Microphysical structures and hydrometeor phase in convection using radar Doppler spectra at Darwin, Australia

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Abstract

To understand the microphysical processes that impact diabatic heating and cloud lifetimes in convection, we need to characterize the spatial distribution of supercooled liquid water. To address this observational challenge, vertically pointing active sensors at the Darwin Atmospheric Radiation Measurement (ARM) site are used to classify cloud phase within a deep convective cloud in a shallow to deep convection transitional case. The cloud cannot be fully observed by a lidar due to signal attenuation. Thus we develop an objective method for identifying hydrometeor classes, including mixed-phase conditions, using k-means clustering on parameters that describe the shape of the Doppler spectra from vertically pointing Ka band cloud radar. This approach shows that multiple, overlapping mixed-phase layers exist within the cloud, rather than a single region of supercooled liquid, indicating complexity to how ice growth and diabatic heating occurs in the vertical structure of the cloud.

1 Introduction

The presence of supercooled liquid water in clouds has a significant feedback on the radiative and latent heating in clouds [e.g. *Krueger et al.*, 1995; *McCoy et al.*, 2016; *Morrison et al.*, 2012]. In convective clouds, strong latent heating from the rapid formation of cloud drops warms the surrounding air and fuels the development of the cloud. The distribution of liquid layers in deep convective clouds and the microphysical processes that help form these layers are largely uncertain due to the difficulty in measuring convective cloud properties and distinguishing mixed-phase conditions using either remote sensors or aircraft in situ measurements [*Battaglia et*

al., 2016; *Baumgardner et al.*, 2017; *Rosenfeld and Woodley*, 2000; *Tan et al.*, 2016]. The processes responsible for cloud hydrometeor phase are not well represented in global climate models (GCMs) leading to uncertainty in calculating the magnitude of the cloud-phase feedback to climate change [*IPCC*, 2013; *Tan et al.*, 2016; *Zhao et al.*, 2016].

Ice nucleation and ice crystal growth are important contributors to convective cloud processes. Ice nucleation in temperatures between about 0° and -40° C depends on the availability of heterogeneous ice nuclei, as well as secondary ice production processes (i.e. Hallet-Mossop mechanism), both uncertain in GCMs. However, simply improving the ice nucleation scheme in global climate models alone does not produce the observed regional and temperature dependence of supercooled liquid [*Komurcu et al.* [2014]. Ice growth mechanisms, like the Wegener-Bergeron-Findeisen (WBF) process, where ice crystals grow at the expense of evaporating cloud drops, are also very important and depend on the colocation of liquid water and ice particles within the cloud in addition to the vertical velocity and thermodynamic conditions of the cloud [*Korolev*, 2007; *Krueger et al.*, 1995]. The scale of these processes, which are much smaller than GCM grid sizes, continues to challenge the representation of microphysical processes in GCMs [*Tan and Storelvmo*, 2016; *Tan et al.*, 2016], and is the primary source of uncertainty in GCM simulations of phase partitioning in mixed-phase clouds [*Cesana et al.*, 2015; *Forbes and Ahlgrimm*, 2014; *Tan and Storelvmo*, 2016].

Thus to understand the impact of hydrometeor phase on cloud growth and properties we need to observe not just the amount of supercooled liquid water within clouds, but how it is distributed within the cloud volume. Several studies have examined the spatial scales of supercooled liquid water in mixed-phase clouds. Aircraft in situ observations, which are limited to providing measurements with a spatial averaging of 100 m (i.e. 1 s average), show that inhomogeneities in

the spatial locations of liquid and ice in mixed-phase clouds occur on spatial scales from kms to within 100 m [*Fu and Hollars*, 2004; *Korolev et al.*, 2003]. Using a satellite based multispectral imager with 2 m resolution, *Chylek and Borel* [2004] found spatial variability of cloud phase in arctic mixed-phase stratiform clouds with a spatial scale on the order of tens of meters. Reconciling the scales of spatial inhomogeneities on which cloud phase depends is an important step to improving model representations.

Fewer observations of mixed-phase conditions exist in convective clouds because of the additional challenges of flying through strong convective updrafts and interpreting remote sensing data in optically thick or precipitating conditions. Aircraft flights through deep convection [*Rosenfeld and Woodley*, 2000] and precipitation radar retrievals [*Dolan et al.*, 2013; *Xu and Zipser*, 2015] confirm theory that higher updraft speeds create supercooled liquid higher in the cloud, including increased invigoration of convection under high CCN concentrations [*Peng et al.*, 2016; *Rosenfeld et al.*, 2008]. However, measurements of mixed-phase conditions in convective clouds remain difficult, and new measurement methods to observe them are a developing area of research. For example, spectral reflectivity measurements taken from aircraft flying beside deep convective clouds are being used to derive vertical distributions of supercooled liquid within deep convection [*Jäkel et al.*, 2017].

