for the cases in Deng et al 2010. For the ER2
131 case (Figures 9 and 10 of Deng et al., 2010), the median, mean and standard deviation of the CVI/2C-ICE
132 and 2DS/2C-ICE IWCs was 1.05, 1.21 +/-2.51 and 0.69, 0.78 +/- 0.46 respectively. For the CloudSat and
133 CALIPSO case (Figure 11 and 12 of Deng et al., 2010), the median, mean and standard deviation of the

134 CVI/2C-ICE and 2DS/2C-ICE IWCs was 1.31, 1.74 +/- 3.2 and 1.09, 1.54+/- 4.1 respectively. Based on
135 the IWCs from two instruments, we conclude that the uncertainty of 2C-ICE IWC is around 30% .

136

137 2.2 DARDAR

138 Similar to the 2C-ICE product, the DARDAR (raDAR/liDAR) cloud product is a synergetic
139 ice cloud retrieval algorithm derived from the combination of the CloudSat dBZ_e and CALIPSO β
140 using a variational method for retrieving profiles of σ , IWC and r_e . DARDAR was developed at
141 the University of Reading by Drs. Julien Delanoë and Robin Hogan, (Delanoë and Hogan 2008,
142 2010). There are several differences between 2C-ICE and DARDAR. First, DARDAR is retrieved
143 using the CALIPSO vertical resolution (60 m) instead of the CloudSat vertical resolution as in 2C-
144 ICE. Second, the multiple scattering in the lidar signal is accounted with a fast multiple-scattering
145 code (Hogan 2006) instead of assuming a constant multiple scattering factor as in 2C-ICE. Third,
146 the lidar backscatter to extinction ratio is retrieved rather than assumed to be a constant as in 2C-
147 ICE. Fourth, no parameterizations of radar or lidar signals are used for the lidar-only or radar-only
148 regions of the ice cloud profile. Empirical relationships are heavily relied on for those regions in
149 the DARDAR algorithm. Fifth, the DARDAR product assumes a “unified” PSD given by Field et
150 al. [2005]. The mass-size and area-size relation of non spherical particles is considered using
151 relationships derived from in situ measurements (Francis et al. [1998], Brown and Francis [1995]).

152

153 2.3 CWC-RVOD

154 The CloudSat Radar-Visible Optical Depth Cloud Water Content Product (2B-CWC-RVOD)
155 contains estimates of cloud liquid and ice water content and effective radius that is derived using a
156 combination of dBZ_e together with estimates of visible optical depth derived from MODIS
157 reflectances (from the CloudSat 2B-TAU product) to constrain the cloud retrievals more tightly

158 than in the radar-only product (2B-CWC-RO, *Austin et al.* 2009) presumably yielding more
159 accurate results.

160 The forward model in the retrieval algorithm assumes the ice particles to be spheres with a
161 lognormal PSD. IWC is defined as the third-moment of the PSD over all possible ice particle sizes
162 assuming a constant ice density ($\rho_i = 917 \text{ kg m}^{-3}$). The optimization iteration is initialized with an
163 a priori PSD specified by the temperature dependences obtained from in situ data [*Austin et al.*,
164 2009], with the temperature information obtained from ECMWF operational analyses. Several ice
165 cloud microphysical retrieval algorithms are compared in *Heymsfield et al.* [2008], using
166 simulated reflectivity and optical depth values based on cloud probe measurements. The mean
167 retrieved-to-measured ratio for IWC from the CloudSat RVOD algorithm is found to be 1.27 ± 0.78
168 when equivalent radar reflectivity is greater than -28 dBZ_e . While most of the IWC retrievals are
169 within $\pm 25\%$ of the true value, the algorithm exhibits high bias of over 50% when IWC is less than
170 $\sim 100 \text{ mg m}^{-3}$, with some of the biases related to the potential errors in the measured extinction for
171 small ice crystals in the probe data; therefore the estimated systematic error for IWC is likely
172 $\pm 40\%$ [*Heymsfield et al.*, 2008].

173

174 2.4 CALIPSO extinction at 5 km

175 The CALIPSO σ retrievals are provided at horizontal resolutions of 5, 20 and 80 km, which
176 corresponds, respectively to averages of 15, 60 and 240 consecutive lidar profiles (Young and
177 Vaughan 2008). In this study we use the 5 km data. In the retrieval, the lidar multiple scattering is
178 considered a constant (0.6) as in the 2C-ICE product. There are two types of data labeled by data
179 quality control information in the data files: constrained or unconstrained. Whenever possible, σ
180 solutions are constrained by a determination of the two-way transmittance provided by the

181 boundary location algorithm. To accomplish this, an adjustment of the particulate lidar ratio is
182 made iteratively using a variable secant algorithm as described in Froberg (1966, section 2.2) until
183 the retrieved particulate two-way transmittance differs from an assumed constraint by less than a
184 specified tolerance. The assumption of constant lidar ratio in the CALIPSO retrieval is probably
185 one of the largest factors affecting the lidar extinction comparisons. We found that the histogram
186 of retrieved lidar ratio for constrained cases in 2007 is peaked at 30 with a half width of about 10
187 (not shown).

188 For the unconstrained cases, where the lidar signal is fully attenuated or in contact with the
189 surface, the retrieval of correct extinction profiles obviously depends on the predetermined lidar
190 ratio. However, for the algorithm iteration, the retrieved profile may diverge from the correct
191 values if incorrect estimates of the lidar ratio, multiple scattering function, or correction for the
192 attenuation of overlying features are used. The CALIPSO team chooses to adjust the lidar ratio to
193 prevent divergence in features (Young et al 2009). Upon detecting divergence, the profile solver
194 algorithm is terminated, and then restarted using a modified value of the lidar ratio. For solutions
195 diverging in the positive direction, the lidar ratio is reduced, and for solutions diverging in the
196 negative direction, the lidar ratio is increased. These cases account for only about 3% of all ice
197 cloud profiles based on data collected in 2007.

198

199 *2.5 SPartICus*

200 Comparison of different retrieval datasets provides information on algorithm consistency and
201 reliability. Since there is no standard measurement of in situ microphysical cloud properties as the
202 absolute truth for retrieval algorithm evaluation, it is presumptuous to call a comparison of remote
203 retrievals with in situ measurements a “validation” of the retrieval products. Also, since there is

204 no standard measurement for comparison, it is not possible to rigorously formulate an uncertainty
205 (see for example, Abernethy and Benedict 1984; Bevington and Robinson 1992). However, with
206 proper understanding of the limitations of both remote and in situ instrumentation, it is possible to
207 compare the measurements, assess consistency, and formulate interpretations based on physical
208 principals. Uncertainties in cloud particle probe measurements have been discussed by many
209 investigators. For example, Korolev et al. (1998) and Korolev et al (2005) discuss uncertainties in
210 2D-C particle imaging probes. Lawson et al. (2006) discuss uncertainties in the 2D-S particle
211 imaging probe. Korolev et al. (2010) discuss the effects of shattering on the 2D-C and CIP probes
212 and Lawson (2011) discusses shattering on the 2D-S probe. The SPartICus field campaign, as a
213 major effort of the DOE ARM Aerial Facility program, took place over the central United States
214 from January through June, 2010 using the SPEC Incorporated Lear 25 research aircraft (Lawson,
215 2011). Approximately 200 hours of research time were devoted to measurements in ice clouds
216 over the ARM Southern Great Plains ground site as well as under the A-Train satellite
217 constellation. SPartICus provides a collection of microphysical data that includes the 2D stereo
218 probe (2D-S), measuring ice particle size distribution $10 < D < 3000 \mu\text{m}$. The 2D-S is a critical
219 instrument for quantifying concentration of ice cloud particles because the probe and subsequent
220 data analysis methodologies are designed to minimize the extent to which shattered ice crystal
221 remnants bias reported particle numbers (Lawson et al 2006; Lawson 2011). Processing of 2D-S
222 image data is a complex process that has evolved based on both theoretical and empirical
223 approaches. The processing can loosely be divided into three broad steps:

224 – Various methods to determine “characteristic” lengths, L_i , and areas, A_i , of an image.

225 – Removal of what are called here “spurious” events (also referred to as artifact rejection),
226 which can include electronic noise, optical contamination, particle shattering and splashing
227 effects.

228 – Various methods, M_i , of estimating the bulk physical parameters; concentration,
229 extinction, and mass as functions of size. These include correction for diffraction effects
230 based on the Korolev (2007) methodology and adjustments to sample volume as a function
231 of particle size.

232 For M_1 processing we use the dimension along the direction of flight and include all particles,
233 whether they are completely contained within the image frame (commonly referred to as “all in”)
234 or not. For M_2 , M_4 and M_6 processing we use the all in technique. M_4 processing also includes
235 the Korolev (2007) correction for out of focus images. The Sparticus data were processed using
236 M_4 for sizes up to 365 microns, and M_1 for all larger images. See Appendix A and B in Lawson
237 (2011) for an explanation of the various 'M' processing techniques and other details. Comparisons
238 of 2D-S derived IWC in aged tropical cirrus anvils agree very well with measurements from a
239 counterflow virtual impactor (Twohy et al. 1997) in the TC⁴ field campaign (Mitchell et al. 2009;
240 Lawson et al. 2010; Mace, 2010). For example, for the ER2 case evaluated in Deng et al 2010, the
241 median, mean and standard deviation of the 2DS/CVI IWC ratios are 0.66, 0.69 +/- 0.31
242 respectively. While for the CloudSat and CALIPSO case, the median, mean and standard
243 deviation of the 2DS/CVI IWC ratios are 0.91, 1.33+/- 3.53 respectively.

244 The 2D-S estimates of cloud properties reported here are based on preliminary analysis and
245 archiving by SPEC. The archived data are thought to be reliable, however, as with most datasets
246 processed soon after a field campaign, refinements and improvements in data are an evolutionary
247 process.

