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Retrievals of riming and snow density from vertically-pointing Doppler radars

S. L. Mason^{1,2}, C. J. Chiu³, R. J. Hogan^{1,4}, D. Moisseev^{5,6}, S. Kneifel⁷

4	¹ Department of Meteorology, University of Reading, Reading, UK
5	² National Centre for Earth Observation (NCEO), University of Reading, Reading, UK
6	³ Colorado State University, Fort Collins, Colorado, USA
7	⁴ European Centre for Medium-range Weather Forecasts (ECMWF), Reading, UK
8	⁵ Institute for Atmospheric and Earth System Research/Physics, Faculty of Science, University of Helsinki, Finland
9	⁶ Finnish Meteorological Institute, Helsinki, Finland
10	⁷ Institute of Geophysics and Meteorology, University of Cologne, Cologne, Germany

Key Points:

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12	•	The CAPTIVATE optimal estimation retrieval algorithm is applied to zenith-pointing
13		Doppler cloud radars deployed during the Biogenic Aerosolos-Effects on Clouds and
14		Climate field campaign (BAECC 2014), in Hyytiälä, Finland.
15	•	Doppler velocity is exploited to retrieve a parameter that modulates the mass, area and
16		radar backscatter cross-sections to represent the continuum of particle morphologies
17		from unrimed aggregates to graupel and hail.
18	•	The retrieval provides insights into microphysical processes including aggregation
19		and riming. Retrieved particle density is correlated with the availability of super-
20		cooled liquid water, demonstrating potential to use the retrieval to diagnose embedded
21		layers of mixed-phase clouds.

Corresponding author: S. L. Mason, s.l.mason@reading.ac.uk

22 Abstract

Retrievals of ice and snow are made from Ka- and W-band zenith-pointing Doppler radars at 23 Hyytiälä, Finland, during the snow experiment (SNEX) component of the Biogenic Aerosols: 24 Effects on Clouds and Climate (BAECC 2014) field campaign. In a novel optimal estimation 25 retrieval, mean Doppler velocity is exploited to retrieve a "density factor" parameter which 26 modulates the mass, shape, terminal velocity and backscatter cross-sections of ice particles. 27 In a case study including aggregate snow and graupel we find that snow rate and ensemble 28 mean ice density can be retrieved to within 50 % of in-situ measurements at the surface us-29 ing dual-frequency Doppler radar retrievals. While Doppler measurements are essential to 30 the retrieval of particle density, the dual-frequency ratio provides a strong constraint on parti-31 cle size. The retrieved density factor is strongly correlated with liquid water path, indicating 32 that riming is the primary process by which the density factor is modulated. Using liquid wa-33 ter path as a proxy for riming, profiles classified as unrimed snow, rimed snow and graupel 34 exhibit distinct features characteristic of aggregation and riming processes, suggesting the 35 potential to make estimates of process rates from these retrievals. We discuss the potential 36 application of the technique to future satellite missions. 37

1 Introduction

Estimates of the global volume and distribution of snow are critical to understanding 39 the atmospheric water budget and surface hydrology. While the first generation of space-40 borne cloud and precipitation radars has greatly improved the detection of snow, remote-41 sensed estimates of snow mass flux and its microphysical properties remain highly uncer-42 tain. Understanding the microphysics of snow production within ice clouds is also critical 43 to global rainfall: CloudSat 94-GHz radar [Stephens et al., 2002] observations reveal that 44 85-90% of all precipitation events in the extratropics and poles originate in the ice phase, 45 and that 34-40% of rain events in the subtropics and tropics fall from melting ice [Field and 46 Heymsfield, 2015]. CloudSat snow retrievals [e.g. Liu, 2008; Kulie and Bennartz, 2009] have 47 enabled the first remote-sensed estimates of snow over remote polar regions [Palerme et al., 48 2014], and surveys of snow regimes [Chen et al., 2016; Kulie et al., 2016], but further micro-49 physical insights are anticipated from upcoming satellite missions. The first of a second gen-50 eration of satellite radars is the dual-frequency precipitation radar (DPR) aboard the global 51 precipitation measurement mission [GPM; Hou et al., 2014]; however, initial comparisons 52 suggest DPR detects only about one-third of the mass of snow seen by CloudSat, concen-53

trated in the heaviest 5% of snow events [*Casella et al.*, 2017]. Work is ongoing to better
evaluate remote-sensed snow rate at the surface [e.g. *Heymsfield et al.*, 2016] with the aim of
reducing uncertainties in retrievals from current satellite capability and informing the design
of future satellite sensors.

Remote-sensing of ice and snow requires knowledge of the morphology of ice par-58 ticles, which may be any combination of pristine ice crystals grown by vapour deposition, 59 aggregates or fragments formed from interactions between ice particles, or rimed particles 60 and graupel having collected liquid drops in mixed-phase cloud. While a majority of snow 61 is assumed to fall as aggregate snowflakes [Langleben, 1954], the masses and fallspeeds of 62 ice particles remain fundamental to uncertainties in radar retrievals [Hiley et al., 2011]. Ice 63 particle properties are especially uncertain in and below mixed-phase clouds, which are com-64 mon in the extratropics and poles [Hogan et al., 2003, 2004; Cesana et al., 2012], radiatively 65 important in the polar regions and extratropics [e.g. Shupe et al., 2004], imperfectly detected 66 by spaceborne radar and lidar [e.g. Ceccaldi et al., 2013], and poorly represented in models 67 [e.g. Tan et al., 2016]. Studies at ground stations have attributed 40% or more of the mass of 68 snow to rimed ice [Harimaya and Sato, 1989; Mitchell et al., 1990; Moisseev et al., 2017], 69 suggesting large uncertainties in remote-sensed estimates of snow rate while riming goes 70 undiagnosed, and riming has been strongly associated with heavy accumulation events in 71 mountainous regions [Grazioli et al., 2015]. Remote-sensed estimates of snow stand to be 72 improved by the capability to diagnose riming in mixed-phase clouds, hence to better esti-73 mate ice particle properties and the mass flux of snow. 74

Recent ground-based measurement campaigns have facilitated studies of snow micro-75 physics using deployments of advanced radars, lidars and passive remote-sensors co-located 76 with in situ measurements of snow particles [e.g. Szyrmer and Zawadzki, 2014; Petäjä et al., 77 2016]. Combined particle imaging and snow gauge instruments have enabled the quantifi-78 cation of ice bulk density and rime mass [Tiira et al., 2016; Moisseev et al., 2017; von Ler-79 ber et al., 2017; Grazioli et al., 2015], building upon previous studies characterising particle 80 morphologies and degrees of riming [e.g. Harimaya and Sato, 1989; Mitchell et al., 1990]. 81 These campaigns provide opportunities to evaluate and intercompare the representation of 82 ice and mixed-phase microphysics used in numerical models [Lin et al., 2011; Morrison and 83 Milbrandt, 2015; Morrison et al., 2015], as well as of ice particle morphology and growth 84 processes as they relate to radar backscatter [Kneifel et al., 2011; Leinonen and Szyrmer, 85 2015]. Triple-frequency radar measurements have allowed for the evaluation of particle mod-86

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els using the signatures of rimed and unrimed ice particles [Kneifel et al., 2015; Stein et al., 87 2015], a technique that has recently been applied to colocated CloudSat and GPM measure-88 ments [Yin et al., 2017]. With Doppler radar capability, the morphology of snow can also be 89 inferred from terminal velocities of particles to estimate the degree of riming [Mosimann, 90 1995] or the density of rimed aggregates [Szyrmer and Zawadzki, 2014; ?], and it is possible 91 in some cases to distinguish ice from cloud droplets using Doppler spectra in mixed-phase 92 cloud [Kalesse et al., 2016]. Recent ground-based remote-sensing and in situ measurement 93 campaigns have demonstrated the application of Doppler and multiple-frequency radar ob-94 servations to improved retrievals of snow and riming. 95

In this study we demonstrate the novel retrieval of the properties of snow particles us-96 ing vertically-pointing dual-frequency Doppler radars at Hyytiälä, Finland. Mean Doppler 97 velocity, a measure of the terminal velocity of hydrometeors, is used to estimate a parameter 98 that modulates the properties of ice particles along a continuum from unrimed aggregates 99 to graupel and hail. The retrieval is carried out within the optimal estimation framework for 100 Cloud Aerosol and Precipitation from mulTiple Instruments using a VAriational TEchnique 101 (CAPTIVATE), which provides the flexibility to assimilate observed variables from a range 102 of ground-based instruments. We consider the contribution of Doppler velocity and dual-103 frequency radar reflectivity measurements to the retrieval, and compare against retrievals in 104 which particle density does not vary. The retrieved snow rate, particle size distribution and 105 bulk density are evaluated against in-situ measurements at the surface. This method for es-106 timating ice particle morphology from mean Doppler velocity should be applicable to the 107 network of ARM and Cloudnet [Illingworth et al., 2007] "supersites" with multi-frequency 108 Doppler radars, as well as to the upcoming ESA/JAXA Earth Cloud Aerosol Radiation Ex-109 plorer [EarthCARE; Illingworth et al., 2015], which will feature the first spaceborne Doppler 110 cloud radar in synergy with lidar and radiometers. In addition to Doppler capability, space-111 borne multiple-frequency cloud radars have long been of interest to further improve global 112 observations of ice clouds and snow [Hogan and Illingworth, 1999; Tanelli et al., 2009; Löh-113 nert et al., 2011; Leinonen and Szyrmer, 2015; National Academies of Sciences Engineering 114 and Medicine, 2018]. 115

The paper is structured as follows: we describe the components of the CAPTIVATE retrieval framework pertinent to estimates of ice and snow from radar measurements, with a focus on formulating a new parameter with which to represent ice particles over a range of densities from unrimed aggregates to graupel and hail (Section 2), and lay out the mea-

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surements and atmospheric state data used for the present study (Section 3). We then present
the results of retrievals for a case study of a frontal snow event with significant riming (Section 4.1), and a statistical evaluation of a retrieval of 10 snow events over a 2 month observation period (Section 4.2). In our concluding remarks we consider applications of the retrieval to future satellite radar missions (Section 5).

2 Retrieval framework

- The CAPTIVATE retrieval framework [Mason et al., 2017] has been developed for 126 radar-lidar-radiometer synergy retrievals from EarthCARE [Illingworth et al., 2015]. CAP-127 TIVATE therefore includes instrument forward-models for the Doppler radar and high-spectral 128 resolution lidar aboard EarthCARE, but is also designed to be easily configurable for active 129 and passive sensors on ground-based and airborne platforms. Here we focus on the retrieval 130 of snow from zenith-pointing ground-based radar measurements. The retrieval of ice and 131 snow builds upon the methods employed for the synergy of CloudSat/CALIPSO observations 132 [Delanoë and Hogan, 2008, 2010]; the novelty of the present retrieval is the availability of 133 Doppler velocity measurements. 134
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2.1 Cost function and minimization

The retrieval operates on a column-by-column basis to make an optimal estimate of the vector of state variables **x** that best explains the observed variables **y** within the bounds of prior expectations and measurement uncertainties [*Rodgers*, 2000]. The optimal estimate is that which minimizes the cost function

$$J = \frac{1}{2}\delta \mathbf{x}^{\mathsf{T}} \mathbf{B}^{-1} \delta \mathbf{x} + \frac{1}{2}\delta \mathbf{y}^{\mathsf{T}} \mathbf{R}^{-1} \delta \mathbf{y} + J_c(\mathbf{x}), \qquad (1)$$

where $\delta \mathbf{x} = \mathbf{x} - \mathbf{x}_a$ is the difference between the state vector and its prior, and **B** the er-140 ror covariance matrix of the priors; $\delta \mathbf{y} = \mathbf{y} - H(\mathbf{x})$ is the difference between the observed 141 variables and the forward-modelled observations $H(\mathbf{x})$, and **R** the error covariances of the 142 observations and forward models; and $J_c(\mathbf{x})$ optionally applies regularization constraints to 143 the vertical profile of the state vector [Twomey, 1977]. By quantifying uncertainties in the 144 prior estimates of the state, measurement errors, and uncertainties in the implementation of 145 the forward-models, the retrieval yields a robust best-estimate of the state variables and their 146 associated error uncertainties. The cost function is minimized by iterating on the state vec-147 tor from the prior in the direction of the first and second derivatives of the cost function [the 148

¹⁴⁹ Levenberg-Marquadt method; *Rodgers*, 2000]. The derivatives are computed efficiently and

transparently using the combined array and automatic differentiation C++ software library,

¹⁵¹ Adept [*Hogan*, 2014, 2017].

The vectors of state variables through the vertical profile \mathbf{x}_i for *n* classes of hydrometeor are retrieved from the observed variables \mathbf{y}_i of *m* instruments:

$$\mathbf{x} = \begin{pmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \vdots \\ \mathbf{x}_n \end{pmatrix}, \qquad \mathbf{y} = \begin{pmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \\ \vdots \\ \mathbf{y}_m \end{pmatrix}.$$

Both the selection of appropriate state variables for ice particles (Section 2.3) and the formulation of a radar forward-model for the observed variables (Section 2.4) depend on an underlying physical representation of ice particles: their size distribution, shape and mass, and their terminal fallspeeds.

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2.2 Representation of ice particle properties

The bulk quantities of primary interest for remote-sensing are related to integrals over the particle size distribution (PSD; N(D)) with the average properties of ice particles, as a function of maximum particle dimension D. Unless stated otherwise, SI units are used. The ice water content (IWC) requires the mass of ice particles, m(D):

$$IWC = \int_0^\infty m(D) N(D) \, dD,\tag{2}$$

while the mass flux or snow rate also includes particle terminal velocities, v(D):

$$S = \int_0^\infty v(D) \, m(D) \, N(D) \, dD. \tag{3}$$

A characteristic bulk density of ice particles can be calculated as a volume flux-weighted
 density:

$$\overline{\rho} = \frac{\int_0^\infty m(D) v(D) N(D) dD}{\frac{\pi}{6} AR \int_0^\infty D^3 v(D) N(D) dD}$$
(4)

where *AR* is the aspect ratio of a horizontally-aligned oblate spheroid enclosing the particle. A volume flux-weighted density for ease of comparison with estimates derived from in
situ measurements of accumulation with a snow gauge [e.g. *Moisseev et al.*, 2017; *von Ler- ber et al.*, 2017]. While integrated quantities such as snow rate are especially sensitive to
the formulation of the mass-size relation [*Heymsfield et al.*, 2010; *Delanoë et al.*, 2014], in

this study it will also be important to relate the mass and shape of particles to their terminal

velocity in order to retrieve the morphology of snow particles from Doppler radar measure ments.

In the following sections we first describe the PSD (Section 2.2.1), then the mass-size (Section 2.2.2) and area-size (Section 2.2.3) relations for a range of ice particles, and finally how particle properties are combined to estimate terminal fallspeeds (Section 2.2.4).