Vertically pointing cloud lidar and radar observations have the potential to remotely characterize the presence and spatial scales of liquid layers in convective clouds because of their high temporal and spatial resolution. While lidar measurements have been used extensively to identify liquid in clouds [e.g., *Cesana et al.*, 2016; *Hogan et al.*, 2003; *Riihimaki et al.*, 2012; *Sassen*, 1991], lidar quickly attenuates in the presence of liquid, thus limiting the ability to fully probe the cloud. In this study, we demonstrate an algorithm based on Doppler spectra measured by a

high-resolution, vertically pointing Ka-band radar to identify regions (micro-structures) of supercooled liquid. The use of Doppler spectra has previously been demonstrated to be useful for identifying mixed-phase conditions in stratiform clouds in high latitudes [e.g., *Kalesse et al.*, 2016; *Luke et al.*, 2010; *Riihimaki et al.*, 2016], and in a few case studies of convective anvils [*Giangrande et al.*, 2016; *Shupe et al.*, 2004]. Here we apply a k-means clustering algorithm on Doppler spectra shape parameters to identify mixed-phase microstructures within a convective cloud at Darwin, Australia. Because the Ka-band radar attenuates in heavy precipitation, the technique will not work in heavily-precipitating deep convective cores. However, it is a promising technique in developing and weakly precipitating convection and stratiform regions associated with deep convection. This allows us to investigate shallow to deep convection transition cases, a regime that is difficult to observe with precipitation radars. These measurements are used to examine the potential contribution of liquid microstructures to the WBF process in convective clouds, which could have important implications for future observational-modeling studies.

2 Observational data

Data used in this study was measured at the Department of Energy Atmospheric Radiation Measurement (ARM) observational facility in Darwin, Australia [*Mather et al.*, 1998]. Raman lidar data was processed using the Feature detection and EXtinction retrieval (FEX) algorithm [*Thorsen and Fu*, 2015; *Thorsen et al.*, 2015]. In this study, we use the FEX-derived 355 nm backscatter, depolarization ratio, and feature mask.

Column liquid water path was retrieved from a microwave radiometer (MWR) measuring radiances at 23.8 and 31.4 GHz [*Gaustad*, 2011], using a physical optimal estimation retrieval method [*Turner et al.*, 2007]. These measurements are generally accurate to 20-30 g/m^2.

Radar Doppler spectra comes from the vertically pointing Ka ARM Zenith Radar (KAZR) that operates at a frequency of 35 GHz [*Bharadwaj et al.*, 2011; *Widener et al.*, 2012]. In addition to the original spectra data, we use the MicroARSCL higher order data product [*Jensen et al.*, 2016] which eliminates radar artifacts, identifies multiple peaks in the spectra, and calculates moments and other statistical descriptions of the spectral peaks [*Kollias et al.*, 2007].

Heavy rainfall can bias both the MWR and KAZR data. However, in the case presented here, a tipping bucket rain gauge measures no precipitation reaching the surface. Therefore, the MWR should have no water pooling on the window, and the rain rate is insufficient to attenuate the KAZR.

Temperature and humidity profiles are taken from radiosondes launched at 11:00 and 23:00 UTC [*Holdridge et al.*, 1994]. This information is supplemented with higher temporal resolution temperature profiles from the Raman Lidar [*Sivaraman and Flynn*, 2009], though temperature information is only available below the heights where the lidar attenuates.

3 Evidence of supercooled liquid

We examine a deep convective cloud observed by multiple sensors at the Darwin, Australia ARM site on May 17, 2013, from approximately 20:00 to 22:00 UTC (Figure 1). This case was chosen because it is both scientifically interesting and well suited to the strengths of the instrumentation we are using. The case represents a transition case from congestus to isolated

deep convection, a challenging transition to simulate accurately in models. It is also an ideal candidate for developing our retrieval method because the Raman lidar sees a significant portion of the cloud, providing validation data for the development of the KAZR methodology. Additionally, because the precipitation intensity is fairly low, attenuation of the KAZR is not a concern.

Raman lidar observations indicate that several layers containing supercooled liquid water can be found within the cloud. Figure 1c shows high backscatter values at points labeled B and D, consistent with high particle number concentrations found with liquid drops. Directly above these layers, the lidar is attenuated, another strong indicator of liquid. Peaks are found in column liquid water path observations around the times (20:20 and 20:40 UTC) when the Raman Lidar is attenuated.

