Airborne observations of the microphysical structure of two contrasting cirrus clouds

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Abstract
We present detailed airborne in situ measurements of cloud microphysics in two midlatitude cirrus clouds, collected as part of the Cirrus Coupled Cloud-Radiation Experiment. A new habit recognition algorithm for sorting cloud particle images using a neural network is introduced. Both flights observed clouds that were related to frontal systems, but one was actively developing while the other dissipated as it was sampled. The two clouds showed distinct differences in particle number, habit, and size. However, a number of common features were observed in the 2-D stereo data set, including a distinct bimodal size distribution within the higher-temperature regions of the clouds. This may result from a combination of local heterogeneous nucleation and large particles sedimenting from aloft. Both clouds had small ice crystals (<100 μm) present at all levels. However, this small ice mode is not present in observations from a holographic probe. This raises the possibility that the small ice observed by optical array probes may at least be in part an instrument artifact due to the counting of out-of-focus large particles as small ice. The concentrations of ice crystals were a factor ~10 higher in the actively growing cloud with the stronger updrafts, with a mean concentration of 261 L⁻¹ compared to 29 L⁻¹ in the decaying case. Particles larger than 700 μm were largely absent from the decaying cirrus case. A comparison with ice-nucleating particle parameterizations suggests that for the developing case the ice concentrations at the lowest temperatures are best explained by homogenous nucleation.

1. Introduction
Upper tropospheric ice clouds, known as cirrus, have a significant impact on the climate both globally and regionally [Guiñard et al., 2012]. Cirrus clouds contribute to both the Earth’s albedo and the greenhouse effect by reflecting incoming solar radiation and absorbing outgoing terrestrial radiation, respectively. The net contribution of these two competing mechanisms to the Earth’s radiation budget is greatly dependent on the cloud microphysical structure. Microphysical parameters such as the ice crystal concentration, size, and shape have all been shown to have a significant impact on the cloud radiative properties [Ackerman et al., 1988; Labonnote et al., 2000; Kristjánsson et al., 2000; Yang et al., 2012]. However, these parameters all exhibit substantial spatiotemporal variability due to their complex dependence on the meteorology present as the cloud forms, evolves, and decays [Lawson et al., 2006a; Baran, 2012].

Ice crystals can either nucleate directly from the liquid phase (homogenous nucleation) or on an aerosol surface (heterogeneous nucleation). In cirrus clouds both mechanisms can be present competing for water vapor [Barahona et al., 2010; Sullivan et al., 2015]. Recent measurements of ice crystal residuals suggest that heterogeneous nucleation is the leading mechanism for cirrus formation [Cziczo et al., 2013; Cziczo and Froyd, 2014]. This is inconsistent with older studies and model simulations that highlight the important role of homogeneous nucleation [Heymsfield and Miloshevich, 1995; Gallagher et al., 2005; Liu et al., 2012; Zhang et al., 2013]. At temperatures greater than ~238 K homogenous nucleation is statistically improbable. However, below 236 K all remaining liquid cloud droplets will rapidly freeze homogeneously [Pruppacher and Klett, 1997; Murray et al., 2010].

Cirrus clouds cover approximately 30% of the Earth’s surface [Stubenrauch et al., 2006]. Their formation can be associated with a variety of atmospheric processes covering a wide range of spatial scales, such as frontal systems, Rossby wave breaking, mountain waves, and deep convection [Garett et al., 2004; Spichtinger et al., 2005; Eixmann et al., 2010]. Many of the processes leading to cirrus formation cannot be explicitly resolved in global climate models and therefore need to be parameterized.
The evolution of cirrus proceeds through several broad phases: clear-sky ice super saturation, nucleation, growth, and sedimentation/sublimation [Diao et al., 2014]. However, this is complicated because these processes may occur simultaneously within different regions of the same cloud [Heymsfield and Miloshevich, 1995]. Ice crystal growth rates are dependent on crystal shape/habit and super saturation [Bailey and Hallett, 2012]. The growth of crystals reduces water saturation, which will diminish new particle formation [Kärcher and Lohmann, 2002; Lohmann et al., 2008]. A cloud can dissipate when water vapor is sufficiently depleted that sublimation occurs [Heymsfield and Miloshevich, 1995] or when large crystals precipitate out of the cloud, which is largely dependent on the cloud dynamics [Heymsfield et al., 2013].

Cirrus clouds are one of the largest sources of uncertainties in climate models [Zelinka et al., 2012; Boucher et al., 2013; Zelinka et al., 2013]. Model simulations of cirrus microphysics still struggle to accurately predict cirrus formation, its evolution, and radiative properties [Eidhammer et al., 2014; Shi et al., 2014; Muhlbauer et al., 2015]. In order to develop and evaluate parameterizations of these processes, there is a need for robust measurements of the variability of microphysical parameters under different environmental conditions [Muhlbauer et al., 2015]. In the past, our understanding of cirrus microphysics has been based upon observations that may contain significant analytical artifacts due to crystals shattering on the inlet of probes, causing biases in the measurement of particle size distributions [McFarquhar et al., 2007; Jensen et al., 2009; Korolev et al., 2011].

The microphysical and radiative properties of cirrus clouds presented here were measured as part of the Cirrus Coupled Cloud-Radiation Experiment (CIRCCREX). Sorties were performed from Prestwick, UK, by the Facility for Airborne Atmospheric Measurements (FAAM) Bae-146 research aircraft. A total of six flights were performed during the ongoing CIRCCREX project; this paper focuses on flights on the 11 and 13 March 2015 that used in situ instrumentation to extensively probe the microphysical structure of two contrasting cirrus cases. The other flights had a greater focus on remote sensing of cirrus clouds and will be presented in separate papers.

A leading objective of this paper is to use state of the art observations to describe microphysical differences in clouds that have small but distinguishable differences in their dynamical and thermodynamic characteristics. In section 2, we describe analytical techniques and data processing. A new cloud particle habit recognition algorithm is introduced, and its classification accuracy is assessed. Section 2.4 describes the meteorological setting of the two flights. Section 3 presents the microphysical sampling. Section 4 discusses and contrasts the origin and evolution of the ice crystals. The dimensional properties of different ice crystal habits are examined and compared to parameterizations from previous studies. The paper is briefly summarized in section 5.

2. Methods

2.1. Instrumentation and Measurements

During the CIRCCREX flights the FAAM Bae-146 was fitted with an array of aerosol, thermodynamic, radiometric, and cloud microphysical instrumentation. Cloud particle concentration and size measurements were made using a 2DS (2-D stereo) optical array probe (OAP, SPEC Inc., USA, described in Lawson et al. [2006b]). The 2DS consists of two orthogonal 128-photodiode arrays with image resolution of 10 μm, allowing it to sample the nominal particle size range of 10 to 1280 μm in each channel. Further details on this instrument, its performance on board this specific aircraft, its data processing, and the corrections applied to its measurements can be found in Crosier et al. [2011].

