USE OF RADAR DOPPLER SPECTRA IN ARCTIC MIXED-PHASE CLOUD STUDIES

A Dissertation in
Meteorology
by
Guo Yu

© 2013 Guo Yu

Submitted in Partial Fulfillment
of the Requirements
for the Degree of

Doctor of Philosophy

December 2013
The dissertation of Guo Yu was reviewed and approved* by the following:

Johannes Verlinde
Professor of Meteorology
Chair of Graduate Program
Dissertation Advisor, Chair of Committee

Eugene E. Clothiaux
Professor of Meteorology

Jerry Y. Harrington
Associate Professor of Meteorology

Runze Li
Distinguished Professor of Statistics and Professor of Public Health Sciences

Kultegin Aydin
Professor of Electrical Engineering
Department Head of Electrical Engineering

*Signatures are on file in the Graduate School.
Abstract

Stratiform clouds across the globe frequently contain both liquid- and ice-particles within the same region of the atmosphere; that is, they are often mixed-phase clouds. Modeling the processes of mixed-phase stratiform clouds remains a challenge. Progress is slow in part because of the dearth of observations that shed light on critical processes in these clouds. Recent availability of high quality millimeter-wave cloud radar Doppler spectra is an important new source of information on the micro-physical and dynamical processes within these clouds.

In the current study a radar Doppler spectrum simulator is used to produce in-cloud radar Doppler spectra from outputs of large eddy simulations with detailed bin microphysics. These model-simulated radar Doppler spectra are compared with observed radar Doppler spectra for the case study period via comparisons of reflectivity, mean Doppler velocity, and spectrum width, as well as estimates of volume-mean vertical air velocities and hydrometeor fall speeds extracted from the spectra. The results indicate that there is a mismatch in the important processes governing model and observed mixed-phase clouds, including cloud vertical air motion structures, ice nucleation, ice aggregation, and how the model increases ice particle fall speeds as particles gain mass. In order to improve mixed-phase cloud parameterizations in models, specific observations to constrain model parameters are required.

Retrieving and quantifying the radiatively important liquid-phase particles within mixed-phase clouds remains a challenge because the radar signal is frequently dominated by the returns from the ice particles within these clouds. The ice masks the small reflectivity contributions from the liquid phase. To extract these small liquid-phase contributions a spectral deconvolution algorithm is developed that separates them from MMCR/KAZR Doppler-velocity spectra in which ice-particle returns dominate. In this approach spectra are first decomposed using a continuous wavelet transform. The resulting coefficients are then used to iden-
tify regions in the spectra where cloud-liquid drops contribute; Gaussian distributions are subsequently fit to these regions. Results from this algorithm indicate that this approach is capable of separating the cloud-liquid drop and ice-particle contributions to the radar Doppler spectra. In the process volume-mean vertical air velocities, turbulent broadening and mean ice-particle fall speeds are also extracted.

Statistics of the macro-physical, micro-physical, thermodynamical, and dynamical properties of mixed-phase clouds are characterized using a month of ground-based measurements collected during October 2011 at Barrow, Alaska. Cloud layer temperature is the primary factor that determines mixed-phase cloud properties. One-hour mixed-phase cloud events are classified into cold and warm cases. Clouds in category 1 (warm) were lower, thinner and had weaker and liquid-dominated precipitation, while clouds in category 2 (cold) were higher, thicker and had more intense and ice-dominated precipitation. Precipitation reflectivities and reflectivity-weighted mean precipitation fall speeds are found to increase with vertical air motion. Ice particles generally form, grow and fall out of the cloud layer in updraft regions. Ice precipitation processes also play a role in determining the macro-physical properties and liquid microphysics of these clouds.

The newly developed spectral deconvolution algorithm enables us to investigate relationships between cloud macro-physical, micro-physical, thermodynamical and dynamical properties based on long-term observations of mixed-phase clouds. Studies on these relationships derived from long-term observation will strengthen our understanding of the physical processes in Arctic mixed-phase clouds, which is necessary to develop more sophisticated parameterizations to partition cloud phases in climate models.
Table of Contents

List of Figures vii
List of Tables ix
Acknowledgments x

Chapter 1
Introduction 1
1.1 Dissertation Outline ........................................ 3

Chapter 2
Evaluating models of mixed-phase cloud processes using radar Doppler spectra 5
2.1 Introduction .................................................... 6
2.2 Data and Methodology ......................................... 7
2.3 Results .......................................................... 12
2.4 Discussion ...................................................... 18
2.5 Conclusion ...................................................... 23

Chapter 3
Mixed-Phase Cloud Phase Partitioning Using Millimeter-Wavelength Cloud Radar Doppler Velocity Spectra 25
3.1 Introduction ..................................................... 26
3.2 Method .......................................................... 29
3.2.1 Extracting Cloud Liquid Drop Mode Candidates ....... 30
3.2.2 Selecting the Cloud Liquid Drop Mode ................. 33
3.2.3 Automated Cloud Event Selection Criteria ............. 37
3.3 Validation of Algorithm Retrievals ......................... 38
3.4 Results ......................................................... 40
   3.4.1 First Case Study Period ............................... 41
   3.4.2 Second Case Study Period ....................... 44
   3.4.3 Statistics for Single-Layer Low-Level Clouds in October 2011 48
3.5 Discussion .................................................. 52
3.6 Summary and Conclusions ............................... 55

Chapter 4
Statistics of Arctic mixed-phase cloud properties based on one month of observations 58
  4.1 Introduction ............................................. 58
  4.2 Data and Methodology ................................ 60
  4.3 Results .................................................. 65
     4.3.1 Macro-physical properties ....................... 66
     4.3.2 Thermodynamic properties ....................... 67
     4.3.3 Micro-physical properties ....................... 68
     4.3.4 Joint Distributions ............................... 71
  4.4 Discussion ................................................ 80
  4.5 Summary and Conclusions ............................. 82

Chapter 5
Summary and Conclusions ................................. 84

Bibliography .................................................. 88
## List of Figures

2.1 Steps to generate a simulated Doppler spectra .......................... 9
2.2 Frequency histograms of the vertical velocity .......................... 13
2.3 Frequency histograms of the moments ................................. 14
2.4 Frequency of occurrence histograms of the standard deviations of sub-grid vertical air velocity variances from the radar observations (shaded) and diagnosed from the model low-density (solid black line) and high-density (dashed black line) ice particle simulations. The mean of the observed histogram is represented by the solid red vertical line, whereas the means of the low- and high-density ice particle simulation histograms are represented by the solid and dashed black vertical lines. ........................................... 16
2.5 Frequency histograms of the moments (larger wind shear) ......... 17
2.6 Time series of the estimated vertical air motion ..................... 21

3.1 Examples of radar Doppler spectra ................................. 29
3.2 The continuous wavelet transform analysis ......................... 32
3.3 Examples of membership functions ................................. 36
3.4 Comparisons between the retrieved and model values ............ 40
3.5 Error analysis of the comparison between the retrieved and model values ........................................... 41
3.6 Observed total reflectivity from 21:00 - 22:00 UTC on 14 October 2011 ......................................................... 42
3.7 Retrievals from 21:00 - 22:00 UTC on 14 October 2011 ........... 43
3.8 Retrievals for a shorter period during case one ..................... 44
3.9 Joint distributions for case one .................................... 45
3.10 Observed total reflectivities from 11:00 - 12:00 UTC on 8 October 2011 ......................................................... 46
3.11 Retrievals from 11:00 - 12:00 UTC on 8 October 2011 ........... 47
3.12 Retrievals for shorter period during case two ..................... 48
3.13 Joint distributions for case two .................................... 49
3.14 Comparisons near cloud base ..................................... 50
3.15 Normalized frequency of occurrences of the retrieved volume-mean vertical air velocities ............................................ 52
3.16 LWPs comparisons for both cases and a coefficient variation ..... 54

4.1 Normalized frequency of occurrence distributions of cloud top and base temperatures ................................................. 62
4.2 Example of the mixed-phase cloud observed on October 8 2011 .. 63
4.3 Example of the mixed-phase cloud observed on October 23 2011 .. 64
4.4 Normalized frequency of occurrence distributions of mixed-phase cloud macro-physical properties .......................... 65
4.5 Normalized frequency of occurrence distributions of mixed-phase cloud thermodynamic properties ........................... 67
4.6 Normalized frequency of occurrence distributions of radar moments 69
4.7 Normalized frequency of occurrence distributions of radar retrievals based on spectrum deconvolution algorithm .......... 70
4.8 The contour frequency distribution of mixed-phase cloud properties as a function of layer-mean vertical velocity ............... 72
4.9 Relationships between layer-mean vertical air motion and mixed-phase cloud properties .............................................. 73
4.10 The contour frequency distribution of mixed-phase cloud properties derived using spectrum deconvolution algorithm ........ 75
4.11 The relationships of mixed-phase cloud properties derived using spectrum deconvolution algorithm .......................... 76
4.12 The contour frequency distributions of maximum precipitation reflectivity as a function of maximum liquid reflectivity ........ 78
4.13 Relationships between maximum precipitation reflectivity and maximum liquid reflectivity ....................................... 78
4.14 Comparisons on cloud events with same layer thickness .......... 81
List of Tables

3.1 Radar Doppler spectra classifier ........................................... 35
3.2 Cloud event case selection criteria. ....................................... 37
Acknowledgments

Foremost, I would like to express my sincere thanks to my Ph.D committee, Johannes Verlinde, Eugene Clothiaux, Jerry Harrington, Runze Li and Kultegin Aydin. I especially appreciate the membership from Prof. Johannes Verlinde over the past five years, and I am so grateful for his continuous support of my Ph.D study and research, for his patience, motivation, enthusiasm, and immense knowledge. His guidance helped me in all the time of research and writing of this thesis. I could not have imagined having a better advisor and mentor for my Ph.D study. I also offer my sincere appreciation to Prof. Eugene Clothiaux for giving so much of his time and effort through his help to benefit my research and education as a graduate student.

I appreciate many contributions that many scientists have made to the research I present in this dissertation, particularly Andy Ackerman, Ann Fridlind, Alex Avramov, and Giovanni Botta in Chapter 2 and 3. I also thank Ed Luke and Pavlos Kollias providing the seed for the technique described in this dissertation. Finally, I offer my gratitude for support through the U.S. Department of Energy’s Atmospheric Science Program Atmospheric System Research, an Office of Science, Office of Biological and Environmental Research program, under Grant No. DE-FG02-05ER64058.
Observational and modeling studies suggest that higher latitude climate warming is occurring at twice the rate compared to lower latitudes (Hansen et al., 2010; Parry et al., 2007; Rigor et al., 2000; Serreze et al., 2009), a process known as polar amplification. Observations show a reduction in summer ice extent (Fetterer et al., 2010). In September 2012, areal sea ice extent decreased to well below the previous record minimum established in 2007 (Parkinson and Comiso, 2013). Clouds play an important, yet complicated, role in the processes interacting with Arctic surface environments. Kay et al. (2008) and Kay and Gettelman (2009) point out that changes of Arctic mixed-phase cloud properties may have accounted for the significant summer sea ice losses in recent years.

Mixed-phase cloud is defined as a system with liquid and ice coexisting near each other. Arctic stratiform mixed-phase clouds cover large areas of this region and occur during all seasons of the year (Shupe, 2011), though most frequently during the spring and fall transition seasons (Shupe et al., 2006). They are persistent systems that can last for days, even weeks, despite the inherent instability of cloud liquid drop and ice particle co-existence (Shupe, 2011; Verlinde et al., 2007; Zuidema et al., 2005). Mixed-phase clouds are optically thicker than ice-only clouds and they impact the surface short- and long-wave radiative fluxes (Curry et al., 1996; Shupe and Intrieri, 2004), and thus the Arctic surface energy budget. The impacts of mixed-phase clouds vary with their relative amounts of liquid and ice, but can be large because of their frequent occurrences, large areal coverage and long lifetimes.
Studies of mixed-phase clouds properties are crucial to accurate estimation of the Arctic surface energy budget. However, our understanding of Arctic mixed-phase clouds is still relatively limited, in part a result of observational challenges in observing super-cooled liquid clouds embedded within ice precipitation and in part because the delicately linked dynamical, micro-physical and radiative processes in mixed-phase clouds present challenges for models of all scales (Gorodetskaya et al., 2008; Klein et al., 2009; Morrison et al., 2011). Modeling studies have shown that the characteristics of mixed-phase clouds are impacted by ice nucleus number concentration (Fan et al., 2009; Fridlind et al., 2007; Harrington et al., 1999; Morrison and Pinto, 2006; Prenni et al., 2007; Solomon et al., 2009), ice crystal habit (Avramov and Harrington, 2010), and ice habit evolution (Sulia and Harrington, 2011). Models still have difficulty reproducing observations of Arctic cloud properties (e.g., liquid water path, ice/liquid water content ratio, and ice particle concentration) due to the large uncertainties in the representation of ice formation and growth processes (Klein et al., 2009).

The lifetime of these clouds depends on the boundary-layer moisture and heat budgets, which depend on radiative cooling, entrainment of overlying air, fluxes at the surface, and large-scale advective tendencies. For the liquid water budgets, the dominant source is condensation in supersaturated updrafts and the sinks are evaporation in unsaturated downdrafts and losses to precipitation (e.g., drizzle and falling ice particles). The forcing for the updrafts depends on surface fluxes and cloud-top radiative cooling, while cloud water content loss to ice precipitation is a strong function of the ice crystal number concentrations and habits.

In general, larger scale models do not resolve these smaller scale cloud processes; they must be parameterized based on the resolved variables. In simpler micro-physical schemes phase-partitioning is parameterized based on temperature (Boucher et al., 1995; Gregory and Morris, 1996; Smith, 1990; Tiedtke, 1993). However, McFarquhar et al. (2007) showed that parameterizations solely based on temperature are not able to accurately predict cloud liquid water contents in Arctic mixed-phase clouds. More parameters should be considered, such as large scale vertical air motion (Tremblay et al., 1996), sub-grid scale convection and waves (Hogan et al., 2003) and/or ice-forming nuclei (IFN) (Harrington et al., 1999; Jiang et al., 2000; Prenni et al., 2007). In response, more sophisticated parameteriza-
tions have been developed and implemented in large-scale models (Morrison and Gettelman, 2008; Salzmann et al., 2010; Bretherton and Park, 2009; Park and Bretherton, 2009; Gettelman et al., 2010). While these led to improvements in the representation of clouds, more work is needed (Barton et al., 2012). Observations of how cloud processes are related to key factors, such as temperature, cloud draft structures and ice/liquid properties, are needed to evaluate and improve these parameterizations.

Super-cooled liquid layers embedded within Arctic mixed-phase clouds impact their cloud radiative properties, dynamics and microphysics. Despite the importance of super-cooled liquid layers in mixed-phase clouds, retrieving cloud-liquid profile properties [e.g. cloud-liquid water content (LWC)] remains a challenge today due to the limitations of the various instruments used to observe cloud liquid when both liquid and ice coexist (Shupe et al., 2008c). Radar signals are dominated by the larger ice particles, radiometric retrievals only provide layer-averaged values, and lidar signals attenuate quickly in the cloud liquid layers. There are no robust, widely applicable methods for deriving the profiles of cloud-liquid drop effective radius ($R_e$) and only limited possibilities for vertically profiling LWC (Illingworth et al., 2007; Zuidema et al., 2005).

This dissertation aims to develop a method to retrieve some micro-physical properties of cloud-liquid layers in mixed-phase clouds based on radar observations. By separating cloud-liquid drop mode contributions to radar Doppler spectra, cloud-liquid drop and ice-particle micro-physical properties can be analyzed separately. In combination with other ground-based observations an investigation is undertaken on understanding the critical processes that impact mixed-phase cloud properties.

1.1 Dissertation Outline

The main purpose of this dissertation is to demonstrate the value of using radar Doppler spectra to study mixed-phase cloud properties in the Arctic. In particular, analysis of radar Doppler spectra offers additional information on cloud properties than the traditional three moments method (Deng and Mace, 2006), thereby providing a better path forward for evaluating model simulations of mixed-
phase clouds. The spectral deconvolution method developed in Chapter 3 builds on the work of Luke et al. (2010) and Luke and Kollias (2013) that extracts the weak cloud-liquid drop mode contributions from the total radar return in profiles of radar Doppler spectra. The cloud liquid drop mode contribution to total reflectivity, the volume-mean vertical air motion, sub-volume vertical velocity variance and ice particle mean fall speed can be estimated based on the separation. The automated spectral deconvolution method allows us to apply it to long-term sets of radar observations.

The remainder of this dissertation is organized as follows. Chapter 2 demonstrates the usage of radar Doppler spectra for model-observation comparisons. Chapter 3 offers a thorough description of the spectral deconvolution algorithm and its performance based on model-simulated radar Doppler spectra as well as radar and microwave radiometer observations. Chapter 4 investigates the statistics of the mixed-phase cloud properties that occurred at the Department of Energy Atmospheric Radiation Measurement program North Slope of Alaska site in October 2011. Chapter 4 also explores the joint distributions between cloud macro- and microphysics, thermodynamics and dynamics of mixed-phase clouds in order to better understand the physical processes within mixed-phase clouds, especially the interactions between different cloud phases. Finally, Chapter 5 provides the summary and conclusions.
Evaluating models of mixed-phase cloud processes using radar Doppler spectra

Modeling the processes of mixed-phase stratiform clouds remains a challenge. Progress is slow in part because of the dearth of observations that shed light on critical processes in these clouds. We apply a radar Doppler spectrum simulator to outputs from a large-eddy simulation with detailed bin microphysics for a North Slope of Alaska case on 8 April 2008 to produce in-cloud radar Doppler spectra. These simulated spectra are subsequently assessed with observed radar Doppler spectra for this case via comparisons of reflectivity, mean Doppler velocity, spectrum width, estimated volume-mean air motion and hydrometeor fall speed extracted from the spectra. By characterizing variability in estimated volume-mean air motions and radar Doppler spectrum widths, the impacts of model dynamics and microphysics on the spectrum widths can be decoupled. This decoupling avoids compensating behaviors in model dynamics and microphysics that evidently lead to favorable comparisons with observations of mean Doppler velocities, thereby providing a more stringent assessment of model performance.
2.1 Introduction

Modeling the processes of mixed-phase stratiform clouds remains a challenge, as is illustrated in the literature regarding Arctic stratus clouds. Arctic mixed-phase clouds are unlike stratus clouds elsewhere, unique in terms of their cloud dynamical and micro-physical processes and the thermodynamical environment in which they most commonly occur. Arctic mixed-phase clouds can persist for days, despite the fact that a mixture of supercooled liquid droplets and ice particles is micro-physically unstable, at least in the absence of sufficiently strong updrafts (Korolev and Field, 2008). Modeling studies have shown that the characteristics of these mixed-phase clouds are impacted by ice nucleus number concentration (Fan et al., 2009; Fridlind et al., 2007; Harrington et al., 1999; Morrison and Pinto, 2006; Prenni et al., 2007; Solomon et al., 2009), ice crystal habit (Avramov and Harrington, 2010), and ice habit evolution (Sulia and Harrington, 2011).