Thorsen and Fu [2015] classified feature type from ARM Raman Lidar data, distinguishing liquid, ice, and horizontally oriented ice using thresholds of backscatter and depolarization ratio, thermodynamic information, and rules to adjust for nearby classifications. The results of this classification (Fig. 1g) indicate multiple liquid layers within the deep convective cloud that begins around 20:00 UTC.

4 Identifying mixed-phase layers from radar Doppler spectra

Various moments of the KAZR Doppler spectra are shown in the right column of Figure 1. The liquid layers detected by the Raman Lidar (Fig 1g) are not readily apparent in reflectivity, mean velocity, or spectrum width (Figs 1b, 1d, and 1f respectively) as they are in the lidar backscatter (Fig. 1c). Yet examining individual Doppler spectra does show properties that can distinguish

cloud phase. Figure 2 shows radar Doppler spectra from five individual points in time and height identified with circles and corresponding letters in Figure 1.

The Doppler spectrum plotted in Fig. 2d corresponds to a region above the melting layer that the Raman Lidar indicates contains liquid hydrometeors. The Doppler spectra shows two distinct peaks: one large peak with a negative (downward) mean velocity of about 1 m/s, and a second smaller peak with a positive (upward) mean velocity of about 0.5 m/s. These two distinct peaks correspond to two distinct populations of hydrometeors within the measured cloud volume, a group of larger falling particles and smaller rising particles. Given the confirmation of liquid water from the lidar and microwave radiometer, we can confidently interpret the smaller peak as a signal from liquid cloud droplets. A bright band is seen in the reflectivity around 5 km in height, indicating the existence of falling ice crystals that are coated with water as they melt [e.g., *Austin and Bemis*, 1950]. Point D is above the melting layer and radar bright band, so it is likely that the larger peak corresponds to falling ice. The shape of the ice peak (Fig 2d) is distinct from the Doppler spectrum of a rain hydrometeor (Fig 2e) with its much broader peak and stronger fall velocity.

The Doppler spectra in Fig 2b and 2c both have peaks around 1 m/s with relatively high intensities, similar to the ice peak in Fig 2d. However, the peak in Fig 2b is broader and positively skewed, an indication of the merging of a large and a smaller peak that are not as distinct as those in Fig 2d. This point also corresponds to a region that very likely contains liquid water as determined by the high Raman Lidar backscatter, lidar attenuation (Fig 1c), and liquid water path (Fig 1a). Thus the interpretation that this is also a mixed-phase layer is quite reasonable. Above this mixed-phase point, we see a Doppler spectrum that contains a small peak with a weak fall speed (Fig 2a), and this corresponds to a layer at the top of the cloud with

smaller reflectivities (Fig 1b), Doppler velocities (Fig 1d), and spectrum width (Fig 1f). We interpret this region of small, slowly falling particles as small ice particles because the temperatures are below -25° C, the Doppler velocities are all toward the ground indicating there is unlikely an updraft required to sustain liquid, and this region of the cloud does not attenuate the lidar.

Manual interpretation of radar Doppler spectra can be quite effective, but is inefficient for large data sets. Thus we wish to identify statistical descriptors of Doppler spectra that can be used in an automated algorithm. We apply a k-means clustering algorithm [*Arthur and Vassilvitskii*, 2007; *MacQueen*, 1967] to identify three clusters in various combinations of variables describing the Doppler spectra. K-means clustering is an objective method of dividing a set of data points into a specified number of clusters by minimizing the distances between the data points and centroids of those clusters. The algorithm iteratively determines the centroids and which cluster each data point belongs to, thus we only specify the number of clusters to be identified and which variables to use to define the parameter space. We found that the most effective combination of radar variables was spectrum width (Fig 1f), left slope (Fig 1h), and right slope (Fig. 1j) based on a comparison of the clustering results (e.g. Fig. 1i) to the phase classes determined from Raman Lidar data (Fig. 1g). Left slope and right slope are the slopes from the primary peak of the Doppler spectra to the noise floor on the left or right tail respectively. The results of this clustering can be seen in Figure 1i, with each of the three clusters shown in a different color. The ice, mixed, and precipitation labels are assumed for the clusters based on the manual interpretation of individual Doppler spectra described above. In addition to the clusters, radar pixels with a secondary peak (like that shown in Fig. 2d) are indicated in black. These points are also likely to be mixed-phase when observed in the cloud itself.