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2.2.1 Particle size distribution

The PSD is represented as a normalized spectrum of the form

$$N(D) = N_w F(D/D_0).$$
⁽⁵⁾

where N_w is the normalized number concentration, D_0 is the median volume diameter [*Tes*-

tud et al., 2001], and the function $F(D/D_0)$ can be either that of the normalized gamma dis-

tribution [*Testud et al.*, 2001; *Illingworth and Blackman*, 2002; *Delanoë et al.*, 2005], or the

¹⁸⁰ universal modified gamma distribution derived by *Field et al.* [2005] for extratropical ice

clouds [see also *Field et al.*, 2007; *Delanoë and Hogan*, 2008]. The normalized number con-

centration can be estimated from the moments of the PSD:

$$N_w = M_2^4 / M_3^3 \tag{6}$$

where M_n is the n^{th} moment. When using the gamma function a constant shape parameter of $\mu = 2$ is assumed in order to simplify the representation of the PSD; the shape parameter makes the smallest contribution to uncertainties in the retrieved ice water content [*Delanoë et al.*, 2005]. In practice for the present study, the differences between the retrieved quantities using the normalized gamma and *Field et al.* [2005] PSD were found to be within the uncertainty of the retrievals; in the results presented here the *Field et al.* [2005] PSD is used unless otherwise stated.

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2.2.2 Mass-size relations

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Ice particle mass is expressed as a function of maximum dimension by the power law

$$m(D) = a_m D^{b_m},\tag{7}$$

where the prefactor a_m scales the density of ice at all sizes, and the exponent b_m controls the size-dependence of particle mass and is related to the particle growth mechanism or shape of the particle. Aggregate snowflakes have exponents around $b_m = 2$, close to the theoretical value for fractals [*Westbrook et al.*, 2004; *Stein et al.*, 2015]. More rounded graupel and hail particles have exponents closer to $b_m = 3$, the physical maximum for spheres [*Leinonen and Moisseev*, 2015].

While snow particles are observed to vary greatly in morphology, the majority of snow 198 is thought to fall as aggregate snowflakes [Langleben, 1954]—indeed, the mass-size rela-199 tions used for ice and snow tend to be derived from measurements dominated by unrimed 200 aggregates. We follow the approach of Hogan et al. [2012], who showed that in-situ mea-201 surements of cirrus were consistent with radar reflectivities when the mass-size relation de-202 rived for "aggregates of unrimed bullets, columns and side-planes" by Brown and Francis 203 [1995] was used. In this representation the smallest particles are assumed to be solid quasi-204 spheroidal ice crystals, while larger aggregates occupy the volume of a horizontally-aligned 205 oblate spheroid with an aspect ratio-that between the minimum (vertical) dimension and the 206 maximum (horizontal) dimension—of AR = 0.6. Hogan et al. [2012] found that this value 207 provided a good fit to a database of aircraft measurements as well as other studies in the liter-208 ature. Combining dual-polarization weather radar and surface based snowfall measurements 209 at Hyytiälä, [Li et al., 2018] found that the aspect ratio varies with riming fraction between 210 0.4 and 0.9, while analysis of PIP images by Tiira et al. [2016] yielded a median aspect ratio 211 of 0.72. However, the applicability of particle images to derive particle geometrical prop-212 erties was questioned by Jiang et al. [2017]; hence, Tiira et al. [2016] also used a single as-213 pect ratio value of 0.6 for density retrievals. In the present study it was found that assuming 214 AR = 0.8 instead of AR = 0.6 led to an increase in retrieved ice water content of approxi-215 mately 20%, demonstrating that the shape and orientation of ice particles is an important 216 uncertainty in the remote-sensing of snow [see also Hogan and Westbrook, 2014]. 217

How does riming affect the mass-size relation of snow? Numerical analogues for "bal-218 listic" collisions between ice particles (aggregation) and between ice particles and super-219 cooled liquid drops (riming) suggest that aggregating particles will retain mass-size expo-220 nents around $b_m = 2$, while those growing by riming will tend toward exponents of $b_m = 3$ 221 [Jullien, 1992]. A conceptual model for riming introduced by Heymsfield [1982] proposes a 222 two stage process for the riming of aggregate snowflakes [see also Morrison and Milbrandt, 223 2015; Moisseev et al., 2017], in which an aggregate is first "filled in" by freezing supercooled 224 drops, increasing the mass of the particle but not its size: this increases the prefactor of the 225 mass-size relation while the exponent remains close to $b_m = 2$ [e.g. Szyrmer and Zawadzki, 226

2014; Morrison and Milbrandt, 2015; Moisseev et al., 2017; von Lerber et al., 2017]. That 227 the first stage of riming does not scale the exponent of the mass-size relation is consistent 228 with earlier studies of rimed snow [e.g. Harimaya and Sato, 1989; Mitchell et al., 1990]. 229 Once the particle geometry is closed by in-filling, it is classified as graupel. In this second 230 stage rime is accreted to the outside of the particle, adding to both its mass and diameter, and 231 as the particles become rounder in shape the exponent approaches $b_m = 3$ [Mitchell, 1996]. 232 The morphology of an ice particle encodes a history of multiple and interacting processes, 233 including aggregation and transitions between stages of riming, which may be observed mi-234 croscopically [Fujiyoshi and Wakahama, 1985] or tracked within a microphysical parame-235 terization scheme [Morrison et al., 2015; Morrison and Milbrandt, 2015], but are unlikely to 236 be instantaneously grasped by remote sensing. In a modelling study Leinonen and Szyrmer 237 [2015] compared particles that have grown first by aggregation then riming to those that have 238 grown by simultaneous aggregation and riming. While it was found that aggregation and 239 riming, whether in series or in parallel, form particles that are indistinguishable in terms of 240 radar backscatter—an important result for remote-sensing—the corresponding mass-size re-241 lations were distinct: when riming followed aggregation the exponent was found to remain 242 close to $b_m = 2.1$ until a relatively high degree of riming; but when riming and aggrega-243 tion were simultaneous the exponent varied significantly even at low degrees of riming. This 244 complicates the two-stage conceptual model of riming. While we may attempt to formulate a 245 representation of the range of morphologies and densities of ice particles for remote-sensing 246 applications, the possibility of multiple interacting ice processes means we should be cau-247 tious about attributing all variations in particle density to riming. 248

It has been observed that the mass-size relations derived from studies of snow and ice 249 form a continuum of ice particles from unrimed snowflakes to graupel and hail [Lin and 250 *Colle*, 2011]; Fig. 1 shows the mass-size prefactors and exponents a_m and b_m in cgs units 251 and converted where necessary into terms of maximum particle dimension D. Particles with 252 low mass-size prefactors and exponents—in the lower left part of the diagram—include a 253 range of unrimed aggregates, as well as other low-density species such as dendrites, needles 254 and columns. Measurements of unrimed snow from ground-based studies [*Tiira et al.*, 2016; 255 von Lerber et al., 2017] are consistent with aircraft studies of ice clouds [Heymsfield and 256 Westbrook, 2010; Brown and Francis, 1995], with b_m varying between 1.9 and 2.1. Larger 257 mass-size prefactors and exponents—in the centre to the upper-right part of the diagram— 258 include denser or more compact particles of various kinds, often with some degree of rim-259

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ing. Exponents for rimed aggregates and low-density graupel are between 2.1 and 2.4 [Er-260 fani and Mitchell, 2017; von Lerber et al., 2017]; while for lump graupel and hail classifi-261 cations [Mitchell, 1996; Mace and Benson, 2017; Zikmunda and Vali, 1972] the exponent 262 approaches 3.0. We note that the position on the mass-size relation diagram is not solely 263 related to the effect of riming, especially for slender 1- and 2-dimensional species such as 264 columns and dendrites: for example, the rimed dendrites in Erfani and Mitchell [2017] have 265 a lower mass-size exponent than the unrimed dendrites; and the different sizes of hexagonal 266 columns in *Mitchell* [1996] range from the upper-right part of the diagram for the smallest 267 columns, to the extreme lower-left for the largest. 268

Variations in ice particle density have been parameterized in many ways. Fixed den-275 sities can be assumed depending on the cloud type, with low-density aggregates in strati-276 form cloud and graupel-like particles in convective cloud [e.g. Grecu et al., 2016]. Lin et al. 277 [2011] parameterize ice density according to temperature. Szyrmer and Zawadzki [2014] 278 demonstrate a radar retrieval of lightly rimed snow from ground-based dual-frequency Doppler 279 radars in which the prefactor a_m is scaled to increase the density of ice due to riming, while 280 the exponent is fixed at $b_m = 2$. Similarly, *Moisseev et al.* [2017] represented the density of 281 snow by scaling the prefactor of the mass-size relation and holding the exponent constant. 282

In order to represent a continuum of ice particles from unrimed and rimed aggregates to graupel and hail, we parameterize particle mass based on a "density factor" r (grey line in Fig. 1) that is continuous between the mass-size relation for the unrimed aggregates of *Brown and Francis* [1995] ($m = 0.0121 D^{1.9}$ kg where r = 0) and that of oblate spheroids of solid ice ($m = 288 D^3$ kg at r = 1). The parameterized exponent varies linearly with density factor between these two reference points ($b_m = 1.9$ and $b_m = 3$):

$$b'_m(r) = 3r + 1.9(1 - r), \tag{8}$$

while the prefactor is scaled according to the requirement that particle masses are equivalent for all *r* at some critical diameter D_c , which can be calculated as $(0.0121/288)^{1/(3-1.9)} = 105 \,\mu\text{m}$, similar to the transition from quasi-spheroids to aggregates in *Hogan et al.* [2012]. Normalizing by the critical diameter, the mass-size relation for all particles can be expressed

$$m(D,r) = a'_m \left(\frac{D}{D_c}\right)^{b'_m},\tag{9}$$

where the normalized prefactor $a'_m = a_m D_c^{b_m} = 33.3 \,\mu\text{g}$ is the particle mass at the critical diameter. A similar normalized mass-size relation was employed in *Szyrmer and Zawadzki*



Figure 1. A comparison of m(D) power-law prefactors and exponents. Coloured circles show a_m , b_m for various studies of ice and snow. Black markers correspond to particle types summarized in *Mitchell* [1996]; where multiple markers of a particular type are shown, their relative size indicates the size range for which the mass-size relation was derived. Unrimed aggregates [*Brown and Francis*, 1995] and spheroids of solid ice define the mass-size relation as a function of density factor r: the grey line indicates the values of a_m , b_m parameterized by the density factor in the range -0.17 < r < 1.0.

[2014] [see also *Maahn et al.*, 2015; *Maahn and Löhnert*, 2017], but in that study the critical diameter was selected to be close to the median particle diameter to minimize the effect of fixing the exponent of the mass-size relation $b_m = 2$. In the present retrieval all particles smaller than the critical diameter are assumed to be solid quasi-spheroids; expressed another way, the fractional volume of a particle occupied by ice is given by the ice fraction,

$$f(D,r) = \begin{cases} 1.0 & D \le D_{\rm c} \\ (D/D_{\rm c})^{b'_{\rm m}-3} & D > D_{\rm c} \end{cases}$$
(10)

³⁰⁰ The ice fraction-size relation for a range of density factors is shown in Fig. 3.

In terms of the density factor, the unrimed and lightly-rimed snow correspond to low values (r < 0.3), and heavily-rimed snow and graupel [*von Lerber et al.*, 2017; *Mace and Benson*, 2017] relate to higher values (0.3 < r < 0.7). While r = 1 is the upper limit, small negative density factors are possible, and allow for the representation of particles with lower densities such as dendrites [*Erfani and Mitchell*, 2017] or large hexagonal columns [*Mitchell*, 1996].

We note that the density factor is not intended to explicitly represent the effect of the 307 riming process on the mass of a particle, but allows for a smooth transition between unrimed 308 and rimed aggregates to graupel and hail which we hope will be sufficient to allow an esti-309 mate of ice morphology based on particle fallspeeds. The density factor pivots the mass-size 310 relation of ice particles larger than the critical diameter (Fig. 3), but without representing 311 the transition features that would corresponding to the multiple stages of riming. A more 312 process-oriented parameterisation of the "in-filling" stage of rimed aggregate snowflakes 313 would be to scale the mass-size prefactor with the density factor, while the exponent re-314 mains constant. While this would better represent the conceptual model of the riming pro-315 cess, it would not encompass the observed variability in the mass-size relations of unrimed 316 snowflakes, or the transition to graupel-like particles. A comparison of the two parameterisa-317 tions indicated that the retrieval was not strongly sensitive to the representation of the density 318 factor, especially for estimates of unrimed to moderately rimed aggregates. With additional 319 observational evidence, a more complex representation of the effects of riming on particle 320 morphology-including expected changes in the masses and shapes of particles during dif-321 ferent stages of riming-may allow for improved retrievals and better quantified uncertain-322 ties. This should be the subject of future work. 323

2.2.3 Area-size relation

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Similar to the mass-size relation, the cross-sectional area of ice particles is expressed as a power law:

$$A = a_A D^{b_A}.$$
 (11)

The area-size relation of unrimed aggregates is derived from the mass-size [Brown and Fran-327 cis, 1995] and mass-area relations [Francis et al., 1998] from aircraft measurements of cirrus 328 clouds $A = 0.02038 D^{1.624} m^2$ in SI units and in terms of maximum dimension. The geo-329 metric upper limit for horizontally-aligned oblate spheroids with maximum dimension on 330 the horizontal plane is $A = \pi/4 D^2 m^2$. A comparison of area-size relations from a range 331 of studies (Fig. 2) again shows a relationship between the prefactors and exponents across 332 particle types: lower density factors are consistent with unrimed ice particles [Schmitt and 333 Heymsfield, 2010; Mace and Benson, 2017], and larger density factors with rimed parti-334 cles [Heymsfield and Kajikawa, 1987], graupel and hail [Mitchell, 1996]. While increases 335 in cross-sectional area are consistent with the conceptual model of riming leading to the in-336 filling of aggregates and a transition to rounded graupel-like particles, there is significant 337 variability between particle types: for example, columns may retain low cross-sectional areas 338 despite riming, while riming may have little effect on the cross-sectional area of plates. 339

To represent the increased cross-sectional area of rimed aggregates and graupel, we scale the area-size relation by the density factor r; however, to represent the more rounded shapes of heavily rimed aggregates and graupel, the cross-sectional area is maximized for $r = r_{max}$, so that

$$b'_{A} = 2\frac{r}{r_{\max}} + 1.624(1 - \frac{r}{r_{\max}}).$$
 (12)

The prefactor is scaled by a critical diameter D_{c_A} , the size at which the cross-sectional area of unrimed aggregates and spheres are equal, which can be calculated to be 61 μm . The normalized area-size relation is therefore

$$A = a'_A \left(\frac{D}{D_{c_A}}\right)^{b'_A} \tag{13}$$

where the modified prefactor is the area at the critical diameter $a'_A = a_A D_{c_A}^{b'_A}$. Most rimed and unrimed aggregates correspond to density factors r < 0.3, while quasi-spheroidal and heavily rimed particles, graupel and hail have $r \approx r_{max}$. A marginally more complex areasize relation that better fits the observations would be to allow both the prefactor and exponent to vary for $r < r_{max}$, before scaling only the prefactor up to r = 1.