The lifetime of these clouds depends on the boundary-layer moisture and heat budgets, which depend on radiative cooling, entrainment of overlying air, fluxes at the surface, and large-scale advective tendencies. For the budget of liquid water within a cloud, the dominant source is condensation in supersaturated updrafts and the sinks are evaporation in unsaturated downdrafts and losses to precipitation (e.g., drizzle and falling ice particles). The forcing for the updrafts depends on surface fluxes and cloud-top radiative cooling, while the loss to ice is a strong function of the ice crystal number concentrations and habits, with the habit determining both vapor growth rates and times in cloud (through its fall speed). The habit in turn is dependent upon the rate of aggregation and riming. Models have difficulty reproducing observations of Arctic cloud properties (e.g., liquid water path, ice/liquid water ratio, and ice concentration) due to the large uncertainties in the representation of ice formation and growth processes (Klein et al., 2009). Observational data are needed to constrain and improve the treatment of ice microphysics in Arctic mixed-phase clouds.

In order to evaluate the parameterizations of ice formation and growth processes in models, Doppler spectra obtained by cloud radar have been used based on the comparisons of reflectivity and mean Doppler velocity (Avramov et al., 2011; Botta et al., 2011; van Diedenhoven et al., 2009). Avramov et al. (2011) and a companion
paper by Botta et al. (2011) used a large-eddy simulation (LES) model, the Distributed Hydrodynamic Aerosol and Radiative Modeling Application (DHARMA) with (size-resolved) bin microphysics to study a low-lying mixed-phase cloud layer observed during the Indirect and Semi-Direct Aerosol Campaign (ISDAC; McFarquhar et al., 2011). Their results produced reasonable agreement with the in-situ measurements, radar reflectivity, and mean Doppler velocity.

Our study extends the analysis of results from the modeling studies of Avramov et al. (2011) and Botta et al. (2011). Model output is imported to a forward simulator that generates simulated radar Doppler spectra. The first three moments of the radar Doppler spectra (reflectivity, mean Doppler velocity, and spectrum width), the volume-mean vertical air motions and fall speeds of the hydrometeors are estimated from both the observed and model-simulated radar Doppler spectra within cloud layers. The model-derived quantities are subsequently compared to those extracted from the observed radar Doppler spectra. By investigating variability in estimated volume-mean vertical air motions and spectrum widths, the impacts of model dynamics and microphysics on the spectrum widths can be decoupled, providing a stronger test of the fidelity of the model ice particle properties.

2.2 Data and Methodology

The observed radar Doppler spectra are from the Ka-band Millimeter-wave Cloud Radar (MMCR) previously located at the Atmospheric Radiation Measurement (ARM) program’s Climate Research Facility (ACRF) site at Barrow, AK. Data are from the boundary layer mode from 17:00 - 18:00 UTC on 8 April 2008 when the observed cloud depth matched reasonably well that of the cloud simulated by the LES.

The size-resolved bin microphysics model used in DHARMA is described in detail elsewhere (Ackerman et al., 1995, 2004; Fridlind et al., 2007, 2012). Three types of hydrometeors, liquid droplets, pristine snow (dendrites), and aggregates, are used to represent the cloud particles in each grid cell in the simulation. The aggregation process is explicitly simulated and Avramov et al. (2011) show that the size range of transition from single crystals to aggregated crystals closely matches observations. For our comparisons, we picked two cases reported in Botta et al.
(2011), one case assuming low-density dendrites and aggregates (best case simulation identified by Avramov et al. (2011) and a second case assuming high-density dendrites and aggregates. These simulations were intended to bracket the actual likely range of ice crystal densities based on observations.

Each hydrometeor type in the model is characterized in number concentration per unit air volume in 32 mass-doubling bins. The hydrometeor fall speed depends on the particle’s mass, maximum dimension, projected area, and aspect ratio (Böhm, 1989, 1992). These hydrometeor characteristics, together with the model-resolved vertical velocity and the sub-grid vertical velocity variance, determine the simulated radar Doppler spectrum at a given grid cell.

The radar simulator used in this study is adapted from the forward model developed by Kollias et al. (2011). A model-simulated radar Doppler spectrum is generated for each model grid cell using the particle size distributions (PSDs), fall speeds and appropriate backscattering cross sections of each hydrometeor class. The backscattering cross sections of liquid and pristine snow, the maximum sizes of which are less than half of the MMCR wavelength, are based on Rayleigh scattering theory, while the backscattering cross sections of aggregates are based on the model developed by Botta et al. (2011).

Figure 2.1 demonstrates the process to generate a model-simulated radar Doppler spectrum. In order to perform the model versus observation comparison it is necessary to account for the differences in volume between the model and observations. Assuming the horizontal wind at the height of 1000 m is $\sim 10 \text{ m s}^{-1}$, the radar resolution is 45 m in the vertical and approximately $15 \text{ m} \times 5 \text{ m}$ in the horizontal for the 1 s data collection period and $\sim 5 \text{ m}$ beamwidth at this height. Model grid resolution is 15 m in the vertical and $50 \text{ m} \times 50 \text{ m}$ in the horizontal. To match the radar vertical resolution, model output from three vertically adjacent grid cells are averaged to produce a simulated spectrum. We do not try to match the horizontal resolutions because averaging observed radar Doppler spectra produces undesirable results (Giangrande et al., 2001). The consequence of the different horizontal resolutions is that one may expect greater variability in the large model volumes.

The quiet-air fall spectrum (Fig. 2.1a; we adopt the convention that upward motion is positive) calculated from the PSD, backscattering cross sections, and fall speeds is shifted by the mean vertical air motion (Fig. 2.1b) and convolved with
Figure 2.1. Illustration of the steps used to generate a model-simulated radar Doppler spectrum. The quiet-air spectrum (a) is shifted by the volume-mean vertical air motion (b) and convolved with the distribution of velocities (i.e., sub-grid vertical velocity variance) about the mean (c). Finally, thermal noise is added (d). Cloud droplet, snow and aggregate spectra are presented in red, blue and grey in (a), whereas the solid black lines in (b), (c) and (d) represent the total reflectivity. The volume-mean vertical air motion ($w_{\text{actual}}$) and its estimate ($w_{\text{estimated}}$), the mean Doppler velocity ($V_D$), and the estimated mean particle fall speed ($V_{fs}$) are indicated. In this figure positive velocities mean upward motion and negative velocities mean downward motion.

A spectral broadening term (Fig. 2.1c). For vertically pointing radar, the spectral broadening term is given by

$$\sigma^2 = \sigma_T^2 + \sigma_s^2 + \sigma_d^2 + \sigma_B^2$$  \hspace{1cm} (2.1)

where $\sigma_T^2$ is the variance caused by turbulence, $\sigma_s^2$ is the variance due to both vertical and horizontal shear of the vertical velocity, $\sigma_d^2$ is the variance due to the PSD and particle fall velocity spread, and $\sigma_B^2$ is the variance due to the radar
beamwidth (Kollias et al., 2001; Shupe et al., 2008b). Finally, thermal noise is added to the convolved spectra (Fig. 2.1d) using the method described by Zrnić (1975).

We compare in-cloud model-simulated radar Doppler spectra from the entire model domain for a single time slice to an hour of radar measurements. Our comparison is limited to cloud-layer spectra, while comparisons carried out in Avramov et al. (2011) include both cloud- and sub-cloud layer spectra. The cloud layer is defined in the measurements by the best estimate, lidar-derived cloud-base height and the radar-derived cloud top reported in the ARM Active Remote Sensing of Clouds (ARSCL) product (Clothiaux et al., 2000). The model cloud layer is defined as the model grid points in a column where the liquid water content (LWC) is larger than $0.01 \text{ g m}^{-3}$. We selected in-cloud comparisons only in order to enable us to estimate the volume-mean vertical air motions and hence volume-mean hydrometeor fall speeds, which differ from the measured mean vertical Doppler velocities by the volume-mean vertical air motion. An estimate of the air motion may be obtained from the assumption that small cloud droplets move with the air (Gossard, 1994), which restricts retrieval of volume-mean vertical air motions to the cloud layer where liquid droplets exist.

In any in-cloud radar Doppler spectrum, the first bin of reflectivity above the noise floor going from positive to negative velocities is produced by the smallest cloud-liquid droplets and, therefore, the corresponding velocity is used to estimate the volume-mean vertical air motion. However, this estimate will be in error, with the error in the volume-mean vertical air motion estimation depending on spectral broadening and/or the amount of liquid water in the volume. If liquid drop reflectivities are small and below the noise floor, the first bin of reflectivity above the noise will correspond to faster falling ice particles, which will cause underestimation of the volume-mean vertical air motion. On the other hand, turbulence broadening causes an overestimation of the air motion. In Fig. 2.1c, the estimated volume-mean vertical air motion is represented by the velocity corresponding to the right edge of the spectrum. The difference between estimated and actual volume-mean vertical air velocity is due to broadening from turbulence, wind shear and the radar antenna beamwidth. The magnitude of this difference may vary throughout a cloud.
Model turbulence strength is evaluated by comparing the model grid cell sub-grid vertical velocity variances as expressed as standard deviations to those derived from dissipation rates estimated from the radar measurements (Shupe et al., 2012, 2008b). The standard deviation $\sigma_T$ of sub-grid vertical velocity variance is related to the dissipation rate by

$$\varepsilon = \frac{2\pi}{L_s^{2/3}} \left( \frac{2\sigma_T^2}{3a} \right)^{3/2}$$

where the Kolmogorov constant $a = 0.5$ and $L_s = U + 2R \sin(\theta/2)$ is the length of the scattering volume for the 1-s dwell time. The mean wind speed $U = 10 \, \text{m s}^{-1}$, R is the range to the scattering volume, and the radar beamwidth is $\theta = 0.31^\circ$.

The variance due to wind shear ($\sigma_s^2$) is estimated using the model resolved vertical wind field. Horizontal shear of the vertical wind ($k_h$) is calculated using the vertical velocity differences between adjacent grid cells at the same height and vertical shear of the vertical wind ($k_v$) calculated from the vertical velocity change over 45 m (i.e., three vertically adjacent grids). Then $\sigma_s^2$ is estimated as Gossard and Strauch (1983) and Kollias et al. (2001)

$$\sigma_s^2 = \frac{k_h^2 R^2 \theta^2}{2.76} + \frac{k_v^2 \delta_v^2}{12}$$

where $k_v$ and $k_h$ are the shears (in inverse second, or $s^{-1}$), R is the range to the sample volume (in meters), $\theta$ is the radar beamwidth (in radians) and $\delta_v$ is the vertical resolution of the sample volume (45 m).

The variance due to radar beamwidth ($\sigma_B^2$) is estimated as Gossard and Strauch (1983)

$$\sigma_B^2 = \frac{U^2 \theta^2}{2.76}$$

where the mean wind speed $U = 10 \, \text{m s}^{-1}$.

While the estimated volume-mean vertical air motions retrieved from the observed and model-simulated radar Doppler spectra have a known error, the error is of the same nature in the two sets of quantities. As a result, in this study we use differences between the observed and model-derived estimated volume-mean vertical air motions and not their absolute values. To remove this error one must
be able to identify the peak of the cloud-liquid drop distribution contribution to the radar Doppler spectra (i.e. the location of $w_{\text{actual}}$ in Fig. 2.1d), which was not possible with the observations used in this study.

The performance of the LES model is evaluated by comparing histograms of the estimated volume-mean vertical air motions, standard deviations of sub-grid vertical velocity variances, reflectivities, mean Doppler velocities, spectrum widths, and mean hydrometeor fall speeds from a single snapshot of the model domain and one hour of MMCR data. The histograms are comprised of a total of 79180 data points from model-simulated radar Doppler spectra using low-density ice particles, 71074 data points from model-simulated radar Doppler spectra using high-density ice particles, and 7436 data points from measured spectra.

2.3 Results

We first compare estimated volume-mean vertical air motions retrieved from the observed and model-simulated radar Doppler spectra with the actual model-resolved vertical air motions for the low-density ice particle model simulation (Fig. 2.2; Similar results were obtained for the high-density ice simulation). The mean of the estimated volume-mean air motion retrieved from the model-simulated radar Doppler spectra is $0.17 \text{ m s}^{-1}$ (solid black vertical line in Fig. 2.2a), an overestimation by $0.19 \text{ m s}^{-1}$ of the mean model-resolved vertical air motions of $-0.02 \text{ m s}^{-1}$ (dashed black vertical line in Fig. 2.2a). (Note that the analysis here omits the subsidence imposed for the simulations, which at cloud top is about $-0.01 \text{ m s}^{-1}$). The mean for the observed spectra is $(0.40 \text{ m s}^{-1})$, suggesting an underestimation of spectral broadening in the model simulation if we assume that the mean of the volume-mean vertical air motion over an hour is $0 \text{ m s}^{-1}$. The difference between the means of the estimated volume-mean vertical air motions derived from observed and model-simulated radar Doppler spectra may be caused by model underestimation of either liquid water content, sub-grid turbulence, wind shear and/or horizontal wind speeds.

Large differences in the histograms of radar reflectivity between the two simulations and the observations are evident (Fig. 2.3a). Both simulations produced distinct peaks for the liquid-dominated cloud top (at -30 dBZ) and the ice domi-
Figure 2.2. a) Frequency of occurrence histograms of the estimated volume-mean vertical air velocities retrieved from the observed (shaded) and simulated (solid line) radar Doppler spectra along with the model-resolved vertical velocity histogram (dashed line). The means of the observed histograms are represented by the solid red vertical lines, whereas the means of the low- and high-density ice particle simulation histograms are represented by the solid and dashed black vertical lines. b) Same as a) but for the model-simulated radar Doppler spectra generated using increased wind shear. In this figure positive velocities mean upward motion and negative velocities mean downward motion.

In contrast to the reflectivity comparisons, both high- and low-density ice particle simulation histograms of the mean Doppler velocity are in good agreement with the observations (Fig. 2.3b). This result can be understood by considering...
Figure 2.3. Frequency of occurrence histograms of a) radar reflectivities, b) mean Doppler velocities, c) spectrum widths, and d) mean particle fall speeds from the observations (shaded) and model simulations with high-density (dashed black lines) and low-density (solid black lines) ice particles. The means of the observed histograms are represented by solid red vertical lines, whereas the means of the low- and high-density ice particle simulation histograms are represented by the solid and dashed black vertical lines. In this figure positive velocities mean upward motion and negative velocities mean downward motion.

that the volume-mean vertical air motions in these clouds are of comparable magnitude to the fall speed of the ice hydrometeors, and thus impact the mean Doppler velocity histograms as well. Fundamentally, the mean Doppler velocity histogram is a reflection of the distribution of the model-resolved vertical speeds, shifted and broadened by the reflectivity-weighted mean particle fall-speeds. The air motion is largely determined by longwave radiative forcing at cloud top, with the magnitude of forcing a strong function of the liquid water content. The amount of liquid is regulated by the moisture and heat budgets of the boundary layer, which include losses to ice reaching the surface. The mean Doppler velocity histogram then is the end result of multiple interacting and potentially compensating factors in the
model.

In order to assess the model performance, we compare the histograms of model-simulated spectrum widths to that from the radar-measured spectra (Fig. 2.3c). The mean value of the observed spectrum widths is near 0.2 m s$^{-1}$, which is larger than the means for both simulations (0.13 m s$^{-1}$ and 0.15 m s$^{-1}$ for the low- and high-density ice particle simulations). The Doppler spectrum width is determined by the convolution of the quiet-air hydrometeor fall spectrum and a (Gaussian) broadening distribution with variance $\sigma^2$. The discrepancies between the observed and simulated spectrum widths may therefore be caused by either a lack of particles with diverse sizes and fall speeds (hereafter referred to as micro-physical broadening) or too weak model spectral broadening due to an underestimation of turbulence, wind shear, and/or horizontal wind speeds (hereafter referred to as dynamical broadening). On the other hand, the discrepancy between the simulated and observed estimated volume-mean vertical air motions in Fig. 2.2a must be the result of underestimation of the dynamical broadening and/or liquid amount and is independent of micro-physical broadening.

The comparison of mean particle fall speeds (Fig. 2.3d) reveals that both simulation histograms are shifted relative to the retrievals based on the radar observations. The histogram means of the two simulations are similar (-0.46 m s$^{-1}$ for the low-density and -0.48 m s$^{-1}$ for the high-density ice particle simulations), and considerably slower than that from the observations (-0.73 m s$^{-1}$). It should be noted that all of these mean reflectivity-weighted particle fall speeds are impacted by spectral broadening and are over-estimated by the current retrieval technique. Moreover, the spectral broadening applied to the model output may be different from that acting in the observed radar volume; therefore, we cannot make a firm conclusion as to whether or not the model underestimated the ice particle fall speeds as is suggested in Fig. 2.3d. In order to further explore the causes for the observed differences in spectrum widths and estimated particle fall speeds, we look at the separate factors contributing to spectral broadening individually.

A comparison of the spectrum widths (standard deviation) of the model-diagnosed sub-grid vertical air velocity distribution to that diagnosed from radar observations (Shupe et al., 2012) indicates that the model is in reasonable agreement with the observations (Fig. 2.4). This conclusion depends on the assumption that both
Figure 2.4. Frequency of occurrence histograms of the standard deviations of sub-grid vertical air velocity variances from the radar observations (shaded) and diagnosed from the model low-density (solid black line) and high-density (dashed black line) ice particle simulations. The mean of the observed histogram is represented by the solid red vertical line, whereas the means of the low- and high-density ice particle simulation histograms are represented by the solid and dashed black vertical lines.