248
249 In cases with relatively high concentrations of mm-size particles, the 2D-P (an external optical
250 system that images particles in the size range 200 to 6400 microns) tends to overlap the 2D-S PSD
251 and extend it to larger sizes. The SPEC version 3 HVPS was installed for the last month (June
252 2010) of the SPARTICUS field campaign. Based on comparison of between 2D-S and 2D-P or
253 HVPS, no significant concentration of large particles (~1 to 3 mm) were observed by 2D-P or
254 HVPS for the cases we are discussing in the paper, which indicates that 2D-S measurement alone
255 is sufficient to estimate of the PSD moments assessed in this study.

256 During SPARTICUS, the SPEC Lear supported 21 overpasses of the NASA A-Train satellites to
257 obtain cirrus size distribution data in conjunction with sampling by the orbiting remote sensing
258 instruments. Figure 1 shows the retrieved IWC, r_e and σ of 17 cases from DARDAR, CWC-
259 RVOD and CALIPSO σ in comparison with 2C-ICE retrievals. The DARDAR IWC, r_e and σ in
260 the radar region, which includes the radar/lidar overlap and radar-only regions are in reasonable
261 agreement with 2C-ICE, while for the lidar-only region, the DARDAR IWC and σ coefficients are
262 larger than 2C-ICE. CWC-RVOD r_e is about 30% larger than 2C-ICE and DARDAR while IWC
263 is slightly smaller. The CALIPSO σ is very scattered compared with the DARDAR dataset. The
264 overpass flights typically have long horizontal legs sampled during the overpass where the aircraft
265 flew level within cirrus. In Table 1 we listed the 17 flight legs that are used in this study. In the
266 following, the disparities among the retrieval products are investigated with in situ measurements.

267

268 **3 Methodology**

269 For the 17 cases evaluated here, estimates of r_e , IWC and σ derived from A-Train data are
270 compared to in-situ estimates. In situ r_e are derived from the airborne estimates of IWC divided by
271 image projected area. The image projected area measurements are also used to compute σ .

272 Airborne estimates of IWC are estimated using projected area to mass relationships described in
273 Baker and Lawson (2006). Although the mass is not a direct measurement, it has generally
274 compared favorably with other mass in situ measurement such as CVI measurements during the
275 TC⁴ project (Deng et al 2010, Mace et al 2010; Mitchell et al 2009; Lawson et al. 2010).

276 In Figure 2, we show the minimum distance and time lag (Δt) between the SPEC Lear 25 and
277 A-Train during 17 SPartICus flight legs. Case summaries are listed in Table 1. The distances
278 between the Lear and the A-Train satellite tracks range from 1-5 km. The Δt between them are
279 within 15 minutes except for cases 3 and 10. The flight mean temperatures ranged from 215 to 243
280 K.

281 Given the uncertainties in the in situ measurements and due to cloud spatial inhomogeneities
282 and cloud field evolution with time, we seek to devise some criteria that will allow us to avoid
283 obvious inconsistencies between the in situ and satellite data. Because dBZ_e is a basic measurable
284 of CloudSat from which the microphysical properties of interest are derived, and because, at least
285 for the cirrus clouds analyzed here, the 2D-S provides reasonable sampling in the particle size
286 range that contributes to the cloud physical properties, discrepancies between in situ-estimated and
287 CloudSat-measured dBZ_e offer a means of identifying periods when comparisons between the
288 cloud volumes sampled by the Lear 25 and CloudSat are reasonable. To identify such periods
289 for comparison, we estimate dBZ_e by integrating the measured PSD averaged over a distance
290 comparable to a CloudSat footprint weighted by the backscatter coefficients of non-spherical
291 particles calculated using a DDA algorithm as reported by Hong (2007). With this information,
292 we seek to establish criteria based on discrepancies between in situ-estimated and CloudSat-
293 measured dBZ_e. When the discrepancy is larger than some threshold, the clouds sampled by the
294 SPEC Lear and CloudSat will be considered significantly different due to either the cloud field

295 heterogeneity or the cloud temporal changes or advection between the sample times. The deviation
296 of in situ-estimated dBZ_e assuming different particle habits is generally less than $\sim 5 \text{ dBZ}_e$ (Deng et
297 al 2010, Okamoto 2002). So we expect that any threshold will be larger than this value.

298 In Table 2, we list the correlation coefficients of cloud properties between 2D-S products
299 and satellite retrievals (2C-ICE/DARDAR/CWC-RVOD or CALIPSO extinction) from data that
300 are sampled with different thresholds of dBZ_e discrepancy. We see from Table 2 that as the dBZ_e
301 discrepancy decreases from 20 to 8 dBZ_e , the correlation coefficients increase monotonically for
302 all quantities. We also examine the dBZ_e discrepancies as a function of Δt , the minimum distance
303 between the Lear and CloudSat, the standard deviations of in situ measurements, and a cloud field
304 variability parameter derived from MODIS reflectances that is contained in the 2B-Geoprof data
305 set. We find that the dBZ_e discrepancies are well correlated with the in situ measured cloud
306 variability when the discrepancies are less than 15 dBZ_e . We speculate that cloud spatial in-
307 homogeneities and temporal variations are a likely explanation for the better agreement for the
308 cases with lower dBZ_e discrepancy. While the scatter between in situ measurements and the cloud
309 parameters derived from A-Train are reduced as we set tighter dBZ_e thresholds, we find that the
310 qualitative conclusions of this study are not dependent on the threshold chosen. In other words,
311 while the variances of the comparisons to in situ data are dependent on the discrepancy threshold,
312 the overall biases between the in situ- derived quantities and the retrieved products are not a
313 function of the threshold. Therefore, in the following discussion, we focus on the bias and the
314 relative variation in scatter among the various products using comparisons where the dBZ_e
315 discrepancy threshold is set at 10 dBZ_e , unless otherwise stated. Using the Z_e -IWC relation in
316 Hogan et al 2006 and error propagation analysis, we get

317
$$\partial IWC/IWC = \ln(10) \times 0.062 \times \partial \text{dBZ}. \quad (1)$$

318 So, for a 10 dBZe difference, the relative uncertainty of IWC is about 138%.

319

320

321 **4 Retrieval case studies**

322 Because the nature of the retrieval methodology and subsequent results are very dependent on
323 the vertical measurement region (lidar-only, radar/lidar, and radar-only) we present four cases in
324 different cloud scenes to see how the retrieval results compare with each other and with in situ
325 measurements.

326

327 *4.1 Case 1: radar/lidar overlap*

328 On April 1, 2010, the SPEC Lear 25 was co-incident with the A-train overpass and flew
329 near the top of a cirrus layer with mean optical depth of about 2, which was observed by both the
330 CloudSat radar and CALPSO lidar (Figure 3). The latitude and height plot of DARDAR extinction
331 (Fig. 3c) has a similar envelope as CALIPSO (Fig. 3d) in the lidar measurement zone, because
332 DARDAR uses the CALIPSO lidar feature mask to identify ice clouds. However, it has rough
333 edges since it has to eliminate noise at 1.3 km horizontal resolution. For one data point at the flight
334 level, we averaged the 2D-S measurements by 1 minute and satellite retrieval datasets for 240 m in
335 the vertical and 5 km in horizontal directions. The retrieved r_e (Fig. 3f) from 2C-ICE and
336 DARDAR are in close agreement and closely follow the situ measurements, while the CWC-

337 RVOD is generally biased larger by about 35%. The retrieved IWC from 2C-ICE, DARDAR and
338 CWC-RVOD at 38.4° -38.8° N agree very well with the in situ measurements. But for 38.8°-39.0°
339 N, the retrieved IWC is larger, while for 38°-38.4° N, the retrieval is biased smaller than the IWC
340 derived from the in situ measurements. The extinction comparisons are similar.

341 Discrepancies between the retrieval results and the in situ data could be caused by the
342 sampling location differences between the SPEC Lear and the A-Train (3-4 km), and cloud
343 variations between the sample times (6 minutes), as well as the sample errors associated with the
344 instruments. The discrepancy between simulated and measured radar reflectivity from CloudSat
345 sheds some insight on the discrepancy of our comparison. We see from Fig. 3e that the measured
346 dBZ_e are larger than the simulated radar reflectivity from 38.8° to 39°N, while for 38°-38.2°N, the
347 simulated radar reflectivity values are slightly larger than the CPR measured dBZ_e . Moreover, the
348 spatial variations of cloud properties in both regions are larger than the other regions as shown in
349 Fig. 3b. In Fig. 3e, we overplot the MODIS variability index from the CloudSat 2B-GEOPROF
350 product. The MODIS variability indices range from 1 for very uniform to 5 for very heterogeneous
351 (Mace, 2007). Hence larger horizontal heterogeneity are located at 38.8° to 39°N and 38°-38.2°N.
352 Therefore, the cirrus layer variability in these two regions likely contributes to the discrepancies
353 between the retrieval results and the in situ measurements.

354 The cases observed on April 11 and June 11 are also thin clouds observed by both
355 CloudSat and CLAIPSO. However, the correlations between the simulated and measured dBZ_e
356 (Table 1) are very poor, which causes significant differences between the in situ measurement and
357 retrieval results as listed in Table 1, while the DARDAR and 2C-ICE results are very close to each
358 other, which indicates that the SPEC and A-Train instruments sampled different portions of the
359 cirrus layer.

360

361 *4.2 Case 2: a radar/lidar overlapped and radar only retrieval*

362 On April 17, the SPEC Lear 25 flew through a thick anvil layer with mean optical depth
363 around 15. The layer exhibited significant horizontal gradients in cloud physical thickness and
364 cloud microphysical properties (Figure 4). Besides the lower portion observed by radar only, the
365 CALIPSO feature mask also missed the semitransparent clouds at 36.7°N and some part of
366 lidar/radar overlapped region, where the signal may be below the CALIPSO cloud identification
367 threshold at 5 km resolution (Liu et al 2009). All in all, the magnitude of σ and morphology are
368 very similar between 2C-ICE and DARDAR; however, 2C-ICE picks up more clouds with small σ
369 around the cloud boundaries.