Cloud hydrometeor images were also collected using a 3 View-Cloud Particle Imager (3V-CPI, Stratton Park Engineering Company (SPEC) Inc., USA, consisting of a second 2DS probe mounted within the inlet and a cloud particle imager (CPI, SPEC) [Lawson et al., 2001]. A linear fit to the particle number concentrations derived from the two separate 2DS probes has an $R^2$ of 0.95 ($y = 1.2x + 9.8 \text{ L}^{-1}$).

Particle size distributions over the size range 100 to 6400 μm (100 μm pixel resolution) were measured using a CPI 100 optical array probe (Droplet Measurement Technologies) [Baumgardner et al., 2001]. Section 3 presents size distributions from the 2DS and CPI 100; the two probes show good agreement in their overlapping size measurement regions.

The CPI uses a 2-D 1024 x 1024 pixel CCD camera to image particles with 256 gray levels and 2.3 μm pixel resolution. The habits of particles larger than 50 μm were determined from the CPI images using an automatic habit recognition algorithm, which is described in detail in section 2.3. Particles were sorted into the following categories: rosettes, plates, columns/bullets, aggregates, quasi-spherical ice, and spherical (i.e.,
liquid drops). Similar to other studies (and the manufacturer’s guidelines), the CPI size distributions were scaled to the 2DS distributions due to its better defined sample volume [Lawson et al., 2001, 2006a].

The holographic cloud probe, HALOHolo, from the Institute for Atmospheric Physics at the University of Mainz and Max Planck Institute for Chemistry Mainz was operated on 13 March 2015 (flight B895). It has an effective pixel size of 2.95 μm on a 6576 × 4384 detector giving a sample volume of approximately 19 × 13 × 155 mm or ~38 cm³. At 6 frames per second, and an average airspeed of about 100 m s⁻¹, HALOHolo measures a sample every 17 m of flight path, giving a volume sample rate of ~230 cm³ s⁻¹. Particles between 6 μm (2 pixels) and 1 cm (half the detector width) are resolvable in the hologram reconstructions. Ice mass concentrations (ice water content) were determined using a hotwire Nevzorov probe (Sky Phys Tech Inc.), the sensitivity of which is estimated to be 0.002 g m⁻³ [Abel et al., 2014]. The Nevzorov ice water content measurements can be subject to increased uncertainty when large ice particles are present due to its limited sample volume preventing sufficient sample statistics. However, this is not expected to be a significant issue for this work due to the general absence of particles larger than 1 mm (see section 3). A second estimate of the ice water content was made by applying the Brown and Francis [1995] mass-dimension parameterization to the 2DS images. The linear regression fit between the two instruments has the relationship (Nevzorov) = (0.8) (2DS) + (6.7 × 10⁻³ g m⁻³) and an R² of 0.99.

Aerosol size distributions were recorded using a Cloud Aerosol Spectrometer (CAS, Droplet Measurement Technologies, USA) and a Passive Cavity Aerosol Spectrometer Probe (PCASP-100X, Droplet Measurement Technologies). The CAS measures particles in the size range 0.5 to 50 μm using the forward and backscattered light intensity from a diode laser. Particles are sized using Mie scattering theory assuming spherical particles of known refractive index [Baumgardner et al., 2001]. The PCASP measures particles in the size range 0.1 to 3 μm using laser light scattering [Rosenberg et al., 2012]. The aircraft was also fitted with a Cloud Droplet Probe (CDP-100, Droplet Measurement Technologies) for observing cloud droplets between 2 and 50 μm [Lance et al., 2010]. The in-cloud particle size distributions (PSDs) from the CAS, CDP, and PCASP probes are not used in this study because the nonspherical shape of ice crystals means that their sizing cannot be reliably determined (this is discussed further in section 4). A comparison between the CAS and PCASP over a common size range during clear air periods is shown in Figures 1b and 1d. All the cloud and aerosol instruments discussed above were wing mounted on the aircraft.

Observations of the ambient temperature were made using a Rosemount/Goodrich-type 102 total air temperature sensor, which has an uncertainty of 0.3 K. Ambient pressure was recorded with uncertainty of 0.3 hPa. Dew point temperature was measured using a Chilled Mirror Hygrometer (General Eastern GE 1011B) [Petersen and Renfrew, 2009; Allen et al., 2011]. The 3-D wind vector was measured using a deiced Aventech AIMMS-20 turbulence probe, with an estimated uncertainty of ~0.75 m s⁻¹ [Beswick et al., 2008].

2.2. Cloud Probe Data Processing

Several criteria were used to reject particles poorly imaged by the 2DS and CIP 100. Only fully imaged particles were accepted. Particles in contact with the end diodes or “edges” of the probes’ optical array were rejected (i.e., the “all-in” sample volume technique [Heymsfield and Parrish, 1978] was employed). Particles with less than 80% of the pixels filled within their outline were removed, as were particles 1 pixel wide and greater than 5 pixels long, as such particles are due to faulty pixels. Particles whose average position or “center of mass” is outside their external perimeter were also removed, since this is characteristic of out-of-focus images.

Antishatter tips were fitted to the 2DS and to the inlet edge of the 3V-CPI probes to help prevent ice breakup on their leading edges, which would otherwise bias the particle concentration and size measurements [Lawson, 2011; Korolev et al., 2013]. During the 2DS/CIP 100 data processing particle interarrival times (IATs) were used to help identify and minimize any remaining shattering artifacts. Previously, it has been shown that particles with short IATs are generally due to inlet shattering [Field et al., 2006]. During CIRCCREX, IAT histograms showed two distinct modes. The smaller modes associated with shattering were removed by filtering particles with IATs less than 5 × 10⁻⁶ and 1 × 10⁻⁵ s for 11 and 13 March 2015 flights, respectively.