Figure 2. A comparison of power law prefactors and exponents for ice particle area-size relations.

Coloured circles show a_A , b_A derived from a range of aircraft and surface studies. Black markers corre-

- spond to specific particle types summarized in *Mitchell* [1996]. The parameterized area-size relation, which
- varies with density factor between unrimed aggregates [r = 0 Brown and Francis, 1995; Francis et al., 1998]
- and spheres of solid ice ($r = r_{max}$), is shown with a grey line.

Particle area is often expressed as the area ratio, which is the cross-sectional area of the
 particle normalized by area of the circumscribing circle, or

$$A_r(D) = \begin{cases} 1.0 & D \le D_{c_A} \\ (D/D_{c_A})^{b'_A - 2} & D > D_{c_A} \end{cases}$$
(14)

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2.2.4 Velocity-size relation

The boundary layer or hydrodynamic method provides an estimate of the terminal ve-360 locity of a hydrometeor based on size, area ratio and mass [e.g. Mitchell, 1996; Mitchell and 361 Heymsfield, 2005; Khvorostyanov and Curry, 2005; Heymsfield and Westbrook, 2010] or 362 conversely, an estimate of particle mass from measured diameter, cross-sectional area and 363 fallspeed [e.g. von Lerber et al., 2017]. In the previous sections the mass- and area-size re-364 lations for ice particles were expressed as functions of diameter and density factor; hence a 365 look-up table for particle terminal velocities is produced using the method of Heymsfield and 366 Westbrook [2010]. 367

The terminal fallspeed of ice particles v(D, f) for a range of maximum dimensions and ice fractions (see eq. 10) is overlaid with curves corresponding to the mass-size relations for a range of density factors (Fig. 3). As the mean Doppler velocity relates to the reflectivityweighted average of particle fallspeeds, the density factor has the greatest effect on the fallspeeds of the largest particles. While the largest unrimed aggregates do not exceed terminal velocities of 2 m s⁻¹, even low density factors effect significant increases in fallspeed for particles of the same size.

- 379 **2.3 State variables**
- 380

-... Statt variabiles

- 2.3.1 Extinction coefficient and primed number concentration
- The choice of retrieved state variables is flexible within CAPTIVATE, as are any vertical or temporal smoothing applied to the state variables. In this retrieval, a state variable related to the density factor is added to those used for retrievals of ice clouds from radar– lidar synergy described in *Delanoë and Hogan* [2008, 2010]. The first state variable is the visible extinction coefficient of ice in the geometric optics approximation, α_v . The second state variable is the primed number concentration,

$$N_0' = N_w \alpha_v^{-0.6}$$
(15)

-15-

from which the normalized number concentration N_w from (5) can be recovered, since the extinction coefficient is also retrieved. *Delanoë and Hogan* [2008] showed using in situ aircraft data that this choice of state variables for ice allows for a convenient a priori estimation of the primed number concentration as a function of atmospheric temperature (Table. 1). An additional parameter, the lidar extinction-to-backscatter ratio, can also be retrieved in radarlidar synergy applications; however, in this study we assume this variable is constant.

The minimization scheme does not limit the values of retrieved variables, so we formulate state variables such that they remain physically meaningful at all values; this is achieved by using the natural logarithms of N'_0 and α_v .

While these choices of state variables for ice and snow are convenient for the reasons described above, they are not necessarily the most physically meaningful quantities. For comparison with in situ measurements, an integrated quantity such as the melted-equivalent snow rate, as well as the median diameter and normalized number concentration, are more convenient. As the extinction coefficient is an integral over the PSD and the primed number concentration relates to a parameter of the PSD by (15), the two state variables are sufficient to calculate the PSD.

2.3.2 Density index

The natural logarithm of the density factor is not a suitable state vector; the density factor should not exceed r = 1, but small negative values are physically meaningful. Instead we retrieve the density index r', a state variable defined such that:

$$r = \frac{f(r'+r_0) + f(r_0)}{1 - f(r_0)},$$
(16)

407 where

413

403

$$f(x) = \frac{1}{2} + \frac{\tan^{-1} x}{\pi}$$
(17)

and $r_0 = -2$. This transform function has the property that r = 0 when r' = 0, and for any value of r', r is within the range -0.173 to 1.0. The transform is illustrated in Fig. 4.

2.3.3 Representation of the state vector

To reduce the effect of measurement noise on the retrieval, the profile of each state variable is represented as the basis functions of a cubic spline [*Hogan*, 2007]. The degrees of freedom of the retrieval can therefore be controlled by altering the spacing of the basis func-



Figure 3. The terminal fallspeeds v(D, f) of ice particles as a function of maximum dimension D, and ice fraction f. Black lines correspond to the parameterized mass-size relations for density factors between unrimed aggregates (r = 0) and spheroids of solid ice (r = 1). D_c is the diameter below which all particles are represented as dense quasi-spheroidal particles.



Figure 4. The transform function between density index r', the retrieved state variable, and the density factor which modulates the particle properties between unrimed aggregates at r = 0 and spheroids of solid ice at r = 1.

tions, which modifies the effective scales over which features are retrieved [*Rodgers*, 2000].

A Kalman smoother [*Rodgers*, 2000] is applied to the extinction coefficient and density in-

dex, so that the retrieval of these quantities is constrained by adjacent profiles. In the first

⁴²⁰ pass of the smoother the retrieval is constrained by subsequent rays and, on the second pass,

⁴²¹ in both directions. For the retrieval of the density factor, this will have the effect of filtering

out smaller-scale fluctuations in the mean Doppler velocity due to turbulent vertical air mo-

423 tion.

The state vector for ice cloud and snow is therefore

$$\mathbf{x}_{\text{ice}} = \begin{pmatrix} \ln \alpha_{\text{v}} \\ \ln N_0' \\ r' \end{pmatrix}.$$

The prior estimate of the state vector and associated uncertainties represent our knowledge 424 of the state before the measurement vector is assimilated. The values and uncertainties of the 425 priors, and the vertical representation of each state variable are summarized in Table 1; note 426 that the uncertainties in the priors are in terms of the natural logarithm of the physical param-427 eters. From a large database of in situ measurements of ice clouds [Delanoë et al., 2005] an 428 expression has been derived for $\ln N'_0$ as a function of atmospheric temperature, with a vari-429 ance of 1.0 [Fig. 3b in Delanoë and Hogan, 2008], and a similar function of temperature is 430 used for the prior extinction coefficient. When fewer observational variables are used it may 431 be necessary to reduce the number of degrees of freedom by holding some state variables at 432 their a priori values; these state variables can be represented within the retrieval as a "model" 433 variable, wherein its value does not vary but its prior uncertainty is assimilated. 434

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2.4 Observed variables and radar forward model

2.4.1 Reflectivity factor

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The observed variables for each radar are the apparent radar reflectivity factor Z_f and mean Doppler velocity V_f at the radar frequency f. The reflectivity factor is given by

$$Z_f = 10^{18} \frac{\lambda^4}{\pi^5 |K_f|^2} \int_0^\infty \sigma_f(D) N(D) \, dD \tag{18}$$

where λ is the radar wavelength, K_f is the dielectric factor, and $\sigma_f(D)$ is the radar backscatter cross-section. Radar attenuation due to atmospheric gases is modelled from the atmospheric state using *Liebe* [1985], so that this effect is included in the observed and forwardmodelled radar reflectivities.

435 **Table 1.** State variables for ice and snow, their priors, uncertainties and vertical representation. Note that

⁴³⁶ we take as the state variables the natural logarithms of key parameters; stated uncertainties are therefore

⁴³⁷ uncertainties in the natural logarithm of the priors.

State variable \mathbf{x}_i	Prior \mathbf{x}_i^a	Prior uncertainty	Cubic spline
		$\sigma(\mathbf{x}_i^a)$	spacing [m]
Extinction coefficient $\ln \alpha_v$	-9.2103 - 0.03148 <i>T</i>	10.0	150
	(where <i>T</i> is in $^{\circ}C$)		
Primed number concentra-	23.03 - 0.12997 T	1.0	600
tion $\ln N'_0$	(where <i>T</i> is in $^{\circ}C$)		
Density index r'	0.0	1.0	150

Attenuation due to liquid water can be significant for millimetre-wavelength radars, 446 and can either be accounted for by simultaneously retrieving the liquid water content, or by 447 correcting for attenuation in the radar reflectivities prior to the retrieval. The former option 448 is most suited to a radar-lidar-radiometer retrieval wherein the lidar backscatter and a visible 449 radiance may provide adequate constraints; for a radar-only retrieval the available observed 450 variables are dominated by ice, and the retrieval of liquid water content would be undercon-451 strained. Radar reflectivities can be pre-corrected for liquid attenuation based on an esti-452 mate of the liquid water path, such as from a microwave radiometer. In this study we follow 453 the correction described in *Kneifel et al.* [2015]; the vertical distribution of SLW not being 454 known, it is distributed evenly over the lowest 4 km of the atmosphere. Alternative correc-455 tions may be made by assuming all of the attenuation takes place below the lowest radar gate, 456 or by locating the liquid in one or more shallow layers based on other evidence such as a re-457 cent sounding, or Doppler spectra [e.g. Kalesse et al., 2016]. In practice we found that the 458 uncertainty in W-band radar reflectivity between the different corrections was on the order 459 of 1 to 2 dB; this can be accounted for within CAPTIVATE by increasing the observational 460 uncertainty applied to the measurement vector (see Section. 2.4.4). 461

Reflectivity enhancement due to radar multiple scattering can be modelled using the method of *Hogan* [2008]; however, in this application with ground-based narrow beamwidth radars, we assume multiple scattering is negligible. The uncertainty in the radar reflectivity includes both observational and forward-model errors.

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2.4.2 Mean Doppler velocity

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Mean Doppler velocity is the reflectivity-weighted fallspeed of hydrometeors

$$V_f = \frac{\int_0^\infty v(D) \,\sigma_f(D) \,N(D) \,dD}{\int_0^\infty \sigma_f(D) \,N(D) \,dD},\tag{19}$$

where v(D) is corrected for air density, and positive values of mean Doppler velocity are toward the surface. The forward-modelled mean Doppler velocity neglects air motion, the effects of which are also included in the observational uncertainty. In the stratiform snow events in this study we assume that the mean Doppler velocity is dominated by the terminal velocities of hydrometeors rather than vertical air motions. In convective situations or where ice particles are very small, this assumption may not be justified, and would lead to a misdiagnosis of particle density; this will be considered in Section 4.1.

475

2.4.3 Scattering models

In addition to the density and shape of snow particles (Section 2.2), variability in par-476 ticle morphology has a significant impact on the scattering of microwave radiation, which 477 must be approximated within the radar forward-model. The self-similar Rayleigh-Gans ap-478 proximation [SSRGA; Hogan and Westbrook, 2014; Hogan et al., 2017] provides an accurate 479 estimate of the radar backscatter cross-section for unrimed aggregates, but underestimates 480 the radar backscatter of higher-density rimed particles. Snow particles have often been ap-481 proximated by "soft spheroids"-oblate spheroids composed of a homogenous mixture of ice 482 and air—for which the radar backscatter can be estimated using the **T**-matrix method [e.g. 483 Hogan et al., 2012]. Leinonen and Szyrmer [2015] found that soft spheroids provide a good 484 approximation to the backscatter of dense graupel-like particles, but not to rimed aggregates. 485 In both approximations particles are represented as occupying the volume of horizontally-486 aligned oblate spheroids with an aspect ratio of AR = 0.6 [Hogan et al., 2012]. 487

In the absence of an explicit model for rimed aggregates, we represent the backscatter 488 cross-section in the transition from unrimed aggregates to graupel as an external mixture be-489 tween SSRGA ($r \le 0.2$) and soft spheroids ($r \ge 0.5$). These thresholds were selected based 490 on the ranges of density factors associated with mass-size relations for studies of unrimed ag-491 gregates and graupel (Fig. 1). As a check on this representation, the forward-modelled radar 492 backscatter from a gamma distribution of particles was used to generate dual-wavelength ra-493 tios (DWRs) at Ka–W-bands and X–Ka-bands for a range of density factors (Fig. 5); these 494 curves are overlaid with triple-frequency radar measurements from three snow events during 495

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BAECC 2014 [Kneifel et al., 2015, c.f. their Fig. 1]. A thin contour highlights the most fre-496 quent DWRs observed during the snow event that is studied in Section 4.1. The upright band 497 of $DWR_{Ka-W} < 10 \text{ dB}$ and large DWR_{X-Ka} corresponds to the "hook" feature identified for 498 unrimed aggregates, while the flat feature with low DWR_{X-Ka} is associated with denser 499 graupel-like particles. The triple-frequency signatures represented by SSRGA ($r \le 0.2$) 500 resemble those of unrimed aggregates, while the soft spheroids ($r \ge 0.5$) fit the flatter sig-501 nature associated with graupel. This demonstrates that a simple hybrid representation at 502 least qualitatively permits the signatures of unrimed aggregates and dense rimed particles in 503 multiple-frequency radar observations-but does not necessarily address known limitations 504 in the soft spheroid approximation for a range of dense particles [Leinonen and Szyrmer, 505 2015; Hogan et al., 2017]. The modelling and measurement of the morphology and multiple-506 frequency radar scattering of ice particles are of significant research interest [e.g. Kneifel 507 et al., 2018], and improved approximations for the backscatter cross-sections for rimed ag-508 gregates will both reduce uncertainties in the present retrieval, and allow for increased confi-509 dence in multiple-frequency radar retrievals of snow. 510

518 2.4.4 Measurement vector

The vector of observed variables for a dual-frequency Doppler radar retrieval is

$$\mathbf{y} = \begin{pmatrix} Z_{f_0} \\ V_{f_0} \\ Z_{f_1} \\ V_{f_1} \end{pmatrix}.$$

In principal more than two radar frequencies could be included in the measurement vector; and in practice, as discussed in the next section, some of the observed variables may not be assimilated in the present study.

The uncertainties in the measurement vector includes the stated measurement error for the instruments (Table 2), other sources of observational uncertainty, and an estimate of the uncertainties in the assumptions that form the basis of the instrument forward-model. For a retrieval that relies upon the mean Doppler velocity to estimate the properties of hydrometeors, the treatment of and sensitivity to uncertainties in Doppler measurements are of particular interest. For the present study we assume uncertainties of 3 dB in the radar reflectivities and 1.0 m s^{-1} in the mean Doppler velocity.



