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1

2 **Normalized Hail Particle Size Distributions from the T-28**

3 **Storm Penetrating Aircraft**

4

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18

19

Abstract

20 Hail and graupel are linked to lightning production and are important components of
21 cloud evolution. Hail can also cause significant damage when it precipitates to the
22 surface. The accurate prediction of the amount and location of hail and graupel and the
23 effects on the other hydrometeor species depends upon the size distribution assumed.
24 Here, we use ~310 km of in-situ observations from flights of the South Dakota School of
25 Mines T-28 storm penetrating aircraft to constrain the representation of the Particle Size
26 Distribution (PSD) of hail. The maximum ~1km hail water content encountered was 9 g
27 m⁻³. Optical probe PSD measurements are normalized using 2-moment normalization
28 relations to obtain an underlying exponential shape. By linking the two normalizing
29 moments through a power-law, a parametrization of the hail PSD is provided based on
30 the hail water content only. Preliminary numerical weather simulations indicate that the
31 new parametrization produces increased radar reflectivity relative to commonly used PSD
32 representations.

33

34 **1. Introduction**

35 Hail is observed on every continent but Antarctica (Cecil and Blankenship, 2012).
36 Significant hail damage to crops and structures occurs often in regions on the flanks of
37 mountain ranges in Europe, North America, South America, southern and eastern Africa,
38 the European portion of Russia, and in China (Court and Griffith, 1986). Large hail is
39 often produced by thunderstorms forming during the warm season in interior continental
40 plains regions, such as the High Plains of the US (Changnon, 1977), the steppes of Russia
41 (Cecil and Blankenship, 2012), and central China (Ni et al., 2016). And storm
42 electrification is intimately tied to the growth of graupel and hail in these storms (See,
43 e.g. MacGorman and Rust 1998, Ch. 3).

44
45 Our objective is to provide guidance on how to parameterize graupel/hail PSDs for use in
46 cloud models. The representation of graupel (heavily rimed particles <5 mm diameter)
47 and hail (heavily rimed particles >5 mm diameter) in models has been shown to be a
48 source of large uncertainty in terms of cloud coverage, precipitation and cloud evolution.
49 The 5mm size threshold for graupel to hail is from the American Meteorological Society
50 glossary definition, but it recognized that model representations that separate graupel and
51 hail will do so based on differing process rates or process pathways. Gilmore et al. (2004)
52 demonstrated using idealized simulations that the precipitation amounts and condensed
53 water species mixing ratios in deep convection were sensitive to the representation of the
54 hail size distribution. Van den Heever and Cotton (2004) described how supercell
55 development could be strongly modified by changing the mean size of hail particles.
56 Similarly Cohen and McCaul (2006) noted that modifying the hail mean size affects the

57 evaporative cooling in downdrafts that then goes on to influence the subsequent evolution
58 of convective storms. But we note that some regional simulations have also shown less
59 sensitivity (e.g. Van Weverberg et al. 2012). Clearly there is great uncertainty related to
60 the representation of graupel and hail that can have an impact on the prediction and
61 simulation of extreme weather phenomena such as large convective systems. Therefore,
62 there is a need to constrain the representation of the particle size distribution of these
63 species in numerical simulations of clouds and storms.

64

65 Graupel and hail particle size distributions (PSD) have been previously derived from
66 hailpads at the surface, from aircraft using foil impactors and from optical array probes
67 (Ulbrich and Atlas, 1982; Cheng and English 1983; Federer and Waldvogel 1975, Spahn
68 and Smith, 1976, Morgan, 1982; Smith and Jansen 1982; Peterson et al. 1991, Musil et al
69 1991, Heymsfield and Musil, 1982). Airborne observations have recorded hail water
70 contents up to 3 g m^{-3} and number concentrations up to 20 m^{-3} for sizes larger than 5mm
71 (Spahn and Smith 1976, Musil et al 1991, Heymsfield and Musil, 1982), while for hail
72 observations at the surface lower hail water contents ($<0.8 \text{ g m}^{-3}$, Cheng and English) and
73 number concentrations ($<4 \text{ m}^{-3}$ for sizes $>4\text{mm}$) have been reported.

74

75 Aircraft based observations have indicated that hail particle sizes are distributed as a
76 negative exponential function with increasing size when sampling is restricted to particles
77 larger than $\sim 5\text{mm}$ (Spahn and Smith, 1976). Size distribution shapes other than a simple
78 exponential have been proposed such as a double exponential to represent different size
79 ranges (Musil et al. 1976; Smith and Jansen, 1982), power laws (Auer and Marwitz

80 1972), gamma distributions (Wong et al. 1988) or truncated exponential distributions
81 (Morgan and Summer 1975). Inclusion of sizes smaller than 5mm can include particles
82 such as raindrops and ice aggregates that can contaminate the hail PSD. Measurements of
83 hail PSDs at the ground can be affected by the loss of smaller hail and graupel due to
84 melting and sublimation, or size sorting effects reducing the frequency of occurrence of
85 smaller particles resulting in gamma- distribution-shaped PSDs (~~e.g. Jameson and~~
86 ~~Srivastava 1978,~~ e.g. Milbrandt and Yau 2005, Kumjian and Ryzhkov 2012, and Loftus
87 et al. 2014). In particular, Jameson and Srivastava (1978) used Doppler and radar
88 reflectivity information to determine hail particle size distributions. They showed that
89 below cloud base the size distributions display markedly modal distributions with a mean
90 size of ~1.5cm while higher up (in the cloud) the hail size distributions become
91 exponential in agreement with in-situ observations.

92

93 Graupel and hail particle densities are often represented as effective densities for a
94 spherical particle with a diameter equal to some characteristic dimension of the actual
95 irregular particle. Previous work, based on observed graupel and hail particles, suggests
96 that for sizes up to 20 mm effective spherical densities (mass/volume of sphere with a
97 diameter equal to the maximum span of the particle) can span a range from 100-910 kg
98 m⁻³ (Magono, 1953; Braham, 1963; Bashkirova and Pershina, 1964; Zikamunda and
99 Vali, 1972; Locatelli & Hobbs, 1974; Heymsfield, 1978; Knight and Heymsfield, 1983;
100 List, 1985). As the particles become larger the specific density of hail derived from the
101 immersion method of estimating density approaches that of solid ice (Prodi, 1970; Vittori
102 and Di Caporiacco, 1959; Macklin et al., 1960). However, as hail grows larger it tends to

103 become less spherical and so the equivalent spherical density will be lower. Recently,
104 Heymsfield et al. (2018) combined multiple datasets using 3D laser scans of individual
105 hailstones collected at the ground to estimate hail volume to show that the effective
106 density of hail particles decreases with size for hail particles (5mm – 5cm).

107

108 For numerical cloud models the representation of graupel and hail density is often done
109 by assuming a constant density. For example densities of 400 and 917 kg m⁻³ for graupel
110 and hail respectively are assumed by Ferrier (1995). Or a power law relationship can be
111 adopted that continuously varies the effective hydrometeor density with size (Heymsfield
112 et al. 2018, H18: $\text{mass}[\text{kg}] = 89.2D[\text{m}]^{2.69}$). Other modellers have attempted to represent
113 the evolution of density from low values to solid ice density by predicting continuous
114 changes to the density throughout cloud lifetime as particles become more heavily rimed
115 (e.g. Mansell et al. 2010, Morrison and Milbrandt 2015).

116

117 Airborne hail spectrometer data has been reported previously but usually on a case study
118 basis (e.g. Spahn and Smith 1976, Smith et al. 1976, Smith and Jansen 1982). For this
119 study, we have synthesized hail spectrometer data from multiple flights of the South
120 Dakota School of Mines and Technology (SDSMT) T-28 storm penetrating aircraft
121 (Detwiler et al. 2012) to produce a normalized PSD that can be used in models that
122 represent hail at heights close to and above the 0°C temperature level. The
123 parametrization can also be potentially used for graupel, but the 5mm lower size
124 threshold of the observations would constitute an assumed extrapolation of these results
125 into the size range more appropriate for graupel. We briefly test our results in a modelling

126 framework in this study but leave the challenge of a more detailed comparison of hail in
127 observed and simulated storms to a later paper. These normalized PSDs do not
128 necessarily apply to observations made at the surface due to melting and evaporation
129 experienced by hail falling below cloud base.