The results of the k-means clustering are quite promising as a more broadly applicable phase classification method for several reasons. First, we note that the three parameters that were of most use in distinguishing hydrometeors were parameters that described the shape of the Doppler spectra and not the intensity of the Radar power return or the value of the Doppler velocity. Thus these values are less dependent on environmental factors like updraft speed or overall particle size, or on the calibration of the radar. Second, the interpretation of these parameters makes physical sense. When attempting to detect a signal in a Doppler spectrum from liquid hydrometeors that is not fully separable from the ice signal, as in Fig. 2b, the merged peak will appear broader (spectrum width larger) and the left tail will be longer (left slope will decrease). We also find that the right slope increases, or shifts to smaller negative numbers, in mixed-phase regions. One possible interpretation of this would be ice particles growing at a faster rate due to riming with larger particles causing an increase in the right slope. While some of these changes in slope can also be measured by the changes in the spectrum skewness as used by *Giangrande et al.* [2016], we found using the left and right slope variables individually to be more effective at identifying the liquid layers than using skewness in this case. It remains to be investigated whether this holds true for a larger set of data.

4 Discussion

Knowledge of not just the existence, but also the location, of supercooled liquid water within a cloud is necessary to understand the microphysical impact. Two important mixed-phase processes, ice nucleation and the growth of ice via the Wegner-Bergeron-Findeisen (WBF) mechanism, depend on the cloud conditions under which supercooled liquid water exists, and our understanding of these mechanisms suffers from lack of observational data to constrain models. Without further information about the cloud hydrometeor particle size distributions and

availability of potential ice nuclei, we can't determine which heterogeneous ice nucleation mechanisms are important in this case. The retrieved information does give interesting insight into the ice growth mechanisms, however.

In addition to the requirement that ice and liquid be in the same physical location, the WBF process also depends on the supersaturation conditions of the cloud. *Korolev and Mazin* [2003] used diffusional growth theory to show that in most cases the supersaturation depends only on vertical velocity, the size distribution of the particles, temperature, and pressure. In Figure 3, we use this method [*Korolev*, 2007; *Korolev and Mazin*, 2003] to calculate a critical maximum updraft velocity and minimum downdraft velocity as a function of the number concentration and mean radius of ice and liquid droplets for the pressure and temperature relevant to one of the mixed-phase sections of our cloud. This mixed-phase region is indicated by the black rectangle in Figure 3a, and 3c, chosen because it is a region with a large number of observations containing two distinct peaks in the KAZR Doppler spectra (e.g. the example shown in Fig 2d). The secondary liquid peak in the Doppler velocity is used as a proxy for the vertical velocity, since the small liquid droplets travel with the motion of the air. The inset in Figure 3c shows a histogram of vertical velocities in this region showing a peak around 0.4 m/s (updraft) and a second peak around -0.2 m/s (downdraft). This range of vertical velocities is indicated by the black dashed lines and dotted areas plotted in Figures 3 b, d. The solid black line indicates the mean observed vertical velocity. The red regions show theoretical vertical velocity thresholds defining WBF conditions. These are plotted with respect to the number concentration times the effective radius of ice/liquid for updrafts/downdrafts. The radar reflectivity does not provide a significant constraint on the number concentration of the particles, so a wide range of possible size distributions for this case is represented in the figure. The threshold values are calculated for

an estimated temperature of -2° C and pressure of 550 mb (solid red line), and the sensitivity to a temperature increase or decrease of 1° C are shown in dashed lines. The overlapping regions of the dotted and red areas show velocities and particle size distributions for which the supersaturation in the cloud indicates that the WBF process would occur.

When the vapor pressure of an air parcel is higher than the equilibrium vapor pressure of both liquid and ice, then diffusion theory predicts that both liquid and ice particles will continue to grow [*Korolev*, 2007]. Figure 3b shows that vertical velocities of even 1 m/s create high enough vapor pressures for this limit to be true for most particle size distributions (region above the red line). Thus, in most deep convective clouds, the vertical velocity is sufficiently strong that both ice and liquid grow simultaneously. Even the relatively weak updraft speeds of 0.2-0.5 m/s in this cloud are likely strong enough to allow for the growth of liquid, though this cannot be confirmed without a better constraint on the ice particle size distribution. In the downdraft regions, however, it appears that the WBF process is relevant and the ice is still growing. The higher updraft speeds occur earlier in the cloud around 20:30, and the downdrafts appear later, after 20:45 (Fig 3c), showing the aging of the cloud.