Figure 5. Joint histogram of measured dual-wavelength ratios (DWRs) for triple-frequency radar observations from the three cases studied in *Kneifel et al.* [2015]; a thin contour encloses the most frequent measurements during the February 21–22 2014 case considered in Section 4.1, highlighting distinct features associated with aggregates and graupel. Black curves represent the forward-modelled DWR for an exponential distribution of particles with density factors from unrimed aggregates (using SSRGA for r < 0.2) to graupel ("soft spheroids" for r > 0.5); the transition between rimed aggregates and graupel is represented by an external mixture of the two approximations to the radar backscatter cross-section.

529 **3 BAECC 2014 data**

530	As part of the Biogenic Aerosols—Effects on Clouds and Climate field campaign
531	[BAECC 2014; Petäjä et al., 2016], the US Department of Energy atmospheric radiation
532	measurement (ARM) program's second mobile facility (AMF2) was deployed at the Univer-
533	sity of Helsinki's Hyytiälä forestry field station (61°51'N, 24°17'E). The remote-sensing and
534	in situ instrumentation, and their deployment are documented in Kneifel et al. [2015]. Be-
535	tween 1 February and 31 March 2014 the snowfall measurement experiment (SNEX) inten-
536	sive observation period (IOP) focused on the measurement of snow microphysics. Remote-
537	sensing observations include vertically-pointing Doppler radars, lidar and microwave ra-
538	diometer instruments, and the state of the atmosphere from reanalysis (Section 3.1) will be
539	evaluated against in situ measurements at the surface (Section 3.2).

540

3.1 Remote sensed measurements

Two vertically-pointing Doppler radars are the primary remote-sensing instruments 541 in this study. The 35 GHz Ka-band Zenith Radar (KAZR) and the 95 GHz Marine W-band 542 cloud radar (MWACR) were deployed at Hyytiälä during the SNEX IOP. Due to a mispoint-543 ing of MWACR, mean Doppler velocity measurements from that radar are not used in this 544 study. It is important that KAZR and MWACR sampling volumes are broadly overlapping; 545 both radar measurements are resampled from approximately 2 s to 120 s. Calibration of 546 MWACR and KAZR against a colocated vertically-pointing X-band radar is carried out as 547 described in Kneifel et al. [2015], after accounting for attenuation due to atmospheric gases 548 and liquid; when X-band radar is not available the most recent calibration is applied, and 549 MWACR radar reflectivity is calibrated against KAZR radar reflectivity at cloud-top after 550 correcting for attenuation. 551

Additional observations are available from the AMF2 high-spectral resolution lidar (HSRL), which measures molecular and particulate backscatter at 532 nm with gate spacing of 30 m and temporal resolution of 120 s. HSRL could be used for radar–lidar synergy retrievals of non-precipitating ice cloud, where the lidar provides valuable information on smaller ice particles and liquid droplets; however, in the rimed snow events of interest here the lidar is completely attenuated by liquid water near the surface. HSRL data are therefore presented alongside the radar data, but are not assimilated in the retrieval.

Instrument	KAZR	MWACR
Frequency	35 GHz	95 GHz
Wavelength	8.6 mm	3.2 mm
Gate spacing	30 m	30 m
Beam width	0.38°	0.3°
Reflectivity uncertainty	1 dB	1 dB
Mean Doppler velocity uncertainty	$0.5ms^{-1}$	n/a

Table 2. AMF2 zenith-pointing radar instruments and observational uncertainties

560	Microwave radiometer (MWR) measurements at 23.8 and 31.4 GHz are used to re-
561	trieve liquid water path (LWP) and water vapour path [Cadeddu et al., 2013]. While mi-
562	crowave radiometer measurements are not included in the retrieval, estimates of LWP pro-
563	vide information on the magnitude of supercooled liquid water (SLW) that are used to cor-
564	rect for radar attenuation due to liquid (discussed above and in Section 2.4) and to provide
565	context for the retrieval of riming based on the availability of supercooled liquid water in
566	mixed-phase clouds [e.g. Kalesse et al., 2016; Moisseev et al., 2017].

To assist in interpreting the remote-sensed data, atmospheric state profiles are obtained from European Centre for Medium-Range Weather Forecasts (ECMWF) re-analysis at 1 hour temporal resolution over the site. Variables are re-interpolated onto a height grid using pressure measurements from 6 hourly radiosondes. Profiles of atmospheric temperature, pressure and humidity are used in the target classification scheme and within the retrieval algorithm to estimate radar attenuation due to atmospheric gases.

Prior to the retrieval remote-sensed and atmospheric data are averaged onto a common grid using the reflectivity-weighted mean Doppler velocity for averaging. A detection
mask is generated for each radar instrument, using the texture of the mean Doppler velocity
[*Helmus and Collis*, 2016] and radar signal-to-noise ratio after subtracting an estimate of the
noise.

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3.2 In situ measurements

The BAECC 2014 campaign provides a valuable opportunity to evaluate remote-sensed estimates of snow against reliable and sustained in situ observations at the surface; this is

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rarely possible at lower latitudes where both in situ and millimeter-wavelength radar mea-581 surements are affected by melting. Images of ice particles from the precipitation imaging 582 package (PIP) video disdrometer [Newman et al., 2009] are converted to measurements of 583 particle number concentration, size, area and fallspeed. The mass of each particle is esti-584 mated from PIP observations of particle size, area and terminal velocity as described in von 585 Lerber et al. [2017]; the maximum dimension of the ice particles are scaled to derive the par-586 ticle masses that result in the best fit with snow accumulation measured by nearby Pluvio 587 snow gauges. PIP measurements at 5 min resolution are used, and shifted by 5 minutes for 588 comparison against remote-sensing measurements around 500 m above ground level. Kneifel 589 et al. [2015] discuss a more precise approach to estimating the time-lag for evaluation against 590 the lowest radar gates, but given the time-averaging used in this retrieval a constant lag was 591 sufficient. 592

The median diameter D_0 and normalized number concentration N_w parameters are derived from the measured particle size distribution. Ice particle bulk density is estimated from PIP measurements using the measured PSD and velocity-size relation, and estimated mass-size relation according to (4) [*von Lerber et al.*, 2017]. This method was found to be consistent with complementary methods using the Pluvio snow accumulation to estimate the bulk density of ice [*Tiira et al.*, 2016; *Moisseev et al.*, 2017].

599 4 Results

- We first demonstrate the retrieval for a case study (Sec. 4.1), before presenting statistical evaluation of retrievals over 10 snow events during the SNEX IOP (Sec. 4.2).
- 602

4.1 Case study: February 21–22 2014

At 23:00 UTC on February 21 2014 a warm occluded front passed over Hyytiälä,

⁶⁰⁴ bringing about an hour of snow dominated by large aggregates. The light pre- and post-

frontal snow was characterised by rimed particles, including both heavily rimed aggregates

- and graupel. With a total melted-equivalent accumulation of 5 mm comprising rimed and
- ⁶⁰⁷ unrimed snow, this event has been extensively studied with in situ [*Tiira et al.*, 2016; *von*
- Lerber et al., 2017; Moisseev et al., 2017] and radar remote-sensing [Kneifel et al., 2015;
- Kalesse et al., 2016] methods. The remote-sensed and in situ measurements for this case are

shown in Figs. 6 and 7, respectively. We divide the case into pre-frontal, frontal and postfrontal regimes.

In the prefrontal regime (18:00 to 23:00 UTC) snowfall is relatively constant with 612 melted-equivalent rates between 0.2 and 1 mm h^{-1} (Fig. 7d) from clouds with tops around 613 5 km and -20 °C (Fig. 6a–c). Particles measured in situ are dominated by a high concen-614 tration of compact ice particles, with bulk densities between $200-400 \text{ kg m}^{-3}$. PIP imagery 615 confirms the presence of graupel during this period [Fig. 14 from Kneifel et al., 2015]. In 616 the hour prior to the front, cloud-top lowers to around 3 km and -15 °C, and relatively little 617 snow is measured at the surface. Moisseev et al. [2017] and von Lerber et al. [2017] note that 618 the low particle counts measured by PIP during this period lead to reduced confidence in the 619 retrieved quantities, and the bulk density (Fig. 7d) is not retrieved here. 620

The frontal regime (23:00 and 00:00 UTC) brings heavier snow with a peak snowfall rate of 4.0 mm h⁻¹, and PIP imagery and measurements indicate large aggregates with median diameters up to 5 mm (Fig. 7d); however, particle fallspeeds do not exceed 1.5 m s^{-1} (Fig. 7b). Here cloud-top is around 9 km and the maximum KAZR reflectivity factor exceeds 20 dBZ near the surface.

The post-frontal regime (00:00 to 03:00 UTC) is dominated by patchy and very light snow with the exception of two showers in which the snow rate exceeds 2 mm h^{-1} ; cloudtop is again between 3 and 5 km. PIP measurements of bulk density are higher than in the pre-frontal period, between 200 and 500 kg m⁻³, and the particle size distribution confirms that the post-frontal snow features a higher concentration of larger and fast-falling particles, which *von Lerber et al.* [2017] noted comprised a mixture of rimed aggregates and graupel.

The presence of rimed snow and graupel throughout the pre- and post-frontal regimes 632 is indicative of persistent mixed-phase cloud layers in the lower atmosphere; however, the 633 vertical distribution of supercooled liquid water cannot be observed directly. The liquid wa-634 ter path retrieved from microwave radiometer (Fig. 6f) and strong HSRL backscatter (Fig. 6d) 635 in the lowest liquid layers suggest that the vertically-integrated amount of liquid water in-636 creases throughout the case, while the cloud base lowers. Above this lowest layer, Kalesse 637 et al. [2016] used Doppler spectra and soundings to infer the presence of embedded mixed-638 phase cloud layers around 1 and 3.2 km. The exception is in the frontal snow, when both mi-639 crowave radiometer and lidar backscatter indicate that the liquid water layers are depleted 640 [Moisseev et al., 2017]. Visual inspection of the mean Doppler velocity (Fig. 6c) hints at the 641

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signature of mixed-phase cloud layers in the reflectivity-weighted average fallspeed of snow 642 particles: the largest near-surface mean Doppler velocities correspond in time to maxima in 643 LWP around 22:00, 01:00 and 02:20 UTC (Fig. 6f) during the pre- and post-frontal regimes, 644 while the frontal regime represents a minimum in both mean Doppler velocity and LWP de-645 spite being the period during which the greatest snow rate and particle size are measured. 646 Through the vertical profile, increases in the mean Doppler velocity are evident at or around 647 1 and 3 km, which may be related to the onset of riming in mixed-phase cloud layers. A more 648 quantitative estimate of riming will be made using the CAPTIVATE retrieval algorithm. 649

The CAPTIVATE retrieval is applied to the February 21 case, assimilating 35- and 659 94-GHz radar reflectivities and 35-GHZ mean Doppler velocity (hereafter "ZZV"). Re-660 call that the 94-GHz Doppler velocity is not used due to a mispointing error. The retrieved 661 state variables are the extinction coefficient, primed number concentration and density in-662 dex (hereafter " $\alpha_v N'_0 r'$ "). As a check on the quality of the retrieval, we confirm that the best 663 estimate of the state can be used to forward-model the observed MWACR radar reflectiv-664 ity (Fig. 8a&b) and KAZR mean Doppler velocity (Fig. 8c&d). Rather than report the val-665 ues of the state variables directly, we derive more physically meaningful parameters from 666 the retrieval: the melted-equivalent snow rate (Fig. 8e), normalized number concentration 667 (Fig. 8f), median diameter (Fig. 8g), and the density factor (Fig. 8h). In the prefrontal regime 668 snow rate reaches $0.1-1.0 \text{ mm h}^{-1}$ below 3 km. In the frontal regime the snow rate exceeds 669 1 mm h^{-1} between 5–7 km above ground level; toward the surface, number concentration 670 decreases while median diameter increases, suggesting growth by aggregation. In the post-671 frontal showers maxima in snow rate correspond to streaks of increased number concentra-672 tion and median diameter. Of primary interest is the retrieval of the density factor, which 673 increases to around r = 0.2 below 3 km in the pre-frontal and post-frontal regimes and up to 674 local maxima of 0.5 to 0.7 near the surface around 22:00, 01:00 and 02:20 UTC; in short, 675 the retrieved density factor maps closely to the regions of high mean Doppler velocity identi-676 fied earlier. In the pre-frontal regime small but non-zero density factors are retrieved in both 677 the cirrus and the midlevel cloud-tops, albeit with large estimated uncertainties (not shown); 678 much of this cirrus occurs below temperatures at which supercooled liquid—and therefore 679 riming-is to be expected (Fig. 6a-c), an occurrence which has not been excluded within 680 the retrieval. As discussed in Section 2.2.2, small non-zero density factors are within the ob-681 served variability of mass-size relations for unrimed particles; however it may also be the 682 case that vertical air motion dominates the mean Doppler velocity in this regions. 683

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Figure 6. AMF2 measurements from Hyytiälä between 2014-02-21 16:00 UTC and 2014-02-22 03:00
UTC. KAZR radar reflectivity (a) and mean Doppler velocity (b); MWACR radar reflectivity (c); HSRL attenuated Mie backscatter (d) and attenuated Rayleigh backscatter (e); and microwave radiometer LWP (f). Note
the different vertical scales for HSRL backscatter (d & e). Black contours are temperature from ECMWF
re-analysis; a darker line at -40°C denotes the temperature below which supercooled liquid water is not
expected.



Figure 7. In situ PIP measurements from Hyytiälä between 2014-02-21 16:00 UTC and 2014-02-22 05:00
UTC. Particle size and fallspeed are measured, while particle mass, snow rate and bulk density are estimated
as described in *von Lerber et al.* [2017].





4.1.1 Profiles

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In addition to assimilating all available radar measurements and retrieving all state variables, it is of interest to explore the relative contributions of Doppler and dual-frequency measurements to the CAPTIVATE retrieval. These configurations are more easily compared at selected profiles, each representing 120 S of averaged radar measurements. We select a profile from each of the snow regimes: a pre-frontal profile at 21:30 UTC (Fig. 9 I), a frontal profile at 23:20 UTC (Fig. 9 II), and a post-frontal profile at 02:20 UTC (Fig. 9 III).