In order to consider the maximum possible range of particle sizes, the whole 2DS size range is used. However, to do this, the size of the 2DS sample volume needs to be carefully considered to ensure sufficient sampling statistics. When sampling low concentrations or using short averaging times, the 2DS sample volume is relatively small and the corresponding counting uncertainty can be large. The sample volume is small for small
particle sizes; for 10 μm particles it is 0.065 L⁻¹ per second of flight time at the airspeeds sampled on this aircraft [Heymsfield and Parrish, 1978]. Several previous studies have disregarded the first one to five size bins from the 2DS for this reason [Jackson et al., 2012; Jensen et al., 2013]. For this work, to ensure sufficient sampling statistics, all 2DS measurements have been averaged to 10 s, unless otherwise noted. To explore the impact of sampling statistics on the measurements, we consider an observed concentration of 10 L⁻¹, which

Figure 1. Aerosol concentrations observed on (a, b) 11 March 2015 and (c, d) 13 March 2015 when out of cloud by the PCASP probe (size range 0.1 to 3 μm) (Figures 1a and 1c) and by both the CAS and PCASP probe (Figures 1b and 1d) within the size range 0.5 to 2 μm.
is at the lower end of the observations described in section 3. If we assume that this is purely due to 10 μm particles, a 10 L⁻¹ concentration corresponds to approximately 7 counts by the 2DS. This results in a counting uncertainty of 37%. Alternatively, if the 2DS concentration is 100 L⁻¹, of again only 10 μm particles, then the counting uncertainty is 12%. In reality, for both cases the particles are not all 10 μm and the counting uncertainty is much lower. When the PSDs are presented (Figure 5), longer averaging times are used (approximately 5 min) to ensure sufficient counts.

The working principle of HALOHolo and the data extraction from its raw holograms has been described previously [see Fugal et al., 2004, 2009]. Though cloud particles are detected down to ~6 μm in size, the effective detection size limit, above which one sees most of the particles of that size, is determined by noise in the hologram reconstruction. This limit is determined empirically for each data set by testing the supervised machine learning algorithm used to separate particles from the noise. For B895, a 50% detection rate was obtained at 25 μm and a greater than 85% detection rate was obtained at 30 μm. Similar to the IAT method for optical array probes described previously, spatial clustering (as opposed to time clustering) is used to identify shattering [Fugal and Shaw, 2009]. For this data set, particles separated by a distance of 6 mm or less were found to be likely shards of shattered particles and were removed from further analysis. An interparticle distance of 6 mm is equivalent to a number concentration of 4500 L⁻¹, which is much higher than observed during this flight.

Unfortunately, no agreed calibration standards exist for ice crystal probes. The only way to have confidence in their measurements is by reducing known systematic sources of uncertainty (as described above) and by comparing independent probes. Here the good agreement between the two 2DS probes and the CIP 100 for particle number concentration and with the Nevzorov for ice water content increases confidence in the utility of these measurements. However, the ice water content is dominated by large ice crystals, meaning that this probe comparison does not help verify the number concentrations of small crystals observed by the 2DS. In section 4 we discuss the comparison between the 2DS and HALOHolo with regard to the possible presence of small ice crystals.

Quality control was performed on the CPI images. Particles that were poorly imaged due to being positioned away from the best focus were rejected by filtering the particles with a focus parameter less that 20 [see Connolly et al., 2007]. Small particles (<50 μm) were also rejected, since they contain insufficient pixels for their habit to be accurately determined. The size and focus thresholds used for habit recognition are somewhat subjective; as a consequence a range of values have been used in the literature [Lawson et al., 2006a; Connolly et al., 2007; Lindqvist et al., 2012; McFarquhar et al., 2013]. For this work, a decision was made on the minimum thresholds where an image could accurately be sorted “by eye.” Using less restrictive thresholds would mean that it is unlikely that an automated method would be able to correctly classify a particle. Here the thresholds used by Lawson et al. [2006a] and Connolly et al. [2007] are found to be appropriate.

### 2.3. Habit Recognition Algorithm

To provide quantitative statistics on the variability of different habits, a supervised automatic habit recognition algorithm was developed and used on the accepted CPI images. The algorithm consists of two main steps: first, features of the particles are extracted and second, these features are compared to those from manually classified habits, known as the training data set. Ideally, the features used should show small variance between particles within the same habit but large differences between habits. Here a feature vector was used with the following nine elements, which meet this criterion.

1. The particle’s circularity ratio is given by equation (1), where \( A \) is the particle’s area and \( P \) is its perimeter.

\[
\text{circularity} = \frac{4\pi A}{P^2}
\]

2. A fast Fourier transform was performed on the radial representation of each particle, as described by Hunter et al. [1984] and Moss and Johnson [1994]. The purpose of this is to determine the frequency of any perimeter periodicity the particle may show. The habit recognition algorithm uses the amplitudes of the 0th, 2nd, 3rd, 4th, 6th, and 8th wave numbers normalized by the sum of the first 32 wave numbers. Spherical drops do not have any outline periodicity; therefore, the amplitude of their 0th wave number will be equal to 1 and all other wave numbers will be zero. More complex shapes will have a lower
amplitude 0th wave number. Columns and bullets are identifiable by the large amplitude of their 2nd wave number, while rosettes show peaks at the higher wave numbers.

3. The transparent area within the particle’s outline was normalized by the total particle area. This metric helps separate optically thin particles, such as hexagonal plates, from more opaque habits (e.g., spherical drops).

4. The convex area ($A_{ch}$) of a particle is the area of the smallest possible convex shape that encompasses the particle [Lindqvist et al., 2012]. The metric $A/A_{ch}$ is used in the habit recognition algorithm. This will be equal to 1 for habits with convex shapes (typically, this includes spherical drops, columns, and hexagonal plates) and less than 1 for habits with concavities (rosettes and aggregates).

The training data set used is based on that described by Lindqvist et al. [2012]. This data set contains over a thousand CPI images from tropical, midlatitude, and arctic clouds that have been manually classified into the following eight categories: plates, columns, bullets, quasi-spherical ice, rosettes, rosette aggregates, plate aggregates, and column aggregates. This was supplemented with a category for spherical drops by adding images collected in liquid cloud regions during CIRCCREX flights.

This data set was used to train a three-layer feed-forward neural network [Hagan and Menhaj, 1994]. Neural networks work by adjusting the weightings and biases that connect the network layers so that the given inputs will result in a specific output [Rumelhart et al., 1986]. The image classification algorithm uses the feature vector for each particle as the input to the network and the selected habit as the output. The training is performed to minimize the mean square error between the target and the network outputs. Training is performed until the mean square error no longer improves.

To test the performance of the algorithm, 15% of the images in the training data set were randomly selected. These were not used to train the network and therefore can be used as an independent test of its performance. The accuracy of the classification changes each time the network is trained due to the different initial weights and biases that are used. This was examined by performing the training 20 times; each time, a different 15% of the images were randomly selected as test data. The mean accuracy of the image classification is found to be 79% (±2% at 1σ). Table 1 shows a confusion matrix comparing how the classification performance varies between habits for the total of the 20 tests. The algorithm performs best for spherical droplets and quasi-spherical ice particles, which are both sorted with the highest precision and sensitivity. However, the algorithm confuses aggregate subcategories and to a lesser extent bullets and columns. Therefore, for the CIRCCREX flights, we do not report a quantitative breakdown of the aggregate subtypes; instead, we combine them into a single category. Bullets and columns are also combined into a single category. The total accuracy of sorting the images into six habits (aggregate, rosette, column/bullet, plate, quasi-spherical, and spherical) is 88%.