130 **2. Hail spectrometer description**

131 The SDSMT Hail Spectrometer was designed and built for use on the T-28 aircraft and is
132 described in detail by Smith and Johnson (1980). The probe is a 1-D optical array probe,
133 and although modified to a 2-D probe in the 1980s, the particle data was still recorded in
134 the archive data used here as 1-D vertical size information collected along roughly
135 horizontal aircraft tracks. The probe was mounted as two pylons under the left wing of
136 the aircraft. A sheet of laser light emitted from one pylon illuminates a photodiode
137 detector array behind a window in the other pylon. The detector array has 128
138 photodiodes with 0.9mm separation. The pylon spacing is 90cm leading to a sample
139 volume of $\sim 10 \text{ m}^3 \text{ s}^{-1}$, or $100 \text{ m}^3 \text{ km}^{-1}$ for a typical 100 m s^{-1} aircraft speed. The
140 maximum number of vertically-arrayed photodiodes occluded as a particle passes through
141 the light sheet is taken as a measure of hail size. Although the photodiode array had a
142 total height of 11.5 cm, size distributions are recorded only in the 5mm to 5cm range,
143 with increasing size bin width as size increases. During missions, guidance from a
144 meteorologist on the ground with access to data from a research-grade weather radar was
145 provided to the pilot so that areas with hail larger than 5 cm could be avoided. Hail this
146 large could have caused serious damage to the armored aircraft.

147 **3. Data treatment**

148 The data analyzed here were obtained with the hail spectrometer on a number of flights in
149 different projects. The counts per size bin (particles that occluded the edge of the detector
150 array were excluded) in 1-s records (Honomichl 2011, Honomichl et al. 2013) were
151 combined with air temperature to filter out regions warmer than the 0°C level. Pilot
152 reports were used to identify the time periods where hail was encountered. Depending on
153 pilot workload during the flight and the main objectives of the project in which the
154 aircraft was participating, hail encounters may not have been always reported by the
155 pilot. But if hail was reported by the pilot then it was present. A time window of +/- 1
156 minute was used to recover 10-s PSDs (~1km horizontal resolution for a typical 100 m s⁻¹
157 airspeed) from that reported time, which given the probes' sample volume, would be able
158 to detect a concentration as low as 0.01m⁻³. Overall, this meant that we used ~310 10-s
159 PSDs, or ~310km of along-track cloud sampling, from 18 flights over Colorado,
160 Oklahoma and Kansas from 1995 to 2003 (see Table 1). These data were from altitudes
161 where the air temperature was between 0 and -12°C and the aircraft was flying straight
162 and level (some profiles were not included due to potential fogging of the optical surfaces
163 in the probe on descent to warmer lower altitudes). Surface radar information was relayed
164 from the ground to the pilot in order to avoid flying in regions with reflectivity > 55 dBZ.
165 Therefore, there is some sampling bias that will mean that the largest hailstones in these
166 storms may have been avoided.

167

168 Other ways of determining when the hail was present were attempted. These included i)
169 listening to the aircraft audio record, which included a track recorded from a microphone

170 attached to the front windscreen, but there was too much background noise to distinguish
171 impacts of hail; ii) inspecting imagery from a Particle Measuring Systems 2D-C optical
172 array probe, but shape information is only robust for particles smaller than 500 microns
173 and these size particles cannot confidently be linked to the population starting at 5mm
174 measured by the hail spectrometer. iii) the occurrence of large particles observed with the
175 hail spectrometer (diameter>4cm) was also considered, but this does not always correlate
176 with when hail was reported. (These large particles might have been large snow
177 aggregates in some cases, for instance.) Therefore, taking PSDs centered around the
178 pilot's hail reports seem the most reliable way to capture hail PSDs. But it is accepted
179 that these will potentially be contaminated by non-hail particles and may miss some that
180 were not reported. If the properties of particles larger than 5mm (the minimum size of the
181 particles detected) are different between the hail regions and non-hail regions then we
182 should be able to observe this by changing the length of the averaging window centered
183 around the pilot report of hail. We tested the impact of varying the length of the time
184 window centred on the pilot report of hail to determine if the choice of +/- 60s was
185 justified. This was done by examining the mean values of measured moments of the
186 PSDs as a function of the window length. Because of the 5mm minimum size threshold
187 for the observations it is expected that hail particles will have higher concentrations than
188 other particle types in this size range. Figure 1 shows the result for the geometric mean
189 of the concentration (other moments show the same behavior). This plot indicates that the
190 mean concentration remains approximately constant for small time periods centred
191 around the pilot report, but rapidly departs towards the mean of the whole dataset that
192 includes non-hail regions as Δt exceeds 100s becoming constant again for $\Delta t > 1000$ s as

193 the non-hail regions dominate the statistics. Therefore a choice of ± 60 s for the window
194 length appears acceptable. Later we will show that inspection of histograms of the PSD
195 moments indicates that the hail population is distinct from the distributions of the whole
196 population. For each PSD the (truncated - 5mm to 5cm) moments are calculated and used
197 to define the fit parameters.

198

199 Additional filtering of the PSDs included removing PSDs that appeared to be
200 contaminated by electronic noise. These PSDs were identified by filtering out
201 anomalously flat distributions of particles counted. Visual inspection of the PSDs
202 indicated that the 2.5-3 cm size bin sometimes reported a much higher number of counts
203 than the neighboring two size bins. This was believed to be possibly due to electronic
204 noise affecting a group of detectors on the probe. To alleviate this problem the particle
205 count in this bin was replaced by the mean of the adjacent size bins. No particle-by-
206 particles information or interarrival time data were available to assess for the effects of
207 particle shattering, but we note that lower resolution probes are less susceptible to the
208 effects of shattering that dominate particles sizes of a few hundred microns and smaller
209 (e.g. Field et al. 2006).

210 **4. Normalizing the Particle Size Distributions**

211 Process rates involving hydrometeor species in bulk microphysics schemes used in cloud
212 models need some assumption about the shape of the size distribution. This is commonly
213 done by assuming a functional form and determining the parameters that define it.

214

215 We can make an assessment of the underlying shape of the PSD by normalizing the
216 observations. To normalize the PSD, no assumption needs to be made about the final
217 shape of the distribution (e.g. Testud et al. 2001, Lee et al. 2004, Field et al. 2007). But
218 because the measured distribution is truncated we will assume a functional form to allow
219 extension of the PSD to smaller and larger sizes. As we will see, an exponential
220 distribution will be adequate to describe the data and we define it as:

$$222 \quad N(D) = N_g \exp(-\lambda D) \quad (1)$$

223
224 where $N(D)dD$ is the particle number concentration [m^{-3} , assuming SI units] between
225 sizes D [m] and $D + dD$. N_g [m^{-4}] and λ [m^{-1}] are the ‘intercept’ and ‘slope’
226 parameters that define the exponential distribution. We did a trial using a generalized
227 gamma function but found that it did not improve the fit much and would still require
228 assumptions about the shape parameter to carry out the exercise of adjusting for the PSD
229 truncation described below.

230

231

232 Numerical weather prediction models that represent hail and/or graupel prognose the
233 water content of this species. To be able to predict the PSD as a function of the total hail
234 water content the mass-size relation needs to be introduced

$$235 \quad m_g = \alpha D^\beta$$

236 Where m_g is the particle mass [kg]. If we assume a spherical geometry then we are
237 assuming a constant bulk density for the hail and β would be 3. However, we make the

238 exponent variable to allow for changing effective spherical density with size. Where
 239 effective density is the density that a sphere of the same maximum size of a non-spherical
 240 particle would possess to have the same mass as the particle.