5 Summary and Outlook

In this work, we showed that vertically pointing active sensors can identify mixed-phase microstructures within a deep convective cloud. These microstructures are particularly interesting given the deficiencies in the parameterizations responsible for ice nucleation and microphysical growth in mixed-phase conditions. For example, *Tan et al.* [2016] suggest that the WBF process, where cloud ice grows rapidly at the expense of liquid, is too efficient in GCMs because parameterizations assume a homogeneous mixture of ice and liquid throughout the cloud

volume, which is often not the case in observations [*Fu and Hollars*, 2004]. The observations in this convective cloud case are no exception, showing multiple layers containing supercooled liquid, rather than its existence over a broad, uniform swath of the cloud. Moreover, the variable vertical velocities in the updrafts of this weak convective cloud likely include regions with sufficiently strong updraft speeds to sustain liquid droplet growth in the presence of ice, and other regions where ice growth occurs at the expense of the liquid.

The detection of multiple liquid layers within convection is a unique observational achievement due to the limitations of many remote sensing instruments. Most passive remote sensors give only a column measurement, rather than probing the vertical structure of a cloud. In active remote sensing, radar frequencies tend to be dominated by large ice and precipitation particles and radar moments like reflectivity are not very sensitive to the small liquid droplets. Lidar observations, though quite effective at detecting liquid, attenuate rapidly once the first liquid layer is reached and are thus unable to identify multiple liquid layers within a column. The KAZR Doppler spectra provide a signature of mixed-phase conditions from either distinct multiple peaks or a merged skewed peak. In this case, k-means clustering on parameters describing the shape of the Doppler spectra (spectrum width, left and right slopes) was able to identify mixed-phase microstructures, including multiple liquid layers within the column.

This case is a good example of the transition from shallow to deep convection showing several congestus clouds followed by an isolated deep convective cloud. Further modeling studies of this case could help identify the latent and radiative impact of the supercooled liquid microstructures on the development of the convective cloud. While the magnitude of the latent heating due to condensation is generally much larger than that of the radiative heating, the vertical structure of latent and radiative heating differ such that both impact the diabatic heating profile and cloud

dynamics [*Jensen and Del Genio*, 2003]. Additionally, the WBF process is a critical microphysical factor impacting the size of convective anvils and their radiative effects [*Krueger et al.*, 1995; *Zhao et al.*, 2016], so understanding the small-scale distribution of liquid can improve our understanding of the impact of this process on the life cycle of deep convection and its associated anvils.

The scale of GCMs is too coarse to capture the supercooled liquid microstructures observed in this case, so in order to improve the representation of mixed-phase microphysical processes in climate predictions, we must develop a statistical understanding of the impact of these microstructures. In the future, we plan to apply this method to a longer time period in order to develop statistics of mixed-phase microstructures within similar cases representing convective cloud populations transitioning from shallow or congestus clouds to deep convection. These statistics will be used to provide a constraint for parameterization development.

Acknowledgments and Data

Figure Captions

Figure 1. Observations of a convective cloud on May 17, 2013 at Darwin, Australia. Panels show MWR liquid water path (a), Raman Lidar profile observations (c,e), moments of the KAZR

Doppler spectra (b,d,f,h,j), and identification of hydrometeor type derived from raman lidar (g) and KAZR (i). Dotted lines in panels (g,i) show 10° C contour lines derived by interpolating twice daily sonde launches, while the solid black line shows the freezing level derived from Raman Lidar measurements. Labeled circles identify individual pixels for which KAZR Doppler spectra are shown in Figure 2.

Figure 2. KAZR Doppler spectra from five individual pixels (time and range gate) during the day. In this sign convention, negative Doppler velocities correspond to falling particles. Panel letters correspond to points labeled with circles in Figure 1. Assignment of the hydrometeor class for each point is described in the text. Estimates of the temperatures are given in the figures for context, with uncertainties of at least 2° C based on differences between Raman Lidar observed temperatures and temperature profiles derived by interpolating radiosondes launched at 11 am and pm UTC.

Figure 3. Mean Doppler Velocity from the primary (a) and secondary (c) peaks of the Doppler spectra, with box indicating mixed-phase region with sufficient secondary peaks to derive vertical velocity. A histogram of secondary peak Doppler velocities (c, inset) shows the vertical velocity range in that section of the cloud. The red regions show theoretical updraft (b) and downdraft (d) velocities for which the Wegener Bergeron Findeisen (WBF) process is valid for a given particle number concentration and mean radius of ice (b) or liquid (d) particles. Red dashed lines show sensitivity of the threshold to temperatures of 1° C below or above the -2° C temperature used in the calculations. The dotted regions (b,d) indicate the range of measured vertical velocities (derived from histogram in panel c), with minimum and maximum vertical velocities (black dashed lines), and mean vertical velocities (solid black line).

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