Assessing the classification accuracy in this way makes two main assumptions. First, it assumes that the manual classification is 100% correct. In reality, the division between some of the habits is subjective.

| Target          | Rosette Aggregate | Column Aggregate | Plate Aggregate | Rosette | Bullet | Column | Plate | Quasi-Spherical | Spherical | Sensitivity (%) |
|-----------------|-------------------|------------------|-----------------|---------|--------|--------|-------|-----------------|-----------|----------------|
| Rosette aggregate | 397               | 9                | 14              | 27      | 0      | 0      | 0     | 0               | 0         | 89             |
| Column aggregate | 19                | 343              | 49              | 48      | 0      | 2      | 0     | 5               | 0         | 74             |
| Plate aggregate  | 47                | 86               | 195             | 17      | 3      | 4      | 8     | 17              | 0         | 52             |
| Rosette         | 46                | 47               | 11              | 326     | 1      | 0      | 0     | 1               | 1         | 75             |
| Bullet          | 0                 | 3                | 13              | 0       | 288    | 47     | 4     | 4               | 0         | 81             |
| Column          | 0                 | 3                | 4               | 0       | 53     | 359    | 10    | 18              | 0         | 80             |
| Plate           | 0                 | 1                | 14              | 0       | 8      | 15     | 176   | 25              | 4         | 72             |
| Quasi-spherical | 0                 | 1                | 3               | 0       | 1      | 2      | 6     | 436             | 6         | 96             |
| Spherical       | 0                 | 0                | 0               | 0       | 0      | 0      | 4     | 99              | 0         | 99             |
| Precision (%)   | 78                | 70               | 64              | 78      | 82     | 84     | 86    | 85              | 90        |                |

The total accuracy for all 9 habits is 79%. This increases to 88% if the images are only sorted into six habits (aggregates, rosette, column/bullet, plate, quasi-spherical, and spherical). The precision for each habit is defined as the algorithm’s number of true positives divided by the total of true and false positives. The sensitivity for each habit is defined as the algorithm’s number of true positives divided by the total of true positives and false negatives.
even when performed manually (see section 3). Second, one of the aims of the training data set was to capture the natural variability within each habit. This was attempted by selecting particles from different locations around the globe [Lindqvist et al., 2012]. However, it is possible that the selection of particles by eye is biased toward more pristine examples of each habit. Therefore, if the particles were not sufficiently similar to those in the training data set, they were not classified. If the output of the network was less than 0.5 for all habits, the image was not classified. For the CIRCCREX flights these images represent approximately 10% of the total population (see Figures 6 and 8). The sorted images were viewed to further examine the skill of the algorithm, and in particular how it varies between habits, as discussed in section 3.

The accuracy of the algorithm described in this work is comparable to the performance of algorithms from previous studies. McFarquhar et al. [1999] also used a neural network technique to classify particle habits and achieved a classification success rate of 85% for columns, 69% for bullet rosettes, and 87% for polycrystals. Lindqvist et al. [2012] quote an 81% accuracy for an eight-habit algorithm, while Lawson et al. [2006a] use a six-habit algorithm that misclassifies 12% of particles.

2.4. Flights and Meteorology Overview
2.4.1. The 11 March 2015 (B894)
Meteorological conditions on 11 March 2015 were characterized by a low-pressure system centered to the northeast of Iceland and high pressure over continental Europe. Figure 2a shows a surface pressure chart for northern Europe. During the flight (nominal FAAM flight number B894) a cold front that was aligned north-south across the UK moved eastward. The associated cirrus cloud was sampled by the aircraft off the northeast UK coast between the altitudes 6500 and 8500 m. The flight tracks are shown in Figure 2c (black line) overlaying the MODIS (Moderate Resolution Imaging Spectroradiometer)-derived cloud top temperature from the 10:55 UT overpass. The cloud top temperature is approximately 220 K. A series of level runs and vertical profiles were performed through the cloud layer, covering the temperature range 230 to 239 K. The sampling occurred between approximately 10:00 and 11:45 UT, during which period the satellite imagery shows the cirrus to be developing. Vertical cross sections of the flight tracks for this flight and on 13 March 2015 are shown in Figure 3. Back trajectories show that the sampled air mass had traveled across the Atlantic Ocean. Over the previous 7 days the air mass remained within the free troposphere and had negligible surface influence.

2.4.2. The 13 March 2015 (B895)
On 13 March 2015 (B895) the aircraft sampled a decaying band of cirrus north of the UK coast, between the altitudes 6000 and 9000 m (226 to 245 K). The position of the aircraft is shown in Figure 2d along with the MODIS cloud top temperature from the 10:40 UT overpass. Cloud top temperature is shown to be slightly higher than the previous flight at approximately 226 K. The synoptic chart (Figure 2b) shows low pressure over continental Europe. An occluded front was orientated north-south across the UK. The associated band of cloud was relatively stationary in position while being sampled between 10:30 and 11:50 UT. Satellite imagery shows the cirrus to be dissipating over this period, and by 13:00 UT the cirrus sampled by the aircraft is no longer visible. This flight had a comparable air mass history to 11 March 2015 with Atlantic origin and minimal surface influence.

3. Results
In-cloud particle concentrations (10 to 1280 \(\mu\)m) from both flights are summarized in Figure 4 (blue lines). On 11 March 2015 concentrations were approximately an order of magnitude higher than 13 March 2015. The mean in-cloud 2DS concentration (0.1 Hz data) was 261 L\(^{-1}\) (371 L\(^{-1}\) at 1 standard deviation, \(\sigma\)) on 11 March 2015, compared to 29 L\(^{-1}\) (53 L\(^{-1}\) at 1 \(\sigma\)) on 13 March 2015. Both flights show a broad trend of decreasing number concentrations with decreasing altitude. The concentrations differ by a factor 10 between the highest and lowest temperatures sampled (Figures 4a and 4c, black lines). In contrast, ice water contents show positive correlation with temperature (Figures 4b and 4d). Blue box and whisker plots show results from HALO-Holo (Figure 4c) on 13 March 2015, which show a similar trend to the 2DS but have lower absolute concentrations with a mean of 7 L\(^{-1}\) (7 L\(^{-1}\) at 1 \(\sigma\)).