The ZZV- $\alpha_v N'_0 r'$ retrieval of the pre-frontal profile (Fig. 9 I) shows snow rate increas-696 ing below 3 km to approximately 0.5 mm h^{-1} at the surface, concurrent with an increase in 697 the density factor to around r = 0.3 below 1 km. Large uncertainties in the retrieved density 698 factor reflect a large observational uncertainty of 1 m s^{-1} in the Doppler velocity; however, 699 we find that the retrieved density factor is robust to changes in the observational uncertainty. 700 When Doppler velocity is not assimilated (ZZ- $\alpha_v N'_0 r'$) there is little constraint on the den-701 sity factor, which remains close to r = 0. This leads to an underestimate in forward-modelled 702 mean Doppler velocity of as much as 1 m s^{-1} below 2 km, and N_w greater by a factor of 5 703 than that of ZZV– $\alpha_v N'_0 r'$; that is, when dense rimed particles are not retrieved, the lower 704 density of ice is compensated by a larger concentration of snow particles such that the snow 705 rate differs only slightly from that of ZZV- $\alpha_v N'_0 r'$. The ZZ- $\alpha_v N'_0 r'$ retrieval is very simi-706 lar to one in which Doppler velocity is available, but where all snow is assumed to be un-707 rimed aggregates (ZZV- $\alpha_v N'_0$; not shown). Conversely, when only MWACR reflectivities 708 are assimilated and the full state vector is retrieved (Z94V– $\alpha_v N'_0 r'$; the dark green line in 709 Fig. 9 I), the PSD diverges significantly from ZZV- $\alpha_{\nu}N_0'r'$. A much lower number concen-710 tration of larger particles is retrieved, with median diameter a factor of two larger than that 711 of $ZZV - \alpha_v N'_0 r'$. Despite a lower density factor, this retrieval appears well-constrained by 712 the Doppler velocity—but the forward-modelled DWR indicates that the larger particles lead 713 to an error in Ka-band reflectivity of around 4 dB near the surface. This is an example of an 714 under-constrained retrieval in which three state variables are estimated from two measured 715 variables. A better-posed retrieval can be made by treating the primed number concentration 716 as a model variable which does not vary from the prior Z94V– $\alpha_v r'$ (the bright green line in 717 Fig. 9). The results of this retrieval much more closely resemble ZZV– $\alpha_v N'_0 r'$, with reduced 718 errors in forward-modelled DWR and values of N'_0 and D_0 closer to their priors; therefore 719 in subsequent profiles only the Z94V– $\alpha_v r'$ will be compared with ZZV– $\alpha_v N'_0 r'$ and ZZ– 720 $\alpha_v N'_0 r'$. 721

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Figure 9. Forward-modelled measured variables and retrieved snow rate, normalized number concentration, median diameter and density factor for ZZV, Z94V and ZZ retrievals, for a profile at 21:30 UTC (I), 23:20 UTC (II) and 02:20 UTC (III) within the pre-frontal regime. Black solid lines indicate the observed variables, and dashed lines indicate the prior retrieved variables. Shading indicates the 5th to 95th percentile uncertainty of the retrieval.

In the frontal regime (Fig. 9 II) there is generally good agreement between retrievals, 722 which consistently represent a snow rate of 1 to 2 mm h^{-1} below 4 km; this relatively constant 723 mass flux corresponds with increasing median diameter and decreasing number concentra-724 tion consistent with strong aggregation in the shower, and confirmed by the large aggregate 725 snowflakes observed at the surface (Fig. 7). Both ZZV and Z94V diagnose smallnon-zero 726 density factors below about 4 km, without which ZZ under-estimates the mean Doppler ve-727 locity by around 0.5 m s^{-1} . In the mid-levels Z94V overestimates KAZR radar reflectivities, 728 once again due to a smaller concentration of larger particles. In most other regards the re-729 trievals are similar until near cloud-top, where relatively large Doppler velocities lead to the 730 retrieval of small to moderate density factors in ZZV and Z94V which are unphysical (the 731 contours in Fig. 6 indicate that the temperature is below -40° C at these heights), and may be 732 a result of vertical air motion in the cirrus. In stratiform precipitation, the retrieval of dense 733 ice due to small-scale turbulent features in vertical air motion is somewhat suppressed by 734 the use of a Kalman smoother in the retrieval of the density index; however, it would also be 735 possible within CAPTIVATE to reduce prior uncertainty in the density factor where riming 736 is unlikely, or to apply higher uncertainties to mean Doppler velocity measurements where 737 larger contributions from vertical air motion are expected. 738

In the postfrontal regime (Fig. 9 III) the Doppler velocity reaches 3 m s^{-1} below 1 km, 739 where ZZV and Z94V estimate density factors around r = 0.6; ZZ does not diagnose resolve 740 this increase in particle density, and the corresponding forward-modelled mean Doppler ve-741 locity differs from observations by almost 2 m s⁻¹ along with overestimates in both number 742 concentration and median size. While ZZV and Z94V converge upon similar PSDs below 743 1.5 km where the Doppler signal is strong, near the top of the cloud Z94V remains closer to 744 its priors (recall that N'_0 does not vary in this retrieval), leading to a much higher concentra-745 tion of small particles and a significant under-estimate of the KAZR radar reflectivity above 746 1.5 km. 747

While the uncertainties in the retrieved density factor are constrained in the parts of the profile where the mean Doppler velocity of denser particles differ significantly from that of unrimed aggregates—typically below 2 or 3 km in these profiles—very large density factor uncertainties are evident aloft. In these regions the Doppler velocity contains little information about variations in density because the smallest particles are assumed to be solid quasispheroidal particles for all values of the density factor (see Fig. 3).

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4.1.2 Comparison against in situ measurements

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We now evaluate the CAPTIVATE retrievals against in situ measurements at the surface; ZZV, Z94V and ZZ estimates of snow rate, normalized number concentration, median diameter, and bulk density averaged over the radar gates up to 600 m above ground level are compared against those from PIP (Fig. 10).

All of the CAPTIVATE retrievals of snow rate are within the range of uncertainty of PIP snow rate, with under-estimates of up to 50 % especially evident in frontal and postfrontal showers. As was also the case in the analysis of profiles, the estimated snow rates are remarkably consistent between the different retrievals; this is despite significant differences in estimates of particle size, number concentration and density.

As they often compensate for one another, the parameters of the PSD are evaluated 769 together. ZZV and ZZ estimates of median diameter (Fig 10c) are within 50 % of PIP mea-770 surements, and estimates of normalized number concentration (Fig 10b) are usually within 771 the retrieval uncertainty—with errors of up to a factor of five—of PIP measurements. With-772 out a dual-frequency constraint on particle size and therefore fewer state variables retrieved, 773 the Z94V– $\alpha_v r'$ estimates of N'_0 and D_0 are less able to resolve the distinct snow regimes: in 774 the pre-frontal period Z94V number concentrations exceed PIP measurements by up to an or-775 der of magnitude while particle sizes may be double the surface observations; the inverse is 776 true in the post-frontal period. 777

Finally we evaluate the retrieval against in situ measurements of bulk density (Fig. 10d). 778 The volume flux-weighted bulk density is estimated from retrieved particle properties consis-779 tent with eq. 4, in which the mass- and velocity-size relations are modulated by the retrieved 780 density factor. We compare this remote-sensed estimate against two in situ retrievals of bulk 781 density from PIP measurements [von Lerber et al., 2017] and a combination of PIP and Plu-782 vio snow gauge measurements [Moisseev et al., 2017] to constrain the total accumulation; we 783 note that the former method was calibrated against the latter, so these two retrievals are not 784 independent. The retrieved density factor and median diameter are both important to the es-785 timated bulk density; when constrained by both Doppler and dual-frequency measurements, 786 ZZV is therefore broadly capable of resolving the bulk density measured by PIP, although 787 we note underestimates of 25-50 % between 20:30 and 22:00 in the pre-frontal period, and 788 between 01:00 and 01:45 in the post-frontal period. Errors in Z94V estimates of median di-789 ameter can either exacerbate (in the pre-frontal regime) or mask (in the post-frontal) errors 790



Figure 10. Time series comparing mean retrieved variables over the lowest radar gates (between 300 m and 600 m) against the in situ PIP measurements at the surface. Shaded areas indicate the 5th and 95th percentile uncertainty of the retrieval. Surface observations are shifted by 5 minutes. The bulk ice density is discontinuous where very small median diameter leads to erroneously high densities, as discussed in *von Lerber et al.* [2017].

⁷⁹¹ in the bulk density: as discussed above, with a weaker constraint on particle size Z94V does ⁷⁹² not resolve the compact graupel ahead of the front, and underestimates post-frontal particle ⁷⁹³ size. Conversely, without Doppler information the bulk density estimates from ZZ are chiefly ⁷⁹⁴ a function of particle size: density rarely exceeds 200 kg m⁻³ except immediately ahead of ⁷⁹⁵ the front, when median diameters of less than 1 mm are estimated.

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4.1.3 Riming as an indicator of mixed-phase cloud

While CAPTIVATE has been developed for radar-lidar-radiometer synergy retrievals, 797 in the present case the lidar is fully extinguished within less than 1 km of the surface in the 798 lowest of several shallow layers of mixed-phase cloud. Our retrievals assimilate radar reflec-799 tivity and mean Doppler velocity, both of which are dominated by backscatter from larger 800 ice particles; the Doppler spectrum or its higher moments can sometimes be used to iden-801 tify the presence of liquid cloud [Kalesse et al., 2016], although the broader applicability of 802 these methods can be limited, especially for retrievals from airborne and spaceborne plat-803 forms where spectral broadening is significant [e.g. *Illingworth et al.*, 2015]. The density of 804 ice particles has been retrieved based on mean Doppler velocity, relying on approximations 805 to the morphology of ice particles from unrimed aggregates to graupel and their associated 806 terminal fallspeeds. We hypothesise that the primary process by which high density factors 807 occur is the riming of ice particles within mixed-phase clouds. An independent source of in-808 formation on the potential for riming is LWP retrieved from the microwave radiometer; von 809 Lerber et al. [2017] used LWP as a proxy for riming, and the connection between LWP and 810 rime mass fraction is also demonstrated from in situ retrievals in Moisseev et al. [2017]. 811

For the present case, the timeseries of LWP is strongly correlated to the CAPTIVATE 812 retrievals of density factor in the near-surface gates (Fig. 11a; ZZV- $\alpha_v N'_0 r'$). The highest 813 density factors correspond to the presence of significant mixed-phase cloud in the pre- and 814 post-frontal periods, and the dominance of unrimed aggregates to the depletion of liquid ev-815 ident during the frontal snow. The scatter plot of the LWP versus the retrieved density factor 816 (Fig. 11b) is coloured by the mean Doppler velocity and sized by retrieved median diameter. 817 At low LWP particles tend to be large unrimed aggregates with mean Doppler velocities less 818 than 2 m s⁻¹. Moderate LWP profiles correspond to particles ranging from larger rimed ag-819 gregates with 0.0 < r < 0.2, to compact rimed aggregates (0.2 < r < 0.5). At high LWP the 820 snow is dominated by graupel (0.5 < r < 0.8), with some instances of larger, fast-falling and 821 heavily-rimed aggregates. 822

In summary, the February 21 2014 case study includes significant riming below around 826 3 km during pre- and post-frontal snow, interrupted by a frontal shower dominated by large 827 aggregate snowflakes. Mean Doppler velocity provides an effective constraint on estimates 828 of the density factor, retrieved values of which varied from $r \approx 0.1$ for unrimed aggregates 829 $r \approx 0.6$ for graupel. Dual-frequency radar reflectivity proved critical to constraining esti-830 mates of the particle size distribution, leading to significant improvements in retrieved quan-831 tities when compared with in situ measurements at the surface. While the single-frequency 832 retrieval was capable of similar estimates of snow rate and density factor, the retrieval was 833 better constrained when a single parameter of the PSD was retrieved, leading to estimates 834 closer to the priors in which compact pre-frontal graupel was not resolved. Our hypothesis 835 that the retrieved density factor varies chiefly due to the riming of ice particles in mixed-836 phase cloud layers is supported by a strong association between the density factor and an 837 independent estimate of supercooled liquid water. 838

4.2 SNEX 2014 IOP

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In this section the LWP is used as an indicator of the availability of SLW for riming, 840 hence to distinguish between unrimed and rimed snow, and heavily rimed snow or graupel. 841 Snow events during the SNEX IOP were identified by von Lerber et al. [2017] wherein sig-842 nificant snow was falling at the surface and the surface temperature was below freezing (Ta-843 ble 3). A probability density function of LWP over the SNEX IOP (Fig. 12a) illustrates that, 844 while the majority of the snow events during the period occurred in low-LWP conditions, 845 significant SLW is relatively frequent during the IOP. Following a similar distinction made 846 in von Lerber et al. [2017], three ranges of LWP are used to distinguish between unrimed 847 $(LWP < 0.1 \text{ kg m}^{-2})$, moderately rimed $(0.1 \le LWP < 0.3 \text{ kg m}^{-2})$, and heavily rimed snow 848 or graupel (LWP ≥ 0.3 kg m⁻²). In that study the mass-size and fallspeed-size relations from 849 in situ measurements of particles were shown to be consistent with the LWP classification. 850 Unrimed snow accounts for just over half of the profiles; rimed snow around 30 %, and grau-851 pel around 10 %; in the rest, no significant snow was measured and the profile was skipped. 852 While the unrimed snow is associated with the coldest surface temperatures (Fig. 12b) on 853 average, all three categories are most frequent at temperatures just below freezing; it is not 854 evident that the riming events can be distinguished by temperature. Similarly, the low-LWP 855 regime includes almost all events with low relative humidities (Fig. 12c), but all categories 856 occur most frequently at relative humidities greater than around 90 %. 857



Figure 11. Time series (a) and scatter plot (b) of $ZZV - \alpha_v N'_0 r'$ density factor in the lowest radar gates (300m to 600m) against LWP measured by the microwave radiometer. In the scatter plot the markers are coloured by the mean Doppler velocity, and sized according to the retrieved median diameter.

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Surface temperature (°C) Date (UTC) 2014 Melted-equivalent Min Max accumulation [mm] *1 Feb 00:00-06:00 7.4 -9.8-8.9*1 Feb 10:00—16:00 -7.9 -7.01.4 2 Feb 16:00-19:00 1.7 -5.4-5.2 12 Feb 04:00-09:00 0.8 -1.00.0 15 Feb 21:00-16 Feb 02:00 -2.1-1.02.6 21 Feb 16:00-22 Feb 03:30 5.0 -2.70.0 15 Mar 05:00-07:00 0.3 -2.0-1.3 *18 Mar 08:00-19:00 4.4 -3.8 -1.819 Mar 00:00-20:00 1.5 -7.3 -3.7 20 Mar 16:00-00:00 6.1 -4.3-1.3

Table 3.Snow events during SNEX 2014 IOP

* Denotes events where dual-frequency radar data were not always available.

The CAPTIVATE best estimate $(ZZV - \alpha_v N'_0 r')$ was run over approximately 55 hours of available dual-frequency Doppler radar data. Joint histograms of the profile of forwardmodelled observed variables and retrieved variables are shown for each of the LWP classifications (Fig. 13).