The broadening due to horizontal wind speed is small because of the narrow radar antenna beamwidth. The differences between estimated vertical air motions from the model and observations cannot be explained by this term either. The model mean liquid water path (LWP) is 35 g m$^{-2}$, which compares well with the retrieved mean LWP of 36 g m$^{-2}$ from 17:00 - 18:00 UTC obtained from a microwave radiometer. Thus, the only dynamical broadening term left that can account for the discrepancy in estimated volume-mean vertical air motion is wind shear. On the other hand, the spectrum width discrepancy may depend on the
Figure 2.5. Frequency of occurrence histograms for a) spectrum widths and b) mean particle fall speeds obtained from the observations (shaded) and the low-density (solid black line) and high-density (dashed black line) ice particle simulations with artificially increased wind shear. The means of the observed histograms are represented by the solid red vertical lines, whereas the means of the low- and high-density ice particle simulation histograms are represented by the solid and dashed black vertical lines. In this figure positive velocities mean upward motion and negative velocities mean downward motion.

wind shear contribution as well as micro-physical broadening.

Because of a lack of accurate vertical velocity measurements, it is hard to evaluate the model vertical wind shear. In the model simulations the mean horizontal and vertical shear of the vertical wind is 0.0024 s\(^{-1}\) and 0.0028 s\(^{-1}\), corresponding to 0.12 m s\(^{-1}\) and 0.13 m s\(^{-1}\) vertical velocity changes over 50 m in the horizontal and 45 m in the vertical, respectively. To match the observed estimated volume-mean vertical air motion, the wind shears were increased by a factor of 3. A new set of simulated spectra was generated based on the same model output except using the increased wind shears. Fig. 2.2b shows that this artificial increase in the dynamical broadening term leads to good agreement between the estimated volume-mean vertical air velocities retrieved from the simulated and observed spectra, suggesting that we have the approximately the correct magnitude for the dynamical broadening.

To explore whether the increased dynamical broadening contributions can explain all the discrepancies noted in Fig. 2.3, we evaluate simulation/observation comparisons but with using the greater dynamical broadening value for the estimated spectrum widths and mean particle fall speeds (Fig. 2.5). The reflectivity and mean Doppler velocity histograms are not shown, as in Fig. 2.3, because dy-
namical broadening has no impact on either variable and they are identical to the results shown in Figs. 2.3a and 2.3b. As expected, the low-density ice particle simulation spectrum widths increased from 0.13 m s\(^{-1}\) to 0.17 m s\(^{-1}\) and the high-density ice particle simulation widths increased from 0.15 m s\(^{-1}\) to 0.19 m s\(^{-1}\). The low-density ice particle simulation mean spectrum width still underestimates the observed mean spectrum width of 0.20 m s\(^{-1}\), but the high-density ice particle simulation provides a closer match. The spectrum width is determined by both dynamical and micro-physical broadening. Using our earlier conclusion that we have appropriately accounted for the dynamical broadening, we now conclude that the remaining discrepancy must be attributed to insufficient micro-physical broadening, or a lack of sufficient spread in the model ice particle fall speeds.

After increasing the dynamical broadening, the simulated mean particle fall speeds (-0.66 m s\(^{-1}\) for the low- and -0.65 m s\(^{-1}\) for the high-density ice particle simulations) are still slower than that from the observations (-0.73 m s\(^{-1}\)). These discrepancies may be caused by the lack of faster-falling ice particles in the low-density ice particle simulation and the lack of stronger updrafts in the high-density ice particle simulation that keep ice particles with larger fall speeds within the cloud layer.

### 2.4 Discussion

Various studies have shown that the maintenance and characteristics of low-level, mixed-phase Arctic clouds are sensitive to the details of their ice microphysical parameterizations. However, it is very difficult to evaluate the fidelity of any parameterization against observations because all measurements are incomplete in some way. The carefully constructed study by Avramov et al. (2011) used both in situ aircraft and cloud radar measurements to evaluate several parameter settings in the DHARMA ice microphysics parameterization. In this paper, we extended that evaluation to include more data available from the radar Doppler spectra, motivated in part by the results presented in their Fig. 6 where they showed histogram comparisons of volume-mean vertical air motions and reflectivity-weighted mean particle fall speeds.

Similar to Avramov et al. (2011), van Diedenhoven et al. (2009) and Fridlind
et al. (2012), all of whom used the same methodology to compare observations of mean Doppler velocity to simulations (of the same model, but with variations in the micro-physical parameterizations), we found that the simulated mean Doppler velocity histograms were not sensitive to micro-physical assumptions. All these works, including this study, used the same model that accounts for the nucleation scavenging process to prognose ice concentration. In these studies, increasing ice particle fall speeds results in ice mass loss from the cloud layer which cannot be replenished because the ice nuclei (IN) are depleted, and the mean Doppler velocity becomes mostly an indicator of the model-resolved vertical wind. This conclusion is supported by the results reported by Fridlind et al. (2012) who found that the mean Doppler velocity distributions are affected by convective intensity.

The insensitivity of mean Doppler velocity histograms to micro-physical assumptions may not hold for models with diagnostically specified ice particle concentrations. In such models ice particles can reach a quasi-steady state between growth by vapor deposition and fall speed at cloud base such that there is no significant ice mass loss in the cloud layer (Yang et al., 2013). For example, Fan et al. (2009), who used IN recycling from ice sublimation to maintain ice particle number concentrations, found that doubling the model ice particle fall speeds produced better comparisons to observations of probability distributions of mean Doppler velocity as a function of height. This result should extend to any model with diagnosed ice concentrations. This conclusion is somewhat supported by the results from Ovchinnikov et al. (2011) who reported that the ice particle number concentrations have an impact on the strength of their model eddy circulations and thus the histograms of mean Doppler velocity.

There is one more possibility. When the relative change of ice particle fall speeds in response to changes in the micro-physical parameterization is small compared to the model-resolved vertical velocity, mean Doppler velocity distributions are dominated by the model-resolved vertical velocity distribution. Iguchi et al. (2012) in a study of shallow convective clouds suggested that differences in the profiles of the mean of the mean Doppler velocities between the model and observations could be attributed to differences in the volume-mean vertical air motions.

We conclude from this discussion that the mean Doppler velocity is not a strong constraint to either model dynamics or microphysics. Good agreement between a
model and observations only implies that the particles fall at about the right speeds under the impact of model-resolved flow fields, but one cannot address whether the distributions of ice particle fall speeds and vertical winds are separately consistent with the observations.

In order to address this perceived shortcoming of previous comparisons, it is necessary to decouple the contributions of the volume-mean vertical air motions and the ice particle fall speeds to the mean Doppler velocities to show that the good correspondence between histograms of the model and observations is not a result of compensating behaviors in these two contributing factors. However, due to the lack of accurate volume-mean vertical air motion measurements, it is difficult to separate the contributions of the volume-mean vertical air motions and ice particle fall speeds to the observed mean Doppler velocities.

A qualitative analysis of the variation of estimated volume-mean vertical air motion retrieved from the recorded Doppler spectra used in this study is presented in Fig. 2.6. These vertical velocities are taken from the nearest range gate to the 2/3 cloud depth height, with small-scale fluctuations (individual cells) filtered from the time series by application of a zero-phase digital filter with 10 minute averaging. Generally, the mean of the volume-mean vertical air motions is expected $\sim 0 \, m \, s^{-1}$ over the 7 hour period shown. Thus, the fluctuations of the estimated volume-mean vertical air motions around the fitted line (black dashed line) indicate weak mesoscale updrafts and downdrafts. The hour analyzed in this study (17:00-18:00 UTC) is characterized by a weak mean updraft ($\sim 0.1 \, m \, s^{-1}$), a factor not accounted for in the LES for which the mean of the volume-mean vertical air motions is $0 \, m \, s^{-1}$. Thus, the model draft structures, lacking the mesoscale updraft, compensated by having ice particles fall slower with a narrower range of ice particle fall speeds than the retrievals. The good agreement between the histograms of model and observed mean Doppler velocities (Fig. 2.3b) can be explained by model updrafts that are generally weaker than the retrieved updrafts.

Comparisons of estimated volume-mean vertical air motions provide a potential solution to decouple dynamical and micro-physical broadening impacts on the Doppler spectrum widths. The comparisons indicate an underestimation of dynamical broadening in both simulations, the suggested cause of which is the result of too small horizontal and vertical shear of the vertical wind in the model. Un-
Figure 2.6. Time series of the estimated volume-mean vertical air motions retrieved from the recorded radar Doppler spectra from 17:00 - 24:00 UTC on 8 April 2008. The dashed black line is a fitted straight line to the data.

Fortunately, without accurate vertical air motion measurements it is difficult to quantitatively evaluate the model shear of the vertical wind. However, even after increasing the model wind shear by a factor of 3 to account for the differences in estimated volume-mean vertical air motions, the discrepancies between model and observed Doppler spectrum widths and mean particle fall speeds still exist, which may only be explained by the model microphysics.

The in-cloud comparisons revealed that the model produces a cloud-top reflectivity distribution much narrower than that observed by radar (Fig. 2.3a). This narrow reflectivity distribution is consistent with the much tighter distribution of cloud-top liquid water contents revealed in the models via comparisons with in situ measurements (Avramov et al., 2011; Figs. 10 and 15), indicating a much more homogeneous cloud layer in the simulations. Despite these inconsistencies, the low-density ice simulation accurately captured the ice mass as represented by the reflectivity histograms.

Morrison et al. (2012), Avramov and Harrington (2010), Sulia and Harrington (2011), and Ovchinnikov et al. (2011), among others, point to the interlinked dependencies of the influence of ice concentration, ice particle habit, and internal dynamics on processes in stratiform mixed-phase clouds. The liquid/ice phase partitioning in mixed-phase clouds is the result of a delicate balance between the
processes that deplete supercooled liquid (ice growth and precipitation loss) and processes that resupply moisture (radiative cooling, turbulent fluxes from above and below, and large scale forcing) (Sulia and Harrington, 2011). The total ice mass at cloud base is the result of the accumulated growth of all the ice particles along their trajectories through the cloud, the details of which depend on the growth history of each particle up to that point. Our analysis suggest that the low-density ice particle simulation, though reaching a balance of processes that compare well to several sets of independent measurements, may have attained that balance at a point different from the observations. The evidence points to the way the ice micro-physical processes are represented in the model.

Most micro-physical schemes use one or more prescribed ice particle size distribution shape parameters along with some combination of mass-size, area-size and/or fall velocity-size relationships to capture the ice micro-physical processes (Morrison et al., 2005). More sophisticated schemes require specification of habit type and several parameters relating mass, area, and aspect ratio to characterize ice processes based on observations, but allow the particle size distribution to evolve based on the growth processes encountered. These more sophisticated schemes generally reproduce the observations better when ice particle properties for the simulated case are known from in situ measurements (Fridlind et al., 2012). At the same time the greater detail available on the ice particles and their distributions in size allow more sophisticated evaluation of the schemes. The differences revealed by our analysis can be the result of a combination of factors, including problems in mesoscale or boundary-layer dynamics, to restrictive mass-size and size-area relationships for single ice crystals or aggregates, or as Sulia and Harrington (2011) have suggested, a requirement that the habit of the ice crystals must evolve throughout their growth history in order to accurately capture both vapor depositional mass growth and ice particle fall speed.

The problem with accurately representing ice particle fall speeds has long been recognized in the field (see discussions in Böhm (1989), Böhm (1992), Mitchell and Heymsfield (2005), Westbrook (2008), and Heymsfield and Westbrook (2010), among others). Simultaneous measurements of ice crystal mass, size, shape, and fall speed are critical to proceed, yet these measurements are tedious to obtain and only limited numbers of sampled particles contribute to our understanding
(see discussion in Heymsfield and Westbrook (2010)). New measurement devices capable of collecting large numbers of samples are imperative.

The disagreement between the model and observations derives from a general lack of model ice particles with diverse fall speeds, especially ones with faster-falling speeds. These fast-falling particles must be aggregates, because in situ observations revealed that the ice particles were either dendrites, all of which fall too slow, or aggregates (Avramov et al., 2011). The low-density ice particle simulation that generally reproduced the particle size distribution well has no ice particle fall speeds exceeding 0.5 m s\(^{-1}\) (Fig. 7 in Avramov et al. (2011)), and therefore produced a narrow spread of ice particle fall speeds and small spectral broadening. The high-density aggregates fall faster, but are effectively removed from the cloud as precipitation so that the in-cloud ice particle size distribution lacks the larger, faster-falling particles. The reflectivities and mean ice particle fall speeds from the high-density ice particle simulation differ from the observations, even though the spectrum width compares well to the observations after matching the dynamical broadening.

Aggregates are the end result of ice particle nucleation which determines the ice crystal number concentration, vapor depositional growth and ice-ice particle collisions. All these processes must be captured accurately in the evolving model cloud to bring the model to the correct balance point. Progress will require attention to all aspects of ice growth in the models.

### 2.5 Conclusion

Recent technological advances that make the routine recording of radar Doppler spectra possible opened the door to more extensive evaluation of large-eddy simulations with bin micro-physical parameterizations. Output from simulations can be used to produce simulated radar Doppler spectra that subsequently may be analyzed in identical fashion to observed radar Doppler spectra to separate the different contributions of the dynamics and microphysics on the radar moments.

Results from this study show that the additional evidence gained by separating the dynamical and micro-physical contributions may be used to identify possible problem areas in model parameterizations. In this particular case, our analysis of
two simulations with differences in their characterization of ice particle densities suggests that both model simulations underestimated horizontal and vertical shear of the vertical velocity. After increasing the vertical air motion shear to account for the difference in dynamical broadening of the radar Doppler spectra, the residual discrepancies between model and observed spectrum widths and particle fall speeds can only explained by model microphysics.

It should be noted that the purpose of using low- and high-density ice particles in the two model simulations was not to reproduce the actual case, but to provide a range of ice particle properties. Thus, a more diverse population of ice particles with properties resulting from some combination of ice from these low- and high density ice particle simulations may provide a better estimate of the actual distribution of hydrometeors. Moreover, the weaker model updrafts and slower falling ice combined to produce good agreement with mean Doppler velocity measurements of stronger updrafts and faster falling ice. This result is interpreted as an indication that there is a mismatch in the important processes governing model and observed mixed-phase clouds, including cloud vertical air motion structures, ice nucleation, ice aggregation, and how the model increases ice particle fall speeds as particles gain mass.

As microphysics models increase in complexity, so do the requirements for observations to constrain model parameters. Simultaneous measurements of ice crystal mass, size, shape, and fall speed are critical to proceed, yet these measurements are currently limited to small numbers of sampled particles (Heymsfield and Westbrook, 2010). Also required are specific observations of other important processes, including cloud dynamics, ice nucleation, aggregation, and precipitation rate.
Retrieving and quantifying cloud liquid drop contributions to the radar returns from mixed-phase clouds remain a challenge because the radar signal is frequently dominated by the returns from the ice particles within the radar sample volume. We present a technique that extracts the weak cloud liquid drop contributions from the total radar returns in profiling cloud radar Doppler velocity spectra. Individual spectra are first decomposed using a continuous wavelet transform, the resulting coefficients of which are used to identify the region in the spectra where cloud liquid drops contribute. By assuming that the liquid contribution to each Doppler spectrum is Gaussian shaped and always at a predictable location in the spectrum, the cloud liquid drop contribution may be estimated by fitting a Gaussian distribution centered on the velocity of an appropriate peak in the wavelet coefficients. The cloud liquid drop contribution to reflectivity, the volume-mean vertical air motion, sub-volume vertical velocity variance and ice particle mean fall speed can be estimated based on the separation of the liquid contribution to the radar Doppler spectrum. The algorithm is evaluated using synthetic spectra
produced from outputs of a state-of-the-art Large Eddy Simulation model study of an Arctic mixed-phase cloud. Retrievals based on Ka-band ARM Zenith Radar observational data from Barrow, Alaska, during October 2011 are also presented. Statistics for one month of retrievals demonstrate that the algorithm generally performs well. This retrieval algorithm provides a step along the path to improving our understanding of the micro-physical and dynamical processes within mixed-phase clouds, which in turn is necessary for developing better parameterizations in models.

3.1 Introduction

Mixed-phase clouds are systems where liquid and ice particles coexist with each other, usually within the regions of the clouds. They occur frequently during all seasons in the Arctic (Shupe, 2011) and can persist for days, even weeks (Shupe et al., 2006). These widespread, long-lived Arctic mixed-phase clouds have a strong impact on the Arctic surface energy budget (Curry and Ebert, 1992; Shupe and Intrieri, 2004; Sun and Shine, 1994; Turner, 2005; Walsh and Chapman, 1998; Zuidema et al., 2005) and have been shown to play an important role in Arctic summertime sea ice loss (Kay et al., 2008; Kay and Gettelman, 2009).

The radiative forcing, dynamics and microphysics of mixed-phase clouds are impacted by super-cooled liquid layers embedded within them. Even a small amount of liquid in a mixed-phase cloud can have a dramatic effect on the cloud radiative properties (Sun and Shine, 1994). For example, a cloud with liquid water path as low as 30 g m$^{-2}$ acts as a blackbody emitter (Shupe and Intrieri, 2004). The presence of super-cooled liquid layers in mixed-phase clouds may also impact the structure of the boundary layer through the influence of cloud-top radiative cooling (Morrison and Pinto, 2006). Moreover, the existence of liquid may change the ice growth mode because it enables riming. Despite the importance of super-cooled liquid layers in mixed-phase clouds, retrieving cloud-liquid profile properties (e.g. liquid water content (LWC)) remains a challenge today due to the limitations of the various instruments used to observe cloud liquid when both liquid and ice co-exist (Shupe et al., 2008c). The most accurate method today for estimating LWC profiles in mixed-phase clouds is a scaled adiabatic LWC approach which can be
implemented with temperature soundings and cloud boundaries identified from radar and lidar measurements.