370 Similar to case one, r_e from 2C-ICE and DARDAR agree well with in situ measurements,
371 while CWC-RVOD is biased larger by ~45%. IWC from 2C-ICE, DARDAR and CWC-RVOD
372 are very close. The dip at 36.95°N is not observed by in situ measurement. Retrieved extinctions
373 from 2C-ICE and DARDAR are very close to the in situ measurements except the dip at 36.95° N.
374 The larger disagreement between retrieval and in situ measurement at 36.74° and 36.95°N is again
375 collocated with regions of significant heterogeneity as indicated by the MODIS variability index
376 in Fig. 4e.

377 The CALIPSO extinction, whenever there is a value, is generally smaller than the other
378 retrieval results and the in situ measurements. The discrepancy may be caused by the 5 km
379 averaging of signals when the horizontal gradient in this complex scene is large, since the retrieval
380 of σ is highly nonlinear with respect to β . This systematic bias of CALIPSO σ in thick clouds was
381 also observed in Mioche et al., (2009) when compared with in situ measurement during the
382 CIRCLE-2 experiment.

383

384 *4.3 Case 3: Lidar only retrieval*

385 On April 22, the SPEC Lear 25 flew through a thin cirrus layer which had relatively large
386 spatial variations and was mainly observed by the CALIPSO lidar (Figure 5). The spatial
387 variations are not well represented by the MODIS variability index because the cloud remained
388 generally optically thin. The CloudSat CPR observed short segments at 39.1° and 39.2° N at the 9
389 km level. Figure 5e shows the CloudSat CPR measured dBZ_e and 2C-ICE parameterized dBZ_e in
390 the lidar-only region. We find that the parameterized radar reflectivity in the lidar-only region is
391 less than approximately -30 dBZ_e . The correlation between the 2C-ICE dBZ_e and the in situ
392 simulated radar reflectivity is very poor. One must keep in mind, however, that the purpose of
393 parameterizing the radar reflectivity in the lidar-only regions is to provide the retrieval algorithm
394 with a constraint so that the numerical inversion can proceed seamlessly through the layer. Our
395 approach simply tells the algorithm that the reflectivity in this region is smaller than the CloudSat
396 radar minimum sensitivity but highly uncertain. For this purpose, the approach is useful.

397 For the radar/lidar overlap region at 39.2°N, the 2C-ICE retrieval and IWC from CWC-
398 RVOD agree well with in situ measurements, but for radar/lidar overlap region at 39.1°N, the
399 retrieved IWC and extinction from 2C-ICE are smaller than in situ measurement since the
400 observed radar reflectivity by CloudSat CPR is smaller than that simulated from the in situ data.

401 The correlation between the 2C-ICE and DARDAR extinction is very poor. The DARDAR
402 retrieval is close to 2C-ICE only for the short radar-lidar overlap periods at 39.1° and 39.2°N. For
403 the lidar-only region, r_e , IWC and σ from DARDAR are larger than 2C-ICE and also larger than
404 itself in the sections where radar and lidar are overlapping. This appears to be an inconsistency in
405 DARDAR because if it were correct, then the simulated radar reflectivity in the lidar-only region

406 would be even larger than the radar/lidar region. These results suggest that the technique of
407 parameterizing the radar reflectivity in the lidar-only region to provide a weak dBZ_e constraint
408 allows 2C-ICE to provide more consistent results than the DARDAR product in lidar-only
409 regions. The σ from CALIPSO is larger than 2C-ICE and in situ measurements. The final lidar
410 ratio in the CALIPSO extinction retrieval is found to be reduced by 50% from the initial value for
411 the flight mean, This is the only flight among the 17 flights with significant reduction in
412 CALIPSO lidar ratio.

413 The March 30 cases are very similar to the April 22 case discussed above: a thin cirrus
414 case mainly observed by CALIPSO lidar. As shown in Table 1 for these three legs, DARDAR
415 retrieved IWC and σ , as well as the CALIPSO σ , are significantly overestimated.

416 *4.4 Case 4: An opaque ice cloud*

417 On June 12, the SPEC Lear 25 flew through the middle of an optically thick ice cloud near the
418 boundaries of our defined radar only and radar-lidar overlapped region where CALIPSO is heavily
419 attenuated (Figure 6). Again, the 2C-ICE algorithm identified more clouds with smaller extinction
420 coefficients around the cloud boundaries than did the DARDAR algorithm. The simulated and
421 measured radar reflectivities in Fig. 6e have a high correlation coefficient (0.9) and small
422 discrepancy. CWC-RVOD re is still biased larger than the other retrieval datasets and in situ
423 measurements by ~30%. IWC and extinctions from the retrievals are close to the in situ
424 measurements except around the 42.3° N, where the 2C-ICE is smaller than DARDAR but close
425 to the in situ measurements.

426 The March 26 and April 24 cases 9 in Table 1 are also thick clouds cases where the SPEC
427 Lear 25 mainly flew through the border of our defined radar only and radar/lidar overlapped
428 regions.

429

430 **5 Statistical comparison and discussion**

431 Figures 7, 8, and 9 show statistical comparisons of the retrieved IWC, r_e , and σ from the
432 satellite algorithms compared to 2D-S cloud properties for the 17 underflights of the A-Train by
433 the Lear 25 during SPaRiCus. Overall, we find that 2C-ICE and DARDAR show a generally
434 strong agreement with one another and with the in situ measurements. This consistent
435 performance can be seen in Figure 7 where the three quantities (IWC, r_e , σ) are strongly correlated
436 with the in situ data with minimal overall bias although the scatter is around a factor of 2 for IWC
437 and σ , which is about the scale of uncertainty derived from Equation 1 for a 10 dBZe discrepancy
438 between in situ derived and CloudSat measured radar reflectivities. The histograms (Figure 8)
439 confirm the generally strong agreement between the in situ data and 2C-ICE and DARDAR.
440 However, subtle differences in the retrieved data sets that were identified in the case studies seem
441 to emerge as well in the histograms and the flight-mean ratios. The IWC for instance shows a
442 strong modal peak near 0.1 g/m^3 that the retrievals and the in situ data both produce. 2C-ICE
443 however seems to show a tendency to have a frequency of occurrence of low IWC that is more
444 frequent than the 2D-S, and DARDAR seems to capture the overall distribution with more fidelity
445 compared to 2D-S. Breaking the IWC distribution in regions where radar contributes to the
446 retrieval and where lidar contributes to the retrieval, it seems as though the higher occurrence of
447 low IWC seems to be more frequent in the lidar regions. This tendency can also be seen in the
448 flight-mean ratios in Figure 9 with a persistent IWC ratio slightly less than 1 for 2C-ICE compared
449 to the in situ data. DARDAR, in the flight-mean statistics does appear to be more scattered overall
450 than 2C-ICE. This variability can be identified in Figure 7 and the slightly lower correlation
451 coefficient for σ and IWC.

452 The visible extinction coefficient (σ) shows a strong bimodal structure with a primary
453 mode near 0.5 km^{-1} and a secondary peak near 1 km^{-1} . It seems evident that 2C-ICE and
454 DARDAR are able to capture the essential characteristics of these distributions. However, both
455 algorithms tend not to produce the secondary mode near 1 km^{-1} as frequently as does the 2D-S. It
456 can be seen that this tendency is more pronounced in the lidar region. The CALIPSO σ histogram
457 does not seem to reproduce the 1 km^{-1} peak very well although the agreement at the smaller values
458 of extinction seems strong. This bias in the CALIPSO extinction can be identified in the scatter
459 plots in Figure 7 and in the flight means statistics in Figure 9.

460 The r_e frequency distributions for all data combined have a single peak near $30 \mu\text{m}$. Both
461 2C-ICE and DARDAR tend to make this peak too prominent compared to the in situ data. We
462 further divide the data to the lidar region and radar region instead of lidar-only or radar-only
463 region to increase the number of data points in each subset. For the radar region, DARDAR and
464 2C-ICE are very close to one another. For the lidar region, the probability density for small
465 particles around $20 \mu\text{m}$ increases for in situ measurements and 2C-ICE, but not for DARDAR,
466 This better correlation of 2C-ICE r_e with in situ measured r_e than DARDAR r_e can be identified in
467 the scatter plots in Figure 7 too. Therefore, we find that 2C-ICE seems to reproduce the r_e
468 histogram with somewhat more fidelity than DARDAR. .

469 The problems with CWC-RVOD that are discussed in the case studies are strikingly
470 evident in the statistical comparisons where a slightly low bias in the IWC and a significant high
471 bias in the r_e is evident even though the correlation coefficients of RVOD with 2D-S are similar to
472 DARDAR and 2C-ICE.

473 Relationships among remote sensing measureables and cloud microphysical properties are
474 shown in Figure 10. The Ze-IWC relations from in situ, 2C-ICE and DARDAR datasets in Figure

475 10a are generally consistent with one another. The IWC-normalized extinction and radar
476 reflectivity are plotted as a function of effective radius in figure 10b and c for data filtered for the
477 10 dBZ discrepancy between in situ-derived and CloudSat-measured values. These two relations
478 are very sensitive to the ice particle size-ice particle mass and ice particle size-ice particle cross
479 sectional area empirical relations assumed in the algorithms but more strongly a function of the ice
480 bulk microphysics and radar and lidar measurements than the size-mass and size-area relations
481 themselves. Therefore they are used here to illustrate the discrepancies among algorithm results
482 and in situ measurements. The in situ data are, overall, very scattered. For extinction (Figure 10b),
483 2C-ICE and DARDAR agree reasonably well with in situ measurements. For Z_e (Figure 10c), the
484 2C-ICE results follow the 2D-S measurements but intersects with DARDAR data at about 0 dBZ,
485 while CWC-RVOD is shifted to the left by about $20\mu\text{m}$ with respect to 2C-ICE. This may explain
486 why the CWC-RVOD r_e is significantly larger than the other retrieval results and in situ
487 measurements. Considering the similarity in the Z_e -IWC relationships and the disparity in
488 Z_e /IWC-size relation for CWC-RVOD when evaluated with the other products suggests that the
489 size-area empirical relation in CWC-RVOD is very different from other algorithms since r_e is
490 defined as the ratio of mass to area.