Figure 5 shows PSDs from the 2DS averaged over individual runs/vertical profiles through the cloud (approximately 5 to 10 min). Throughout both flights the highest number concentrations were observed at the smallest sizes. Previous work has suggested that the concentrations of small particles in cirrus clouds
can be significantly overestimated due to crystals shattering on the inlet of probes [McFarquhar et al., 2007; Jensen et al., 2009; Korolev et al., 2011]. The effects of this were thoroughly examined by varying the particle IAT threshold used during the data processing. As described in section 2.2, the shattering mode in the IAT histogram was clearly separated from the ambient mode. A more restrictive IAT threshold was found to cause a uniform decrease in concentrations across the PSD. This suggests that the chosen thresholds are appropriate and effectively removing shattered particles.

During both flights at temperatures below 230 K the particles were small, generally no larger than 300/400 μm. At higher temperatures larger particles were increasingly prevalent. At 237 to 239 K a second mode in the PSD is distinct at ~200 μm, with a trough in concentrations at approximately 70 to 100 μm. This bimodal structure is also present if the measurements are averaged over a shorter period (e.g., 30 s), suggesting that it is not an artifact of averaging data over a whole aircraft run (this is discussed further in section 4). A number of previous studies have reported bimodal PSDs in cirrus clouds [Heymsfield and Miloshevich, 1995; Ivanova et al., 2001; Lawson et al., 2006a; Zhao et al., 2011; Cotton et al., 2013; Jackson et al., 2015]. These studies have generally found the division between modes to be between 100 and
125 μm [Jackson et al., 2015]. For the older studies, inlet shattering has been proposed as a mechanism for generating the bimodality [Lawson et al., 2006a]. However, more recent works such as Cotton et al. [2013] and Jackson et al. [2015] and CIRCCREX (this work) still observe two modes even after the shattering artifacts have been removed. Section 4 discusses the possibility that the mode at small sizes is a 2DS artifact due to out-of-focus large particles being incorrectly sized.

Figure 3. Latitudinal and longitudinal cross sections of the flights tracks on (a) 11 March 2015 and (b) 13 March 2015. Flights tracks are colored by the cloud particle concentration in the size range 10 to 1280 μm from the 2DS probe.
Figure 4. Black box and whisker plots show the total concentrations from the 2DS probe (10 to 1280 μm) for (a, b) 11 March 2015 and (c, d) 13 March 2015. (e, f) The same as Figures 4a and 4c, respectively, except that at temperatures greater than 236 K the 2DS concentration is for particles larger than 50 μm. These particles can unambiguously be classified as ice crystals. Boxes correspond to the 25th and 75th percentiles, while whiskers are the 10th and 90th percentiles and markers are outliers. Orange box and whisker plots show the ice mass concentrations from the Nevzorov probe for 11 March 2015 (Figure 4b) and 13 March 2015 (Figure 4d). Blue box and whisker plots show HALOHolo concentrations for 13 March 2015. Red lines are the concentration of ice-nucleating particles predicted by the DeMott et al. [2010] parameterization for different aerosol inputs (see text for further details). Grey lines are the predicted ice-nucleating particles from the Cooper [1986] parameterization.
Figure 5. Particle size distributions from the 2DS (black lines) and CIP 100 (red lines) probes for different temperature regions for (a) 11 March 2015 and (b) 13 March 2015. The comparison with HALOHolo (blue markers) is shown on 13 March 2015 (Figure 5b). The PSDs have been averaged over individual runs/profiles made by the FAAM BAe-146. Particle size is calculated as the mean of the horizontal and vertical extents as measured by the 2DS.
Figure 5. (continued)
For the 11 March 2015 flight particles larger than 1000 μm were observed, up to the maximum size detectable by the 2DS probe. In contrast, on 13 March 2015 the concentration of particles greater than 200 to 300 μm declines rapidly and few particles were observed larger than 700 μm.

Figure 6 shows results from the CPI habit recognition algorithm for different temperature regions within the cloud. Sample images showing the contrast between higher and lower temperature regions of the clouds are shown in Figures 7a and 7b for 11 March 2015 case and Figures 7c and 7d for 13 March 2015 case. The

Figure 6. Proportions of particle habits observed by the CPI within different temperature regions of the clouds for (a) 11 March 2015 and (b) 13 March 2015. The temperatures correspond to the same runs/profiles shown in Figure 5.
11 March 2015 case shows a transition from being dominated by quasi-spherical particles at lower temperatures (230 to 234 K), to aggregates becoming more prevalent at higher temperatures (237 to 239 K). An increase in the proportion of columns and rosettes is also observed; however, these habits account for a significantly smaller proportion of the total population (less than ~5%). This change in habit is coincident with the bimodality in the PSD (Figure 5a at 237 to 239 K), suggesting that aggregation is involved in the development of the second mode at larger sizes. This is also seen in Figure 8 where the habit proportions are shown as a function of particle size. Aggregates are increasingly prevalent at larger sizes and dominate above 200 μm.

Several caveats to this should be acknowledged. First, crystals that appear to be aggregates could also have achieved their composite shape due to growth within several different temperature regions of the cloud. This would lead to a crystal acquiring various protuberances that are distinctive of different habits [Lawson et al., 2006a]. Such crystals are not easily identifiable from aggregates either by eye or with image processing algorithms. Therefore, the aggregate category represents the sum of these two processes. Second, larger particles are generally more easily classified both by eye and automatically. It has been suggested that to some extent this may be responsible for a trend of more irregular particles being found lower in cirrus clouds [Lawson et al., 2006a].
Figure 8. Proportion of habits as a function of particle size for the cirrus sampling during flights (a) 11 March 2015 and (b) 13 March 2015.
The 13 March 2015 flight shows more complex behavior; again, quasi-spherical particles were generally more abundant at lower temperatures. However, there is not the same trend of an increasing proportion of aggregates with temperature. Instead, there are large increases in the proportion of rosettes and columns, which both account for a significantly larger fraction during this flight than on 11 March 2015. During the 13 March 2015 flight, rosettes account for 10 to 30% of total particles, while columns account for 5 to 15%. In contrast, on 11 March 2015 they were both typically less than 5%. Examining the CPI images by eye, the 13 March 2015 flight shows distinctly more rosettes, qualitatively supporting the automatic habit recognition. The rosettes that were present on 11 March 2015 were generally less pristine and show signs of aggregation.

The observations at 239 K and 245 K on 13 March 2015 do not show the same behavior as those on 11 March 2015. Their PSDs are not as strongly bimodal, while quasi-spherical particles are more abundant at the expense of rosettes when compared to the observations at 234 and 237 K.

Plates were found to be the most challenging habit to detect automatically. It is possible that their concentrations given in Figure 6 are overestimated by approximately 50%. Pristine plates were observed during both flights, but they only account for a small proportion of the total crystals (less than 2%). This is in agreement with field work [Gallagher et al., 2005; Lawson et al., 2006a] and laboratory studies for low updraft velocities [Connolly et al., 2004]. However, older studies had previously suggested that plates were more abundant in cirrus clouds [Heymsfield and Platt, 1984].