241

242 For the normalization we define the n^{th} complete moment of the PSD as

$$243 \quad M_n = \int_0^\infty D^n N(D) dD = \frac{N_g \Gamma(n+1)}{\lambda^{n+1}}, \quad (2)$$

244 where Γ is the gamma function. We note that the use of the observed size distribution
 245 necessarily means that we are dealing with truncated distributions that in this case start at
 246 5mm (D_l) and end at 5cm (D_u). Therefore we have the n^{th} truncated moment of the
 247 observed distribution as

$$248 \quad m_n = \int_{D_l}^{D_u} D^n N(D) dD = \frac{N_g}{\lambda^{n+1}} [\gamma(n+1, \lambda D_u) - \gamma(n+1, \lambda D_l)], \quad (3)$$

249 where γ is the incomplete gamma function.

250

251 If the characteristic size of the distribution approaches these thresholds sizes (5mm or
 252 5cm) the measured moments will be biased relative to a distribution that extends from 0
 253 to infinity. We also note that due to the relatively small sample size available that
 254 moment estimates are likely to be biased (e.g. Smith and Kliche, 2005). Using ratios of
 255 moments can mitigate this effect to some extent.

256

257 Two moments (integrating from 0 to infinity) can be combined to define a characteristic
 258 size for the PSD. Here we choose the β th and the $\beta + 1$ st moments. This quotient gives
 259 mass weighted mean size, D_m .

260

261
$$D_m = \frac{\int \alpha D^{\beta+1} N_g \exp(-\lambda D) dD}{\int \alpha D^{\beta} N_g \exp(-\lambda D) dD} = \frac{M_{\beta+1}}{M_{\beta}} = \frac{\beta + 1}{\lambda}, \quad (4)$$

262 and rearranging gives the slope parameter,

263

264
$$\lambda = \frac{(\beta + 1)M_{\beta}}{M_{\beta+1}}. \quad (5)$$

265 We can now use the assumption about the size distribution shape and the estimate of the
266 slope parameter to compute complete moments from the measured truncated moments.

267 By using the initial estimate of λ derived from the measurements we can use a
268 rearrangement of (2) and (3):

269
$$M_n = m_n \frac{\Gamma(n+1)}{\gamma(n+1, \lambda D_u) - \gamma(n+1, \lambda D_l)} \quad (6)$$

270 to provide improved estimates of the complete moment. The new estimates of the
271 complete moment are then used to update the estimate of λ and the process is iterated
272 until λ values become unchanging (within 1%). An approach like this was previously
273 used by Vivekanandan et al., 2004, for droplet distributions and Tian et al., 2010, for ice
274 crystal size distributions.

275

276 Once we have the complete moments and the updated exponential parameters we can
277 proceed by assuming integrals from zero to infinity. The intercept parameter for the
278 exponential can be linked to hail water mass, W [kg m^{-3}], through the β th moment

279
$$W = \alpha M_{\beta} = \frac{\Gamma(\beta + 1) \alpha N_g}{\lambda^{\beta+1}}. \quad (7)$$

280

281 Rearranging for N_g and substituting for λ gives

282

$$283 \quad N_g = \frac{(\beta + 1)^{(\beta+1)} M_\beta^{\beta+2}}{\Gamma(\beta + 1) M_{\beta+1}^{(\beta+1)}} . \quad (8)$$

284

285 Finally, substituting N_g and λ into eq. 1 leads to

286

$$287 \quad N(D) \frac{M_{\beta+1}^{\beta+1}}{M_\beta^{\beta+2}} = \frac{(\beta + 1)^{\beta+1}}{\Gamma(\beta + 1)} \exp\left(-(\beta + 1) \frac{M_\beta}{M_{\beta+1}} D\right) \quad (9)$$

288

289 This is similar to the normalization proposed by Sekhon and Srivastava (1971) but differs

290 in that this expression is independent of density assumptions about hail if we assume a

291 constant bulk density . For spheres, the density information resides in α which has

292 canceled out. If a variable bulk density ($\beta \neq 3$) is assumed then density will start to enter

293 the normalization through the value of β . If we assume $\beta = 3$ then plotting $\frac{M_4^4}{M_3^5} N(D)$

294 against $\frac{M_3}{M_4} D$ should collapse the data onto an exponential distribution with intercept $\frac{256}{6}$

295 and slope of -4 if the data are well represented by an exponential distribution. If this

296 collapse agrees with the predicted behavior then this supports our choice of assuming an

297 exponential distribution as the functional form for the hail PSD.

298

299 For an exponential distribution, to predict the PSD, two moments are required that a

300 cloud model would ideally predict to completely define the distribution. Typically a

301 ‘double-moment microphysics scheme’ would predict number concentration and mass
302 concentration as required. However, many models used for numerical weather prediction
303 currently use single moment representations and only predict mass concentration. If one
304 moment can be parameterized as a function of the other then it will be possible to predict
305 the PSD given one moment alone (e.g. Milbrant and Yau 2005b, Thompson et al. 2008,
306 Zhang et al. 2008, Wainwright et al 2014) which would be convenient for bulk
307 microphysics representations that predict hail water content but not number
308 concentration.

309
310

311 We can relate moments to each other by adopting an empirical power law with a and b as
312 constants (e.g. see Testud et al. 2001)

313

$$314 \quad M_{\beta+1} = aM_{\beta}^b, \quad (10)$$

315

316 which allows the PSD parameters (N_g, λ) to be defined by the hail water content alone
317 and its link to M_{β} as follows through combining (eq. 5,7)

318

$$319 \quad \lambda = \frac{\Gamma(\beta + 2)}{\Gamma(\beta + 1)} \frac{W^{1-b}}{a \alpha^{1-b}} \quad (11)$$

320

$$321 \quad N_g = \frac{\Gamma(\beta + 2)^{\beta+1}}{\Gamma(\beta + 1)^{\beta+2}} \frac{\alpha^{(b-1)(\beta+1)-1}}{a^{\beta+1}} W^{1+(\beta+1)(1-b)} \quad (12)$$

322

323 Some microphysical representations formulate N_g in terms of λ (e.g. Ferrier 1994). If we
324 eliminate W between eqs 11 and 12 we get

$$325 \quad N_g = N_{0g} \lambda^\delta \quad (13)$$

326 Where

$$327 \quad N_{0g} = \left[\frac{\Gamma(\beta + 1)^b}{\Gamma(\beta + 2)} a \right]^{\frac{1}{1-b}} \quad (14)$$

328 And

$$329 \quad \delta = \frac{1 + (\beta + 1)(1 - b)}{(1 - b)} \quad (15)$$

330 **5. Results**

331 Size distributions from the hail periods (~310 10-s periods, equivalent to ~310km of
332 sampling) are shown in Figure 2. The sizes cover the range from 5mm to 5cm; a range of
333 sizes large snowflakes as well as hail can attain, potentially leading to overlap between
334 the populations. Overplotted are mean PSDs for 0.01, 0.1, 1.0 and 10 g m⁻³ hail water
335 contents (using Heymsfield et al. 2018: H18 mass[kg]=89.2D[m]^{2.69}). This indicates a
336 tendency for the PSD to become broader as the intercept parameter increases. ▯

337 Normalized histograms of moments of the PSD show a distinct difference between the
338 PSDs dominated by the hail population and when all 10-sec PSDs from the set of flights
339 are considered (Fig. 3). All of the moments for the hail population exhibit higher modal
340 values than for the background population indicating higher water content and number
341 concentrations for particles with size >5mm. Figure 3e uses the H18 relation to estimate

342 the hail water contents that reach a maximum of 9 g m^{-3} for 1 10s period (approximately
343 1 km distance) and exhibit a mode in the observations $\sim 0.1 \text{ g m}^{-3}$. Characteristic size is
344 the mass weighted mean size assuming a mass-size exponent of 2.69. This histogram
345 (Fig. 3f) indicates that the maximum mass weighted mean sizes encountered reaches
346 $\sim 3\text{cm}$, while the mean is $\sim 1\text{cm}$.