The unrimed snow (Fig. 13-I; $LWP < 0.1 \text{ kg m}^{-3}$) is associated with the lowest mean 865 Doppler velocities (Fig. 13-Ib), which average around 1 m s^{-1} near the surface and never ex-866 ceed 2 m s^{-1} . The corresponding median density factor (Fig. 13-Ig) is between 0 and 0.2 867 below 4 km; this is consistent with the finding of Moisseev et al. [2017] that the mass-size of 868 unrimed aggregate snow at Hyytiälä is consistently higher than that of Brown and Francis 869 [1995], corresponding to roughly r = 0.15 in Fig. 1. In the earlier profile of unrimed snow 870 (Fig. 9 II) it was noted that ice water content remained constant with height near the surface 871 while diameter increased and number concentration decreased; these characteristic features 872 of aggregation are robustly present in approximately 30 hours of aggregate snowfall, with 873 the median snow rate (Fig. 13-Id) constant below 3 km, concurrent with an increase in me-874 dian size (Fig. 13-If) and a decrease in number concentration (Fig. 13-Ie) toward the surface. 875 The gradient in D_0 represents roughly a doubling in median particle diameter over 2 km. The 876 Ka-W dual-wavelength ratio increases below 3 or 4 km to a median of around 5 dB; how-877 ever, comparison to the triple-frequency data (Fig. 5) shows that values in this range are not 878 unique to either aggregates or graupel; a third radar frequency would provide valuable infor-879 mation to help constrain a retrieval based on the different scattering signatures of unrimed 880 aggregates and heavily rimed particles.

In the rimed snow (Fig. 13 II; $0.1 \le LWP < 0.3 \text{ kg m}^{-3}$) mean Doppler velocities 882 (Fig. 13IIb) are between 1 and 2 m s^{-1} near the surface, corresponding to density factors 883 that increase below about 4 km to between 0 and 0.4 in the lowest 2 km. Unlike the unrimed 884 snow, the snow rate (Fig. 13 IId) continues to increase toward the surface, indicating an ad-885 dition of ice water content which may be due to accretion of supercooled liquid or vapour 886 deposition. The near-surface gradients of N'_0 and D_0 (Fig. 13 IIe & f) are not significantly 887 reduced from those in unrimed snow, so it seems likely that a mix of aggregation, riming and 888 deposition processes occur within this regime. 889

Finally, the heavily rimed snow or graupel (Fig. 13 III; $LWP \ge 0.3 \text{ kg m}^{-3}$) is associated with mean Doppler velocities (Fig. 13 IIIb) up to 3 m s⁻¹ and density factors (Fig. 13 IIIg) increasing steeply below 3 km up to as much as r = 0.5 with a median around r = 0.3.

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Unlike the unrimed and rimed snow regimes, the snow rate in this regime increases rapidly 893 toward the surface, with the median snow rate increasing by an order of magnitude over the 894 lowest 2 to 3 km—a rate similar to that in the upper-level clouds of all regimes—however, 895 D_0 and N'_0 are near-constant in the lower levels. This is consistent with an accretion of mass 896 due to riming, although deposition cannot be ruled out. An increase in normalized number 897 concentration may be discernible near the surface (Fig. 13 IIIg), perhaps suggesting a relative 898 increase in the concentration of small particles, or a breakup of larger particles. This may 800 be indicative of a secondary ice generation process such as rime splintering; however, more 900 work would be required to confirm this, and to what degree the present retrieval may help in 901 the study of secondary ice processes. 902

An evaluation of the CAPTIVATE retrieval over all available dual-frequency Doppler radar data from the SNEX IOP has shown characteristic differences between the profiles of snow rate, PSD parameters and density factor between profiles of unrimed and rimed snow. LWP provides a suitable proxy to distinguish between unrimed and heavily rimed snow events. This initial analysis has focused on demonstrating the potential to resolve key microphysical processes from the Doppler velocity; however, many other analyses of the meteorological and thermodynamical context of riming and aggregation processes may be envisaged.

5 Discussion and conclusions

The morphology of an ice particle is a record of the microphysical processes by which 911 it forms; in this study we have proposed a simple parameterisation for the representation of 912 the wide range of ice particle densities and shapes from unrimed aggregate snowflakes to 913 graupel and hail. Remote-sensed estimates of snow typically assume snow particles that re-914 semble unrimed aggregates; however, riming is both a critical process for surface hydrology 915 and a control on radiatively-important mixed-phase clouds which are difficult to remote-916 sense and poorly represented in numerical models. We have demonstrated a method for di-917 agnosing riming within the framework of CAPTIVATE, an optimal estimation algorithm for 918 radar-lidar-radiometer retrievals of clouds, aerosols and precipitation. 919

The retrieved density factor modulates the density, shape and radar scattering crosssection of ice particles, and is chiefly inferred from mean Doppler velocity, a measure of reflectivity-weighted particle terminal velocities. Many refinements to this parameterisation may be envisaged to better represent the microphysical processes in question, and the

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sensitivity of the retrieval to the formulation of the density factor and its effect on the mass, 924 area and scattering cross-sections of ice particles requires further study. An alternative pa-925 rameterisation intended to more closely resemble the conceptual model for the riming of 926 aggregate snowflakes was tested using a reference mass-size relation for unrimed aggregates 927 at Hyytiälä [von Lerber et al., 2017] with a constant exponent of $b_m = 2.1$, and where only 928 the prefactor of the mass-size relation was scaled with the density factor. This representa-929 tion is more consistent with the conceptual model of the "in-filling" stage of riming, but does 930 not encompass the observed variability amongst unrimed snowflakes or the higher exponents 931 of heavily rimed graupel-like particles. The retrieved snow rate and PSD were not strongly 932 sensitive to changes in how particle density is allowed to vary, suggesting the two parame-933 terisations allow for similar representation of unrimed to lightly rimed aggregates despite 934 some change in the mass-size exponent; however, in situ measurements of snow rate and bulk 935 particle density agreed better with the original retrieval in the densest post-frontal snow, sug-936 gesting the advantages of representing a broader range of particle morphologies, especially 937 of heavily rimed graupel-like particles. Our prior density factor of r = 0 relates to the un-938 rimed aggregates of Brown and Francis [1995], but it may be possible to implement more 939 sophisticated priors or constraints on the retrieval based on the atmospheric state [e.g. Lin 940 and Colle, 2011; Szyrmer and Zawadzki, 2014], or from regional climatologies, to better 941 resolve this variability; for example, Moisseev et al. [2017] showed that the lowest-density 942 particles at Hyytiälä were significantly more dense than those of Brown and Francis [1995], 943 and this could be represented with an updated prior of $r \approx 0.15$ near the surface. Concurrent 944 remote-sensed and in situ measurements from the BAECC 2014 campaign have provided an 945 invaluable opportunity to evaluate retrievals of rimed snow. Sustained particle imaging and 946 multiple-frequency radar measurements from Hyytiälä and other ARM and CloudNet "super-947 sites" will provide critical datasets for the improved representation of snow microphysics, as 948 well as validation for future satellite retrievals. 949

The CAPTIVATE retrieval was applied to vertically-pointing Ka- and W-band Doppler radar measurements from 10 snow events over the SNEX IOP of BAECC 2014. Dual-frequency and Doppler radar measurements provided sufficient information to retrieve two parameters of the PSD as well as the density factor. The dual-frequency radar reflectivities and mean Doppler velocity make distinct contributions to the retrieval, with radar reflectivities at Kaand W bands providing a strong constraint on the particle size distribution but relatively little information on density; Doppler velocity provided the sole constraint on the density factor.

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Estimates of near-surface snow rate were within 50 % of in situ measurements both with and 957 without Doppler and dual-frequency measurements, showing a remarkably robust retrieval of 958 ice water content from 94-GHz radar reflectivity; however, to accurately estimate the param-959 eters of the PSD as well as the bulk ice density, it was important to have both dual-frequency 960 and Doppler information. With the recent availability of multiple-frequency Doppler radar 961 observations of snow, and supported by observational and theoretical insights into the triple-962 frequency signatures of rimed and unrimed ice [e.g. Kneifel et al., 2018], it will become in-963 creasingly important to quantify the information content of each additional observational 964 variable within an optimal estimation framework. 965

The retrieval of riming provides an indirect insight into the presence of supercooled liquid water, and it may hence be possible to use spaceborne Doppler radars to better quantify the frequency and distribution of embedded mixed-phase clouds—at least where pre-968 cipitating ice is present. Using LWP as a proxy for riming provided a robust distinction be-969 tween retrieved snow profiles of unrimed aggregates, rimed aggregates and graupel; no such 970 clear distinction was evident in surface temperature or relative humidity. For profiles with 971 low LWP the dominant growth process near the surface was aggregation, while in high-LWP 972 conditions the accretion of ice mass due to riming was evident. The ability to distinguish be-973 tween microphysical processes through the profile suggests the potential for using multiple-974 frequency and Doppler radars to estimate rime mass content and relate it to the budget of 975 supercooled liquid [e.g. Moisseev et al., 2017], as well as to estimate microphysical process 976 rates [e.g. Mace and Benson, 2017]. These features were best resolved in retrievals com-977 bining dual-frequency and Doppler measurements; however, the onset of riming was also 978 reliably detected with single-frequency radar retrievals, which could be sufficient to provide 979 improved insights into the position of embedded mixed-phase layers within optically thick 980 ice clouds from space. 981

In the mixed-phase cloud situations in which riming occurs, ground-based lidars are 982 quickly attenuated by liquid water near the surface. Therefore it was not possible in this 983 study to exploit radar-lidar synergy, either for the retrieval of ice [e.g. Delanoë and Hogan, 984 2010] or for a simultaneous estimate of ice and liquid; instead a correction for liquid atten-985 uation was applied to the radar reflectivity, and the retrieval carried out only for ice. LWP 986 estimates from a co-located microwave radiometer were combined with an assumption about 987 the vertical distribution of liquid water to estimate the radar attenuation as a pre-processing 988 step before the radar retrieval. A more satisfactory approach within the optimal estimation 989

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retrieval framework would be to include a microwave radiometer forward model and perform a synergy retrieval, building upon studies into the active and passive microwave scattering of snow [e.g. *Kneifel et al.*, 2010]. This would provide additional constraints on retrievals of cloud and precipitation to those provided by other passive shortwave and longwave radiances [e.g. *Leinonen et al.*, 2016] or path-integrated attenuation from surface radar backscatter [e.g *Haynes et al.*, 2009; *Hawkness-Smith*, 2010].

The CAPTIVATE retrieval has been developed for the synergy of EarthCARE's 94-996 GHz cloud profiling Doppler radar [Illingworth et al., 2015] with high-spectral resolution at-997 mospheric lidar and multi-spectral imaging radiometer. The capabilities of multiple-frequency 998 Doppler radars—as well as synergies with a range of active and passive measurements in-999 cluding microwave radiometers—are also of interest. In this study we have considered the 1000 contribution of Doppler velocity and dual-frequency radars to the optimal estimation of 1001 snow, following a previous study using airborne dual-frequency Doppler radars for CAP-1002 TIVATE retrievals of tropical rain [Mason et al., 2017]. Retrievals assimilating both dual-1003 frequency and Doppler radar measurements to retrieve two parameters of the ice PSD and 1004 the density factor performed best, producing estimates of particle number concentration, 1005 size and bulk density near the surface that were close to in situ measurements. A single-1006 frequency Doppler radar was best constrained when retrieving a single parameter of the 1007 PSD; however, we demonstrated that such a retrieval was sufficient to diagnose rimed snow 1008 in stratiform snow-wherein the mean Doppler velocity can be assumed to be dominated by 1009 hydrometeor fallspeed and not vertical air motion-and that the retrieval is robust to large 1010 observational uncertainties. The many challenges of making use of Doppler velocity mea-1011 surements from space-including vertical resolution, horizontal averaging [e.g. Kollias et al., 1012 2014], ground clutter, and radar mispointing [e.g. Battaglia and Kollias, 2015]—have not 1013 been considered here, and work is ongoing to apply radar simulators to airborne and ground-1014 based measurements or numerical models to better understand the outlook for retrievals 1015 from EarthCARE [e.g. Battaglia and Tanelli, 2011]. Beyond EarthCARE, the prospect of 1016 spaceborne multiple-frequency Doppler radars [National Academies of Sciences Engineering 1017 and Medicine, 2018] provides opportunities for further advancements in the global remote-1018 sensing of ice, including estimates of the morphology and microphysics of snow and insights 1019 into mixed-phase clouds. 1020

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- 1035 (github.com/dmoisseev/Snow-Retrievals-2014-2015).

1036 **References**

- Battaglia, A., and P. Kollias (2015), Using Ice Clouds for Mitigating the EarthCARE
 Doppler Radar Mispointing, *IEEE Transactions on Geoscience and Remote Sensing*,
 53(4), 2079–2085, doi:10.1109/TGRS.2014.2353219.
- Battaglia, A., and S. Tanelli (2011), DOMUS: DOppler MUltiple-Scattering Simula-
- tor, *IEEE Transactions on Geoscience and Remote Sensing*, 49(1), 442–450, doi:
- 10.1109/TGRS.2010.2052818.
- Brown, P. R. A., and P. N. Francis (1995), Improved Measurements of the Ice Water Content
 in Cirrus Using a Total-Water Probe, *Journal of Atmospheric and Oceanic Technology*,

¹⁰⁴⁵ *12*(2), 410–414, doi:10.1175/1520-0426(1995)012<0410:IMOTIW>2.0.CO;2.