The Department of Energy (DOE) Atmospheric Radiation Measurement (ARM) program profiling millimeter-wavelength cloud radars record Doppler velocity spectra continuously and provide vertically resolved observations with excellent sensitivity to small hydrometeors (Kollias et al., 2007). Observed velocities within the radar Doppler spectra are related to different sizes of hydrometeors with different fall velocities, volume-mean vertical air motions and sub-volume turbulence. The uncertainties in retrieving micro-physical information of hydrometeors based on observations of their fall velocities are mainly from the volume-mean vertical air motion and small scale turbulence within the radar sample volume (Atlas et al., 1973; Battan, 1964; Kollias et al., 2011). Cloud liquid drops have negligible fall speeds and move with the air, thus they may be used as tracers to estimate the volume-mean vertical air motion and small scale turbulence within the radar sample volume (Gossard, 1994; Kollias et al., 2011). If the cloud liquid drop contributions to a radar Doppler spectrum are separated from the other contributors, liquid amount, volume-mean vertical air motion and small scale turbulence within the radar sample volume can be retrieved. However, separation of cloud liquid drop contributions to radar Doppler spectra that also contain ice particle contributions, which are generally dominant, remains a challenge.

For particles much smaller than the radar wavelength, the received radar signal is proportional to the sixth power of the particle sizes, making the power received at the radar particularly sensitive to the presence of large ice particles. The signal backscattered by cloud liquid drops is often a very small portion of the total signal when cloud liquid drops and larger ice particles coexist, which is frequently the case near the bases of clouds. Figure 3.1 demonstrates the evolution of radar signals as different classes of hydrometeors from cloud base to cloud top contribute to them. The left column shows simulated radar Doppler spectra generated from model output using a forward model radar simulator. (Details of the generation of the simulated radar Doppler spectra are provided later in the validation of the retrieval algorithm.) The cloud liquid drop signal (in red) generally increases from cloud base to cloud top because of adiabatic ascent. Near cloud top the majority of the signal comes from cloud liquid drops because ice particle concentrations are
low. The ice particles grow as they fall through the ice-supersaturated cloud, hence signals from ice particles increase with decreasing height. These simulated radar Doppler spectra may be compared to the observed radar Doppler spectra in the right column. The local maxima on the right sides of these observed spectra are likely contributed by cloud liquid drops. However, the cloud liquid drop signal can be ambiguous, and tangled by noise or ice particle signals, as is evident in the top spectrum of the right column. These simple examples show that a sophisticated method to detect and separate the cloud liquid drop signals from the total signals is required to extract vertical profiles of liquid micro-physical properties within mixed-phase clouds from the radar Doppler spectra.

Several radar Doppler spectrum-based deconvolution approaches have been developed to extract cloud liquid drop and precipitation information from liquid clouds (Babb et al., 1999; Gossard, 1994; Gossard et al., 1997). Shupe and Intrieri (2004) and Rambukkange et al. (2011) use peak detection algorithms to separate liquid and ice spectral modes when radar Doppler spectra are bimodal in mixed-phase cloud cases. However, clear separations between cloud liquid drop and precipitation peaks are not frequently observed for precipitation populations with small fall speeds (e.g., drizzle and/or small ice particle precipitation) and the small cloud liquid drop contributions must be identified before they can be extracted. This study builds on the work of Luke et al. (2010) who demonstrated the ability of a continuous wavelet transform (CWT) analysis to detect subtle features in radar Doppler spectra and the recent study by Luke and Kollias (2013) who proposed a new radar Doppler spectrum decomposition approach based on assumed Gaussian shaped cloud liquid drop contributions to the radar Doppler spectra.

Our new algorithm for retrieving cloud-liquid properties within mixed-phase clouds uses a CWT analysis to identify assumed Gaussian shaped cloud liquid drop contributions to the observed radar Doppler spectra. This algorithm is applied to well-defined cloud layers obtained from radar (cloud top) and lidar (cloud base) observations. After extracting cloud liquid drop contributions to the radar Doppler spectra, the volume-mean vertical air motion is estimated by the mean velocity of these cloud liquid drop modes. Cloud liquid water contents are estimated from cloud liquid drop reflectivities using a power law relationship with coefficients set
Figure 3.1. Examples of radar Doppler spectra at different heights from cloud top to cloud base. The plots in the left column are the simulated spectra based on outputs of a large eddy simulation model. The plots in the right column are from KAZR observations. The red lines represent the cloud liquid drop contributions to the spectra whereas the blue lines represent both the cloud liquid drop and ice particle contributions to the spectra. Positive velocities represent upward motion and negative velocities downward motion.

3.2 Method

The rationale for the current method to extract cloud liquid drop modes from radar Doppler spectra of mixed-phase clouds is based on the assumption that radar Doppler spectra can be represented by a linear superposition of several Gaussian distributions, where each Gaussian distribution is produced by a discrete class of...
hydrometeors with a characteristic fall velocity (Melchionna et al., 2008). According to this assumption, any observed radar Doppler spectrum for a mixed-phase cloud is formed by distinct contributions from cloud liquid drop and different precipitation modes (e.g. pristine ice and aggregates), with each mode approximately Gaussian in shape and centered on the mean fall velocity of the hydrometeor class. In this framework the key to identifying the cloud liquid drop mode contribution to a radar Doppler spectrum becomes finding the velocity of the center of the Gaussian-like cloud liquid drop mode. Subsequently, a Gaussian distribution is fit to this region dominated by the cloud liquid drops.

The newly developed algorithm is based on a combination of the continuous wavelet transform (CWT) and fuzzy logic techniques. The CWT analysis is utilized to locate the center of a cloud liquid drop mode. Subsequently, a Gaussian distribution is fitted to the cloud liquid drop mode based on the retrieved velocity of the mode center and the first few spectral points on the edge of the spectrum away from the precipitation particle contributions. The thermal noise fluctuations in radar Doppler spectra can create spurious cloud liquid drop modes; therefore, several possible cloud liquid drop mode candidates are potentially extracted from each radar Doppler spectrum in the CWT analysis. Several properties for each cloud liquid drop mode candidate are calculated, including total reflectivity, mean Doppler velocity, and spectrum width. These results are then synthesized using a fuzzy logic approach that generates composite membership functions which indicate how continuous the cloud liquid drop properties in the given radar sample volume are to those retrieved from nearby ones. The most-probable cloud liquid drop mode is identified based on the continuity of the vertical profile of retrieved cloud liquid drop properties. The properties of the cloud liquid drops are computed from the estimated cloud liquid drop modes across the whole cloud layer after which a neighborhood filtering method is applied to eliminate outliers.

### 3.2.1 Extracting Cloud Liquid Drop Mode Candidates

The first step in the algorithm is to generate three cloud liquid drop mode candidates for each radar Doppler spectrum based on the CWT analysis. In the CWT analysis, a spectrum is convolved with a set of wavelets $\Psi_{a,b}$ (a few examples
are shown in Fig. 3.2a) transformed from a mother wavelet $\Psi$ by a scale coefficient $a$ (corresponding to the width of the wavelet) and a translational coefficient $b \in [-V_{Ny}, +V_{Ny}]$ ($V_{Ny}$ is the Nyquist velocity): $\Psi_{a,b}(\nu) = \Psi[(\nu - b)/a]$, where $\nu$ is Doppler velocity in our case (Addison, 2002; Rioul and Vetterli, 1991). In this study, each radar Doppler spectrum is convolved with second-order Gaussian wavelets (e.g., the wavelets illustrated in Fig. 3.2a) for 33 different scales. Figure 3.2b presents a model-simulated radar Doppler spectrum which is composed of signals from three different hydrometeor populations: cloud liquid drops, snow and aggregates. The result of applying the CWT analysis to this spectrum is a two-dimensional array of coefficients, providing feature localization as a function of both Doppler velocity and wavelet scale (Fig. 3.2c). The locations of cloud liquid drop mode center candidates are estimated based on local maxima in the coefficients at a proper scale in the expected location of the cloud liquid drop mode in the radar Doppler spectrum. The selection of a proper scale is important. If the scale is too small (i.e., scale of $2^{1.75}$ in Fig. 3.2d) fluctuations in the spectrum caused by noise lead to multiple maxima in the coefficient peaks. If the scale is too large (i.e., scale of $2^4$ in Fig. 3.2d) the coefficients often lack a local maximum at the location of the cloud liquid drop mode and only ice particle modes are detected.

The proper scale that captures the contribution from a cloud liquid drop mode is selected using a peak detection scheme. First, the number of peaks ($N_0$) in the coefficients for each wavelet scale is computed. The smallest scale with $N_0$ smaller than or equal to 4 is selected as the appropriate scale $S$. This procedure is applied to eliminate those scales impacted by noise contributions. Possible consequences of this limit are that cloud liquid modes may be rejected if they have a low signal-to-noise ratio or are present in a volume with multiple ice particle modes (Rambukkange et al., 2011). With the proper scale ($S$) in hand the next step is to identify the center velocities of possible Gaussian-shaped cloud liquid drop modes.

Cloud liquid drop modes normally exist on the right (largest velocity) end of KAZR Doppler spectra, as cloud liquid drops generally have the smallest sedimentation velocities. (Note that the ARM program convention for radar Doppler velocity changed from positive velocities towards the radar with the Millimeter-Wavelength Cloud Radar (MMCR) to negative velocities towards the radar with
Figure 3.2. The process of using the CWT analysis to find the centers of cloud liquid drop mode candidates. a) Examples of the second-order Guassian wavelets. b) An example of a model-simulated radar Doppler spectrum. c) The two-dimensional array of coefficients produced by application of the CWT to the model-simulated radar Doppler spectrum. d) Coefficient values at the different scales indicated by dashed lines in c).

When large ice particles coexist with the cloud liquid drops, the cloud liquid drop signals in the radar Doppler spectra are often difficult to discern from the noise, having subtle morphological features not that different from those of the noise. Therefore, we take \( N = \min(N_{\text{tot}}, 3) \) (\( N_{\text{tot}} \) is the total number of local maxima in a coefficient curve) as the number of local maxima (all at the largest upward velocities) in the coefficient curves at scale \( S \) as candidate centers of the cloud liquid drop modes.

These candidates are used as first guesses of the cloud liquid drop mode center. A Gaussian distribution is fitted to each candidate using the spectral power densities at the center location and for the first few velocities on the upward motion edge of the cloud liquid mode contribution to the spectrum. Each of the fitted
Gaussian distributions is subsequently subtracted from the total radar Doppler spectrum and the CWT analysis (using the same selected scale S) is applied to the residual radar Doppler spectrum to produce another coefficient map. If the local maximum in the old coefficient map that corresponds to the candidate being tested does not disappear in the new coefficient map, the candidate cloud liquid drop mode center is moved to the left by one velocity bin and the previous steps are repeated. This process continues until the relevant local maximum in the new coefficient map disappears. The resulting cloud liquid drop mode, represented by a fitted Gaussian distribution centered on the velocity that removes the local maximum, is maintained as a potential candidate. These cloud liquid drop mode search steps are applied to all of the cloud liquid drop mode candidates. At the end of this process there are up to three cloud liquid drop mode candidates, one of which must be classified as the retrieved cloud liquid drop mode.

3.2.2 Selecting the Cloud Liquid Drop Mode

In the next step of the retrieval algorithm, fuzzy logic is applied to the cloud liquid drop mode candidates to select the one that is most likely due to actual cloud liquid drops and not noise or ice. The strength of a fuzzy logic approach lies in its ability to systematically address the natural ambiguities in measurement data, classification, and pattern recognition (Cornman et al., 1998). Fuzzy logic is integral to the retrieval algorithm because of inherent ambiguity in many aspects of cloud liquid drop mode identification.

Cloud liquid drops tend to dominate the population of hydrometeors close to cloud top (McFarquhar et al., 2011). Moving from cloud top to cloud base, the cloud liquid drop signals become progressively more likely to be contaminated by noise and/or mixed with ever larger ice particle signals as ice particles grow as they fall through the cloud layer. The cloud liquid drop mode is most difficult to discern at cloud base where the liquid contributions to the radar Doppler spectra vanish and the ice contributions are typically largest. Thus, cloud liquid drop modes are most easily identified at cloud top, but become progressively more difficult to identify as one approaches cloud base. This reality motivates us to start from the highest altitudes at cloud top and to work down towards cloud base, identifying
cloud liquid modes sequentially one layer at a time. The fuzzy logic scheme is used to identify the cloud liquid drop modes throughout the profile by applying approximate continuity constraints for the cloud liquid and precipitation modes. Selection of the most appropriate candidate as the cloud liquid drop mode is influenced by the four closest retrievals in time and height to the extent that they exist. Three retrievals from the layer immediately above the radar sample volume being processed (from the same profile and its two adjacent profiles in time), as well as the preceding retrieval from the current sample volume, are used to ensure some continuity in the retrievals.

To aid the identification of the cloud liquid drop and precipitation modes, each Doppler spectrum is first characterized into one of three categories: pure liquid, liquid dominated and precipitation dominated based on the vertical location of the spectrum in the cloud, total reflectivity, reflectivity from cloud liquid, mean Doppler velocity, spectrum width, skewness, and adiabatic LWC (Table 1). This straightforward classification step facilitates application of appropriate fuzzy logic membership functions to each spectrum. If the radar sample volume is identified as pure liquid, which happens frequently at cloud top, the cloud liquid drop mode properties are derived from the total spectrum and there is no need to apply fuzzy logic. Only when the radar sample volume is characterized as containing precipitation is fuzzy logic applied.

Membership functions are applied to deviations from reference values for each candidate cloud liquid drop mode reflectivity ($Z_{liq}$), mean Doppler velocity ($V_{liq}$) and Doppler spectrum width ($\sigma_{liq}$). The reference values are the means of the four adjacent (in height and time) cloud liquid drop mode retrieval moments for a precipitation dominated radar sample volume or the means of the current spectrum and cloud liquid drop mode retrieval moments for liquid dominated volume. The fourth, and final, cloud liquid drop mode membership function uses maximum liquid water content ($LWC_{max}$) as an additional constraint. $LWC_{max}$ is estimated from the adiabatic assumption using the temporally closest radiosonde temperature observations and is compared against a retrieved cloud liquid water content (LWC) estimated from the candidate cloud liquid drop mode reflectivity using the simple relationship $LWC = 2Z_{liq}^{0.5}$ (adapted from Frisch et al. (1995)). Under most circumstances $LWC < LWC_{max}$, implicitly providing a higher bound on the
<table>
<thead>
<tr>
<th>Class</th>
<th>Description</th>
<th>Details</th>
<th>Membership Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pure Liquid</td>
<td>Cloud liquid drops only</td>
<td>Radar sample volumes are at cloud top, total reflectivity $&lt; -20$ dBZ, spectrum width $&lt; 0.4 , m , s^{-1}$.</td>
<td></td>
</tr>
<tr>
<td>Liquid Dominated</td>
<td>Cloud liquid drops and precipitation particles are in the same radar sample volume, but the signals from liquid dominate.</td>
<td>Radar sample volumes are within upper half of cloud layer, total reflectivity $&lt; -16$ dBZ, mean Doppler velocity $&lt; 1 , m , s^{-1}$, Skewness $&gt; 0$.</td>
<td>$f_{Z_{\text{tot}}}$, $f_{Z_{\text{liq}}}$, $f_{V_{\text{liq}}}$, $f_{\sigma_{\text{liq}}}$, $f_{LWC}$</td>
</tr>
<tr>
<td>Precipitation Dominated</td>
<td>Cloud liquid drops and precipitation particles are in the same radar sample volume, but the signals from precipitation dominate.</td>
<td>Everything else.</td>
<td>$f_{Z_{\text{liq}}}$, $f_{V_{\text{liq}}}$, $f_{\sigma_{\text{liq}}}$, $f_{LWC}$</td>
</tr>
</tbody>
</table>

**Table 3.1.** Radar Doppler spectra classifier together with the corresponding membership functions.

Examples of these four cloud liquid drop mode membership functions are shown in Fig. 3.3. For the membership functions for the cloud liquid drop mode reflectivity ($f_{Z_{\text{liq}}}$), mean Doppler velocity ($f_{V_{\text{liq}}}$) and spectrum width ($f_{\sigma_{\text{liq}}}$) the membership functions decrease with the difference between the locally retrieved value and the reference value. The LWC membership function ($f_{LWC}$) does not incur a penalty as long as the retrieved LWC is not larger than the theoretical maximum adiabatic LWC.
Once each individual membership function has been evaluated, their values are combined to create a total membership value from

\[ f_{tot} = \frac{a_{Zliq} \times f_{Zliq} + a_{vliq} \times f_{vliq} + a_{\sigma liq} \times f_{\sigma liq}}{a_{Zliq} + a_{vliq} + a_{\sigma liq}} \times f_{LWC}. \]  

(3.1)

The final set of \( f_{tot} \) values (one for each candidate cloud liquid drop mode) represents the temporal consistency of the cloud liquid drop mode properties. The cloud liquid drop mode candidate with the highest value above 0.3 is selected as the retrieval. If no candidate attains a value of 0.3 or greater, a missing value is assigned to the radar sample volume.

When all of the cloud liquid drop modes have been retrieved for a one-hour
<table>
<thead>
<tr>
<th>Instruments</th>
<th>Parameter</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Radiosonde</td>
<td>Cloud layer temperature (T)</td>
<td>-40 °C &lt; T &lt; 0°C</td>
</tr>
<tr>
<td>Ceilometer</td>
<td>Cloud base height standard deviation (σ&lt;sub&gt;cb&lt;/sub&gt;)</td>
<td>σ&lt;sub&gt;cb&lt;/sub&gt; &lt; 50 m</td>
</tr>
<tr>
<td>Microwave radiometer</td>
<td>Cloud layer liquid water path (LWP)</td>
<td>LWP &gt; 25 g m&lt;sup&gt;-2&lt;/sup&gt;</td>
</tr>
<tr>
<td>KAZR</td>
<td>Cloud layer top height (Z&lt;sub&gt;top&lt;/sub&gt;)</td>
<td>Z&lt;sub&gt;top&lt;/sub&gt; &lt; 2500 m</td>
</tr>
<tr>
<td></td>
<td>Cloud layer depth (ΔZ)</td>
<td>200 m &lt; ΔZ &lt; 1000 m</td>
</tr>
</tbody>
</table>

Table 3.2. Cloud event case selection criteria.

period cloud event, their corresponding spectral moments are ordered as two-dimensional arrays in time and height. Missing values from failed retrievals are created by interpolation from nearby values using inverse-distance weighting. Once the array is complete, a local neighborhood (3 × 3) rank-order median smoothing algorithm is applied to the entire array to eliminate outliers.