347

348 Values from the literature for N_g and λ have been presented in Fig. 4a to provide some
349 comparison to the observations. Using the 310 PSD moments, the values for N_g and λ for
350 each PSD have been calculated and plotted in Fig. 4b . For this study N_g and λ have
351 ranges of $2 \times 10^1 - 3 \times 10^4 \text{ m}^{-4}$ and $100 - 900 \text{ m}^{-1}$, respectively. The range of values for this
352 study is in agreement with previous work and towards the lower λ end (i.e. broader
353 distribution) of the range of reported values. Also shown in Figure 4a are some examples
354 of intercept parameter used in cloud microphysical representations of graupel and hail.
355 These intercept values used in the models tend to be above the observed range reported
356 here. For the same water content this would mean that the model particle mean sizes
357 would be smaller, their fallspeed slower and so increase the residence time of the hail
358 within the cloud.

359

360 The hail PSDs have been normalized using the 3rd and 4th moment and plotted in Figure
361 5a. The collapse of the data reduces the spread from 2.5 orders of magnitude (Fig. 2) to
362 about 1 order of magnitude. The normalized distribution is approximated quite well by an
363 exponential distribution (the expected exponential curve for a 3rd and 4th moment

364 normalisation is overplotted: intercept=256/6, slope=-4), supporting our choice of an
365 exponential distribution to represent the PSD.

366

367 Finally, cloud microphysical representations that use a single moment, such as the hail
368 water content to represent hail, need to parameterize one of the moments in terms of the
369 moment prognosed by the model. Figure 5b shows power law relationships between the β
370 and $\beta + 1$ moments where here $\beta=3, 2.69$. It can be seen that the power laws vary slightly
371 in terms of the exponent. The best fit lines to relate the moments shown in figure 5b are

372

$$373 \quad M_4 = 0.10M_3^{1.15} \quad (16)$$

$$374 \quad M_{3.69} = 0.10M_{2.69}^{1.19} \quad (17)$$

375

376 Table 2 uses the power law relation for the moments to generate the parameters required
377 for estimating the PSD based on hail water content only from eqs 11, 12.

378

379 The results indicate that as water content increases, N_g increases and λ decreases as was
380 seen in figure 2. This decrease in λ with increasing water content is similar to behavior
381 reported by Knight et al. (1982) in the US National Hail Research Experiment (conducted
382 in 1972-1976) for increasing precipitation rate based on data from the hail spectrometer
383 and a foil impactor on the SDSMT armored T-28. This means that the intercept parameter
384 (or concentration) increases at the same time as the distribution gets broader (or mass
385 weighted mean particle size gets larger).

386

387 Figure 4b includes two results for the single moment parameterization, using equation 13
388 with values given in table 2 overplotted, as curves. The grey curve uses a constant bulk
389 density to relate size to mass, while the black curve is based on the mass-size
390 relationship from H18. In principle a double moment representation of hail would be able
391 to better cover this phase space. But because the hail PSD representation has been
392 reduced to a single moment, it is not able to cover all of the phase space that the observed
393 size distributions explore, and instead follows a trajectory that bisects the data.
394 Microphysics process rates or diagnostics ultimately use different moments of the size
395 distribution. For a parametrization of the PSD based on the mass moment that is close to
396 3 the least well predicted moments of interest are expected to be the number
397 concentration (0^{th}) and the radar reflectivity (6^{th}). Figure 6 shows the predicted and
398 measured (adjusted to represent a PSD extending from zero to infinity in particle size as
399 described above) 0^{th} , 6^{th} moments and the exponential distribution parameters (λ , N_g).
400 The geometric means and standard deviations suggest that, over the range of the data
401 used, the mean predicted values are a factor of 1.4 and 0.6 of the measured values for M_0
402 and M_6 , respectively. Geometric standard deviations indicate that the variability is a
403 factor of 3 around the mean value. Similarly the parametrized values of λ and N_g based
404 on water content (table 2) can be compared to those derived from the PSDs and the mean
405 bias and standard deviation can be assessed of the ratio of parametrized to observed. It
406 was found that for λ -parametrized/ λ -observed the mean and standard deviation was 1.2
407 and 0.5. And for $\log_{10}(N_g\text{-parametrized}/N_g\text{-observed})$ the mean and standard deviation
408 was 0.2 and 0.6. The parametrized N_g is more biased than the parametrized λ because it is
409 more related to number concentration than the mass defined reference moment used in

410 the analysis. A parametrization using the concentration could be constructed to reduce the
411 bias in N_g , but because the moments of the process rates that are important
412 (sedimentation, collection) are closer to the moment linked to the water content (~ 3) it
413 would be less useful for modelling.

414 **6. Model testing**

415
416 We have used the Met Office Unified Model to test the impact of changing the rimed
417 particle PSD relationship. The model uses a single mass only representation of graupel
418 based on a gamma distribution: $N(D)=N_g D^\mu \exp(-\lambda D)$, where N_g is given by equation 13.
419 In the operational model the values are: $N_{0g}=5e25$, $\delta=-4.0$, $\mu=2.5$ ('Control') and an
420 effective density of 500kg m^{-3} is assumed. For the test we take the values for the same
421 density in table 2: ('This study') $N_{0g}=7.9e9$, $\delta=-2.58$, $\mu=0$ (where $\mu=0$ comes from the
422 assumption of an exponential distribution) and the values for a more widely used
423 assumption based on Lin et al. (1983): $N_{0g}=4e4$, $\delta=0.0$, $\mu=0$ ('Lin'), for comparison.
424 Strictly, the PSD observations and parametrization is for hail particles between 5mm and
425 5cm in size. However, we have applied the PSD to all rimed particles represented in the
426 model. We note that radar reflectivity is derived directly from the hail size distribution
427 ($Z_e \sim D^6$) parameters assuming a constant density of 500kg m^{-3} , assuring consistency
428 between the microphysical treatment of the hail and the radar response.
429 The case study is from the 20th May 2013, where an EF5 tornado caused significant
430 damage in and around the city of Moore, Oklahoma. The model configuration is as
431 described in Stratton et al (2018), but with a finer horizontal grid resolution of 1.5 km and
432 70 vertical levels with stretched vertical spacing ($\sim 100\text{m}$ at 1km). The domain of the
433 simulation is as shown in figure 7. The model is initialized at 00Z on 20 May 2013 and

434 run for 24 hours. Model fields are inspected and compared for T+20 (to coincide with the
435 reported timing of the tornado on the ground). Here we will comment on the qualitative
436 differences in simulated reflectivity patterns due to changing the PSD alone and leave the
437 challenge of verification with data for a later paper. The ability to reproduce observed
438 radar reflectivities is a challenging problem. It relies on the accurate representation of not
439 only the hail/graupel particle size distribution but also 1) the microphysical process rates
440 that provide sources and sinks for graupel/hail, that are highly uncertain; 2) the radar
441 forward model to convert the model PSD into reflectivity and the radar wavelength
442 assumed; 3) accurate reflectivities from the other condensed water species that will
443 contribute to the radar response and impact the sources and sinks of graupel/hail.
444 The points 1,2 and 3 will be different for different numerical weather models. Our
445 approach here is to demonstrate the relative response of the model using the new PSD
446 relative to using a classic one from the literature to provide motivation for others to
447 assess the impact of this PSD in their model. This work provides an in situ based
448 observational constraint around which more uncertain aspects such as microphysical hail
449 source (e.g. riming and droplet freezing) and sink rates (e.g. melting and shedding) can be
450 tuned.

451 From figure 4 it is clear that the diagnosed concentrations will be lower in the
452 parametrization proposed in this study than is ordinarily used. This will mean that for the
453 same water mass there will be lower concentrations of particles but the mean size and
454 hence mean fallspeed will be larger. Therefore, for larger particles we would expect that,
455 all things being equal, we will see reduced hail water paths and potentially increased
456 radar reflectivity signals (if not offset by reduced water mass). Figure 7 shows the result

457 of the test compared to the UM control PSD representation and the widely used Lin et al.
458 (1983) PSD representation. The control and Lin PSD produce similar results in terms of
459 composite reflectivity, hail water path and a lack of hail seen at the surface. For the new
460 PSD presented in this work, it can be seen that the radar composite reflectivity
461 (maximum reflectivity in the vertical column) increases, while the hail water path
462 decreases. The new PSD is the only representation that indicates hail at the surface with
463 max hail sizes of up to 25 mm.