- Cadeddu, M. P., J. C. Liljegren, and D. D. Turner (2013), The Atmospheric radiation mea-
- ¹⁰⁴⁷ surement (ARM) program network of microwave radiometers: instrumentation, data, and
- retrievals, *Atmospheric Measurement Techniques*, 6(9), 2359–2372, doi:10.5194/amt-6 2359-2013.
- Casella, D., G. Panegrossi, P. Sanò, A. C. Marra, S. Dietrich, B. T. Johnson, and
 M. S. Kulie (2017), Evaluation of the GPM-DPR snowfall detection capabil-
- ity: Comparison with CloudSat-CPR, *Atmospheric Research*, 197, 64–75, doi:

-44-

1053	10.1016/J.ATMOSRES.2017.06.018.
1054	Ceccaldi, M., J. Delanoë, R. J. Hogan, N. L. Pounder, A. Protat, and J. Pelon (2013), From
1055	CloudSat-CALIPSO to EarthCare: Evolution of the DARDAR cloud classification and
1056	its comparison to airborne radar-lidar observations, Journal of Geophysical Research:
1057	Atmospheres, 118(14), 7962-7981, doi:10.1002/jgrd.50579.
1058	Cesana, G., J. E. Kay, H. Chepfer, J. M. English, and G. de Boer (2012), Ubiquitous
1059	low-level liquid-containing Arctic clouds: New observations and climate model
1060	constraints from CALIPSO-GOCCP, Geophysical Research Letters, 39(20), doi:
1061	10.1029/2012GL053385.
1062	Chen, S., Y. Hong, M. Kulie, A. Behrangi, P. M. Stepanian, Q. Cao, Y. You, J. Zhang, J. Hu,
1063	and X. Zhang (2016), Comparison of snowfall estimates from the NASA CloudSat Cloud
1064	Profiling Radar and NOAA/NSSL Multi-Radar Multi-Sensor System, Journal of Hydrol-
1065	ogy, 541, 862–872, doi:10.1016/j.jhydrol.2016.07.047.
1066	Delanoë, J., and R. J. Hogan (2010), Combined CloudSat-CALIPSO-MODIS retrievals
1067	of the properties of ice clouds, Journal of Geophysical Research: Atmospheres, 115(4),
1068	D00H29, doi:10.1029/2009JD012346.
1069	Delanoë, J., A. Protat, J. Testud, D. Bouniol, A. J. Heymsfield, A. Bansemer, P. R. A. Brown,
1070	and R. M. Forbes (2005), Statistical properties of the normalized ice particle size distribu-
1071	tion, Journal of Geophysical Research, 110(D10), D10,201, doi:10.1029/2004JD005405.
1072	Delanoë, J. M. E., and R. J. Hogan (2008), A variational scheme for retrieving ice cloud
1073	properties from combined radar, lidar, and infrared radiometer, Journal of Geophysical
1074	Research, 113(D7), D07,204, doi:10.1029/2007JD009000.
1075	Delanoë, J. M. E., A. J. Heymsfield, A. Protat, A. Bansemer, and R. J. Hogan (2014), Nor-
1076	malized particle size distribution for remote sensing application, Journal of Geophysical
1077	Research: Atmospheres, 119(7), 4204-4227, doi:10.1002/2013JD020700.
1078	Erfani, E., and D. L. Mitchell (2017), Growth of ice particle mass and projected area during
1079	riming, Atmospheric Chemistry and Physics, 17(2), 1241-1257, doi:10.5194/acp-17-1241-
1080	2017.
1081	Field, P. R., and A. J. Heymsfield (2015), Importance of snow to global precipitation, Geo-
1082	physical Research Letters, 42(21), doi:10.1002/2015GL065497.
1083	Field, P. R., R. J. Hogan, P. R. A. Brown, A. J. Illingworth, T. W. Choularton, and R. J. Cot-
1084	ton (2005), Parametrization of ice-particle size distributions for mid-latitude stratiform
1085	cloud, Quarterly Journal of the Royal Meteorological Society, 131(609), 1997-2017, doi:

-45-

1086	10.1256/qj.04.134.
------	--------------------

1092

- Field, P. R., A. J. Heymsfield, and A. Bansemer (2007), Snow Size Distribution Parame terization for Midlatitude and Tropical Ice Clouds, *Journal of the Atmospheric Sciences*,
 64(12), 4346–4365, doi:10.1175/2007JAS2344.1.
- Francis, P. N., P. Hignett, and A. Macke (1998), The retrieval of cirrus cloud properties from aircraft multi-spectral reflectance measurements during EUCREX'93, *Quarterly Journal*

of the Royal Meteorological Society, 124(548), 1273–1291, doi:10.1002/qj.49712454812.

- ¹⁰⁹³ Fujiyoshi, Y., and G. Wakahama (1985), On Snow Particles Comprising an Aggre-
- gate, Journal of the Atmospheric Sciences, 42(15), 1667–1674, doi:10.1175/1520 0469(1985)042<1667:OSPCAA>2.0.CO;2.
- Grazioli, J., G. Lloyd, L. Panziera, C. R. Hoyle, P. J. Connolly, J. Henneberger, and A. Berne
 (2015), Polarimetric radar and in situ observations of riming and snowfall microphysics
 during CLACE 2014, *Atmospheric Chemistry and Physics*, *15*(23), 13,787–13,802, doi:
- 1099 10.5194/acp-15-13787-2015.
- Grecu, M., W. S. Olson, S. J. Munchak, S. Ringerud, L. Liao, Z. Haddad, B. L. Kelley, and
 S. F. McLaughlin (2016), The GPM Combined Algorithm, *Journal of Atmospheric and Oceanic Technology*, *33*(10), 2225–2245, doi:10.1175/JTECH-D-16-0019.1.
- Harimaya, T., and M. Sato (1989), Measurement of the Riming Amount on Snowflakes,
 Journal of the Faculty of Science, Hokkaido University. Series 7, Geophysics, 8(4), 355–
 366.
- Hawkness-Smith, L. (2010), A novel retrieval of liquid water path and a evaluation of the
 representation of drizzle in numerical models, Ph.D. thesis, University of Reading.
- Haynes, J. M., T. S. L'Ecuyer, G. L. Stephens, S. D. Miller, C. Mitrescu, N. B. Wood, and
- S. Tanelli (2009), Rainfall retrieval over the ocean with spaceborne W-band radar, *Journal* of Geophysical Research, 114, D00A22, doi:10.1029/2008JD009973.
- Helmus, J. J., and S. M. Collis (2016), The Python ARM Radar Toolkit (Py-ART), a Library
 for Working with Weather Radar Data in the Python Programming Language, *Journal of Open Research Software*, 4(1), doi:10.5334/jors.119.
- Heymsfield, A. J. (1982), A Comparative Study of the Rates of Development of Potential
- Graupel and Hail Embryos in High Plains Storms, *Journal of the Atmospheric Sciences*,
 39(12), 2867–2897, doi:10.1175/1520-0469(1982)039<2867:ACSOTR>2.0.CO;2.
- Heymsfield, A. J., and M. Kajikawa (1987), An Improved Approach to Calculating Terminal
 Velocities of Plate-like Crystals and Graupel, *Journal of the Atmospheric Sciences*, 44(7),

1119	1088–1099, doi:10.1175/1520-0469(1987)044<1088:AIATCT>2.0.CO;2.
1120	Heymsfield, A. J., and L. M. Miloshevich (2003), Parameterizations for the
1121	Cross-Sectional Area and Extinction of Cirrus and Stratiform Ice Cloud Parti-
1122	cles, Journal of the Atmospheric Sciences, 60(7), 936-956, doi:10.1175/1520-
1123	0469(2003)060<0936:PFTCSA>2.0.CO;2.
1124	Heymsfield, A. J., and C. D. Westbrook (2010), Advances in the Estimation of Ice Particle
1125	Fall Speeds Using Laboratory and Field Measurements, Journal of the Atmospheric Sci-
1126	ences, 67(8), 2469–2482, doi:10.1175/2010JAS3379.1.
1127	Heymsfield, A. J., C. Schmitt, A. Bansemer, and C. H. Twohy (2010), Improved Representa-
1128	tion of Ice Particle Masses Based on Observations in Natural Clouds, Journal of the Atmo-
1129	spheric Sciences, 67(10), 3303-3318, doi:10.1175/2010JAS3507.1.
1130	Heymsfield, A. J., S. Y. Matrosov, and N. B. Wood (2016), Toward Improving Ice Water
1131	Content and Snow-Rate Retrievals from Radars. Part I: X and W Bands, Emphasizing
1132	CloudSat, Journal of Applied Meteorology and Climatology, 55(9), 2063-2090, doi:
1133	10.1175/JAMC-D-15-0290.1.
1134	Hiley, M. J., M. S. Kulie, and R. Bennartz (2011), Uncertainty Analysis for CloudSat Snow-
1135	fall Retrievals, Journal of Applied Meteorology and Climatology, 50(2), 399-418, doi:
1136	10.1175/2010JAMC2505.1.
1137	Hogan, R. J. (2007), A Variational Scheme for Retrieving Rainfall Rate and Hail Reflectiv-
1138	ity Fraction from Polarization Radar, Journal of Applied Meteorology and Climatology,
1139	46(10), 1544–1564, doi:10.1175/JAM2550.1.
1140	Hogan, R. J. (2008), Fast Lidar and Radar Multiple-Scattering Models. Part I: Small-Angle
1141	Scattering Using the Photon VarianceâĂŞCovariance Method, Journal of the Atmospheric
1142	Sciences, 65(12), 3621-3635, doi:10.1175/2008JAS2642.1.
1143	Hogan, R. J. (2014), Fast Reverse-Mode Automatic Differentiation using Expression
1144	Templates in C++, ACM Transactions on Mathematical Software, 40(4), 1–16, doi:
1145	10.1145/2560359.
1146	Hogan, R. J. (2017), Adept 2.0: a combined automatic differentiation and array library for
1147	C++, doi:10.5281/ZENODO.1004730.
1148	Hogan, R. J., and A. J. Illingworth (1999), The Potential of Spaceborne Dual-
1149	Wavelength Radar to Make Global Measurements of Cirrus Clouds, Journal
1150	of Atmospheric and Oceanic Technology, 16(5), 518–531, doi:10.1175/1520-
1151	0426(1999)016<0518:TPOSDW>2.0.CO;2.

-47-

1152	Hogan, R. J., and C. D. Westbrook (2014), Equation for the Microwave Backscatter Cross
1153	Section of Aggregate Snowflakes Using the Self-Similar Rayleigh-Gans Approximation,
1154	Journal of the Atmospheric Sciences, 71(9), 3292–3301, doi:10.1175/JAS-D-13-0347.1.
1155	Hogan, R. J., P. N. Francis, H. Flentje, A. J. Illingworth, M. Quante, and J. Pelon (2003),
1156	Characteristics of mixed-phase clouds. I: Lidar, radar and aircraft observations from
1157	CLARE'98, Quarterly Journal of the Royal Meteorological Society, 129(592), 2089–2116,
1158	doi:10.1256/rj.01.208.
1159	Hogan, R. J., M. D. Behera, E. J. O'Connor, and A. J. Illingworth (2004), Estimate of the
1160	global distribution of stratiform supercooled liquid water clouds using the LITE lidar,
1161	Geophysical Research Letters, 31(5), L05,106, doi:10.1029/2003GL018977.
1162	Hogan, R. J., L. Tian, P. R. A. Brown, C. D. Westbrook, A. J. Heymsfield, and J. D. Eastment
1163	(2012), Radar Scattering from Ice Aggregates Using the Horizontally Aligned Oblate
1164	Spheroid Approximation, Journal of Applied Meteorology and Climatology, 51(3), 655-
1165	671, doi:10.1175/JAMC-D-11-074.1.
1166	Hogan, R. J., R. Honeyager, J. Tyynelä, and S. Kneifel (2017), Calculating the millimetre-
1167	wave scattering phase function of snowflakes using the self-similar Rayleigh-Gans Ap-
1168	proximation, Quarterly Journal of the Royal Meteorological Society, 143(703), 834–844,
1169	doi:10.1002/qj.2968.
1170	Hou, A. Y., R. K. Kakar, S. Neeck, A. A. Azarbarzin, C. D. Kummerow, M. Kojima, R. Oki,
1171	K. Nakamura, and T. Iguchi (2014), The Global Precipitation Measurement Mission, Bul-
1172	letin of the American Meteorological Society, 95(5), 701-722, doi:10.1175/BAMS-D-13-
1173	00164.1.
1174	Illingworth, A. J., and T. M. Blackman (2002), The Need to Represent Raindrop Size Spec-
1175	tra as Normalized Gamma Distributions for the Interpretation of Polarization Radar
1176	Observations, Journal of Applied Meteorology, 41(3), 286–297, doi:10.1175/1520-
1177	0450(2002)041<0286:TNTRRS>2.0.CO;2.
1178	Illingworth, A. J., R. J. Hogan, E. J. O'Connor, D. Bouniol, J. Delanoë, J. Pelon, A. Pro-
1179	tat, M. E. Brooks, N. Gaussiat, D. R. Wilson, D. P. Donovan, H. K. Baltink, GJ. van
1180	Zadelhoff, J. D. Eastment, J. W. F. Goddard, C. L. Wrench, M. Haeffelin, O. A. Krasnov,
1181	H. W. J. Russchenberg, JM. Piriou, F. Vinit, A. Seifert, A. M. Tompkins, and U. Willén
1182	(2007), Cloudnet, Bulletin of the American Meteorological Society, 88(6), 883-898, doi:
1183	10.1175/BAMS-88-6-883.

1184	Illingworth, A. J., H. W. Barker, A. Beljaars, M. Ceccaldi, H. Chepfer, N. Clerbaux,
1185	J. Cole, J. Delanoë, C. Domenech, D. P. Donovan, S. Fukuda, M. Hirakata, R. J. Hogan,
1186	A. Huenerbein, P. Kollias, T. Kubota, T. Nakajima, T. Y. Nakajima, T. Nishizawa, Y. Ohno.
1187	H. Okamoto, R. Oki, K. Sato, M. Satoh, M. W. Shephard, A. Velázquez-Blázquez,
1188	U. Wandinger, T. Wehr, and GJ. van Zadelhoff (2015), The EarthCARE Satellite: The
1189	Next Step Forward in Global Measurements of Clouds, Aerosols, Precipitation, and
1190	Radiation, Bulletin of the American Meteorological Society, 96(8), 1311-1332, doi:
1191	10.1175/BAMS-D-12-00227.1.
1192	Jiang, Z., M. Oue, J. Verlinde, E. E. Clothiaux, K. Aydin, G. Botta, and Y. Lu (2017), What
1193	Can We Conclude about the Real Aspect Ratios of Ice Particle Aggregates from Two-
1194	Dimensional Images?, Journal of Applied Meteorology and Climatology, 56(3), 725-734,
1195	doi:10.1175/JAMC-D-16-0248.1.
1196	Jullien, R. (1992), The application of fractals to colloidal aggregation, Croatica Chemica
1197	Acta, 65(2), 215–235.
1198	Kalesse, H., W. Szyrmer, S. Kneifel, P. Kollias, and E. Luke (2016), Fingerprints of a riming
1199	event on cloud radar Doppler spectra: observations and modeling, Atmospheric Chemistry
1200	and Physics, 16(5), 2997-3012, doi:10.5194/acp-16-2997-2016.
1201	Khvorostyanov, V. I., and J. A. Curry (2005), Fall Velocities of Hydrometeors in the Atmo-
1202	sphere: Refinements to a Continuous Analytical Power Law, Journal of the Atmospheric
1203	Sciences, 62(12), 4343-4357, doi:10.1175/JAS3622.1.
1204	Kneifel, S., U. Löhnert, A. Battaglia, S. Crewell, and D. Siebler (2010), Snow scattering sig-
1205	nals in ground-based passive microwave radiometer measurements, Journal of Geophysi-
1206	cal Research, 115(D16), D16,214, doi:10.1029/2010JD013856.
1207	Kneifel, S., M. Maahn, G. Peters, and C. Simmer (2011), Observation of snowfall with a
1208	low-power FM-CW K-band radar (Micro Rain Radar), Meteorology and Atmospheric
1209	<i>Physics</i> , 113(1-2), 75–87, doi:10.1007/s00703-011-0142-z.
1210	Kneifel, S., A. von Lerber, J. Tiira, D. Moisseev, P. Kollias, and J. Leinonen (2015), Ob-
1211	served relations between snowfall microphysics and triple-frequency radar measure-
1212	ments, Journal of Geophysical Research: Atmospheres, 120(12), 6034-6055, doi:
1213	10.1002/2015JD023156.
1214	Kneifel, S., J. Dias Neto, D. Ori, D. Moisseev, J. Tyynelä, I. S. Adams, KS. Kuo, R. Ben-
1215	nartz, A. Berne, E. E. Clothiaux, P. Eriksson, A. J. Geer, R. Honeyager, J. Leinonen, and
1216	C. D. Westbrook (2018), Summer Snowfall Workshop: Scattering Properties of Realis-