### 3.2.3 Automated Cloud Event Selection Criteria

The algorithm is designed for use in low-lying, single-layer, mixed-phase clouds with temporally constant cloud base heights. To process long-term datasets an automated method to select appropriate one-hour long cloud events is necessary. Each one-hour period of KAZR data is analyzed in conjunction with observations from radiosondes, a ceilometer, and a microwave radiometer to identify appropriate cloud events for the algorithm (Table 2).

Algorithm performance is sensitive to detection of the cloud base. If the cloud base height is underestimated, regions of precipitating particles below cloud base are treated as a mixture of cloud liquid drops and precipitation. In this case the precipitation mode will be misidentified as a cloud liquid drop mode, contributing to overestimation of cloud liquid amount. Cloud base height is determined from filtered ceilometer measurements. The ceilometer reports up to 3 cloud bases in each profile. The Barrow measurements reveal frequent, small, low-level scud cloud. The height of the persistent cloud base is selected from the 3 cloud bases by
requiring temporal continuity. Specifically, no cloud base height may differ from
the previous (in time) value by more than 200 m. When none of the 3 cloud bases
meet this criterion, the height at this time is left blank, but is later estimated by
interpolation from surrounding accepted values. This approach also corrects for
often erroneously low reported cloud bases during short, intense snow events.

The objective criteria used to identify an acceptable one-hour cloud event are
listed in Table 2. For any particular hour to be selected it has to meet the cloud
layer selection criteria for more than 75% of the profiles. The cloud top must be
below 2500 m to be selected. Cloud thickness, defined as distance between cloud
top and the liquid-cloud base, must be less than 1000 m but greater than 200 m.
As an additional safeguard against errors introduced by heavy snow events, we
require a measure of cloud base height invariance as well. The standard deviation
of the cloud base heights, with the highest and lowest 12.5% of cloud base heights
removed, must be smaller than 50 m. Cloud layer temperatures, determined from
the 1-minute interval Merged Sounding data product (Troyan, 2012), must be
between \(-40 \, ^\circ C\) and \(0 \, ^\circ C\) to ensure that liquid and ice particles can, at least in
principle, co-exist in any cloudy volume. The presence of liquid in the cloud is
determined from the ARM Best Estimate Liquid Water Path product (Turner
et al., 2007), with the minimum acceptable value set to \(25 \, g \, m^{-2}\).

### 3.3 Validation of Algorithm Retrievals

Before applying the retrieval algorithm to radar observations, its performance
is evaluated using output from a Large Eddy Simulation (LES) that is imported
into a radar Doppler spectrum simulator. The simulator is described in detail
in Chapter 2; here we only provide a brief summary. The LES output used is
from the Distributed Hydrodynamic Aerosol and Radiative Modeling Application
(DHARMA) with (size-resolved) bin microphysics (Ackerman et al., 1995; Fridlind
et al., 2007). Three types of hydrometeors - cloud liquid drops, pristine snow and
aggregates - are used to represent the hydrometeors in each grid cell. The model
grid-cell resolved hydrometeor size distributions, resolved vertical velocity, diag-
nosed sub-grid vertical velocity variance, hydrometeor fall speeds, and backscat-
tering cross sections for each hydrometeor type (Botta et al., 2011) determine the
model-simulated radar Doppler spectrum for each grid cell.

We compared cloud liquid drop mode reflectivity, volume-mean air motion and sub-grid vertical velocity variance retrieved by the algorithm when applied to the model-simulated radar Doppler spectra (retrieved values) to those calculated directly from model outputs (model values) across a two-dimensional slice through the model domain at a single model time step (Fig. 3.4). The retrievals captured the general structure of the model fields with an overall bias of approximately 0.12 dB (Fig. 3.5b1), but with some inconsistencies in low reflectivity regions and in downdrafts. Errors in the cloud liquid drop mode reflectivity retrievals occurred mostly near cloud base (Fig. 3.4a3), where liquid water contents are small and cloud liquid drop mode reflectivity signal-to-noise ratios are close to one. Large errors (i.e. errors > 5 dB) occurred mostly when cloud liquid drop mode reflectivities were smaller than -35 dBZ (Fig. 3.5a1).

The retrieved volume-mean vertical air motions (Fig. 3.4b1) generally reproduced the up- and down-draft structures (Fig. 3.4b2), with an overall bias of approximately -0.06 m s\(^{-1}\) (Fig. 3.5b2, negative means downward), close to the mean fall speeds of cloud liquid drops. More uncertainty in the retrievals was found near cloud base because the small cloud liquid drop mode signals in this region make retrievals more difficult (Fig 4b3). Volume-mean vertical air motions were significantly underestimated when cloud liquid drop mode reflectivities were smaller than -35 dBZ (Fig 5a2). Moreover, volume-mean vertical air motions were overestimated towards updrafts due to increased sub-grid vertical velocity variance which increases the difficulty in retrieving cloud liquid drop modes (e.g. the red region near a horizontal location of 1.2 km at height around 1 km in Fig 4b3).

The air sub-grid vertical velocity variance retrievals slightly overestimated the model values (Fig. 3.5b3), but they successfully tracked the turbulent and relatively quiet regions. The bias (an overestimation of 0.04 m s\(^{-1}\)) here may be due to the retrievals containing contributions from both the width of the particle size distribution and turbulence, while the model values only contain the latter.

Application of the retrieval algorithm to the model-simulated spectra produced from DHARMA outputs suggests that this algorithm has the potential to separate cloud liquid drop mode signals from total radar Doppler spectra. Cloud liquid drop mode reflectivity, volume-mean vertical air velocity and sub-grid vertical ve-
Figure 3.4. Comparisons between the retrieved (column 1) and model (column 2) values of a) cloud liquid drop mode reflectivity, b) volume-mean vertical air velocity, and c) sub-volume vertical velocity variance. Column 3 illustrates the spatial distribution of the errors calculated by subtracting the model values from the retrieval values.

Locality variance have been successfully reproduced with quantitative error estimates. Based on DHARMA model outputs, the retrievals tend to slightly underestimates the volume-mean vertical air velocities and overestimate the sub-grid vertical velocity variances in the cloud layer. Near cloud base, the uncertainty in the retrievals is larger due to smaller amounts of liquid.

3.4 Results

The retrieval algorithm was applied to KAZR data collected at the ARM Climate Research Facility (ACRF) North Slope of Alaska (NSA) site during October, 2011. The selection criteria described in Sec. 3.2.3 were applied to identify all
Figure 3.5. Errors as a function of cloud liquid drop reflectivity for (column 1) cloud liquid drop reflectivity, (column 2) volume-mean vertical air velocity, and (column 3) sub-volume vertical velocity variance. The red lines represent median values, whereas the box and whiskers represent 25th, 75th 5th and 95th percentiles of the data). b) Frequency of occurrence histograms of the errors.

hours during which single-layer, mixed-phase stratus or stratocumulus was present over the radar. In total, 185 hours of cloud events appropriate for input to the retrieval algorithm were identified.

3.4.1 First Case Study Period

The first case study period is from 21:00-22:00 UTC on 14 October 2011 when a low-lying, mixed-phased cloud was detected with cloud base heights near 650 m and cloud top heights below 1200 m (Fig. 3.6). Temperatures in the cloud layer were between -5 °C and -10 °C. The reflectivity increased within vertically oriented shafts around 21:13 UTC, 21:33 UTC and 21:50 UTC, indicating periods of heavier precipitation accompanied by thicker cloud layers. The retrieval algorithm was applied to all of the KAZR observations within the cloud layer.

The results obtained by applying the retrieval algorithm to the cloud layer are presented in Fig. 3.7. Panels in the left column are the results before filling in for
missing retrievals and smoothing the retrieved values, whereas panels in the right column are the final retrievals. Although no cloud structure was enforced by the retrieval algorithm, the highest cloud liquid drop mode reflectivities (highest value -14.0 dBZ) occurred near cloud tops (Fig. 3.7a), especially when the cloud layer was thick. Reflectivities tapered off for radar sample volumes closer to cloud base. Cloud liquid drop mode reflectivities varied between -43.5 dBZ close to cloud base and -14.0 dBZ near cloud top.

The retrieved volume-mean vertical air velocities are shown in Fig. 7b in which coherent up- and down-draft regions are identifiable. The maximum updraft retrieved in this case was 1.76 m s\(^{-1}\), while the maximum downdraft was -1.40 m s\(^{-1}\). The standard deviations of the retrieved sub-volume vertical velocity variances ranged 0.02 - 0.45 m s\(^{-1}\) (Fig. 3.7c).

Figure 3.8 takes a closer look at the relationship between the precipitation and cloud liquid drop mode reflectivities and the volume-mean vertical air velocities within a short, 10-minute period 21:25-21:35 UTC on 14 October 2011. Precipitation reflectivities within cloud layers are calculated by subtracting the retrieved cloud liquid drop mode reflectivity from the total reflectivity observed by the KAZR, whereas below the cloud layer the precipitation reflectivity is equal to the total reflectivity.

**Figure 3.6.** Observed total reflectivity from 21:00 - 22:00 UTC on 14 October 2011 recorded by the KAZR. The black line represents the cloud base height retrieved from ceilometer measurements.
Figure 3.7. Retrieved a) cloud liquid drop mode reflectivities, b) volume-mean vertical air velocities, and c) sub-volume vertical velocity variances for 21:00 - 22:00 UTC on 14 October 2011. The plots in the left column are the results before filling in for missing retrievals and smoothing the retrieved values. The plots in the right column are the results after filling in for missing values and smoothing the retrieved values.

No significant discontinuity was found in the precipitation reflectivities across cloud base nor was the precipitation reflectivity pattern distorted near cloud top where the cloud liquid drop and precipitation contributions become closer in magnitude, indicating that the retrieval algorithm had no gross errors in these regions. Precipitation reflectivities were generally larger in updrafts than in downdrafts (also Figs. 3.8a and 3.9a). On the other hand, cloud liquid drop mode reflectivities did not vary much from downdrafts to updrafts (also Figs. 3.8b and 3.9b). The mean precipitation vertical fall speeds increased (i.e., became more negative) with increases in updraft speed and were, on average, downward everywhere in the
Figure 3.8. A short, 10-minute period of a) precipitation reflectivity, b) retrieved cloud liquid drop mode reflectivity, and c) reflectivity-weighted fall speeds of precipitating particles from 21:25 - 21:35 UTC on 14 October 2011. The dark red contour lines represent updrafts and the blue contour lines represent downdrafts.

cloud (Figs. 3.8c and 3.9c).

3.4.2 Second Case Study Period

The second case presented is the one-hour period from 11:00 -12:00 UTC on 8 October 2011 (Fig. 3.10). During this period cloud base and top heights varied little, the in-cloud temperature was around -6 °C, and the highest total reflectivity
was around -15 dBZ. The retrieved cloud liquid drop mode reflectivities, volume-mean vertical air velocities, and standard deviations of the sub-volume vertical velocity variances for this hour are presented in Fig. 3.11. The retrieved cloud liquid drop mode reflectivities (Fig. 3.11a) ranged from -42 dBZ to -19 dBZ with vertical profiles that generally increased from cloud base to cloud top. Coherent updrafts and downdrafts (Fig. 3.11b) were also obtained in the retrieved volume-mean vertical air velocities, with a maximum updraft speed of 1.40 m s\(^{-1}\) and a maximum downdraft speed of -1.66 m s\(^{-1}\). Compared to the previous case study, this case exhibited less temporal variability in the cloud liquid drop mode reflectivities, whereas the updrafts were weaker and the downdrafts stronger than in the previous case.
Figure 3.10. Observed total reflectivities from 11:00 - 12:00 UTC on 8 October 2011 recorded by the KAZR. The black line represents the cloud base height retrieved from ceilometer measurements.

The 10-minute period from 11:18 - 11:28 UTC (Fig. 3.12) provides another closer look at the relationships between retrieved fields. There was a tendency for higher precipitation reflectivity values close to cloud tops above stronger updrafts where the precipitation fall speeds were also largest. All sub-cloud precipitation streaks were closely associated with updraft structures and the reflectivities below downdrafts were the smallest in the sub-cloud region.

Figure 3.13 explores the relationships between precipitation reflectivities, cloud liquid drop mode reflectivities, and precipitation fall speeds and volume-mean vertical air velocities for this hour, and shows the same general results as were found for the previous case period (Fig. 3.9). Precipitation reflectivities and fall speeds were larger in the updrafts than those in the downdrafts (Figs. 3.13a and 3.13c). This is not unexpected because updrafts are regions with higher water saturation, providing favorable conditions for ice growth. Moreover, upward moving air retains ice particles for longer periods in the cloud layer which enhances their growth. When the ice particles become sufficiently large to have fall speeds exceeding the updraft speed, they mostly fall out of the cloud layer through the updrafts. Within the cloud layer they grow through water vapor deposition in near liquid-water saturated conditions, riming and/or aggregation, whereas below the cloud layer ice particle growth by vapor deposition in ice super-saturation conditions and by ag-
Aggregation may still take place. With many ice particles falling out in the updrafts, fewer (and smaller) ice particles are transferred to the downdraft regions. Although the presence of liquid keeps the saturation ratios close to liquid-water saturation, the ice particles experience less time for growth in the downdrafts regions because their fall speeds add to the downdraft speed and minimize their time in cloud. Together, these factors produce greater radar reflectivities within or below the cloud layer in the updraft regions as compared to the downdraft regions.

Figure 3.11. Same as Fig. 3.7, except for 11:00 - 12:00 UTC 8 October 2011.
3.4.3 Statistics for Single-Layer Low-Level Clouds in October 2011

In order to further evaluate the retrieval algorithm, we applied it to a month of KAZR radar Doppler spectra collected at the NSA in October 2011. There were a total of 185 relevant one-hour cloud events across the whole month identified by the automatic selection criteria. Analyses identical to those for the first two case study periods were applied to all 185 cases and summary statistics generated for them.
Assuming that the properties of ice crystals one radar sample volume above and below cloud base are not significantly different, a test of the cloud liquid drop mode reflectivity retrieval is comparison of the first two radar Doppler spectral moments at these two heights. They should become more similar after subtracting the cloud liquid drop mode reflectivities from the within-cloud radar Doppler spectra (Luke and Kollias, 2013);

All profiles from all 185 hours of data are used to generate the frequency of occurrence histograms that show the comparisons between the ice particle reflectivities and mean Doppler velocities from the radar sample volumes one gate above and below cloud base (Fig. 3.14). Cloud liquid drop mode contributions to the total reflectivities are negligible when ice particle reflectivities are large. Thus, at ice particle reflectivities larger than -20 dBZ, both ice particle and total reflectivities

Figure 3.13. Same as Fig. 3.9, except for 11:00 - 12:00 UTC on 8 October 2011.
Figure 3.14. Comparisons of ice particle a) reflectivities and b) mean Doppler velocities for radar sample volumes one gate above and below cloud base. Frequency of occurrences (normalized by dividing by total number of retrievals) smaller than $3 \times 10^{-6}$ are presented as white. The median frequency of occurrence values for ice particle reflectivities one range gate above cloud base for fixed ice particle reflectivity one range gate below cloud base are marked with black circles, whereas median values for the total reflectivities one range gate above cloud base (before subtracting the cloud liquid mode contributions) are marked with black asterisks.

from the radar sample volume one gate above cloud base are similar to those from the radar sample volume one gate below cloud base. When ice particle reflectivities are smaller than -20 dBZ, cloud liquid drop mode contributions to the total reflectivities become comparable to those from the ice particle mode. As such, for ice particle reflectivities smaller than -20 dBZ, the total reflectivities from the radar sample volume one gate above cloud base are significantly larger than those from the radar sample volume one gate below cloud base. When cloud liquid drop mode reflectivities are subtracted the ice particle reflectivities from both heights come to better agreement, though differences remain when ice particle reflectivities are smaller than -38 dBZ. This result is consistent with the algorithm assessment that we performed using model outputs (Fig. 3.5a1), where we showed in the error estimates of the retrieved cloud liquid mode reflectivities that this algorithm performs better when cloud liquid mode reflectivities are greater than -35 dBZ. The ice particle reflectivities across cloud base are quite consistent with only a 0.37 dBZ difference between them on average.

The mean Doppler velocities of the ice particles from radar sample volumes one gate above and below cloud base are compared in Fig. 3.14b. After subtracting the cloud liquid drop mode contributions to the radar Doppler spectra, the mean
Doppler velocities increased in the downwards direction. For mean Doppler velocities smaller than -0.5 m s\(^{-1}\), ice particles from the radar sample volume one gate below cloud base fell faster than those from the radar sample volume one gate above cloud base, which indicates that ice particles keep growing in the sub-cloud layer. This result is consistent with Shupe et al. (2008a) who showed that the layer of saturation with respect to ice extends below the layer of saturation with respect to water by up to 350 m. Ice particle mean Doppler velocities across cloud base were consistent with only a 0.03 m s\(^{-1}\) difference between them on average. These results indicate that removal of retrieved cloud liquid drop mode reflectivities from total reflectivities near cloud base does not introduce spurious ice particle moments. However, this comparison is not of great significance because the cloud liquid drop mode contributions to the radar Doppler spectra near cloud base were generally small.