464

465 **7. Conclusions**

466 Using a comprehensive hail data set collected in-situ at temperatures 0°C and below with
467 an airborne instrument that has large sample volumes relative to data collected at the
468 ground, normalization of the PSD using moments of the distribution indicates that the
469 hail PSD can be represented as an exponential between diameters of 5 mm and 5 cm. Hail
470 water contents of up 9 g m⁻³ (in 10 s or 1km of flight sample) were inferred. Exponential
471 distribution intercept parameters derived from these results suggest that commonly used
472 exponential intercept values for models are larger than observed in-cloud. By linking two
473 moments of the size distribution together with a power law, the parameters of the
474 exponential distribution are predictable from hail water content alone. However, the
475 variability exhibited by the intercept parameters suggests that the ability to predict two
476 moments of the hail distribution may be advantageous for modelling the evolution of hail.
477 The results of our study have considerable utility for modeling the development of
478 graupel and hail within convection. A preliminary test of the new PSD parametrization
479 indicates that radar reflectivities are increased, and more hail is able to survive to fall to

480 the surface at warmer temperatures, relative to simulations with a previous more
481 commonly used PSD representation.

482

483

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489 and preparing the manuscript. AH is supported by the National Science Foundation.

490

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646

647 **Tables**

648

Table 1. List of T-28 campaigns and flights used in analysis. Flight numbers increment serially from flight to flight, beginning in 1972. For more details see:
<https://www.eol.ucar.edu/projects/t28/projects/>

Project name/date	Flights used	Location airport
CHILL 21 July - 3 August 2003	815,819,820	Greely, Colorado
JPOLE/TELEX 15 March - 15 June 2003	798,803	Norman, Oklahoma
CHILL-TEX 3-18 June 2002	781	Greely, Colorado
STEPS May - July 2000	754,756,757,759, 761	Goodland, Kansas
TCAD June 1999	728.729,735	Ft. Collins, Colorado
VORTEX April-June 1995	658,667,668,670	Ft Collins, Colorado/Norman, Oklahoma

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Table 2. Results for different geometry assumptions. All units are SI.								
geometry	α	β	a	b	λ	N_g	N_0g	δ
$\rho = 500$ kg m ⁻³	262	3	0.1	1.15	$98W^{-0.15}$	$57770W^{0.39}$	7.9e9	-2.58
$\rho = 910$ kg m ⁻³	473	3	0.1	1.15	$107W^{-0.15}$	$45820W^{0.39}$	7.9e9	-2.58
H18	89.2	2.69	0.082	1.14	$85W^{-0.19}$	$36570W^{0.30}$	4.7e7	-1.61

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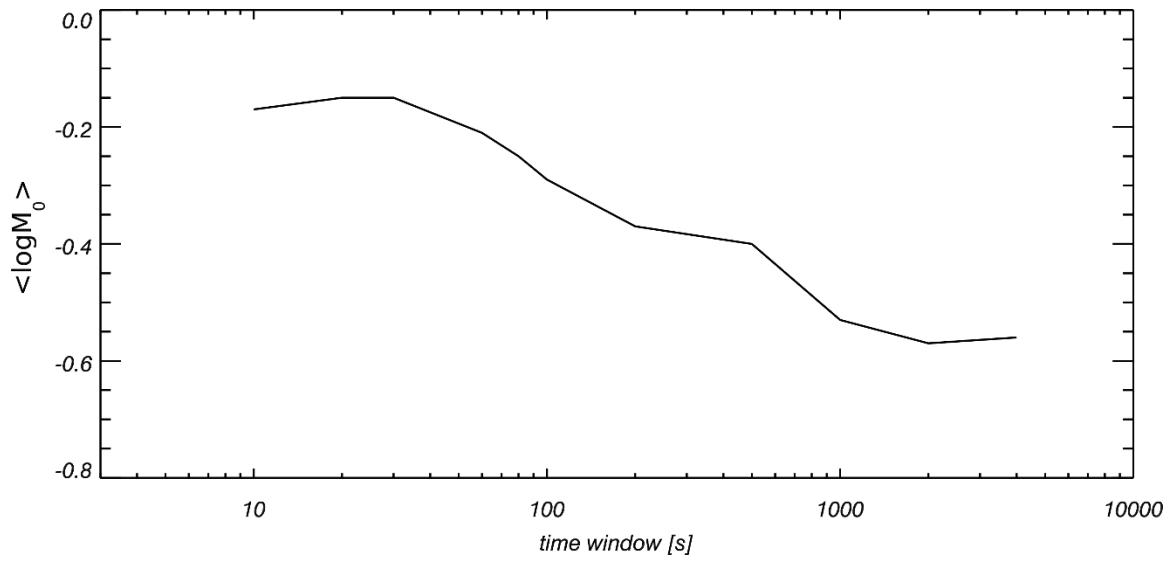
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660 **Figures**



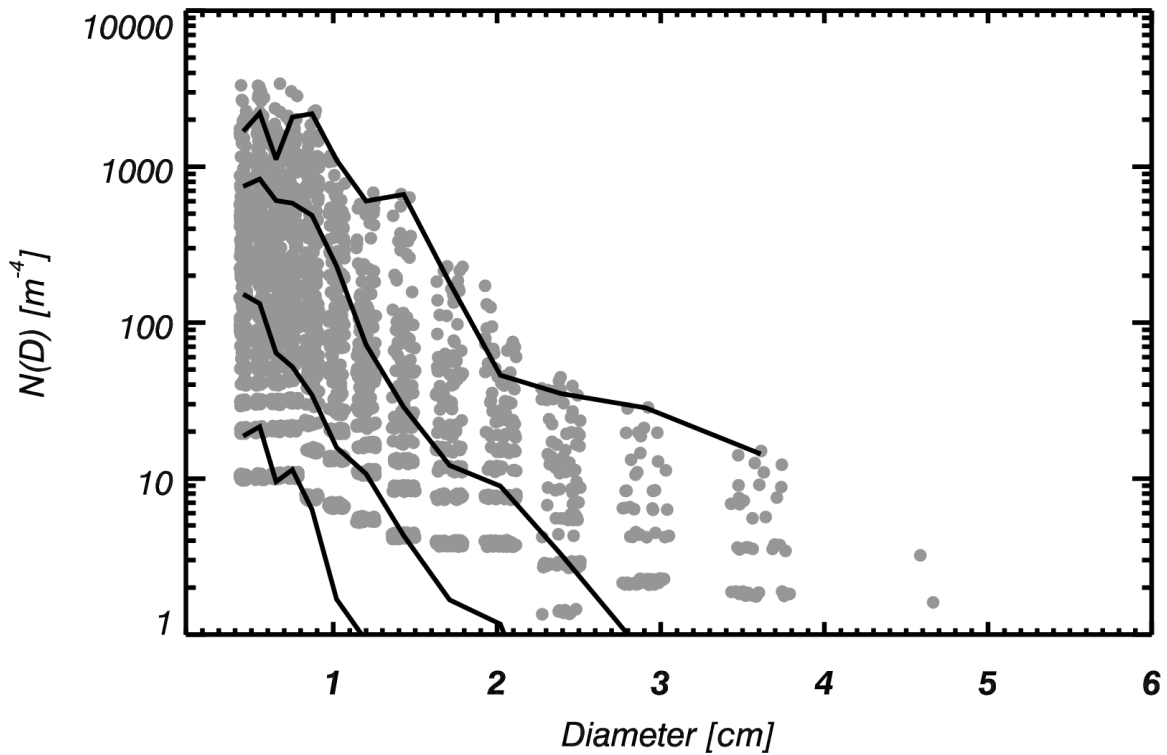
661

662 **Figure 1.** Mean of $\log_{10}M_0$ as a function of length of time window centred on pilot hail

663 report.