For both cases, 11 and 13 March, particles classed by the habit recognition algorithm as spherical drops contribute less than 1% to the total number. It is not possible to discern by eye whether these particles are liquid or spherical ice crystals that have been misclassified.

Due to their lower pixel resolution compared to the CPI, 2DS images were not used for habit recognition. Nonetheless, 2DS images show a trend of decreasing circularity (as defined in section 2.3) with increasing temperature. This is consistent with a transition from quasi-spherical crystals to the more irregular aggregates, rosettes, and columns lower in the cloud, qualitatively supporting the CPI observations.

Aerosol measurements for both flights are summarized in Figure 1. Shown are the out-of-cloud measurements from the full size range of the PCASP probe (0.1 to 3 μm), which shows that higher concentrations were observed on 13 March 2015. Also shown are the aerosol concentrations from both the PCASP and CAS probes over the size range 0.5 to 2 μm. This is an important size range for heterogeneous ice nucleation, since it is where a large proportion of ice-nucleating particles is found [DeMott et al., 2010]. The CAS and PCASP concentrations are found to be comparable over this size range. Similarly higher concentrations in the 0.5 to 2 μm size range were observed on 13 March compared to 11 March 2015. The significance of this with respect to ice nucleation is discussed in section 4.1.

4. Discussion

4.1. Origins of Ice Crystals

This section examines the origin of ice observed during the two CIRCREX flights and whether heterogeneous ice nucleation is sufficient to explain the observed number concentrations. As described previously, 99% of particles larger than 50 μm were classified as ice by the CPI habit recognition algorithm. It is not possible to definitively determine the phase of particles smaller than ~50 μm; however, at temperatures below approximately 236 K any remaining drops will have frozen homogeneously. For this reason, Figures 4e and 4f show the 2DS concentrations that can be unambiguously classified as ice crystals. For both flights the highest concentrations of small ice (less than 100 μm in size) are observed at the lowest temperatures suggesting that this is where most of the ice nucleation is occurring. However, 2DS observes small ice particles at all levels in both clouds, suggesting that nucleation is not restricted to the lowest temperatures. This includes temperature regions that are too high for homogeneous nucleation, implying that heterogeneous nucleation is also making a contribution. Alternatively, these particles may have sedimented from above, but their small size makes this less likely.

An important consideration is whether the small particle mode is an artifact of the 2DS measurement technique. As described previously, the relatively long averaging periods ensure sufficient counting statistics, while
measurements collected above 237 K, which is higher than the lowest temperatures sampled during this work. The aerosol input to the parameterization was determined using the PCASP probe over the appropriate size range. To examine how aerosol variability affects the predicted INP, the parameterization was calculated using four different concentrations. For each range, the strict filtering by IAT described in section 3 suggests that shattered particles have been effectively removed. However, it has been suggested that IAT algorithms may not be able to remove 100% of shattered particles [Korolev and Field, 2015].

An additional artifact may be caused by out-of-focus particles. Particles that pass through the edge of the sample volume may be poorly imaged and as a consequence only obscure a few pixels and therefore be miss sized as smaller particles. Since the 2DS sample volume is size dependent and decreases for particles below 150 μm, this could lead to a significant overestimate of the concentration of small particles. As described in section 2.2, several steps were performed during data processing to remove out-of-focus particles. Particles with less than 80% of the 2DS pixels filled within their external perimeter were removed, as were particles whose center was outside of their external perimeter. However, this may not remove the very smallest and isolated out-of-focus particle remnants. To further examine the presence of small particles, we consider the concentrations of particles between 10 and 50 μm observed by the CAS and CDP probes. The exact sizing of particles measured by these probes is likely to be inaccurate due to the nonspherical nature of the ice crystals (as discussed in section 2.1). Although the CDP was fitted with antishatter tips, its data (along with those from the CAS) may also be susceptible to some ice particle shattering. IAT filtering is not possible on their data sets. Despite this, the CDP and CAS may still be used to provide a broad indication as to whether particles are present at these sizes (<50 μm). Both probes suggest similarly high concentrations of small particles to those measured by the 2DS (Table 2).

During the flight on 13 March 2015 the digital holographic imager probe HALOHolo was also operated on the aircraft. This probe has a near-uniform sample volume from 6 μm to several millimeters so should not be subject to the same uncertainty due to out-of-focus particles as the 2DS. At sizes larger than 35 μm HALOHolo’s detection rate is estimated to be 90%. As can be seen in Figure 5b HALOHolo does not show the same trend with antishatter tips, its data (along with those from the CAS) may also be susceptible to some ice particle shattering. IAT filtering is not possible on their data sets. Despite this, the CDP and CAS may still be used to provide a broad indication as to whether particles are present at these sizes (<50 μm). Both probes suggest similarly high concentrations of small particles to those measured by the 2DS (Table 2).

From these additional investigations, it is clear that further measurements are needed to unequivocally determine whether cirrus bimodal PSDs observed by optical array probes in this and previous studies [e.g., Cotton et al., 2013; Jackson et al., 2015] are an instrument artifact. However, this comparison with the holographic technique in the 13 March case suggests that they should at least be treated with caution.

Since ice-nucleating particle (INP) concentrations were not directly measured during these case studies, we use several parameterizations that are commonly used to predict their number. Figure 4 shows these parameterizations and highlights the wide range of predicted INP concentrations, which makes drawing robust conclusions difficult. Figures 4a and 4c (red lines) show the INP concentrations calculated using the DeMott et al. [2010] parameterization for the two cirrus flights using the local aerosol and ambient temperature. The aerosol input to the parameterization was determined using the PCASP probe over the appropriate size range. To examine how aerosol variability affects the predicted INP, the parameterization was calculated using four different concentrations. For each flight, out-of-cloud aerosol observations were selected over the same altitude range as the sampled cloud (as shown in Figure 1). The 25, 50, 75, and 90th percentile aerosol concentrations were then used as input to the parameterization. The parameterization is only based on measurements collected above 237 K, which is higher than the lowest temperatures sampled during this work.
(226 to 245 K). Therefore, the relationship needs to be extrapolated for comparison to the lowest-temperature CIRCCREX measurements, resulting in increased uncertainty. For 13 March 2015 DeMott et al. [2010] give reasonable agreement at the higher-temperature regions (Figure 4c), especially if only particles larger than 50 μm are considered. The parameterization and measurements then diverge at the lower temperatures. Agreement is significantly poorer on 11 March 2015 with the parameterization underestimating compared to the measurements. Even using the highest aerosol input at cloud top temperature (see section 2.4), the predicted INP of 19 L\(^{-1}\) does not approach the observed particle concentrations.