491

492 **6 Summary**

493 In this study we evaluate four published ice cloud retrieval algorithms that use some
494 combinations of A-Train data against in situ measurements that were collected during the
495 SPartICus field campaign. The data sets evaluated include CloudSat 2C-ICE and CWC-RVOD
496 standard products, the DARDAR retrievals, and extinctions derived by the CALIPSO Team. The
497 case studies show that cloud spatial and temporal variations are considerable requiring the data to

498 be carefully screened for consistency before reasonable comparisons can be made. Because
499 SPartICus collected data under 21 overpasses of the A-Train in various types of cirrus over a
500 period of six months, we are still able to make reasonable statistical evaluations of the data sets
501 even after carefully removing inconsistent sections of flight legs. The discrepancies between the in
502 situ simulated and CloudSat radar measured dBZ_e appears to be a reasonable indicator for spatial
503 or temporal inhomogeneity to guide the comparisons. When the discrepancy between remotely
504 sensed and in-situ derived dBZ_e is less than 10 dBZ_e , the flight mean ratios of retrieved-to-
505 estimated IWC for 2C-ICE, DARDAR and CWC_RVOD are 1.12, 1.59, and 1.02, respectively.
506 For r_e , the flight mean ratios are 1.05, 1.18, and 1.61, respectively. For extinction, the flight mean
507 ratios for 2C-ICE, DARDAR and CALIPSO are 1.03, 1.42, and 0.97, respectively.

508 The CloudSat 2C-ICE product is in very close agreement generally with the DARDAR
509 dataset. However, using a parameterized radar reflectivity in the lidar-only regions of ice layers in
510 the 2C-ICE algorithm does seem to provide an extra useful constraint since it effectively informs
511 the algorithm that the radar reflectivity is less than the minimum measureable CloudSat radar
512 reflectivity. The DARDAR algorithms tend to overestimate IWC and extinction in the lidar-only
513 region in the cases examined here. The differences in mass-size and area-size relations between
514 CloudSat 2C-ICE and DARDAR may also contribute to some subtle difference between the two
515 datasets. It is also interesting to note that the more sophisticated approaches to treating multiple
516 scattering of the lidar signal and the lidar ratio in DARDAR do not seem to provide significant
517 benefit over the simple treatment in 2C-ICE as compared with the in situ data. It is likely that
518 other sources of uncertainties, such as the mass-dimensional and area-dimensional assumptions as
519 well as the assumption of the functional forms of the particle size distributions, are more
520 significant sources than the treatment of lidar multiple scattering and lidar ratio. It is likely that

521 these more sophisticated methodologies will be beneficial once these other sources of uncertainty
522 can be reduced.

523 The r_e from the CWC-RVOD dataset is significantly biased larger than the other retrieval
524 products and in situ measurements by about 40%. The assumption of solid spherical ice particles
525 with bulk ice density might be responsible for this bias.

526 For CALIPSO extinction at 5 km resolution, the underestimation found from this study and
527 Mioche et al 2009 may be due to 5 km averaging when the clouds generally have spatial scales of
528 variability that are smaller than this averaging length. The lidar ratio assumptions in the CALIPSO
529 retrieval is probably one of the factors affecting the lidar extinction comparisons. Compared to
530 CALIPSO and DARDAR, CloudSat 2C-ICE picks up more cloud volume around cloud
531 boundaries with low extinction and IWC, either due to a lenient ice cloud identification threshold
532 in the lidar-only region or due to a coarser vertical resolution.

533 Finally, we note that while there are differences in the details, the use of radar-lidar synergy in
534 cirrus cloud property retrieval does seem to provide a very reasonable approximation of what is
535 actually observed in nature. This is a significant finding because it suggests that A-Train retrieval
536 results can be used to investigate the important processes that maintain cirrus in the global
537 atmosphere and that parameterizations of these processes can be confidently developed from these
538 data for eventual implementation in global models.

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545 **Acknowledgement:** This research is supported by NASA through a contract from the Jet
546 Propulsion Laboratory, California Institute of Technology, under a contract with NASA
547 (CloudSat). This work was also supported through NASA Grants NNX10AM42G (GM) and
548 NNX10AN18G and from the Environmental Science Division of the U.S. Department of Energy
549 (Grant DE-FG0398ER62571). The authors thank the members of the CloudSat and CALIPSO
550 science teams for their hard efforts providing the corresponding datasets. DARDAR ice cloud
551 product is downloaded from DARDAR project website ([http://www.icare.univ-](http://www.icare.univ-lille1.fr/projects/dardar/index.php?rubrique=documentation_dardar_cloud)
552 [lille1.fr/projects/dardar/index.php?rubrique=documentation_dardar_cloud](http://www.icare.univ-lille1.fr/projects/dardar/index.php?rubrique=documentation_dardar_cloud)). In situ Data were
553 obtained from the Atmospheric Radiation Measurement (ARM) Program sponsored by the U.S.
554 Department of Energy, Office of Science, Office of Biological and Environmental Research,
555 Climate and Environmental Sciences Division. The authors would also like to thank the
556 anonymous reviewers for their important comments and suggestions.

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Figure captions

Figure 1 Retrieved cloud properties from DARDAR, CWC-RVOD, and CALIPSO extinction in comparison with 2C-ICE for the 17 cases during the SPARTICUS project.

Figure 2 a) Time duration (Δt) between the SPEC Lear 25 and NASA A-Train satellite for 17 coordinated flight legs from January to June 2010. b) Minimum distance (distance) between the SPEC Lear 25 and NASA A-Train. c) CloudSat measured or 2C-ICE parameterized radar reflectivity in the lidar only region (blue) and simulated radar reflectivity (black) from 2D-S measured particle size distribution, mass-size, and area-size relations on SPEC Lear 25.

Figure 3 The color contour plots show the height and latitude cross section of a) radar/lidar observation zones from 2C-ICE product for April 1, 2010 case, (b-d) are extinctions from 2C-ICE, DARDAR and CALIPSO products, respectively. Right hand side shows e) the measured radar reflectivity (blue) and derived radar reflectivity (black) from 2D-S measurements on the Lear 25, f-h) comparisons of r_e , IWC and extinction from 2C-ICE (red asterisk), DARDAR (blue asterisk), CWC_RVOD (black asterisk) and 2D-S measurements (black line). i) 2D-S measured particle size distribution $N(D)$. The MODIS variability index from CloudSat 2B-GEOPROF product is times by 5 and overplotted in e with blue plus. It ranges from 1 to 5, corresponding to CloudSat scenes from highly uniform, uniform, weakly variable, variable, to high variable.

Figure 4 The same as figure 3 but for thick anvil case on April 17, 2010.

Figure 5 The same as figure 3 but for a thin cirrus case on April 22, 2010.

Figure 6 The same as figure 3 but for a thick cirrus case on June 12, 2010.

Figure 7 The scatter plots of retrieved cloud properties in comparison with 1-min 2D-S measurements from the sub-sampled dataset when radar reflectivity discrepancy is less than 10 dBZ_e. Bottom row is for 2C-ICE, middle row for DARDAR, and top row for CWC RVOD and CALIPSO extinction. The correlation coefficients (r) are noted in each panel. The blue lines are the mean.

Figure 8 Histogram comparisons of cloud properties such as r_e , extinction and IWC between retrieval datasets and 2D-S measurements. The three columns are for all regions (including lidar only, radar-lidar, and radar-only), lidar region, and radar regions, respectively. See the text for more details.

Figure 9 Flight mean ratio and standard deviation of retrieved-to-measured IWC, r_e and extinction for each retrieval method. These results are for the dataset selected using radar reflectivity discrepancy less than 10 dBZ_e. For CWC-RVOD (CALIPSO extinction), the averaged is for regions with radar (lidar) measurements.