664

665

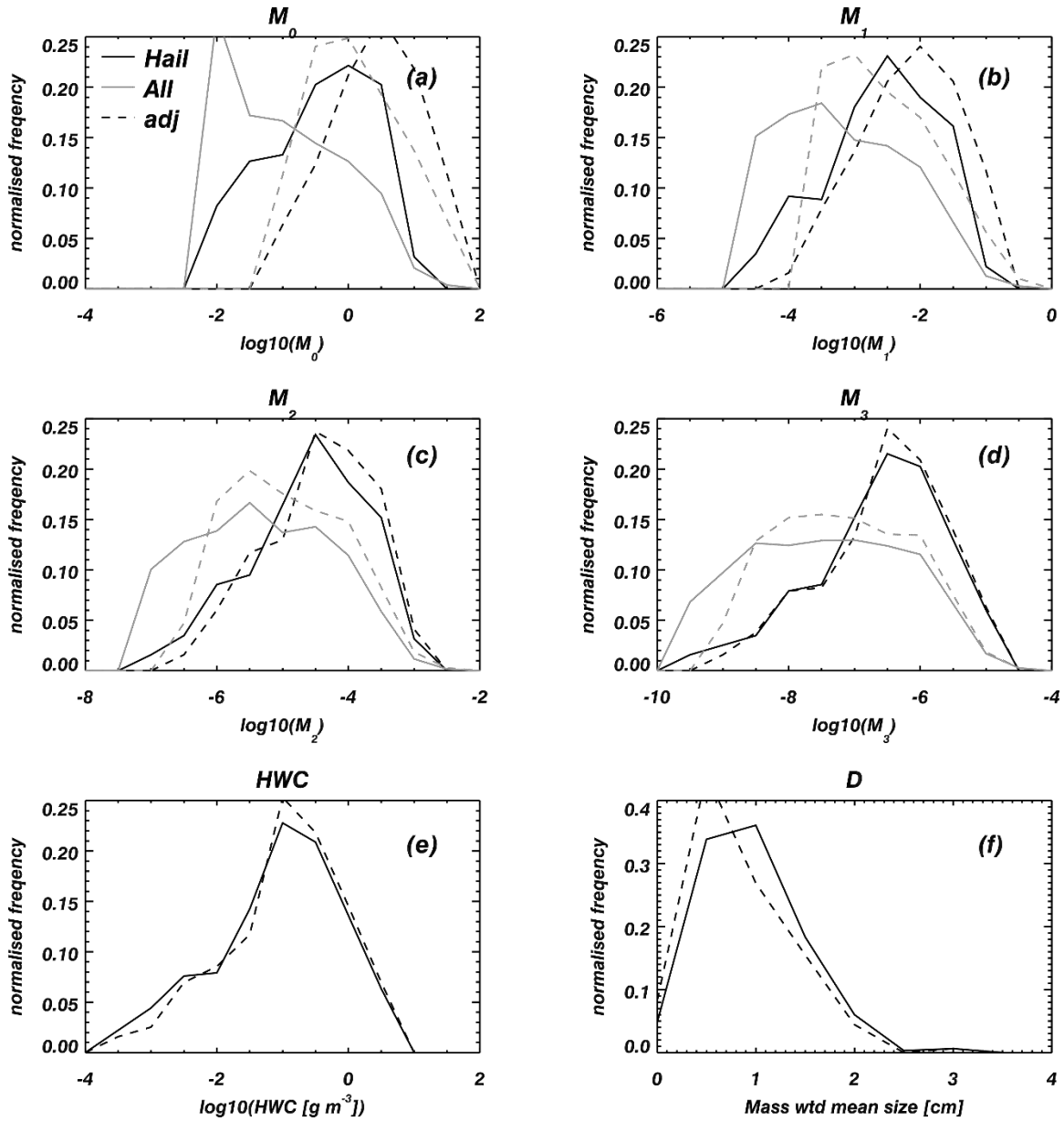


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668 **Figure 2.** Particle size distributions, each computed using 10-s of data ($100\ m^3$, 1km
 669 distance). All the data from the regions associated with pilot reports ($\pm 60s$) of hail are
 670 shown as gray circles (310 10-s periods). Slight offset of the plotted data along the size
 671 axis is shown for clarity. Overplotted as solid lines are mean PSDs for hail water contents
 672 of 0.01, 0.1, 1 and $10\ g\ m^{-3}$ from bottom to top.

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674

675 **Figure 3.** Normalized histograms of different moments of the PSD demonstrating that the

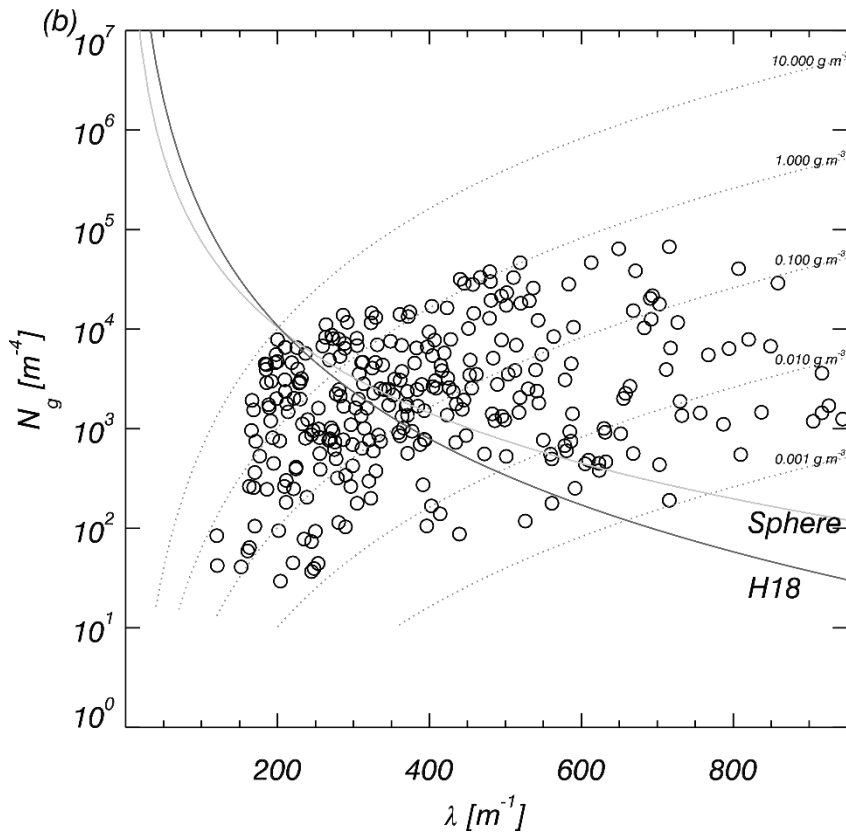
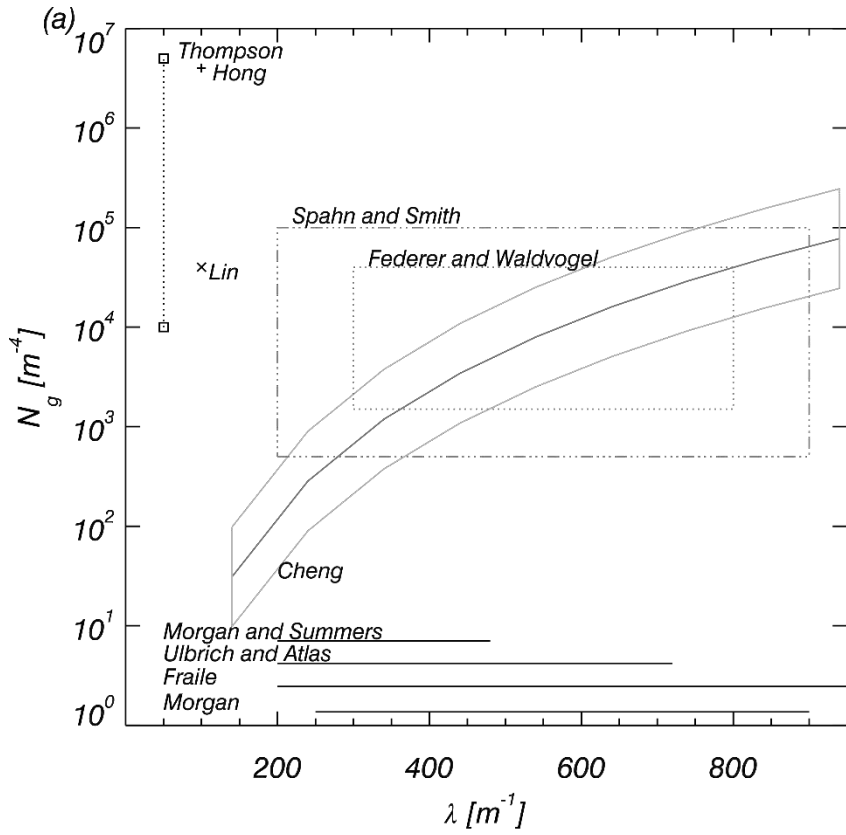
676 population chosen to represent the hail is different from the overall population. (a) –(d)