- tic Frozen Hydrometeors from Simulations and Observations, as well as Defining a New 1217 Standard for Scattering Databases, Bulletin of the American Meteorological Society, 99(3), 1218 ES55-ES58, doi:10.1175/BAMS-D-17-0208.1. 1219 Kollias, P., S. Tanelli, A. Battaglia, and A. Tatarevic (2014), Evaluation of EarthCARE 1220 Cloud Profiling Radar Doppler Velocity Measurements in Particle Sedimentation 1221 Regimes, Journal of Atmospheric and Oceanic Technology, 31(2), 366–386, doi: 1222 10.1175/JTECH-D-11-00202.1. 1223 Kulie, M. S., and R. Bennartz (2009), Utilizing Spaceborne Radars to Retrieve Dry 1224 Snowfall, Journal of Applied Meteorology and Climatology, 48(12), 2564–2580, doi: 1225 10.1175/2009JAMC2193.1. 1226 Kulie, M. S., L. Milani, N. B. Wood, S. A. Tushaus, R. Bennartz, and T. S. L'Ecuyer (2016), 1227 A Shallow Cumuliform Snowfall Census Using Spaceborne Radar, Journal of Hydromete-1228 orology, 17(4), 1261-1279, doi:10.1175/JHM-D-15-0123.1. 1229 Langleben, M. P. (1954), The terminal velocity of snowflakes, Quarterly Journal of the 1230 Royal Meteorological Society, 80(344), 174–181, doi:10.1002/qj.49708034404. 1231 Leinonen, J., and D. Moisseev (2015), What do triple-frequency radar signatures reveal 1232 about aggregate snowflakes?, Journal of Geophysical Research: Atmospheres, 120(1), 1233 229-239, doi:10.1002/2014JD022072. 1234 Leinonen, J., and W. Szyrmer (2015), Radar signatures of snowflake riming: A modeling 1235 study, Earth and Space Science, 2(8), 346-358, doi:10.1002/2015EA000102. 1236 Leinonen, J., M. D. Lebsock, G. L. Stephens, and K. Suzuki (2016), Improved Retrieval of 1237 Cloud Liquid Water from CloudSat and MODIS, Journal of Applied Meteorology and 1238 Climatology, 55(8), 1831–1844, doi:10.1175/JAMC-D-16-0077.1. 1239 Li, H., D. Moisseev, and A. von Lerber (2018), How Does Riming Affect Dual-Polarization 1240 Radar Observations and Snowflake Shape?, Journal of Geophysical Research: Atmo-1241 spheres, 123(11), 6070-6081, doi:10.1029/2017JD028186. 1242 Liebe, H. J. (1985), An updated model for millimeter wave propagation in moist air, Radio 1243 Science, 20(5), 1069-1089. 1244 Lin, Y., and B. A. Colle (2011), A New Bulk Microphysical Scheme That Includes Rim-1245 ing Intensity and Temperature-Dependent Ice Characteristics, Monthly Weather Review, 1246 139(3), 1013-1035, doi:10.1175/2010MWR3293.1. 1247
- Lin, Y., L. J. Donner, and B. A. Colle (2011), Parameterization of Riming Intensity and Its Impact on Ice Fall Speed Using ARM Data, *Monthly Weather Review*, *139*(3), 1036–1047,

1250	doi:10.1175/2010MWR3299.1.
1251	Liu, G. (2008), Deriving snow cloud characteristics from CloudSat observations, Journal of
1252	Geophysical Research, 113(D8), D00A09, doi:10.1029/2007JD009766.
1253	Löhnert, U., S. Kneifel, A. Battaglia, M. Hagen, L. Hirsch, and S. Crewell (2011), A Mul-
1254	tisensor Approach Toward a Better Understanding of Snowfall Microphysics: The
1255	TOSCA Project, Bulletin of the American Meteorological Society, 92(5), 613-628, doi:
1256	10.1175/2010BAMS2909.1.
1257	Maahn, M., and U. Löhnert (2017), Potential of Higher-Order Moments and Slopes of the
1258	Radar Doppler Spectrum for Retrieving Microphysical and Kinematic Properties of Arc-
1259	tic Ice Clouds, Journal of Applied Meteorology and Climatology, 56(2), 263-282, doi:
1260	10.1175/JAMC-D-16-0020.1.
1261	Maahn, M., U. Löhnert, P. Kollias, R. C. Jackson, and G. M. McFarquhar (2015), Developing
1262	and Evaluating Ice Cloud Parameterizations for Forward Modeling of Radar Moments
1263	Using in situ Aircraft Observations, Journal of Atmospheric and Oceanic Technology,
1264	<i>32</i> (5), 880–903, doi:10.1175/JTECH-D-14-00112.1.
1265	Mace, G., and S. Benson (2017), Diagnosing Cloud Microphysical Process Information from
1266	Remote Sensing Measurements—A Feasibility Study Using Aircraft Data. Part I: Tropical
1267	Anvils Measured during TC4, Journal of Applied Meteorology and Climatology, 56(3),
1268	633–649, doi:10.1175/JAMC-D-16-0083.1.
1269	Mason, S. L., J. C. Chiu, R. J. Hogan, and L. Tian (2017), Improved rain-rate and drop-
1270	size retrievals from airborne and spaceborne Doppler radar, Atmospheric Chemistry and
1271	Physics Discussions, pp. 1–34, doi:10.5194/acp-2017-280.
1272	Mitchell, D. (1996), Use of mass-and area-dimensional power laws for determining precipita-
1273	tion particle terminal velocities, Journal of the atmospheric sciences.
1274	Mitchell, D. L., and A. J. Heymsfield (2005), Refinements in the Treatment of Ice Particle
1275	Terminal Velocities, Highlighting Aggregates, Journal of the Atmospheric Sciences, 62(5),
1276	1637–1644, doi:10.1175/JAS3413.1.
1277	Mitchell, D. L., R. Zhang, and R. L. Pitter (1990), Mass-Dimensional Relationships for Ice
1278	Particles and the Influence of Riming on Snowfall Rates, Journal of Applied Meteorology,
1279	29(2), 153–163, doi:10.1175/1520-0450(1990)029<0153:MDRFIP>2.0.CO;2.
1280	Moisseev, D., A. von Lerber, and J. Tiira (2017), Quantifying the effect of riming on snow-
1281	fall using ground-based observations, Journal of Geophysical Research: Atmospheres,
1282	122, doi:10.1002/2016JD026272.

1283	Morrison, H., and J. A. Milbrandt (2015), Parameterization of Cloud Microphysics Based
1284	on the Prediction of Bulk Ice Particle Properties. Part I: Scheme Description and Ideal-
1285	ized Tests, Journal of the Atmospheric Sciences, 72(1), 287-311, doi:10.1175/JAS-D-14-
1286	0065.1.
1287	Morrison, H., J. A. Milbrandt, G. H. Bryan, K. Ikeda, S. A. Tessendorf, and G. Thompson
1288	(2015), Parameterization of Cloud Microphysics Based on the Prediction of Bulk Ice Par-
1289	ticle Properties. Part II: Case Study Comparisons with Observations and Other Schemes,
1290	Journal of the Atmospheric Sciences, 72(1), 312–339, doi:10.1175/JAS-D-14-0066.1.
1291	Mosimann, L. (1995), An improved method for determining the degree of snow crystal rim-
1292	ing by vertical Doppler radar, Atmospheric Research, 37(4), 305–323, doi:10.1016/0169-
1293	8095(94)00050-N.
1294	National Academies of Sciences Engineering and Medicine (2018), Thriving on Our Chang-
1295	ing Planet: A Decadal Strategy for Earth Observation from Space, National Academies
1296	Press, Washington, D.C., doi:10.17226/24938.
1297	Newman, A. J., P. A. Kucera, and L. F. Bliven (2009), Presenting the Snowflake Video
1298	Imager (SVI), Journal of Atmospheric and Oceanic Technology, 26(2), 167-179, doi:
1299	10.1175/2008JTECHA1148.1.
1300	Palerme, C., J. E. Kay, C. Genthon, T. L'Ecuyer, N. B. Wood, and C. Claud (2014), How
1301	much snow falls on the Antarctic ice sheet?, The Cryosphere, 8(4), 1577–1587, doi:
1302	10.5194/tc-8-1577-2014.
1303	Petäjä, T., E. J. O'Connor, D. Moisseev, V. A. Sinclair, A. J. Manninen, R. Väänänen, A. von
1304	Lerber, J. A. Thornton, K. Nicoll, W. Petersen, V. Chandrasekar, J. N. Smith, P. M. Win-
1305	kler, O. Krüger, H. Hakola, H. Timonen, D. Brus, T. Laurila, E. Asmi, ML. Riekkola,
1306	L. Mona, P. Massoli, R. Engelmann, M. Komppula, J. Wang, C. Kuang, J. Bäck, A. Virta-
1307	nen, J. Levula, M. Ritsche, and N. Hickmon (2016), BAECC: A Field Campaign to Elu-
1308	cidate the Impact of Biogenic Aerosols on Clouds and Climate, Bulletin of the American
1309	Meteorological Society, 97(10), 1909–1928, doi:10.1175/BAMS-D-14-00199.1.
1310	Rodgers, C. D. (2000), Inverse methods for atmospheric sounding: theory and practice,
1311	World Scientific, Singapore.
1312	Schmitt, C. G., and A. J. Heymsfield (2010), The Dimensional Characteristics of Ice Crystal
1313	Aggregates from Fractal Geometry, Journal of the Atmospheric Sciences, 67(5), 1605-
1314	1616, doi:10.1175/2009JAS3187.1.

1315	Shupe, M. D., P. Kollias, S. Y. Matrosov, and T. L. Schneider (2004), Deriving Mixed-Phase
1316	Cloud Properties from Doppler Radar Spectra, Journal of Atmospheric and Oceanic Tech-
1317	nology, 21(4), 660–670, doi:10.1175/1520-0426(2004)021<0660:DMCPFD>2.0.CO;2.
1318	Stein, T. H. M., C. D. Westbrook, and J. C. Nicol (2015), Fractal geometry of aggregate
1319	snowflakes revealed by triple-wavelength radar measurements, Geophysical Research Let-
1320	ters, 42(1), 176–183, doi:10.1002/2014GL062170.
1321	Stephens, G. L., D. G. Vane, R. J. Boain, G. G. Mace, K. Sassen, Z. Wang, A. J. Illingworth,
1322	E. J. O'Connor, W. B. Rossow, S. L. Durden, and others (2002), The CloudSat mission
1323	and the A-Train: A new dimension of space-based observations of clouds and precipita-
1324	tion, Bulletin of the American Meteorological Society, 83(12), 1771âĂŞ1790.
1325	Szyrmer, W., and I. Zawadzki (2014), Snow Studies. Part III: Theoretical Derivations for
1326	the Ensemble Retrieval of Snow Microphysics from Dual-Wavelength Vertically Pointing
1327	Radars, Journal of the Atmospheric Sciences, 71(3), 1158–1170, doi:10.1175/JAS-D-12-
1328	0285.1.
1329	Tan, I., T. Storelvmo, and M. D. M. Zelinka (2016), Observational constraints on mixed-
1330	phase clouds imply higher climate sensitivity, Science, 352(6282), 224-227, doi:
1331	10.1126/science.aad5300.
1332	Tanelli, S., S. L. Durden, E. Im, G. M. Heymsfield, P. Racette, and D. O. Starr (2009), Next-
1333	generation spaceborne Cloud Profiling Radars, in 2009 IEEE Radar Conference, pp. 1-4,
1334	IEEE, doi:10.1109/RADAR.2009.4977116.
1335	Testud, J., S. Oury, R. A. Black, P. Amayenc, and X. Dou (2001), The Concept of âĂIJNor-
1336	malizedâĂİ Distribution to Describe Raindrop Spectra: A Tool for Cloud Physics
1337	and Cloud Remote Sensing, Journal of Applied Meteorology, 40(6), 1118–1140, doi:
1338	10.1175/1520-0450(2001)040<1118:TCONDT>2.0.CO;2.
1339	Tiira, J., D. N. Moisseev, A. von Lerber, D. Ori, A. Tokay, L. F. Bliven, and W. Petersen
1340	(2016), Ensemble mean density and its connection to other microphysical properties of
1341	falling snow as observed in Southern Finland, Atmospheric Measurement Techniques,
1342	9(9), 4825–4841, doi:10.5194/amt-9-4825-2016.
1343	Twomey, S. (1977), Introduction to the Mathematics of Inversion in Remote Sensing and
1344	Indirect, Elsevier Scientific Publishing.
1345	von Lerber, A., D. Moisseev, L. F. Bliven, W. Petersen, AM. Harri, and V. Chandrasekar
1346	(2017), Microphysical Properties of Snow and Their Link to Ze-S Relations during
1347	BAECC 2014, Journal of Applied Meteorology and Climatology, 56(6), 1561–1582, doi:

10.1175/JAMC-D-16-0379.1. 1348

1355

- Westbrook, C. D., R. C. Ball, P. R. Field, and A. J. Heymsfield (2004), Theory of growth by 1349 differential sedimentation, with application to snowflake formation, Physical Review E, 1350 70(2), 021,403, doi:10.1103/PhysRevE.70.021403. 1351
- Yin, M., G. Liu, R. Honeyager, and F. Joseph Turk (2017), Observed differences of 1352
- triple-frequency radar signatures between snowflakes in stratiform and convective 1353
- clouds, Journal of Quantitative Spectroscopy and Radiative Transfer, 193, 13-20, doi: 1354 10.1016/J.JQSRT.2017.02.017.
- Zikmunda, J., and G. Vali (1972), Fall Patterns and Fall Velocities of Rimed Ice Crys-1356
- tals, Journal of the Atmospheric Sciences, 29(7), 1334-1347, doi:10.1175/1520-1357
- 0469(1972)029<1334:FPAFVO>2.0.CO;2. 1358



Figure 12. Histograms of remote-sensed LWP (a) and surface temperature (b) and relative humidity (c)
data from all snow events from SNEX IOP, grouped into three LWP classes.