The predictions of INP from Cooper [1986] using only the ambient temperature as input are shown as grey lines on Figures 4a and 4c. The scheme is widely used as part of the Weather Research Forecasting model [Morrison et al., 2009]. The parameterization used is based on measurements down to 248 K, and below 233 K the INPs are typically fixed at a constant value [Thompson et al., 2004]. Despite this, the Cooper [1986] parameterization does a reasonable job in comparison with the 2DS for 11 March 2015; it marginally overestimates the ice concentrations at all but the very lowest temperatures where it underestimates the peak concentrations (Figures 4a and 4e).

Measurements of INP active at temperatures relevant to cirrus are still relatively rare. DeMott et al. [2003] measured INP in cirrus over the western U.S., where concentrations were found to be as high as 300 L\(^{-1}\). This is comparable with mean particle concentration observed on 11 March 2015 of 261 L\(^{-1}\) but significantly less than peak concentrations especially at the lower temperatures.

Based on Cooper [1986] and DeMott et al. [2003], it is possible that the particle concentrations at the higher temperatures can be explained by heterogeneous ice nucleation. However, given the large extrapolations/assumptions needed and range of predicted INP concentrations, this is still highly uncertain. It is plausible that DeMott et al. [2010] is the most applicable INP scheme to the higher-temperature CIRCCREX measurements, since it does not need to be extrapolated to lower temperatures to be applied and uses information about the local aerosol concentrations when predicting INP. This would suggest that on 11 March 2015 the ice crystal concentrations at high temperature are largely due to the homogeneously nucleated particles from aloft being transported to lower altitudes. None of the parameterizations can explain the peak concentrations at the lowest sampled temperatures on 11 March 2015, suggesting that homogeneous nucleation is dominating in these regions. The schemes that agree well for 11 March 2015 overestimate the concentrations for 13 March 2015. A high proportion of rosettes such as was observed on 13 March 2015 is indicative of homogeneous nucleation [Lamb and Verlinde, 2011].

There are several possible explanations for particle concentrations being approximately an order of magnitude higher on 11 March 2015 than on 13 March 2015. First, cloud top temperature on 11 March was approximately 6 K lower than on 13 March 2015 (see section 2.4). At lower temperatures particle growth rates are slower, allowing more particles to form before water vapor supersaturation is depleted [Kärcher and Lohmann, 2002]. The higher ice number concentrations will then be transported from cloud top to the higher-temperature regions sampled by the aircraft.

Figure 9 shows histograms of the vertical wind velocity during in-cloud periods (vertical profiles and mean trends have been removed). The interquartile range of vertical velocities was 0.62 m s\(^{-1}\) and 0.38 m s\(^{-1}\) for the 11 and 13 March 2015, respectively. As a result, a higher fraction of particles would be expected to sediment out of the cloud during 13 March 2015. This may explain the steep decline in concentrations at larger sizes and the absence of particles greater than approximately 700 μm on 13 March 2015 (Figure 5b). A particle’s terminal velocity typically follows a power law relationship with its diameter. A 700 μm diameter particle would have a terminal velocity of approximately 1 m s\(^{-1}\); however, this is also dependent on parameters such as shape, mass, and air pressure [Heymsfield et al., 2013]. The developing cirrus case (11 March 2015) has a higher fraction of quasi-spherical particles generally suggesting more newly frozen droplets. This would be expected given the larger updraft velocities [Kärcher and Lohmann, 2002]; however, ice concentrations are not strongly correlated with the vertical velocity.

Entrainment of dry air into the cloud is another possible reason for the difference in concentrations. Water vapor vertical profiles are not notably different between the two flights (not shown). Given the less turbulent conditions on 13 March 2015, significantly drier air above the cloud would be needed for entrainment to be the dominant cause for the difference in concentrations. However, the water vapor measurements above cloud are noisy due to the very low concentrations, making conclusions uncertain.
4. The aerosol concentration is not thought to be the dominant factor in the difference between the flights. Aerosol concentrations were slightly higher during the decaying cirrus case (13 March 2015, Figure 1), but this is not expected to lead to significant differences in the number of heterogeneous IN (as described above). A significant change in aerosol composition is also thought unlikely given that the clouds are only separated by 2 days and have comparable air mass histories (see section 2.4).

4.2. Ice Crystal Evolution

The following section examines the changing habit and size distributions for the two cirrus cases. The general pattern is one of the falling ice particles from near cloud top growing by aggregation and vapor diffusion. There are some large particles at the lowest temperatures (such as seen in Figure 7) possibly nucleated heterogeneously lower down in the cloud and then carried up. These will tend to reduce peak supersaturations and suppress homogeneous nucleation. Aggregates are present in both clouds but are particularly dominant on 11 March 2015, with single pristine rosettes and columns more evident on 13 March 2015. This difference is probably a result of the much higher concentrations and turbulent conditions on 11 March 2015 resulting in more collisions between particles [Pruppacher and Klett, 1997]. The second mode in the PSD at 200 to 300 μm is characterized by a high proportion of aggregates (Figures 5 and 7).

We now examine the possible microphysical processes in the literature that could lead to a bimodal PSD. Previous modeling studies in deep frontal clouds have proposed that aggregation is needed to simulate bimodal ice size spectra [Field, 2000; Cardwell et al., 2003]. Cardwell et al. [2003] found that the second mode was due to efficient aggregation between particles smaller than the trough in concentrations and particles between the trough and the mode. Mitchell et al. [1996a] hypothesize that aggregation within the small mode can diminish the bimodality, which grows by vapor diffusion, while the large mode grows by vapor diffusion and aggregation. A theoretical study by Khvorostyanov and Curry [2008] suggests that the bimodality forms due to condensation in the small mode, while the large mode is dominated by a combination of vapor growth, turbulent/convective transport, and sedimentation of ice from above. An increasingly distinct bimodality with higher temperature, such as observed during this work, has been suggested to be a consequence of heterogeneous nucleation and large particles sedimenting from above [Zhao et al., 2011].