677 shows the zeroth, first, second and third moments of the size distribution. (e) hail water

678 content. (f) is the mass weighted mean size of the distribution. Solid lines show the

679 original measured moment and the dashed lines are the adjusted moment assuming an

680 exponential distribution integrated from 0 to infinity.

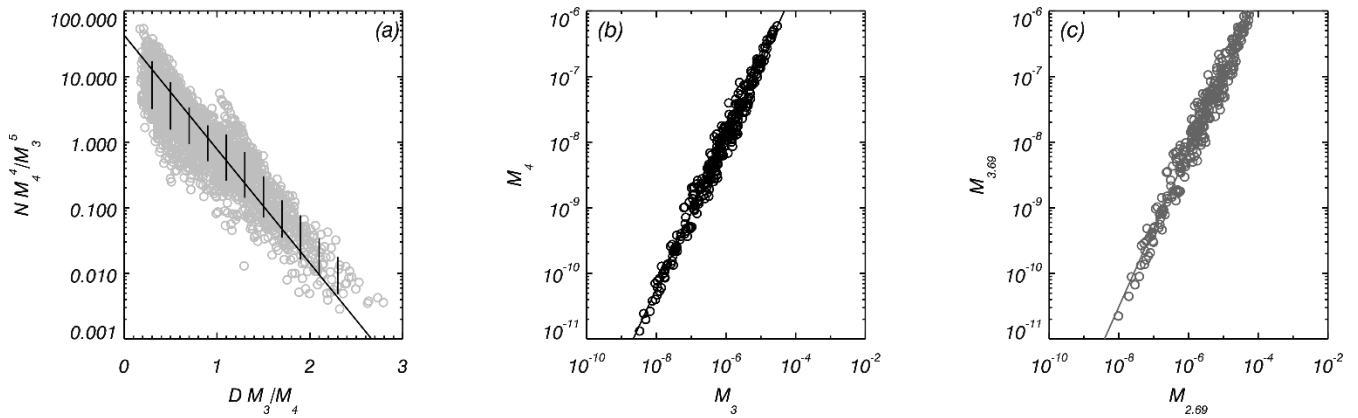


682 **Figure 4.** a) Previous slope and intercept parameters for exponential fits to the PSDs. The
683 boxes (solid: Cheng et al., 1985, also shown is their N_g - λ relationship; dotted: Federer
684 and Waldvogel, 1975; dot-dashed: Smith and Spahn, 1976) show ranges from the
685 literature where slope and intercept were given. The horizontal lines towards the bottom
686 of the panel show the range of slope values from the literature where only the slope was
687 known (usually derived from hailpads). The symbols to the left of the figure indicate
688 intercept values used for microphysics schemes in cloud models. The open squares
689 denote the range used in Thompson et al. 2008. The '+' is from Hong et al. and the 'x'
690 from Lin et al. b) The open circles are the slope and intercept parameters for the hail
691 PSDs in this study. The grey solid curve, marked 'Sphere', represents the λ and N_g
692 values assuming a constant bulk density (it is insensitive to density, but different
693 densities will sit at a different point along the line for the same water content). The black
694 solid curve uses the H18 mass-size relationship. The dotted lines show contours of
695 constant hail water content based on the 500kg m^{-3} sphere density.-

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700 **Figure 5. a)** normalized size distribution using moments 3 and 4 for the hail PSDs. The

701 solid line indicates the theoretically expected curve for an exponential distribution

702 normalized with the 3rd and 4th moment. The variability bars indicate 1 standard

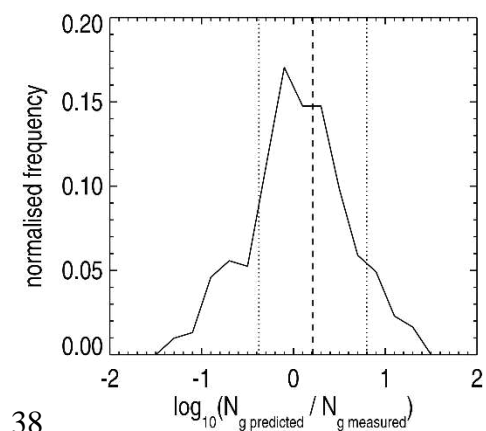
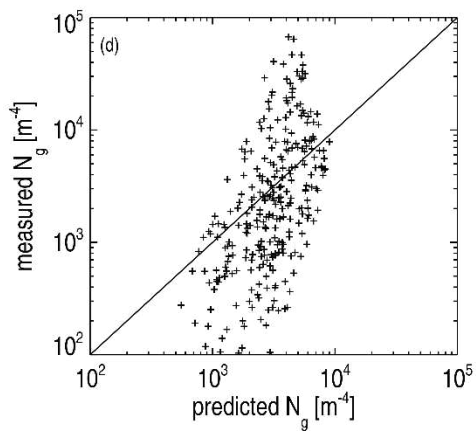
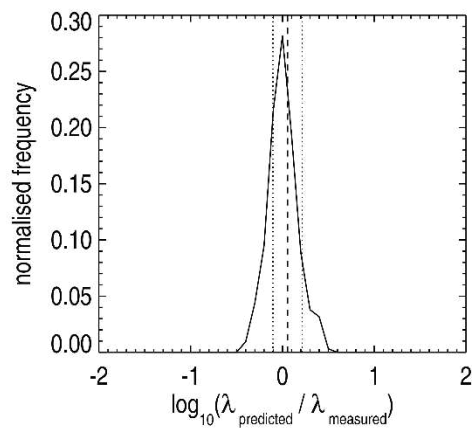
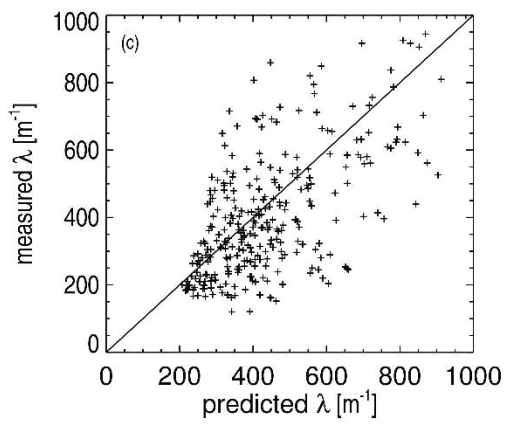
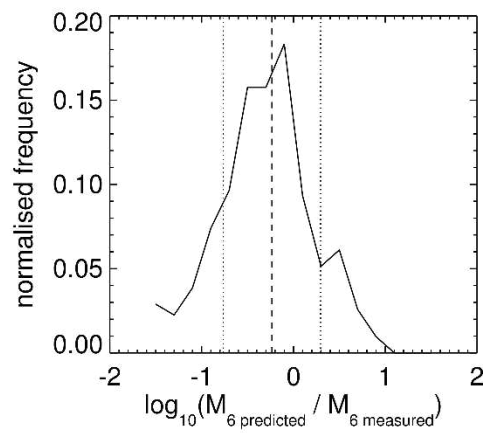
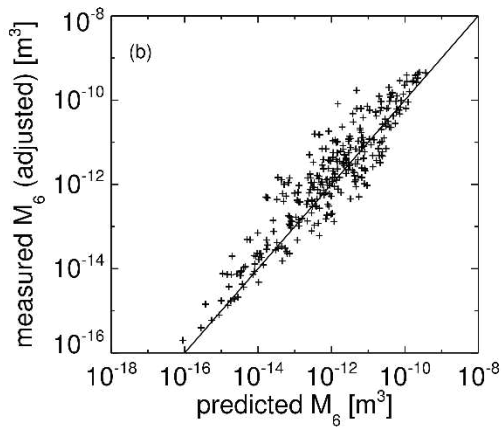
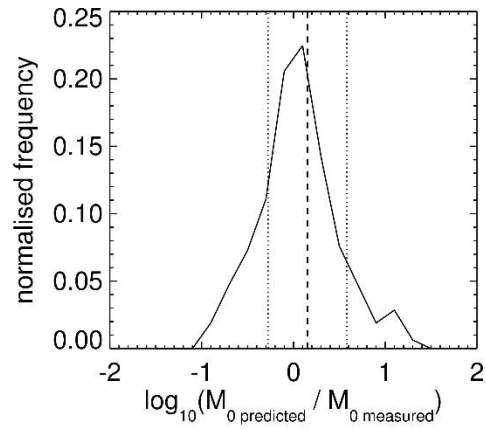
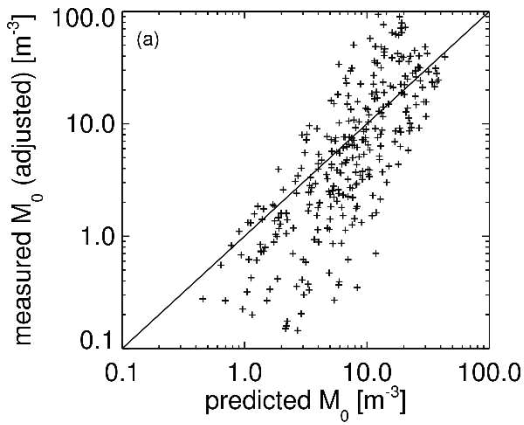
703 deviation in log space (correlation coefficient $r=-0.87$). b) Power law relations between