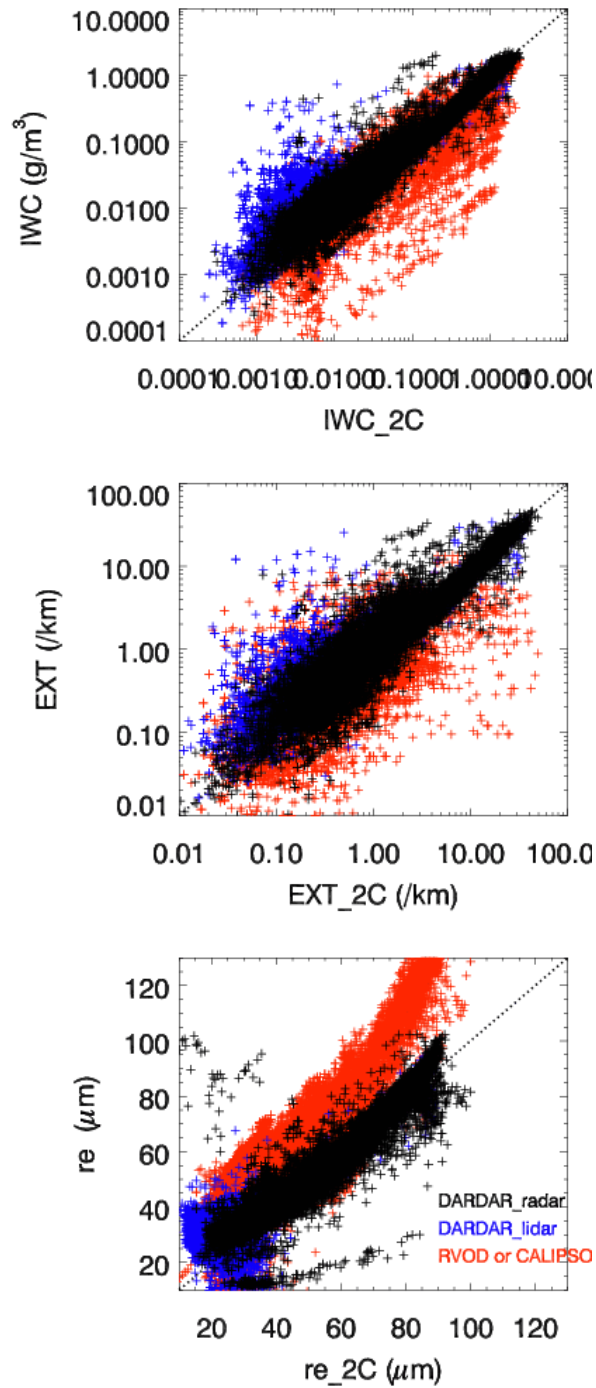
794 Figure 10 Comparisons of Ze-IWC relations (a), IWC normalized extinction (b) and radar
795 reflectivity (d) as a function re from 2C-ICE (red cross), DARDAR (blue cross) CWC-RVOD
796 (orange cross) and 2D-S measurement (black cross).

797 **Table captions**

798
799 Table 1 Summary of 17 flight legs of SPEC Lear 25 under-flying A-Train. For re , IWC , and
800 extinction coefficients, the four numbers are 2D-S leg mean, mean ratio of retrieved-to-measured
801 for 2C-ICE, DARDAR and CWC-RVOD (or CALISPO extinction), respectively. For optical
802 depth (τ), the two numbers are leg mean optical depth and its standard deviation, respectively. r is
803 the correlation coefficients of radar reflectivity between in situ simulated and CloudSat measured
804 (or 2C-ICE parameterized for the lidar only region). Δt and Δs are the time duration and minimum
805 distance between the SPEC Lear 25 and NASA A-Train satellite, respectively. Pink shaded cases
806 are thick clouds cases where the SPEC Lear 25 mainly flew through the border of our defined
807 radar only and radar/lidar overlapped regions. Gray shaded cases are very thin cloud cases where
808 the SPEC Lear 25 mainly flew through the lidar only region.

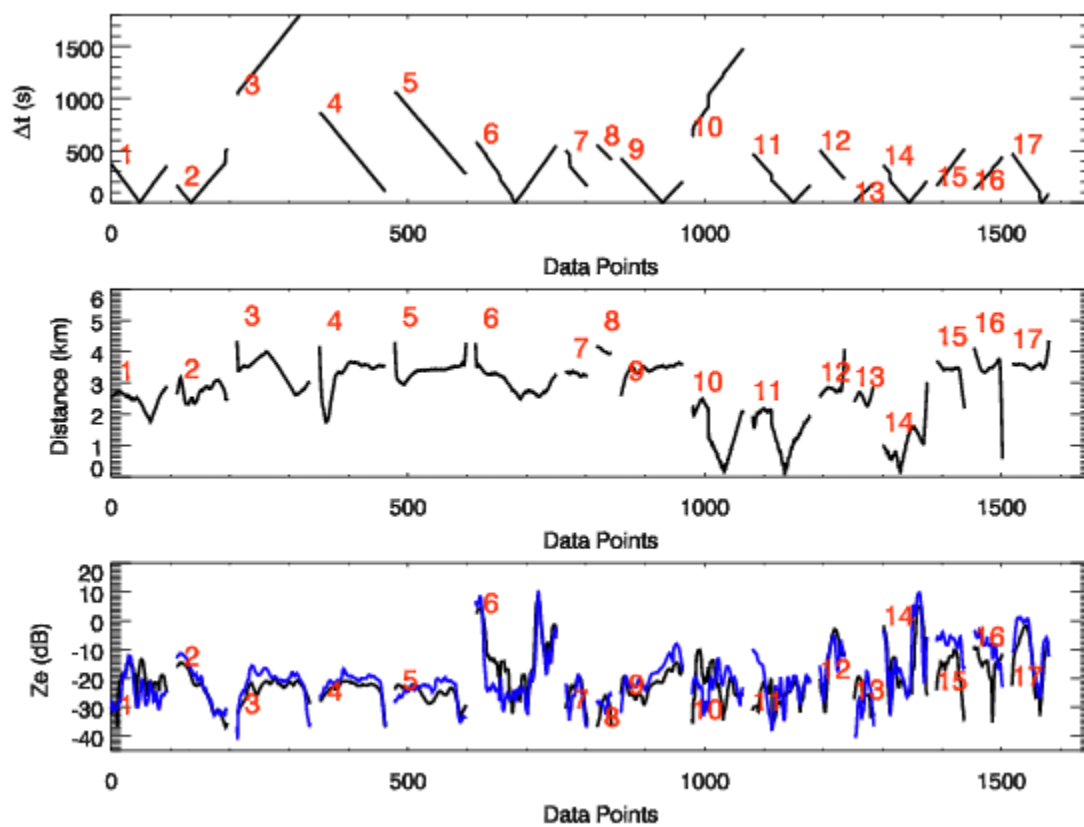
809
810 Table 2. The list of correlation coefficients of cloud properties between 2D-S measurements and
811 satellite retrievals (2C-ICE/DARDAR/CWC-RVOD or CALIPSO extinction) from datasets sub-
812 sampled with different thresholds of dBZ_e between CloudSat measured and 2D-S simulated for 17
813 flight legs. One set of comparisons from datasets selected using a discrepancy threshold less than
814 10 dBZ_e is shown in Figure 7.

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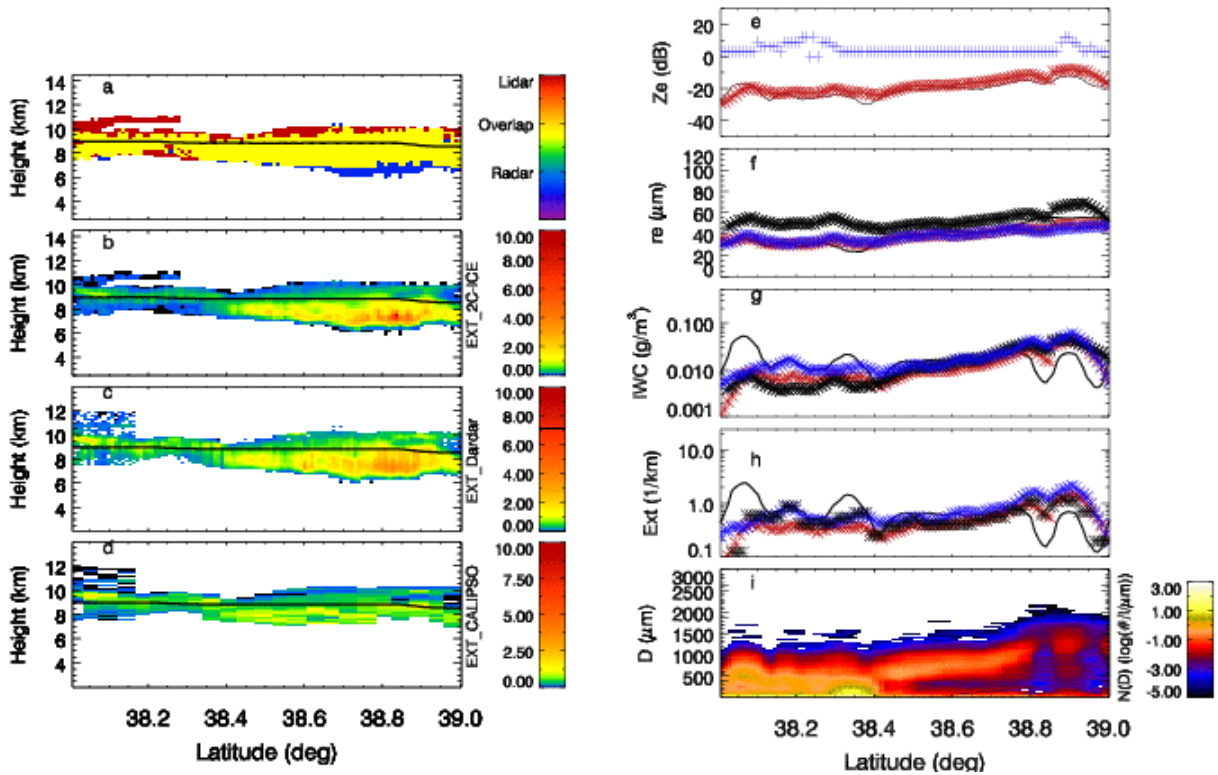
Figure 1. Retrieved cloud properties from DARDAR, CWC-RVOD, and CALIPSO extinction in comparison with 2C-ICE for the 17 cases during the SPartICus project.



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829 Figure 2. a) Time duration (Δt) between the SPEC Lear 25 and NASA A-Train satellite for 17
830 coordinated flight legs from January to June 2010. b) Minimum distance (distance) between the
831 SPEC Lear 25 and NASA A-Train. c) CloudSat measured or 2C-ICE parameterized radar
832 reflectivity in the lidar only region (blue) and simulated radar reflectivity (black) from 2D-S
833 measured particle size distribution, mass-size, and area-size relations on SPEC Lear 25.