Figure 9. Vertical velocity histograms during in-cloud measurements (vertical profiles and mean trend removed).
Figure 10. Particle size distributions from the 2DS probe in updrafts, downdrafts, and quiescent periods during a run at (a) 239 K on 11 March 2015 and (b) 239 K on 13 March 2015.
Figure 10. (continued)
To examine whether the bimodal PSDs are confined to specific regimes (e.g., convective, nucleation, or fall-out) or are uniformly distributed at a particular temperature, we examine the observations at 1 Hz temporal resolution. A sampling frequency of 1 Hz corresponds to a spatial scale of approximately 100 m. Figure 10a (top) shows 2DS PSDs along a run at 239 K on 11 March 2015. Compared to Figure 5, the PSDs are relatively noisy due to the shorter averaging period and increased counting uncertainty. Despite this, two modes can be identified throughout the aircraft run, with a clear trough in concentrations at 70 to 100 μm. To examine whether the bimodal distribution is associated with vertical motions, Figure 10a (bottom) shows an average PSD for this run during updrafts (vertical velocity greater than 0.25 m s⁻¹), downdrafts (less than...
and quiescent periods (between $-0.25$ m s$^{-1}$ and $0.25$ m s$^{-1}$); all three cases show bimodal PSDs. The same analysis was performed for the other runs with bimodal distributions. Similar results were found for the second run at 239 K during the 11 March 2015 case (Figure 5a) and at 234 K on 13 March 2015 (Figure 5b). It should be noted that no significant downdrafts were observed during the 234 K run. The lack of observed relationship between vertical wind and bimodal behavior does not exclude the possibility that mixing is responsible. It is feasible that the vertical mixing has occurred sometime previous to the sampling and the aircraft is just observing the result. Alternatively, it may be occurring at smaller spatial scales than the 100 m (1 Hz) our observations can reliably resolve.

These results suggest that the bimodal PSDs show this behavior down to 100 m spatial scales. The only exception that was found to this is the aircraft run at 239 K on 13 March 2015. Here two regimes were sampled, an updraft region characterized by the lofting of large particles from below and a downdraft region with predominantly small particles (Figure 10b).

Whether the 2DS small particle mode is an instrument artifact or the result of a physical process is an important unresolved issue. This will have important implications for the process understanding and modeling of cirrus microphysics. Furthermore, previous work has shown that small ice particles are one of the major uncertainties in reconciling measurements and simulations of cirrus radiative signatures [Cox et al., 2010].

### 4.3. Particle Dimensional Properties

A particle’s projected area is an important parameter in determining its radiative properties and terminal velocity. Models often parameterize projected area using a power law relationship of the form [Mitchell et al., 1996b; Schmitt and Heymsfield, 2009]

$$A = \alpha D^\beta$$  \hspace{1cm} (2)

where $A$ is the particle’s projected area, $D$ is its maximum dimension, and $\alpha/\beta$ are empirically determined fit coefficients. Figure 11 shows this relationship for different habits observed during CIRCCREX, and Table 3 gives the corresponding fit coefficients. In general, and as expected, columns have the smallest area-to-dimension ratio, while plates have the largest ratio. The coefficient of determination ($R^2$) does not improve dramatically if separate fits are used for each flight. A modest improvement in $R^2$ is found for 11 March 2015 if separate relationships are derived for each habit. However, for 13 March 2015 this is not observed, and this may be related to the lower number of particles during this flight. Also shown in Figure 10 are dimensional relationships that have been derived from previous studies in cirrus clouds. In general, these are shown to be comparable with this work and within the spread of the CIRCCREX data set. When examining the whole data set (Figure 11a), excellent agreement is found with Gallagher et al. [2005] for southern midlatitude cirrus clouds and the theoretical work of Schmitt and Heymsfield [2010]. Lawson et al. [2006a] report slightly higher area-to-dimension ratios; however, their work is still within the range observed during CIRCCREX.
5. Conclusions

The conclusions may be summarized as follows:

1. A new habit recognition algorithm for sorting CPI images into six categories (aggregates, rosette, column/bullet, plate, quasi-spherical, and spherical) using a neural network has been developed. The algorithm has an estimated classification accuracy of 88% when compared to manually classified images.

2. The clouds show evidence for both heterogeneous and homogeneous nucleation of ice particles suggesting that both processes are present.

3. Most nucleation occurs at the lowest temperatures near cloud top where the crystals are mostly small. An optical array probe observes small ice (<100 μm) at all levels in both clouds suggesting ice nucleation at all levels. This includes regions at temperatures too high for homogeneous nucleation (>238 K). It is also possible that these small particles may have been nucleated aloft and then mixed to lower altitudes.

4. Particle size distributions measured by the 2DS probe are generally bimodal at lower levels of the clouds. The first mode is positioned at the smallest detectable sizes (10 μm) and the second mode at 200 to 300 μm. This may be due to a combination of local nucleation for the former and large particles sedimenting from above for the latter.

5. A comparison with a holographic imaging probe suggests that the particle mode at small sizes observed by the optical array probes in this and several previous studies may be, at least be in part, an artifact, possibly due to the partial observation of miss-sized larger particles. However, other scattering probe data (CDP and CAS) lend support for the presence of smaller ice particles (although such probes are not designed for ice particle measurements, so these are subject to significant uncertainty). The presence or absence of such small particles has important implications for understanding cirrus cloud microphysics and radiative properties, and so further investigation of this issue is crucial to further progress.

6. The general trend in the observed cirrus is one of the falling ice particles from near cloud top growing by vapor diffusion and forming larger aggregates particularly in the developing cloud (11 March 2015). As a consequence, ice water contents increase at lower altitudes as the number concentration of crystals decrease. Aggregates are more evident on 11 March 2015 consistent with the larger vertical winds in this cloud and pristine single rosettes more evident in the decaying 13 March 2015 case.

7. The ice crystal concentrations are significantly higher (by a factor ~10) on 11 March flight than 13 March 2015. This is true across the size distribution; however, it is particularly distinct at the largest measured sizes. Particles larger than 700 μm are largely absent in the decaying cirrus case (13 March 2015). It is inferred that these particles have sedimented out of the cloud due to the low turbulence during this case.

8. The developing cirrus (11 March 2015) case has more quasi-spherical particles generally, suggesting newly frozen deliquesced aerosol and droplets.

9. Measured particle concentrations have been compared with two schemes commonly used to parameterize heterogeneous IN concentrations. DeMott et al. [2010] predict significantly less IN than the observed particle concentrations on 11 March 2015; however, it is more comparable for the higher-temperature regions on 13 March 2015. Cooper [1986] gives reasonable agreement for the developing cirrus case for all but the lowest sampled temperatures (226 K), where it is expected that homogeneous nucleation is dominant. In contrast, Cooper [1986] overestimates the concentration for 13 March 2015, which is consistent with the particles falling out of this cloud.

10. We have examined ice crystal area dimension ratios for different habits. These are found to not vary significantly between the two flights and are in good agreement with previous studies.

We have presented comprehensive measurements of cirrus number concentration, habit, and size, together with the local aerosol properties for two very different case studies. Ongoing work is examining these microphysical parameters together with coincident radiation measurements in order to develop more accurate parameterizations of cirrus optical properties for use in numerical weather/climate prediction models.

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