Over a long period the average of the volume-mean vertical air velocities within a cloud layer should be approximately 0 m s\(^{-1}\) as the velocities associated with updrafts and downdrafts should cancel. Figure 3.15 presents a frequency of occurrence histogram of retrieved volume-mean vertical air velocities for all 185 hours of data. The histogram is symmetric with an overall average value of + 0.05 m s\(^{-1}\) (corresponding to upward air motion). This non-zero value for the overall volume-mean vertical air velocity may be the result of selective sampling: all 185 hours in the analysis contain low-altitude clouds, which may be driven by large scale ascent. This result may be compared to estimating the volume-mean vertical air velocity by looking to the first velocity bin with signal exceeding the noise value (i.e. Shupe et al. (2008b)), which, in cloud layers, corresponds to the small cloud liquid drops that move with the ambient air but are in the updraft portion of a turbulent eddy. The dashed line in Fig. 3.15 represents the frequency of occurrence histogram derived from this alternative method. These estimates are known to deviate from the volume-mean vertical air velocity due to spectral broadening by air turbulence, horizontal and vertical shear of the vertical velocity, and the finite radar antenna beamwidth (Shupe et al., 2008b). Our results suggest the mean value of overestimation is 0.56 m s\(^{-1}\), much bigger than the value (0.03 m s\(^{-1}\)) estimated by Shupe et al. (2008b) for the same season of the year (fall season). Applying our mean correction would account for the mean updrafts of 0.5 m s\(^{-1}\).
Figure 3.15. Normalized frequency of occurrences of all of the retrieved volume-mean vertical air velocities from the 185 hours of data (shaded) and their corresponding first-bin velocities (dashed line).

(Shupe et al., 2008b) and 0.4 m s$^{-1}$ (Shupe et al., 2008a) found in these earlier studies.

3.5 Discussion

The potential of the new spectral deconvolution algorithm to retrieve mixed-phase cloud liquid/ice reflectivities, volume-mean vertical air motion, sub-volume vertical velocity variance and mean precipitation fall speed has been demonstrated. However, it is difficult to evaluate these retrieval results because there are no direct observations of these variables to compare with. The only available measurements somewhat related to the retrievals are liquid water paths (LWPs) observed by a nearby microwave radiometer (MWR). The LWP is the integral of the cloud liquid water content (LWC) profile, and LWC is related to the cloud liquid drop mode reflectivity through the underlying cloud liquid drop size distribution (DSD). This drop size distribution is not known and may in fact vary throughout the cloud. In its most general form the relationship may be expressed as
\[ LWC = aZ^b \] (3.2)

where \( b = 0.5 \) is a constant and \( a \) is related to the number concentration and cloud liquid drop size distribution shape (i.e. Frisch et al. (1995)). In general, large coefficients correspond to radar sample volumes with large concentrations of small cloud liquid drops and smaller coefficients to low concentrations of large drops. The conversion from cloud liquid drop mode reflectivity to LWC via Eq. (3.2) depends strongly on the coefficient \( a \). Rather than specifying \( a \) we treat it as a free parameter to be adjusted in order to best match the retrieved LWPs to those from the microwave radiometer. Although the coefficient may be expected to vary between updrafts and downdrafts, we assume that it is constant for any single hour. This assumption is based on slow changes in the larger scale environment in which these clouds exist. A single value for the coefficient is then determined for each hour of a cloud event by minimizing the differences in MWR LWP measurements and radar-retrieved LWPs, the values of which are calculated by vertically accumulating the retrieved cloud-liquid water contents obtained from Eq. (3.2).

Figures 3.16a and 3.16b show the LWPs for the two cases presented in Sec. 4. The correlations between the retrieved LWPs and those from the microwave radiometer are 0.96 and 0.81, with the \( a \) coefficients equal to 4.2 and 5.5, respectively. The two LWC versus \( Z \) relationships are in the range proposed by Atlas (1954) \((LWC = 4.5Z^{0.5})\), Sauvageot and Omar (1987) \((LWC = 5.3Z^{0.54})\), Matrosov et al. (2004) \((LWC = 4.6Z^{0.5})\) for continental clouds and \( LWC = 2.4Z^{0.5} \) for marine clouds) and Fox and Illingworth (1997) \((LWC = 9.3Z^{0.64})\). Thus, with a coarse assumption of a constant coefficient throughout the one-hour period, the retrieved LWPs generally tracked the variations of the values obtained from the MWR.

Figures 3.16c and 3.16d show retrieved LWCs calculated using the constant coefficients. The maximum LWC in the deeper case is 0.86 \( g \ m^{-3} \) compared to 0.60 \( g \ m^{-3} \) for the shallower case. It should be noted that in order to retrieve more accurate LWCs without MWR LWP constraints, better estimates of the coefficient \( a \) are needed. The coefficient \( a \) depends on the number concentration \( N \) and the dispersion \( \sigma \) of the DSD (Frisch et al., 1998), or
In liquid dominated clouds, drops form near cloud base in the updrafts and grow as the parcel in which they are located approached cloud top. In terms of the DSD parameters, \( N \) is fixed close to its value at cloud base, but the mean drop size increases with height in the cloud. The dispersion \( \sigma \) gradually increases as the drops grow via vapor deposition. The cloud liquid drop mode reflectivities generally increase because of the increase in mean size, but the coefficient \( a \) will decrease as a result of the increasing dispersion. The reverse may be expected in the downdrafts.

The situation becomes more complex in mixed-phase cloud with abundant ice
particles. In sufficiently strong updrafts liquid-saturation is maintained and the DSD develops as before. In weaker updrafts the ice grows at the expense of liquid through the Wegener-Bergeron-Findeisen process, likely with impact on N and $\sigma$, and hence the coefficient $a$. Downdrafts, where warming and ice growth combine together, provide a stronger sink term for liquid and cloud liquid drops evaporate faster. Once the smallest drops attain sizes where curvature effects on the equilibrium vapor pressure are felt, the smaller drops will preferentially evaporate thereby maintaining close to liquid-saturation (Sulia and Harrington, 2011). As a consequence, larger drops may either continue growing or experience relatively less evaporation. The impact on the DSD parameters in these ice precipitation dominated cases then is a decrease in N but not necessarily $\sigma$ or the mean cloud drop size. The result is that although the liquid water concentration decreases in the downdraft there may not be a corresponding decrease in reflectivity with height (see Fig. 3.12b) nor a clear dependence of cloud liquid mode reflectivity on volume-mean vertical air velocity (see Fig. 3.13b) because of the changing drop size distribution. However, there may be a significant change in the coefficient $a$.

To explore possible micro-physical and dynamical influences on the values of the $a$ coefficients we calculated $a$ coefficient for every single profile in the hour for both cases. Figures 3.16e and 3.16f show the variations in the coefficient as a function of layer mean vertical velocity. An increasing trend of the coefficient with increasing updraft strength is evident for the ice-dominated case (case one), but not for the liquid-dominated case (case two). These results warrant further investigation of the variation of the coefficient $a$ in response to different dynamical and micro-physical processes before reliable LWCs may be retrieved.

### 3.6 Summary and Conclusions

Supercooled liquid layers have strong impacts on the micro-physical, radiative and dynamical processes in mixed-phase clouds. However, retrieving the micro-physical properties of liquid layers in mixed-phase clouds is difficult because of limitations in the instruments used to measure profiles of cloud liquid drop properties when both liquid and ice phases co-exist. This paper presents a retrieval algorithm that was developed to separate liquid and ice contributions to radar
The retrieval algorithm is based on the assumption that any radar Doppler spectrum is the result of a linear superposition of several Gaussian distributions, each of which represents a discrete class of hydrometeors with a characteristic fall velocity. Hydrometeor classes with distinct mean fall velocities can be identified in radar Doppler spectra using continuous wavelet transform (CWT) and fuzzy logic methods.

The performance of the algorithm is evaluated by applying it to model-simulated radar Doppler spectra. Model-simulated radar Doppler spectra were generated by applying a forward model radar simulator to Large Eddy Simulation (LES) model output. Cloud liquid drop mode reflectivities, volume-mean vertical air velocities, and sub-volume vertical velocity variances retrieved from the model-simulated radar Doppler spectra were compared to values provided directly in the model output. The retrievals of cloud liquid drop mode reflectivities were generally consistent with the original model values with uncertainty less than a factor of 2 (3 dB). The retrieved volume-mean vertical air velocities reproduced the updraft and downdraft structures well, but with an overall bias of approximately -0.06 m s\(^{-1}\). The sub-volume vertical velocity variance retrievals successfully tracked both the turbulent and relatively quiet regions with slight overestimation partly due to the contribution from the width of the particle size distribution.

The retrieval algorithm was also applied to two case study periods using ground-based observations collected at Barrow, Alaska, during October 2011. In both cases the retrieved cloud liquid drop mode reflectivities were physically reasonable with increasing liquid amount with height within the cloud layer. Coherent updraft and downdraft air motions were retrieved in both cases. The LWP comparisons between the retrievals and those measured by a microwave radiometer suggest that the retrieved LWPs generally tracked the variations in LWP.

One month statistics of ice precipitation reflectivities and mean Doppler velocities across cloud base were consistent, indicating that removal of cloud liquid drop mode reflectivities from the radar Doppler spectra near cloud base did not produce spurious radar Doppler spectra near cloud base. The volume-mean vertical air velocities averaged over 185 hours of data were near zero, which is consistent with expected mean vertical air motions of close to zero when averaged over a long
period. Comparisons with the oft-used method of Shupe et al. (2008b) provide an explanation for the reported mean updraft speeds resulting from that method.

Uncertainties in the retrieval algorithm exist because this method relies on reliable cloud base measurements and well-separated fall speeds of different types of hydrometeors (e.g., cloud liquid drops and precipitating ice particles). However, ice particles with slow fall speeds or strong turbulence broadening may cause different hydrometeors to have similar fall speeds, which increase the difficulty of separating the cloud liquid drop and ice particle contributions to the radar Doppler spectra.

Further investigation of the variability in the relationship between cloud liquid drop reflectivity and LWC is needed before reliable LWCs may be retrieved. Such an investigation requires both observational and modeling studies on the impacts of different dynamical and micro-physical processes (e.g. impacts from ice particles) on cloud liquid drop particle size distributions in mixed-phase clouds.
In this chapter, we investigated the statistics of macro- and micro-physical, thermodynamical and dynamical properties of Arctic mixed-phase clouds using the ground-based observations collected during October 2011 at Barrow Alaska. The newly developed spectrum deconvolution algorithm from Chapter 3 was applied to 185 hours of low-level, stratiform Arctic cloud events selected in that month. The separation of cloud liquid drop and precipitation contributions to radar Doppler spectra enables the investigation on the joint distributions between the cloud-drop and precipitation microphysics and vertical air motion. Studies on these relationships derived from long-term observation will strength our understanding of the physical processes in Arctic mixed-phase clouds, which is a necessary to develop more sophisticated parameterizations to partition cloud phases in climate models.

4.1 Introduction

Observational and modeling studies suggest that higher latitude climate warming is occurring at twice the rate compared to lower latitudes (Hansen et al., 2010;
Parry et al., 2007; Rigor et al., 2000; Serreze et al., 2009), a process known as polar amplification. Clouds play an important, yet complicated, role in this process, mostly through impacts on the surface energy budget. Kay et al. (2008) and Kay and Gettelman (2009) suggest that Arctic mixed-phase clouds may have contributed to the record setting minimum areal sea ice extent in the Arctic in 2007 as well as to the significant summer sea ice losses in recent years.

Stratiform mixed-phase clouds cover large areas of the Arctic region and occur frequently during all seasons of the year (Shupe, 2011). They are persistent systems that can last for days, even weeks, despite the inherent instability of cloud-liquid drop and ice particle co-existence (Shupe, 2011; Verlinde et al., 2007; Zuidema et al., 2005). Mixed-phase clouds impact the surface short- and long-wave radiative fluxes (Curry et al., 1996; Shupe and Intrieri, 2004), and thus the Arctic surface energy budget. The impacts of mixed-phase clouds vary with their relative amounts of liquid and ice, but can be large because of their frequent occurrences, large areal coverage and long lifetimes.

Our understanding of Arctic mixed-phase clouds is still relatively limited, in part a result of observational challenges in observing super-cooled liquid clouds embedded in ice precipitation and in part because the delicately linked dynamical, micro-physical and radiative processes in mixed-phase clouds present challenges for models of all scales (Gorodetskaya et al., 2008; Klein et al., 2009; Morrison et al., 2011). Correct partitioning of the water phases in Arctic mixed-phase clouds is critical for getting their impacts on the surface energy budget correct. Liquid in mixed-phase clouds provides the main driver for the cloud motions and dominates cloud radiative impacts on the Arctic surface energy budget, but precipitating ice plays a large role in regulating the lifetimes of these clouds by depleting liquid (Harrington et al., 1999; Jiang et al., 2000).

The liquid water budgets of mixed-phase clouds depend on radiative cooling, entrainment of overlying air, fluxes at the surface, large-scale advective tendencies and internal cloud processes. The dominant source of condensation is in supersaturated updrafts, with sinks consisting of evaporation in unsaturated downdrafts and losses to (primarily) ice precipitation. The forcing for the updrafts depends on surface fluxes and cloud-top radiative cooling, while cloud water content loss to ice precipitation is a strong function of the ice crystal number concentrations and
In general, larger scale models do not resolve these smaller scale cloud processes, which then must be parameterized, based on the resolved variables. In simpler micro-physical schemes phase-partitioning is parameterized based on temperature (Boucher et al., 1995; Gregory and Morris, 1996; Smith, 1990; Tiedtke, 1993). However, McFarquhar et al. (2007) showed that parameterizations solely based on temperature are not able to accurately predict cloud liquid water contents in Arctic mixed-phase clouds. More parameters should be considered, such as large scale vertical air motion (Tremblay et al., 1996), sub-grid scale convection and waves (Hogan et al., 2003) and/or ice-forming nuclei (IFN) (Harrington et al., 1999; Jiang et al., 2000; Prenni et al., 2007). In response, more sophisticated parameterizations have been developed and implemented in large-scale models (Morrison and Gettelman, 2008; Salzmann et al., 2010; Bretherton and Park, 2009; Park and Bretherton, 2009; Gettelman et al., 2010). While these led to improvements in the representation of clouds, more work is needed (Barton et al., 2012). Observations of how cloud processes are related to key factors, such as temperature, cloud draft structures and ice/liquid properties, are needed to evaluate and improve these parameterizations.

### 4.2 Data and Methodology

In this study we investigate interactions between different cloud processes in low-level, mixed-phase, Arctic stratiform clouds using data collected during the month of October 2011 at the Department of Energy (DOE) Atmospheric Radiation Measurement (ARM) program ARM Climate Research Facility (ACRF) in Barrow, Alaska. A total of 185 one-hour periods were selected based on measurements from the Ka-band ARM Zenith Radar (KAZR), a microwave radiometer (MWR), a ceilometer and the ARM Merged Sounding Value Added Product (Troyan, 2012). Details of the automated selection criteria of one-hour long Arctic stratiform mixed-phase cloud events can be found in Chapter 3.

For any particular hour to be selected it has to meet the cloud layer selection criteria. The cloud top must be below 2500 m, cloud thickness must be less than 1000 m but greater than 200 m, the standard deviation of the selected cloud base
heights must be smaller than 50 m, cloud layer temperatures must be between
-40 °C and 0 °C and finally the average LWP of the selected one-hour long Arctic
stratiform mixed-phase cloud event must be no less than 25 g m\(^{-2}\).

In addition to these properties of each one-hour cloud event additional cloud
characteristics are part of this study. We define the precipitation base as the lowest
height in the KAZR total reflectivity profile at which the radar-received signal is
larger than the noise. Cloud layer lapse rates are calculated by dividing cloud
top and base temperature differences by the cloud depth. Ice saturation profiles
are calculated from radiosonde data launched approximately every 12 hours. "Ice
saturated” conditions are considered as those with a relative humidity greater than
98% of ice saturation.

Applying the deconvolution algorithm developed in Chapter 3 to radar Doppler-
velocity spectra obtained by the KAZR in October 2011, the spectra are decom-
posed into cloud-liquid and precipitation contributions for every in-cloud radar
sample volume for all 185 cloud events. Cloud-liquid and precipitation reflect-
tivities, volume-mean vertical air velocities and reflectivity-weighted precipitation
mean fall speeds are estimated from these spectral deconvolution results.

Temperature is a fundamental property of low-level Arctic mixed-phase clouds.
Normalized frequency of occurrence distributions of cloud top and base tempera-
tures retrieved from the merged radiosonde data reveal distinct bimodality for this
particular set of cloud events in October 2011 (Fig. 4.1). The cloud top tempera-
ture distribution has a high temperature peak around -8 °C and a low temperature
peak around -16 °C, while the cloud base temperature distribution had two sep-
parate peaks around -7 °C and -14 °C. Because ice properties and processes are
strongly impacted by the environmental temperature in which the ice is found
(Bailey and Hallett, 2009), we decided to break the set of 185 cloud events into
two categories: those clouds with cloud top and base temperatures 1) higher than
-10 °C and 2) lower than -10 °C. Category 1 contains 44 one-hour events and cat-
egory 2 has 120 events in. The remaining 21 events have cloud base temperatures
higher, but cloud top temperatures lower than -10 °C.

Example cloud events for categories 1 and 2 are displayed in Figs. 4.2 and 4.3,
respectively. The category 1 cloud shown in Fig. 2 is a long-lasting (9 hours from
09:00 - 18:00 UTC on 8 October 2011) stratiform cloud. The cloud base height is
Figure 4.1. Normalized frequency of occurrence distributions of a) cloud top temperature and b) cloud base temperature for 185 hours of data in October 2011. Each distribution is normalized by its maximum value.

indicated by the black line. Cloud top and base heights varied little for the first three hours after which both increased slowly with time. Most of the observed reflectivities in the cloud layer are below -15 dBZ. Reflectivity below cloud base varies from $\sim-5$ dBZ in an ice shower near 09:20 UTC to below the noise level for a period near 14:30 UTC when there was no precipitation. The averaged cloud top and base temperature for this period is $-7.87 \, ^\circ C$ and $-7.84 \, ^\circ C$, respectively. The temperature profile shown in Fig. 4.2d is from the temporally closest (05:33 UTC) radiosonde release. The ice saturation ratio is above 100% in the cloud layer and even some distance below cloud base.

The micro-pulse lidar (MPL) backscattering intensity ($\beta$, Fig. 4.2b) is a maximum near cloud base where numerous small cloud liquid drops exist. The linear depolarization ratio ($\delta$, Fig. 4.2c) is generally small (< 10%). Minimum values for $\delta$ are found at heights just below cloud base where the lidar backscattering is dominated by returns from spherical particle (e.g. swollen cloud condensation nuclei). Evidence for stronger ice showers can be seen in the short intervals of higher $\delta$ around 09:20 UTC and 17:50 UTC, where $\delta$ increases below cloud base, most likely a result of evaporation of liquid precipitation. Support for the contention that most of the period was dominated by liquid precipitation can be seen near 14:00 UTC when all the precipitation evaporated before reaching the ground.