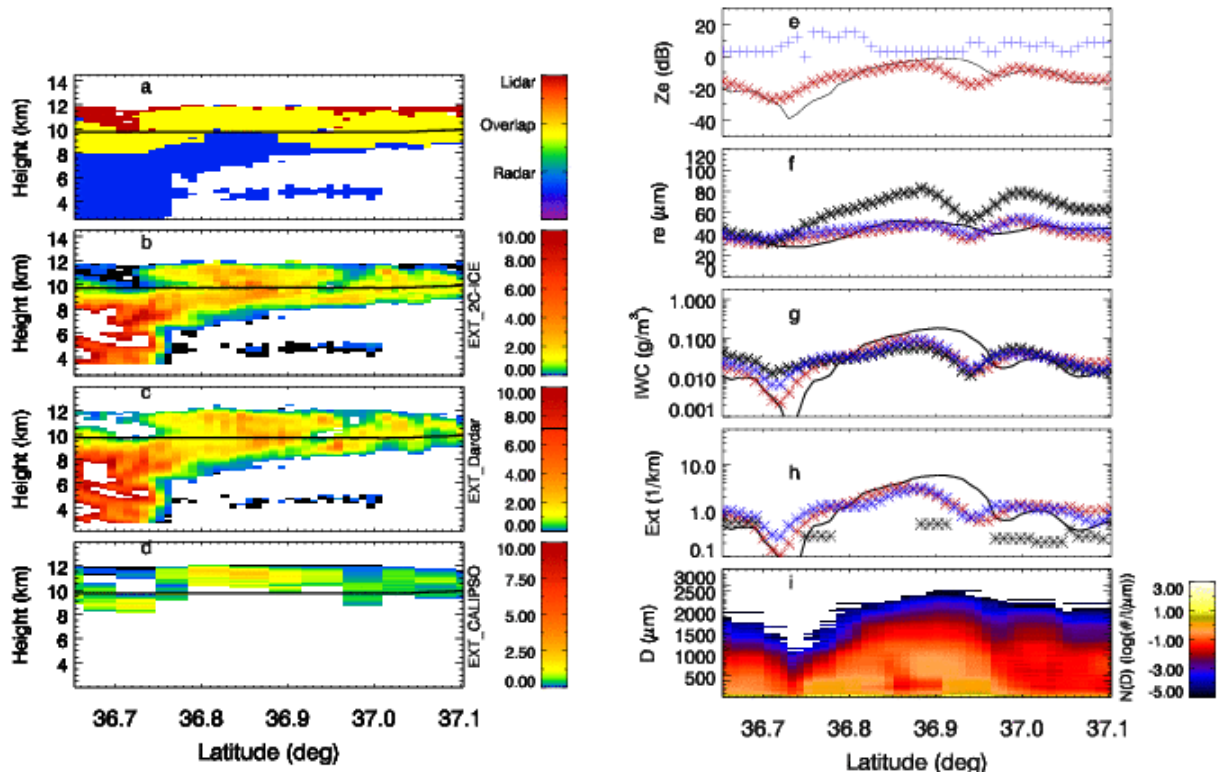
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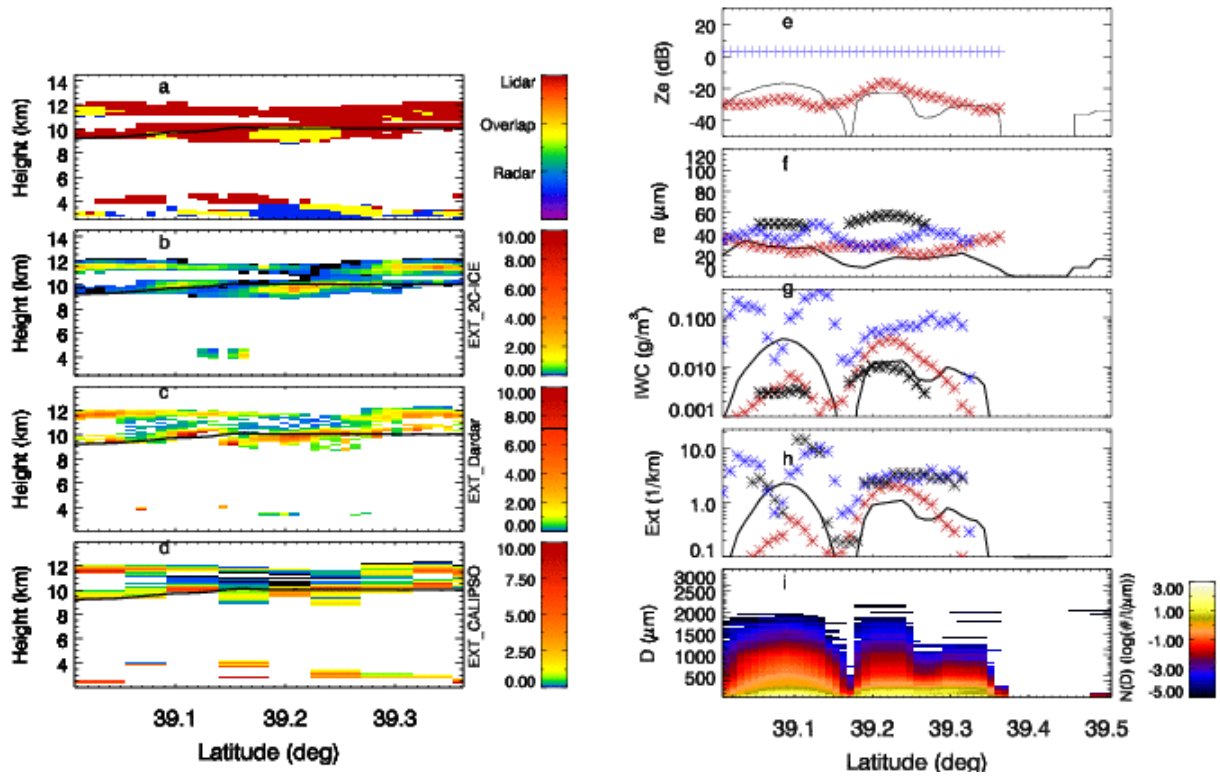
853 Figure 3 The color contour plots show the height and latitude cross section of a) radar/lidar
854 observation zones from 2C-ICE product for April 1, 2010 case, (b-d) are extinctions from 2C-ICE,
855 DARDAR and CALIPSO products, respectively. Right hand side shows e) the measured radar
856 reflectivity (blue) and derived radar reflectivity (black) from 2D-S measurements on the Lear 25,
857 f-h) comparisons of r_e , IWC and extinction from 2C-ICE (red asterisk), DARDAR (blue asterisk),
858 CWC_RVOD (black asterisk) and 2D-S measurements (black line). i) 2D-S measured particle size
859 distribution $N(D)$. The MODIS variability index from CloudSat 2B-GEOPROF product is times
860 by 5 and overplotted in e with blue plus. It ranges from 1 to 5, corresponding to CloudSat scenes
861 from highly uniform, uniform, weakly variable, variable, to high variable.

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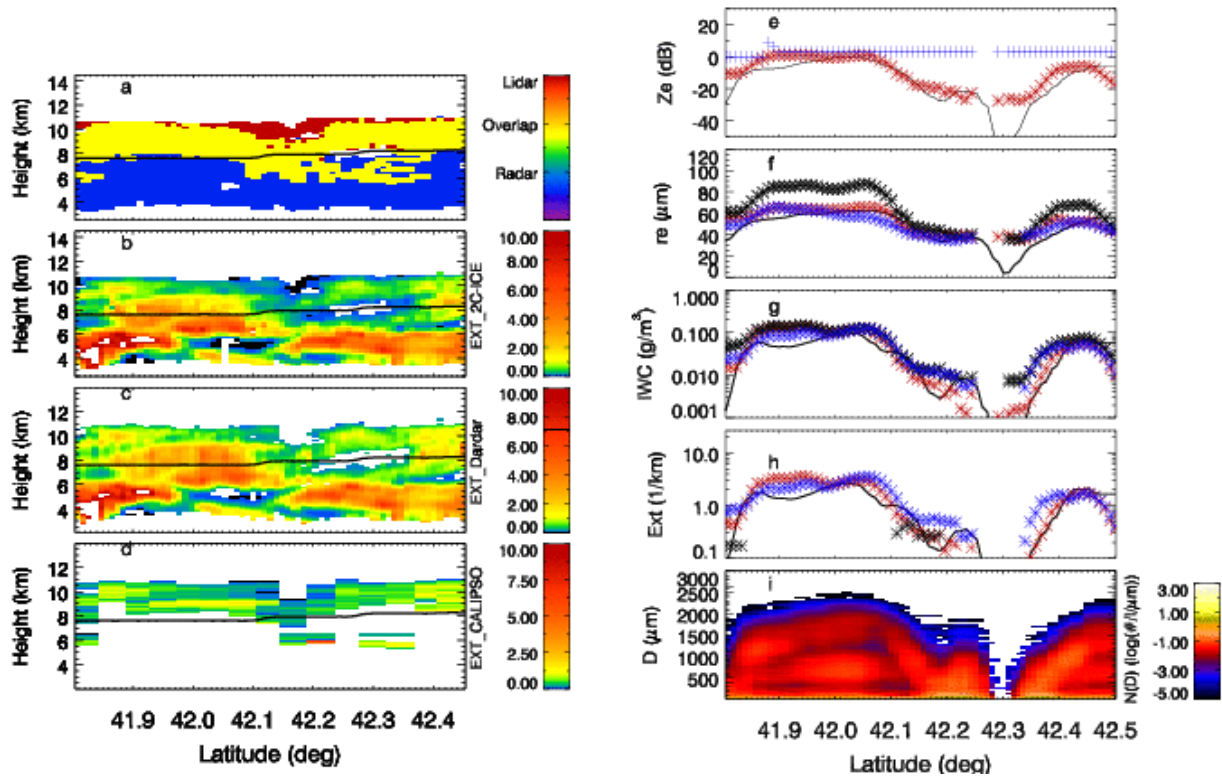
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Figure 4 The same as figure 3 but for thick anvil case on April 17, 2010.