704 moments 3 and 4. c) the same as b) but for moments 2.69 and 3.69. The relationship

705 between $M_3:M_4$ and $M_{2.69}:M_{3.69}$ are shown (correlation coefficients of 0.99,0.98,

706 respectively).

707



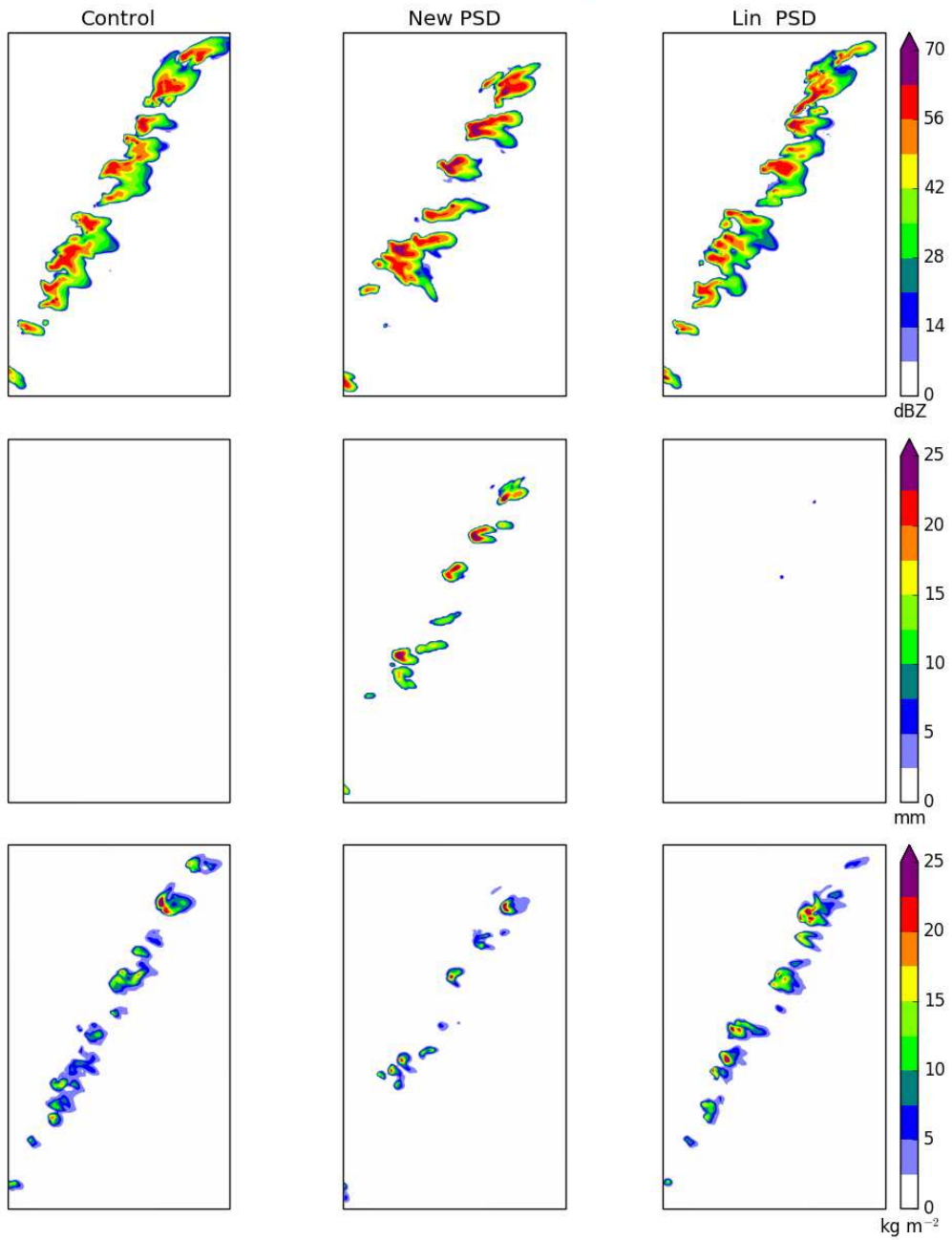
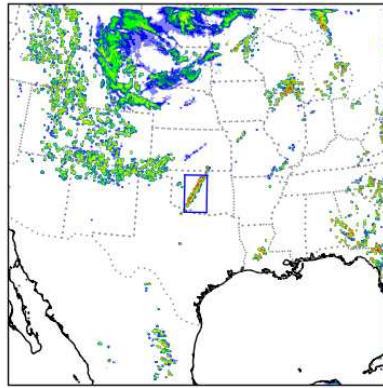
709

710 **Figure 6.** a) predicted complete zeroth moment versus measured adjusted zeroth moment
711 (i.e. concentration). Correlation coefficient $r=0.79$. b) Same as a) but for 6th moment.
712 Correlation coefficient $r=0.94$. c) predicted and measured λ , correlation coefficient
713 $r=0.72$ d) predicted and measured N_g , correlation coefficient $r=0.57$ The 1:1 lines are
714 overplotted for all panels. Right panels show histograms of the logarithm of the ratio of
715 the predicted to measured parameters depicted in the left panels. The geometric mean is

716 shown as a vertical dashed line with 1 geometric standard deviation either side of the
717 mean shown as dotted lines.

718

719



721 Figure 7. Top panel – location map: blue rectangle is region of interest. Model sensitivity
722 tests for 20 UTC 20 May 2013 for PSD settings used for Control (left column), this study
723 (centre column) and Lin et al. (right column). Top row: composite radar reflectivity,
724 middle row: max hail size at surface, bottom row: hail water path.
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726