As a contrast to the category 1 case, a long-lasting category 2 event is shown
Figure 4.2. Example of the mixed-phase cloud observed between 09:00 - 18:00 UTC on 8 October 2011 at Barrow, AK. a) Radar-measured reflectivities, b) micro-pulse lidar (MPL) measured backscattering and c) MPL linear depolarization ratio. The black line in each panel represents the cloud base height retrieved from the ceilometer. d) Temperature (solid black line), dew point (dashed black line), relative humidity with respect to liquid (solid blue line) and relative humidity with respect to ice (blue dashed line) obtained at 05:33 UTC on 8 October 2011.

in Fig. 4.3. This cloud was observed for more than 6 hours on 23 October 2011. Compared to the category 1 case in Fig. 4.2, this category 2 cloud had higher (colder) cloud tops (-16.6 °C) and bases (-13.1 °C), a thicker cloud layer and higher reflectivity. Reflectivity values often exceeded 0 dBZ within and below the cloud layer. The MPL depolarization ratios suggest that the precipitation was dominated by ice, most of which reached the surface. The 18:33 UTC radiosonde release shows
ice super-saturation from 437 m AGL (∼100 m below cloud base) through cloud top (Fig. 4.3d). Thus, ice precipitation would continue growing through vapor deposition below cloud base even as any liquid precipitation evaporated. Even though the lidar cloud base signature is similar to the category 1 case (β high, Fig. 4.3b; δ low, Fig. 4.3c), the linear depolarization ratio at cloud base is higher in this category 2 case, indicating the influence of ice precipitation on this measurement.

The brief comparisons of these examples from the two cloud categories suggest potential differences in cloud macro- and micro-physical properties between them.
Figure 4.4. Normalized frequency of occurrence distributions of mixed-phase cloud macro-physical properties: a) cloud top height, b) cloud liquid layer base height, c) cloud base height including ice precipitation, (d) cloud liquid layer thickness, (e) cloud thickness between cloud top and precipitation base, and (f) ratio of the cloud liquid layer thickness to total thickness including precipitation. The category 1 distributions are represented by the solid black lines, the category 2 statistics by the solid blue lines. The red vertical bar represents the median value of the distribution, the blue star represents the mean value of the distribution, whereas the box and whiskers represent the 25th, 75th 10th and 90th percentiles of the data.

Therefore, separate statistics of the macro-physical, micro-physical and dynamical properties of each category of Arctic stratiform mixed-phase clouds are compiled.

4.3 Results

In this section, the statistics of the macro-physical, thermodynamic, and micro-physical properties of the mixed-phase clouds in both categories are compared. Joint distributions between different cloud properties are presented in order to understand the interactions between different cloud processes.
4.3.1 Macro-physical properties

Figure 4.4 presents the statistics of several macro-physical properties of the mixed-phase clouds, including cloud top height, cloud liquid and precipitation layer base height, and cloud liquid layer thickness retrieved from radar and ceilometer observations. Normalized frequency of occurrence distributions of these parameters were calculated separately for each cloud category. Note that the normalized frequency of occurrence distributions for each parameter are significantly different between the two categories at the 5% significance level.

Generally, mixed-phase clouds in category 1 (warmer clouds) are lower in altitude than those in category 2 (colder clouds, Figs. 4.4a and 4.4b). The median cloud top and base heights in category 1 are ∼800 m and ∼510 m, compared to ∼1100 m and ∼700 m for clouds in category 2. Most category 2 clouds have precipitation reaching the ground or to within 200 m from the surface (Fig. 4.4c), close to the first radar gate height (100 m). While most of the lower and warmer category 1 clouds produced precipitation that reached the surface, 19% of the time precipitation failed to reach the surface, with precipitation bases recorded as high as 1090 m above the surface. Category 1 clouds at times have less productive precipitation processes and/or lower relative humidity (RH) in the (shallower) sub-cloud layer compared to the category 2 clouds. These observations are consistent with warm-cloud dominated precipitation production (such as the case shown in Fig. 4.2) which not only is less effective than cold cloud processes but also more conducive to sub-cloud evaporation given similar sub-cloud vapor states. Both the liquid and precipitation layers for clouds in category 2 are thicker (Fig. 4.4d and 4.4e). Liquid/ice precipitation layer thickness ratio is around 0.4 for both categories (Fig. 4.4f).

The statistics of the macro-physical properties for clouds in each category are consistent with the initial results illustrated by the two examples in Figs. 4.2 and 4.3. Clouds in category 1 were lower, thinner and had weaker precipitation, while clouds in category 2 were higher, thicker and had more intense precipitation.
4.3.2 Thermodynamic properties

Figure 4.5 depicts the statistics of the mixed-phase cloud thermodynamical properties retrieved mainly from radiosonde and the ARM Merged Sounding product. The cloud top and cloud base temperature statistics for the two categories are clearly separated (Figs. 4.5a and 4.5b). As shown in Fig. 4.5c, The median lapse rate in category 2 clouds is \(-7 \, K \, km^{-1}\), consistent with that found by Shupe et al. (2008a); however, 27% of the retrieved lapse rates in the category 1 clouds were above \(0 \, K \, km^{-1}\), which indicates that these lower and warmer clouds often occurred in inversion layers.

The differences in height between the base of the ice saturation layer and the cloud liquid layer (Fig. 4.5d), measured within \(\pm 15\) min from a radiosonde launch, reveal that ice saturation reached below cloud base in both categories; however, this ice saturated layer is deeper for the category 2 clouds. Therefore, ice precipitation from category 2 clouds will experience favorable growth conditions for a
longer distance after falling below cloud base than precipitation from category 1 clouds. The result of this deeper growth layer can be seen in the median height of maximum precipitation reflectivity being well below the cloud liquid layer base for the category 2 clouds (Fig. 4.5e). On the other hand, the mode of maximum precipitation reflectivities for category 1 clouds is near cloud base, with the bulk of the values actually within the cloud liquid layer itself. This pattern is consistent with a weak drizzle process, for which drizzle is kept above cloud base in updrafts and quickly evaporates whenever it manages to fall below cloud base.

### 4.3.3 Micro-physical properties

Figures 4.6 and 4.7 display the statistics of the micro-physical properties retrieved from the KAZR, MPL and MWR. The normalized frequency of occurrence distribution of total reflectivities from category 2 clouds has an obvious bimodality (Fig. 4.6a) which is not apparent in the category 1 cloud distribution. The lower reflectivity modes correspond to radar returns mostly from cloud liquid drops, while the higher reflectivity mode (category 2) and tail (category 1) are due to precipitation returns. The colder category 2 clouds are more conducive to producing higher reflectivity precipitation, mostly through cold-cloud processes that, for these Arctic stratiform clouds, lead to the formation of large ice hydrometeors with larger reflectivity (Botta et al., 2010). Although reflectivities as large as 0 dBZ are observed in the category 1 clouds, they are less frequent, suggesting that ice particles, usually in a form of aggregates, are rare in these warmer clouds.

Figures 4.6b and 4.6c contain results from the other two oft-reported moments of radar Doppler spectra, the mean Doppler velocity and spectrum width. The mean Doppler velocity within a radar sample volume is impacted by the volume-mean vertical air velocity and particle fall speeds. Over a long period, the mean of the volume-mean vertical air motion should be close to 0 m s\(^{-1}\). The larger mean Doppler velocities (~0.4 m s\(^{-1}\)) for category 2 clouds compared to category 1 clouds (~0.2 m s\(^{-1}\)) indicate faster mean particle fall speeds in the colder clouds. In conjunction with the faster falling particles, the observed spectrum widths for category 2 clouds were also higher than for category 1 clouds. Although the observed spectrum widths are determined by several different factors, such as particle
size distributions, turbulence broadening and wind shear, a major contributor to it is effects of the particle size distribution (Shupe et al., 2008b). These results indicate that particles sizes in clouds from category 2 are more diverse.

Although the category 2 clouds are colder and produce more ice, the LWP statistics (Fig. 4.6d) show that these clouds contain more liquid water (median $\sim110 \text{ g m}^{-2}$) than the category 1 clouds (median $\sim80 \text{ g m}^{-2}$), but this may partly be explained by the difference of cloud thickness between the categories. The relative abundance of liquid in category 2 clouds provides a favorable environment for riming and aggregation growth, leading to larger ice particles and higher radar reflectivities, with larger mean Doppler velocities and spectrum widths.

**Figure 4.6.** Same as Fig. 4.4, but for a) total reflectivity, b) mean Doppler velocity, c) spectral width, and d) cloud liquid water path.
Figure 4.7. Same as Fig. 4.4, but for a) cloud liquid drop mode reflectivity, b) precipitation reflectivity, c) volume-mean vertical air velocity, d) reflectivity-weighted mean precipitation fall speed, and e) layer-mean vertical air velocity obtained from applying the deconvolution algorithm to radar Doppler spectra that compose the two categories of cloud events.

Figure 4.7 shows results from the spectral deconvolution algorithm, including cloud-liquid and precipitation mode reflectivity, volume-/layer-mean vertical air velocity and reflectivity-weighted precipitation fall speed. The normalized frequency of occurrence distributions of cloud liquid drop mode reflectivities from clouds in both categories are similar, with a median of ∼-22 dBZ and values ranging from -35 dBZ to -18 dBZ. However, the normalized frequency of occurrence distributions of precipitation reflectivity are significantly different for the two categories. The median precipitation reflectivity in the warmer category 1 clouds is ∼-22 dBZ, similar to that of the cloud liquid drop mode reflectivity distributions in Fig. 4.7a. In contrast, the median value is ∼-8 dBZ for the colder category 2 clouds. Having reflectivities from precipitation particles as low as -22 dBZ implies low concentrations of smaller precipitation particles (e.g. small drizzle or ice). The tail of higher (> 0 dBZ) reflectivity contributions in the distribution suggests that the warmer clouds can at times support heavier precipitation (larger-sized parti-
cles). The large shift in the median value towards higher reflectivity suggests that most of the category 2 clouds are able to precipitate effectively.

Kinematically, the two categories are quite similar as is revealed by the retrieved volume-mean vertical air velocity distributions (Fig. 4.7c). Both categories have median velocities of $\sim 0 \text{ m s}^{-1}$, with a small positive bias ($\sim 0.05 \text{ m s}^{-1}$). A median value close to $0 \text{ m s}^{-1}$ is expected over the more than 40 hours contributing to each distribution because updrafts and downdrafts balance over a long time. The small bias of $\sim 0.05 \text{ m s}^{-1}$ may be the result of our focus on cloud events which may be related to large scale vertical ascent. Vertical air velocities varied over a range between $-0.8 \text{ m s}^{-1}$ and $0.9 \text{ m s}^{-1}$ (10th and 90th percentile of the normalized frequency of occurrence distributions of the vertical air velocity) in category 2 clouds, only slightly larger than that in category 1 clouds. The layer-mean vertical air velocities for the two categories are identical and also centered near $0 \text{ m s}^{-1}$ as shown in Fig 4.7e. The variations of layer-mean vertical air velocities were smaller than those of retrieved volume-mean vertical air velocities because vertical air velocities near cloud top are close to $0 \text{ m s}^{-1}$ and the layer-mean values are averages of the volume-mean values.

The reflectivity-weighted mean precipitation fall speed distributions (Fig. 4.7d) confirm our conclusion drawn from the comparison of mean Doppler velocities that precipitation in category 2 clouds fall faster (median $\sim 0.8 \text{ m s}^{-1}$) than in category 1 clouds (median $\sim 0.65 \text{ m s}^{-1}$). The difference between the distributions for the two categories derives mostly from the fact that very few category 1 clouds produce precipitation with mean fall speeds above $1 \text{ m s}^{-1}$. These larger mean precipitation fall speeds seen in the colder clouds correspond to larger rimed ice crystals or still smallish drizzle drops (diameters $> 200 \mu m$), whereas the fall speeds in the warmer clouds correspond to larger pristine ice crystals and/or smaller drizzle drops ($< 150 \mu m$ diameters).

### 4.3.4 Joint Distributions

In order to explore potential relationships between different cloud properties we generated joint contour frequency distributions and box and whisker plots between various parameters (Figs. 4.8-4.13). Figures 4.8 (contour frequency distributions)
Figure 4.8. The contour frequency distribution of mixed-phase cloud properties: a) cloud thickness and b) LWP as a function of layer-mean vertical velocity. Category 1 results are in the left column and category 2 results in the right column.

and 4.9 (box and whisker plots) explore relationships between cloud layer thickness and LWP as a function of layer-mean vertical air velocity. Figures 4.10 through 4.13 present similar results but between cloud-liquid drop and precipitation mode reflectivity versus volume-mean vertical air velocity and reflectivity-weighted mean precipitation fall speed (Figs. 4.10-4.11) and maximum precipitation reflectivity versus maximum cloud liquid drop mode reflectivity as a contour frequency distributions (Fig. 4.12) and a box and whisker plot (Fig. 4.13). As before, we analyze the two cloud categories separately, but with the understanding that the volume-mean vertical air velocity distributions for the two categories are similar (Fig. 4.7c).

Both cloud layer thickness and LWP increase with stronger updrafts in category 2 clouds (Fig. 4.8a₂, 4.8b₂, 4.9a₂ and 4.9b₂). There is some indication that
cloud liquid layer thickness also increases in stronger downdrafts (Fig. 4.9c2), indicating that cloud thickness may be correlated with the strength of the cloud-scale circulations in the colder category 2 clouds. Although the distributions of retrieved layer-mean vertical air velocities for the two categories are similar, the correlation, if any, between cloud properties and layer-mean vertical air velocity is not clear in the category 1 clouds. One explanation for this difference between the two populations, one dominated by liquid and the other by ice precipitation processes, is that the ice precipitation processes play a role in determining the macro-physical properties of these clouds. The results for the colder clouds are consistent with the conceptual model of Shupe et al. (2008a) who suggest that ice precipitation predominantly falls from the updrafts, thus effectively removing water from the

Figure 4.9. Relationships between cloud layer-mean vertical air velocity and a) cloud thickness and b) LWP. Category 1 results are in the left column and category 2 results in the right column. The horizontal red bar represents the median value, whereas the box and whiskers represent the 25th, 75th, 10th, and 90th percentiles of the data.
parcels prior to entering the downdrafts, causing thinner cloud layers outside of the updraft regions. The drizzle production process, in general, is less effective at removing water from parcels; therefore, it is reasonable to expect better conservation of water in parcels as they navigate their way through the cloud, hence less dependence of cloud thickness on the circulations.

Cloud liquid drop mode reflectivities in category 2 clouds are generally smaller in the updrafts compared to the downdrafts, with the highest median reflectivity observed in weak (0.5 m s⁻¹) downdrafts (Figs. 4.10a₂ and 4.11a₂). The distribution of cloud liquid drop mode reflectivities in the warmer category 1 clouds is distinctly different, with the highest median reflectivity occurring at 0 m s⁻¹ and values dropping with increasing updraft and downdraft speeds (Figs. 4.10a₁ and 4.11a₁).

In order to understand these differences it is necessary to understand the evolution of the cloud liquid drop size distribution and how it is impacted by ice-phase processes as a parcel circulates through the cloud. Cloud liquid drops are condensed in updrafts when adiabatic lifting causes super-saturation with respect to liquid. The initial drops are small with a characteristic relatively narrow distribution in size, and thus relatively smaller reflectivities. Bigger drops (drizzle) are most likely found at cloud tops where the air motion trends towards 0 m s⁻¹ and the cloud liquid drop mode reflectivity peaks. The smallest drops will evaporate fastest in the downdrafts, a result of the influence of the curvature effect on the effective saturation ratio, thus providing a source of vapor to reduce evaporation of the bigger drops, thus allowing these drops to survive longer in the downdrafts (Sulia and Harrington, 2011). The reflectivities in the upper regions of these cloud are determined mostly by the relatively small number of larger drops, which may equally likely be found in the updrafts and downdrafts. The result is a relatively symmetric peak in the contour frequency distribution centered on 0 m s⁻¹ and -23 dBZ in these warm-cloud process dominated clouds (Fig. 4.10a₁). The cause of the almost symmetric drop-off in reflectivity with draft speed (Fig. 4.11a₁) may be explained when one realizes that the strongest vertical air motions are found near cloud base where the reflectivity values are small.

The impact of ice on the cloud liquid drop mode reflectivity may best be understood in the context of the impact of ice on cloud thickness as a function of
Figure 4.10. The contour frequency distribution of mixed-phase cloud properties: a) cloud liquid drop mode reflectivity and b) precipitation reflectivity as a function of volume-mean vertical air velocity; c) precipitation reflectivity as a function of reflectivity-weighted mean precipitation fall speed. Category 1 results are in the left column and category 2 results in the right column.

volume-mean vertical air velocity. Consider first the contour frequency distribution of cloud liquid drop mode reflectivity versus volume-mean vertical air velocity for the category 2 clouds (Fig. 4.10a2). Close inspection of this distribution reveals two peaks, one at about 0 m s\(^{-1}\) vertical velocity with a reflectivity of -21 dBZ and...
Figure 4.11. Box and whisker plots of mixed-phase cloud properties: a) cloud liquid drop mode reflectivity and b) precipitation reflectivity as a function of volume-mean vertical air velocity; c) precipitation reflectivity as a function of reflectivity-weighted mean precipitation fall speed. Category 1 results are in the left column and category 2 results in the right column. The horizontal red bar represents the median value, whereas the box and whiskers represent the 25th, 75th, 10th, and 90th percentiles of the data.
the other centered on 0.3 m s\(^{-1}\) with a reflectivity of -27 dBZ. We invoke the same arguments just used for the category 1 clouds to explain the peak at 0 m s\(^{-1}\) and attribute the cause of the peak at 0.3 m s\(^{-1}\) to the relatively more radar sample volumes in deeper updraft regions (Fig. 4.9a/2) and the effect of ice competition reducing the cloud liquid drop mode reflectivity.