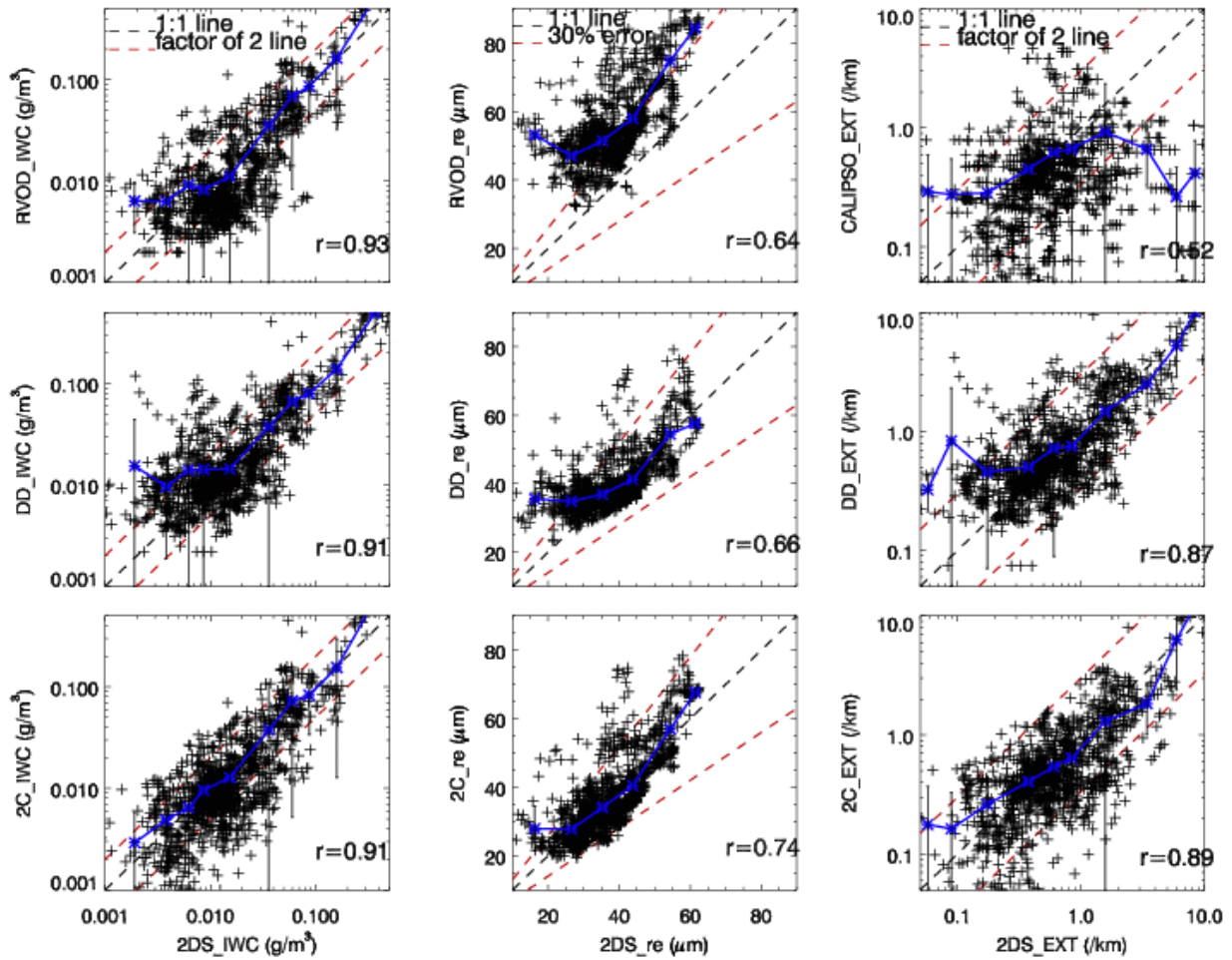
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Figure 5 The same as figure 3 but for a thin cirrus case on April 22, 2010.



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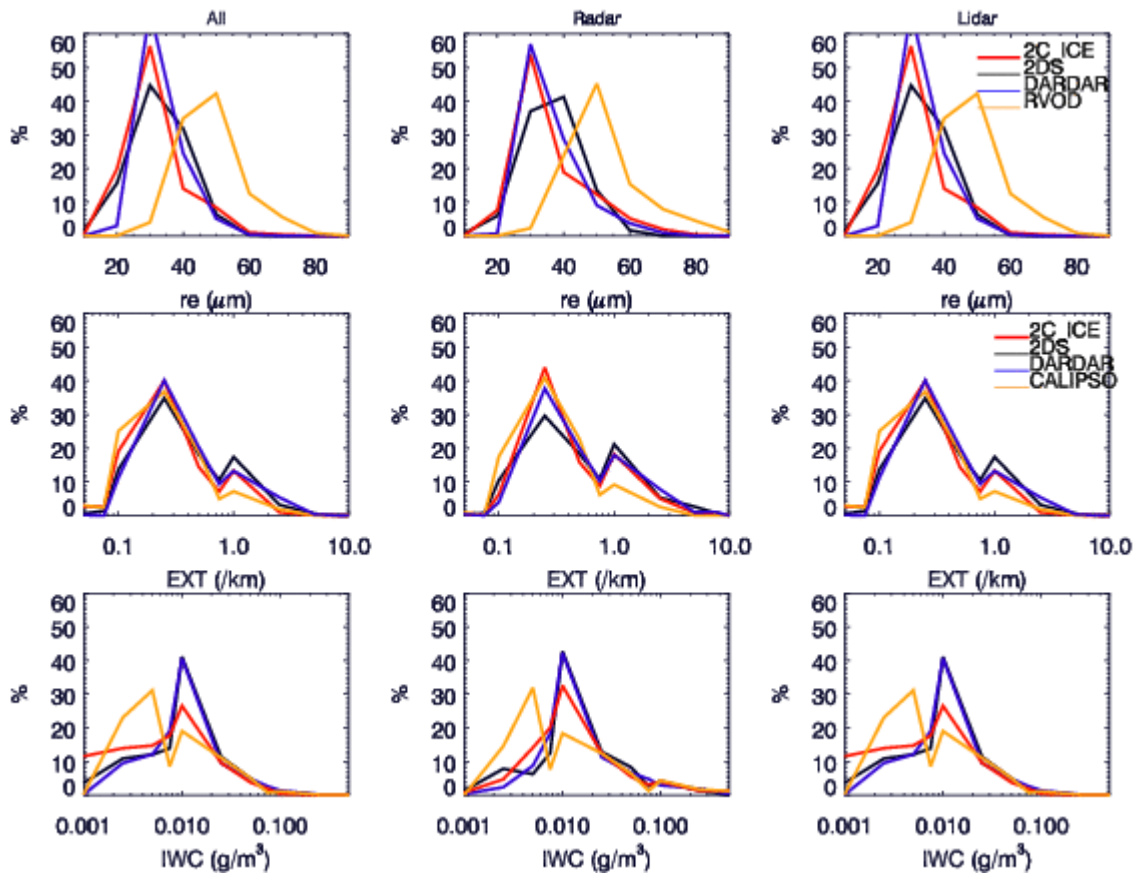
Figure 6 The same as figure 3 but for a thick cirrus case on June 12, 2010.



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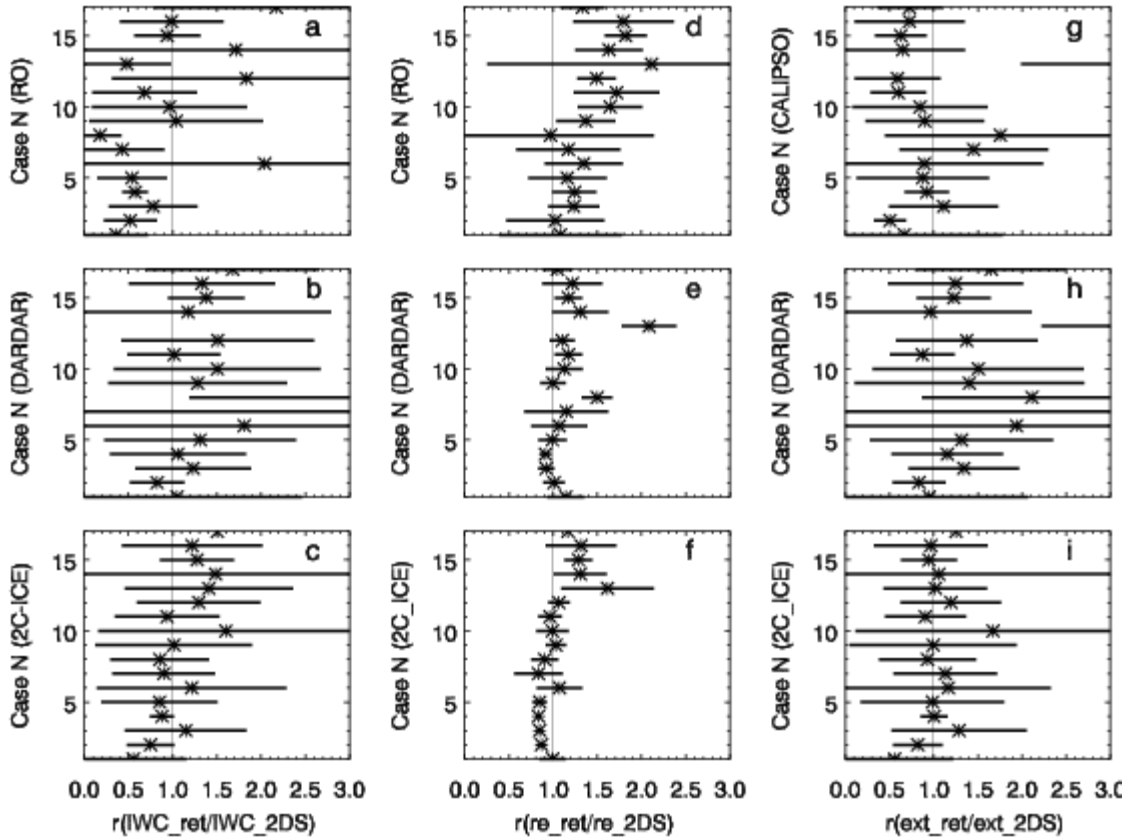
919 Figure 7 The scatter plots of retrieved cloud properties in comparison with 1-min 2D-S
920 measurements from the sub-sampled dataset when radar reflectivity discrepancy is less than 10
921 dBZ_e. Bottom row is for 2C-ICE, middle row for DARDAR, and top row for CWC RVOD and
922 CALIPSO extinction. The correlation coefficients (r) are noted in each panel. The blue lines are
923 the mean.

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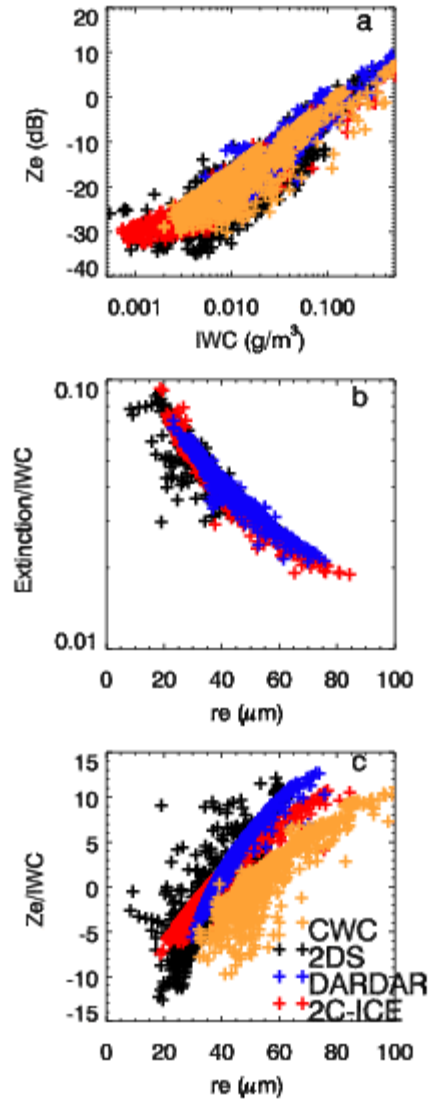
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Figure 8 Histogram comparisons of cloud properties such as re, extinction and IWC between retrieval datasets and 2D-S measurements. The three columns are for all regions (including lidar only, radar-lidar, and radar-only), lidar region, and radar regions, respectively. See the text for more details.



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 952 Figure 9 Case mean ratio and standard deviation of retrieved-to-measured IWC, re and extinction
 953 for each retrieval method. These results are for the dataset selected using radar reflectivity
 954 discrepancy less than 10 dBZe. For CWC-RVOD (CALIPSO extinction), the averaged is for
 955 regions with radar (lidar) measurements.

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 965 Figure 10 Comparisons of Ze-IWC relations (a), IWC normalized extinction (b) and radar
 966 reflectivity (d) as a function re from 2C-ICE (red cross), DARDAR (blue cross) CWC-RVOD
 967 (orange cross) and 2D-S measurement (black cross).

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Table 1 Summary of 17 flight legs of SPEC Lear 25 under-flying A-Train. For r_e , IWC , and extinction coefficients, the four numbers are 2D-S leg mean, mean ratio of retrieved-to-measured for 2C-ICE, DARDAR and CWC-RVOD (or CALISPO extinction), respectively. For optical depth (τ), the two numbers are leg mean optical depth and its standard deviation, respectively. r is the correlation coefficients of radar reflectivity between in situ simulated and CloudSat measured (or 2C-ICE parameterized for the lidar only region). Δt and Δs are the time duration and minimum distance between the SPEC Lear 25 and NASA A-Train satellite, respectively. The thick clouds cases where the SPEC Lear 25 mainly flew through the border of our defined radar only and radar/lidar overlapped regions are shown in italic bold t font. The very thin cloud cases where the SPEC Lear 25 mainly flew through the lidar only region are shown in bold font.

| case | Date/leg | r_e (μm) | IWC (mg/m^3) | Extinction (/km) | τ | r | Δt (s) | Δs (km) | T (K) |
|------|------------|----------------------------|----------------------------------|----------------------------|-------------------|------------|----------------|-----------------|------------|
| 1 | 01/23 | 30.8/0.98/1.11/1.06 | 28.0/0.53/1.01/0.46 | 1.42/0.50/0.89/0.38 | 2.5(1.8) | 0.7 | 182 | 2.4 | 231 |
| 2 | 02/03 | 42.8/0.83/0.99/1.04 | 12.5/0.76/0.76/0.66 | 0.46/0.82/0.79/0.45 | 1.1(0.5) | 0.9 | 135 | 2.7 | 232 |
| 3 | 03/17 leg1 | 42.5/0.84/0.93/1.21 | 8.99/1.12/1.20/0.85 | 0.34/1.31/1.44/1.10 | 1.0(0.3) | 0.7 | 1482 | 3.4 | 231 |
| 4 | 03/17 leg2 | 41.9/0.83/0.91/1.23 | 9.99/0.81/0.99/0.63 | 0.39/0.99/1.11/0.90 | 1.0(0.3) | 0.9 | 501 | 3.3 | 229 |
| 5 | 03/17 leg3 | 37.5/0.83/0.99/1.15 | 9.80/0.83/1.31/0.64 | 0.43/0.97/1.32/0.88 | 1.0(0.3) | 0.4 | 682 | 3.4 | 226 |
| 6 | 03/26 | 44.1/1.04/1.01/1.23 | 77.4/1.13/1.45/2.01 | 2.27/1.16/2.18/0.89 | 13.6(21.1) | 0.9 | 286 | 3.0 | 237 |
| 7 | 03/30 leg1 | 34.9/0.79/1.07/1.18 | 8.70/0.83/5.71/0.53 | 0.39/1.18/4.65/1.50 | 1.2(0.6) | 0.7 | 308 | 3.3 | 221 |
| 8 | 03/30 leg2 | 25.7/0.85/1.45/0.76 | 9.58/0.90/3.12/0.30 | 0.61/0.91/2.35/1.70 | 1.4(0.9) | -0.8 | 498 | 4.0 | 214 |
| 9 | 04/01 | 39.7/1.05/0.99/1.36 | 16.5/0.97/1.28/1.04 | 0.72/0.99/1.40/0.97 | 2.1(1.8) | 0.8 | 178 | 3.4 | 235 |
| 10 | 04/11 leg1 | 34.7/0.95/1.10/1.52 | 19.2/1.59/1.60/1.01 | 0.81/1.67/1.57/0.92 | 2.4(1.3) | -0.2 | 1108 | 1.5 | 225 |
| 11 | 04/11 leg2 | 29.7/0.94/1.21/1.82 | 15.1/0.95/1.01/0.71 | 0.80/0.86/1.36/0.63 | 2.4(1.3) | -0.2 | 160 | 1.5 | 215 |
| 12 | 04/17 | 41.6/0.99/1.08/1.45 | 57.1/1.24/1.38/1.77 | 1.92/1.11/1.26/0.85 | 14.5(17.8) | 0.8 | 363 | 2.8 | 226 |
| 13 | 04/22 | 20.9/1.47/2.04/1.77 | 11.5/1.36/8.26/0.47 | 0.81/1.01/4.57/3.24 | 1.4(0.8) | -0.3 | 81 | 2.5 | 226 |
| 14 | 04/24 | 34.4/1.46/1.49/1.68 | 88.6/1.46/1.21/1.23 | 3.01/1.14/1.17/0.67 | 42.3(47.3) | 0.8 | 143 | 0.9 | 236 |
| 15 | 06/11 leg1 | 41.3/1.44/1.34/1.98 | 40.7/1.25/1.36/0.89 | 1.66/1.01/1.24/0.69 | 2.2(0.9) | -0.1 | 317 | 3.5 | 235 |
| 16 | 06/11 leg2 | 41.7/1.47/1.37/1.98 | 43.3/1.23/1.38/1.03 | 1.64/1.01/1.23/0.70 | 2.2(0.9) | 0.1 | 273 | 3.4 | 236 |
| 17 | 06/12 | 49.7/1.14/1.04/1.33 | 40.5/1.38/1.67/2.17 | 1.19/1.18/1.65/0.71 | 13.9(6.0) | 0.9 | 227 | 3.6 | 243 |

Table 2. The list of correlation coefficients (r) of cloud properties between 2D-S measurements and satellite retrievals (2C-ICE/DARDAR/CWC-RVOD or CALIPSO extinction) from datasets sub-sampled with different thresholds of dBZ_e between CloudSat measured and 2D-S simulated for 17 flight legs. One set of comparisons from datasets selected using a discrepancy threshold less than 10 dBZ_e is shown in Figure 7.

| ΔdBZ_e threshold | r_{re} | r_{IWC} | $r_{\text{extinction}}$ |
|--------------------------------|-----------------|------------------|-------------------------|
| <20 | 0.66/0.55/0.56 | 0.82/0.83/0.84 | 0.79/0.77/0.42 |
| <15 | 0.69/0.59/0.59 | 0.88/0.87/0.90 | 0.85/0.81/0.43 |
| <10 | 0.74/0.66/0.64 | 0.91/0.91/0.93 | 0.89/0.87/0.62 |
| <8 | 0.76/0.67/0.66 | 0.94/0.92/0.95 | 0.92/0.82/0.66 |