The highest precipitation reflectivities are found in the updraft regions of both cloud categories (Figs. 4.10b/1, 4.10b/2, 4.11b/1, and 4.11b/2). The category 2 cloud event precipitation reflectivities increase monotonically with volume-mean vertical air velocity. Although a similar trend is seen in the category 1 clouds the precipitation reflectivity peaks at 0 m s\(^{-1}\) after which it slowly decreases with increasing vertical motion. These results suggest that precipitation preferentially forms and falls out through the updrafts (the strongest vertical air velocities are mostly concentrated in the lower third of the cloud layer) where the ice can grow by aggregation and/or riming. The reflectivity of the precipitating ice in the downdrafts (Figs. 4.10b/2 and 4.11b/2) is lower than in the strong updraft regions and decreases further with increasing downwards air motion, likely in response to number concentration divergence. The weaker relationship between precipitation reflectivity and vertical air velocity in the category 1 clouds may be attributed to the generally low precipitation reflectivity values observed. Although precipitation sized particles are found in the category 1 clouds, they remain sufficiently small that they mostly follow the circulation, spending more time in the updrafts where their fall speeds counter the updrafts and less in the downdrafts.

The dependences between the precipitation reflectivity and the reflectivity-weighted mean particle fall speeds are illustrated in Figs. 4.10c/1, 4.10c/2, 4.11c/1, and 4.11c/2). Both categories reveal high frequencies of occurrence of precipitation with fall speeds at approximately 0.5 m s\(^{-1}\) with a preference for this slow falling precipitation to have lower reflectivity values, but can attain values as high as 0 dBZ in both categories. There appears to be a distinct shift in the relationship at higher reflectivity values in the category 2 clouds. This shift appears to be robust and associated with a separate population of hydrometeors whose fall speeds increase from 0.6 m s\(^{-1}\) up to 2.0 m s\(^{-1}\) as the reflectivity increases from -15 dBZ to 17 dBZ, approximately the maximum value observed with Ka-band radars.

Given the temperature range of the clouds one would expect plate-like crys-
Figure 4.12. The contour frequency distributions of maximum precipitation reflectivity as a function of maximum cloud liquid mode reflectivity in a vertical column. Category 1 results are in the left column and category 2 results in the right column.

Figure 4.13. Box and whisker plots of maximum precipitation reflectivity as a function of maximum cloud liquid drop mode reflectivity in a vertical column. Category 1 results are in the left column and category 2 results in the right column.

tals and coagulated forms of plate-like crystals (aggregates or rimed ice) to be present in these clouds. Populations of dendrites may be expected in the 0.5 $m\ s^{-1}$ reflectivity-weighted mean precipitation fall speed regime, although one would expect higher reflectivity values from such populations (Botta et al., 2013). These particles could potentially be small pristine ice or even small drizzle ($< 200 \mu m$; (Verlinde, J., M.P. Rambukkange, E.E. Clothiaux, G.M. McFarquhar and Eloranta, 2013)). Aggregates may fall a little faster, but not much more than 1
The population of hydrometeors with even faster fall speeds, the total frequency of occurrence which appears to be close to 50%, must therefore be some form of rimed ice.

The contour frequency distributions of the category 1 clouds also suggest the presence of distinct populations of hydrometeors (P1 and P2 in Fig. 4.10c). With cloud layer temperatures between -10 °C and -3 °C ice crystals may vary from being roughly isometric to column-like, and the lidar depolarization ratio suggest that drizzle is prevalent as well. The population P2 has higher reflectivity values than P1, but at the same reflectivity values, fall slower. This comparison and the lidar measurements suggest that the population P1 is likely relatively small drizzle and population P2 likely columnar ice, rimed ice or aggregates, any of which may fall at the observed fall speeds. However, these faster-falling category 1 particles did not occur as frequently as in the category 2 clouds, at least for the clouds sampled during October 2011.

Generally, precipitation is stronger in clouds with higher liquid water contents as such clouds enable more possible pathways for precipitation production. The column-maximum precipitation reflectivity increases with the column-maximum cloud liquid mode reflectivity for both categories (Figs. 4.12 and 4.13). Although the general positive correlation between the maximum precipitation reflectivity and the maximum cloud liquid mode reflectivity holds for both categories, category 1 clouds are less efficient in converting high liquid water contents into precipitation. This can be seen by the large shift in location of the maximum frequency of occurrences between the two categories (Fig. 4.12) and also in the 10 dB to 20 dB downward shift of the median maximum precipitation reflectivity for the same maximum cloud liquid mode reflectivity (Fig. 4.13). The peak frequency in the category 1 clouds is at maximum precipitation reflectivity values in the range from -25 dBZ to -35 dBZ, which corresponds to light drizzle or small ice. The extension to larger maximum precipitation reflectivity values likely corresponds to occasional ice showers. On the hand, consistently strong ice precipitation is observed in the category 2 cloud events, for which the peak frequency is for maximum precipitation reflectivity values around -5 dBZ.

Although the clouds in the different categories exhibited significant differences in terms of their micro-physical properties, both are very important in terms of
their impacts on radiation because both types contain sufficient cloud liquid water paths (Fig. 4.6d) to act as blackbody emitters.

4.4 Discussion

Differences in both macro- and micro-physical properties of mixed-phase clouds were found between two cloud categories as defined by cloud layer temperature. Category 1 clouds have cloud base and cloud top temperatures greater than -10 °C, whereas the category 2 clouds have cloud base and cloud top temperatures less than -10 °C. The most significant difference in cloud microphysics was that clouds with colder temperatures produced more intense precipitation (Fig. 4.7b) and larger amounts of faster-falling (large ice) particles (Fig. 4.10c). This result is consistent with the previous study by de Boer et al. (2011) who found that mixed-phase clouds are more common when the temperature is in the range from -25 °C to -10 °C and liquid clouds are more common than ice-containing clouds at temperatures warmer than -10 °C. This is not surprising because both ice nucleation and growth processes have strong temperature dependences (Bailey and Hallett, 2009; Fukuta and Takahashi, 1999; Hoose and Möhler, 2012). More ice nuclei are activated, thus larger numbers of ice particles may exist in category 2 mixed-phase clouds from. Moreover, in clouds with temperatures lower than -10 °C, ice crystals grow as plate-like ice particles, whose collection coefficients are generally higher than column-like particles (Wang and Ji, 2000), which grow at temperatures larger than -10 °C. Thus, more aggregates may be generated in the category 2 clouds leading to higher reflectivity values and fall speeds as is indicated by the radar observations. Although aerosol properties also impact ice nucleation and ice particle concentrations, wind direction analyses using radiosonde data indicate no significant difference was found in the winds between the two categories.

The larger precipitation particles in category 2 cloud events may be caused by their longer ice growth times, which are related to cloud layer thicknesses. In order to untangle the impacts from cloud thickness and temperature, we selected clouds with layer thicknesses in the narrow range from 330 m to 370 m for further evaluation (Fig. 4.14). For these clouds with approximately the same cloud thickness, clouds with cloud top temperatures in the dendritic growth regime (-17
Figure 4.14. The relationships between a) precipitation reflectivity and cloud top temperature for both cloud categories, b) precipitation reflectivity and volume-mean vertical air velocity for category 1 clouds, and c) precipitation reflectivity and volume-mean vertical air velocity for category 2 clouds.

°C to -13 °C) produced precipitation reflectivities 25 dBZ higher than for clouds with cloud top temperatures in the columnar growth regime (-10 °C to -6 °C). Note that in Fig. 4.14a there is another transition at the upper range of the dendritic growth regime (-19 °C) where there is a drop in precipitation reflectivities of approximately 10 dBZ. This result supports the assertion that the cloud layer temperature determines ice formation and growth. The general relationship of precipitation reflectivity value increase with vertical air motion vertical air motion
increase holds for these cloud layers with similar thicknesses (Fig 4.12b and 4.12c), with the relationship in the warmer clouds becoming more clear.

4.5 Summary and Conclusions

Long-term observations of mixed-phase cloud properties are required to develop more sophisticated parameterizations for phase partitioning in models. In this study, statistics of the macro-physical, micro-physical, thermodynamical, and dynamical properties of mixed-phase clouds are characterized based on a month of ground-based measurements taken during October 2011 at Barrow, Alaska. A newly developed spectral deconvolution algorithm is applied to radar Doppler spectra to retrieve cloud micro-physical properties, such as cloud liquid mode reflectivity, precipitation reflectivity, volume-mean vertical air velocity and reflectivity-weighted mean precipitation fall speed. Relationships between cloud macro-physical, micro-physical, thermodynamical and dynamical properties are investigated based on the joint distributions between them.

Cloud layer temperature is the primary factor that determines mixed-phase cloud properties. A total of 185 one-hour mixed-phase cloud events is classified into colder (bases and tops less than -10 °C) and warmer (bases and tops greater than -10 °C) categories. Statistics of cloud macro- and micro-physics for these two categories display significant differences in cloud thickness, LWP, RH profiles, and precipitation properties. Clouds in category 1 (warmer) were lower, thinner and had weaker precipitation, while clouds in category 2 (colder) were higher, thicker and had more intense precipitation. The ice precipitation processes in category 2 clouds play a role in determining their macro-physical and liquid micro-physical properties.

Vertical air motion also plays an important role on mixed-phase cloud micro-physics. Precipitation reflectivities and reflectivity-weighted mean precipitation fall speeds are found to increase with vertical air motion. This is consistent with a previous study by Shupe et al. (2008a), who find that ice particles generally form, grow and fall out of the cloud layer when these ice particles grow sufficiently large in updrafts. In the downdrafts, vapor below water saturation limits ice formation and growth. Ice particles also experience shorter growth times in downdrafts.
because they fall out of cloud layer faster than those held up in the updrafts.

The relationship between precipitation reflectivity and reflectivity-weighted mean fall speed indicates the frequent occurrence of fast-falling rimed ice in category 2 clouds, whereas in category 1 clouds distinct hydrometeor populations (small drizzle, columnar ice, rimed ice or aggregates) are found.

Despite the differences between the mixed-phase clouds in these two categories, clouds from both categories persist for hours, even days. Based on this one month analysis, mixed-phase clouds can exist in two stable states, with warmer and colder cloud-layer temperatures. As suggested in Morrison et al. (2012), the transitions between mixed-phase cloud states are caused by the large-scale meteorological environment. During each state, the resilience of mixed-phase clouds is the result of local feedbacks between cloud liquid, precipitation, radiation and turbulence. Cloud liquid near cloud top induces long-wave radiative cooling and drives in-cloud turbulence. Turbulent entrainment of moist air from above or below the clouds moistens the cloud layer and helps to sustain them against the mass loss resulting from ice precipitation.

The temperature of -10 °C is used to separate the two categories because it represents a natural dividing line in ice growth processes, but also because the population of shallow mixed-phase clouds observed during October 2011 divided into two distinct populations about this temperature. More observations are needed to obtain comprehensive knowledge of the relationships between cloud macro-physical, micro-physical, thermodynamical, and dynamical properties necessary to develop more sophisticated parameterizations of mixed-phase clouds in models.
In this dissertation we performed an analysis of radar Doppler spectra to advance our understanding of Arctic mixed-phase clouds. The radar Doppler spectra provide newly available information on the micro-physical and dynamical properties of mixed-phase clouds that goes beyond that available in the first three radar Doppler spectra moments (i.e., total reflectivity, mean Doppler velocity and spectral width). The separation of cloud liquid drop and precipitation mode contributions to radar Doppler spectra collected from mixed-phase clouds enables investigation of the microphysics of different hydrometeors and dynamics in them. Improved understanding of the micro-physical and dynamical processes within mixed-phase clouds can in turn be used to evaluate and improve the microphysics and dynamics in models.

In the current study of model-observation comparison, output from large-eddy simulations for a case study on 8 April 2008 at Barrow, Alaska, was imported to a radar simulator to generate the simulated radar Doppler spectra. Subsequently, model simulations were analyzed in identical fashion as radar measured spectra. One important result of the comparisons is that agreement of mean Doppler velocity statistics obtained from model-simulated and observed spectra may due to compensating errors in model dynamics and microphysics. Thus, the mean Doppler velocity, by itself, does not place a strong constraint on either model dynamical or micro-physical processes. Additional comparisons of the estimated volume-mean vertical air velocity and spectrum width enabled the separation of the different contributions of the dynamics and microphysics on these radar-derived parame-
ters. Results from this study indicate that the model underestimates the wind shear of vertical velocity and lacks ice particles with diverse falling speeds. In order to better simulate mixed-phase clouds micro-physical parameterizations within models will require additional complexity, which in turn requires specific observations of important cloud processes, including simultaneous measurements of ice crystal mass, size, shape, and fall speed, as well as cloud dynamics, ice nucleation, aggregation, and precipitation rate.

The spectral deconvolution technique developed in this dissertation is able to separate cloud liquid drop and precipitation mode contributions to radar Doppler spectra. The algorithm is based on the assumption that any radar Doppler spectrum is the result of a linear superposition of several Gaussian distributions, each of which represents a discrete class of hydrometeors with a characteristic fall velocity. The cloud liquid drop mode was identified using continuous wavelet transform (CWT) and fuzzy logic methods. Based on the separation, cloud liquid drop and precipitation mode reflectivities, volume-mean vertical air motion, sub-volume vertical velocity variance and mean precipitation fall speed can be retrieved. The performance of the algorithm was evaluated by applying it to model-simulated radar Doppler spectra which were generated by importing Large Eddy Simulation model (LES) output into a forward model radar simulator. The retrievals from the model-simulated radar Doppler spectra were compared to the values obtained directly from the model output. The results showed that the algorithm generally performed well if cloud liquid drop mode reflectivity was larger than -35 dBZ.

The spectral deconvolution technique was also applied to two one-hour stratiform mixed-phase cloud events during October 2011. The retrieval results for these two cases were physically reasonable with the retrieved cloud liquid drop mode reflectivity increasing from cloud base to cloud top. Coherent updraft and downdraft air motions were retrieved in both cases. LWP comparisons between the retrievals and those measured by a microwave radiometer suggest that the retrieved LWPs generally tracked the variations in LWP retrieved from the microwave radiometer measurements.

Statistics of the macro-physical, micro-physical, thermodynamical, and dynamical properties of mixed-phase clouds were characterized using a month of ground-based measurements during October 2011 at Barrow, Alaska. The newly developed
spectral deconvolution technique was applied to 185 hours of stratiform mixed-phase clouds during this period. The volume-mean vertical air velocities averaged over the 185 hours of data were near zero, which is consistent with expectation that long averages of vertical air velocities should be close to zero.

The 185 one-hour mixed-phase cloud events were divided into two categories based on their cloud top and base temperatures (higher or lower than -10 °C). Clouds in both categories were persistent systems that lasted for hours, even days. However, statistics of cloud macro- and micro-physics from the two categories of mixed-phase clouds display significant differences in cloud top and base heights, cloud thicknesses, LWPs and precipitation properties. The colder mixed-phase clouds (category 2) were higher, thicker, with larger LWPs and more intense and persistent ice precipitation, while the warmer mixed-phase clouds (category 1) were lower, thinner, with smaller LWPs and most likely dominated by liquid precipitation.

Relationships between cloud macro-physical, micro-physical, thermodynamical and dynamical properties were investigated based on the joint distributions between them. Vertical air motion plays an important role on mixed-phase cloud microphysics. Precipitation reflectivity and reflectivity-weighted mean precipitation fall speeds were found to increase with increasing vertical air velocity in colder mixed-phase clouds (category 2). This is consistent with a previous study by Shupe et al. (2008a), who find that ice particles generally form, grow and fall out of the cloud layer when these ice particles grow sufficiently large in updrafts. In the downdrafts, vapor below water saturation limits ice formation and growth. Ice particles also experience shorter growth times in downdrafts because they fall out of cloud layer faster than those held up in the updrafts.

Ice precipitation processes also play a role in determining the macro-physical properties and liquid microphysics of these clouds. Ice precipitation impacts the size distribution of cloud liquid drops and cloud liquid amount through the Wegener-Bergeron-Findeisen process. Thus, the relationship between cloud thickness and cloud liquid mode reflectivities and vertical air velocity are found to be different in colder and warmer category clouds. Because ice precipitation intensity is also a function of vertical air velocity, vertical air motion should be included as a parameter in order to correctly predict phase partitioning in mixed-phase clouds.
Future studies may continue retrieving LWC profiles using the spectral deconvolution algorithm applied to cloud radar Doppler spectra. In these investigations particular attention should be paid to the variability in the relationship between cloud liquid drop mode reflectivity and LWC because it is dependent upon cloud liquid drop concentrations and the spread in the cloud liquid drop sizes, both of which are largely unknown in most observational studies. As such, these investigations must involve, in some way, model constraints on the cloud liquid drop size distributions in mixed-phase clouds.

Currently, the technique developed in Chapter 3 has only been applied to mixed-phase clouds in which both liquid drops and ice particles co-exist. There is no reason to limit its application to only mixed-phase clouds. Its application to liquid clouds with drizzle and rain precipitation should be pursued to further develop and improve this technique.

To develop more sophisticated parameterizations of mixed-phase clouds in large-scale models long-term statistics of mixed-phase cloud macro- and microphysical, thermodynamical and dynamical properties will be necessary. The automatic spectral deconvolution algorithm developed in this thesis and routinely recorded radar Doppler spectra open a door to the generation of such statistics.
Bibliography


Vita
Guo Yu

EDUCATION

Penn State University
Ph.D. in Meteorology
University Park, PA
Dissertation: Use of Radar Doppler Spectra in Arctic Mixed-Phase Cloud Studies

Peking University
M.S. in Atmospheric Science
Beijing, China
Thesis: Observation and Analysis of Characteristics of Orographic Clouds and Precipitation in Qilian Mountains, China

Peking University
B.S. in Atmospheric Science
Beijing, China
Aug. 2001 - May. 2005

RESEARCH EXPERIENCE

Graduate Research Assistant, Dept. of Meteorology, PSU Aug. 2008 - Dec. 2013


TEACHING EXPERIENCE

Teaching Assistant, Penn State University, Department of Meteorology
Atmospheric Dynamics, Fall 2008
Thermal Dynamics, spring 2009

PUBLICATIONS


G. Yu, J. Verlinde, E. E. Clothiaux, A. Avramov, A. S. Ackerman and A. M. Fridlind: Evaluating models of mixed-phase cloud processes (to be submitted)