

DISSERTATION

MICROPHYSICAL RETRIEVAL AND PROFILE CLASSIFICATION FOR GPM DUAL-
FREQUENCY PRECIPITATION RADAR AND GROUND VALIDATION

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ABSTRACT

MICROPHYSICAL RETRIEVAL AND PROFILE CLASSIFICATION FOR GPM DUAL-FREQUENCY PRECIPITATION RADAR AND GROUND VALIDATION

The Global Precipitation Measurement (GPM) mission, planned as the next satellite mission following the Tropical Rainfall Measurement Mission (TRMM), is jointly sponsored by the National Aeronautic and Space Administration (NASA) of USA and the Japanese Aerospace Exploration Agency (JAXA) with additional partners, the Centre National d'Études Spatiales (CNES), the Indian Space Research Organization (ISRO), the National Oceanic and Atmospheric Administration (NOAA), the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT), and others. The core satellite of GPM mission will be equipped with a dual-frequency precipitation radar (DPR) operating at Ku- (13.6 GHz) and Ka- (35.5 GHz) band with the capability to cover $\pm 65^\circ$ latitude of the earth. One primary goal of the DPR is to improve accuracy in estimation of drop size distribution (DSD) parameters of precipitation particles. The estimation of the DSD parameters helps achieve more accurate estimation of precipitation rates. The DSD is also centrally important in the determination of the electromagnetic scattering properties of precipitation media. The combination of data from the two frequency channels, in principle, can provide more accurate estimates of DSD parameters than the TRMM Precipitation radar (TRMM PR) with Ku- band channel only. In this research, a methodology is developed to retrieve DSD parameters for GPM-DPR. Profile classification is a critical module in the microphysical retrieval system for GPM-DPR. The nature of microphysical models and equations for use in the DSD retrieval algorithm are determined by the precipitation type of each profile and the phase state of the hydrometeors. In the GPM era, the Ka- band

channel enables the detection of light rain or snowfall in the mid- and high- latitudes compared to the TRMM PR (Ku- band only). GPM-DPR offers dual-frequency observations (measured reflectivity at Ku- band: $Z_m(K_u)$ and measured reflectivity at Ka- band: $Z_m(K_a)$) along each vertical profile, which provide additional information for investigating the microphysical properties using the difference in measured radar reflectivities at the two frequencies, a quantity often called the measured dual-frequency ratio (*DFRm*) can be defined ($DFRm = Z_m(K_u) - Z_m(K_a)$). Both non-Rayleigh scattering effects and attenuation difference control the shape of the *DFRm* profile. Its pattern is determined by the forward and backscattering properties of the mixed phase and rain media and the backscattering properties of ice. Therefore, *DFRm* could provide better performance in precipitation type classification and hydrometeor profile characterization than TRMM PR. In this research, two methods, precipitation type classification (*PCM*) and hydrometeor profile characterization (*HPC*), are developed to perform profile classification for GPM-DPR using the *DFRm* profile and its range variability. The methods have been implemented into the GPM-DPR day one algorithm.

Ground validation is an integral part of all satellite precipitation missions. Similar to TRMM, the GPM validation falls into the general class of validation and integration of information from space-borne observing platforms with a variety of ground-based measurements. Dual polarization ground radar is a powerful tool that can be used to address a number of important questions that arise in the validation process, especially those associated with precipitation microphysics and algorithm development. Extensive research has also been done regarding accurate retrievals of rain DSDs as well as attenuation correction for dual-polarization ground polarimetric ground radar operating at a single frequency channel has limitation on DSD

retrieval beyond rain region. A dual-frequency and dual-polarization Doppler radar (D3R) operating at the same frequency channels as GPM-DPR has been built. In this research, an algorithm is developed to retrieve DSD parameter for this D3R radar, which will serve as the GPM-DPR ground validation instrument.

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CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Space-borne weather radar mounted on satellites provides a practical means to obtain useful regional as well as global precipitation measurements. The Tropical Rainfall Measuring Mission (TRMM), launched in 1997 jointly sponsored by National Aeronautic and Space Administration (NASA) of USA and the Japanese Aerospace Exploration Agency (JAXA), provided the first detailed and comprehensive dataset of rainfall within tropical areas across the globe (Iguchi et al., 2000). TRMM is a very successful mission and has provided the motivation to obtain broader coverage, both spatially and temporally, than what is provided by TRMM. The Global Precipitation Measurement (GPM) mission, also jointly sponsored by National Aeronautic and Space Administration (NASA) of USA and the Japanese Aerospace Exploration Agency (JAXA), is planned to be the next satellite mission to obtain global precipitation measurements. GPM is a science mission with integrated goals for advancing knowledge of the global water/energy cycle variability as well as improving weather, climate, and hydrological prediction capabilities through more accurate and frequent measurements of global precipitation. The GPM mission architecture consists of satellite instruments flying within a constellation to provide accurate precipitation measurements around the globe every two to four hours. The GPM core satellite will be in an inclined orbit of 65° , allowing coverage up to $\pm 65^\circ$ latitude and correspondingly greater coverage of the earth compared to the TRMM mission with its orbit of $\pm 35^\circ$. Compared to TRMM, GPM will add to the tropical measurements the ability to measure snow and ice precipitation in the higher latitudes. The core satellite will be equipped with a dual-

frequency precipitation radar (DPR) operating at Ku- (13.6 GHz) and Ka- (35.5 GHz) band as well as a passive microwave imager (GMI) with the capability to cover $\pm 65^\circ$ latitude of the earth. One primary goal of the DPR is to improve accuracy in estimating of drop size distribution (DSD) parameters of precipitation. The estimation of the DSD parameters of precipitation particles helps to achieve more accurate estimation of precipitation rate. The DSD is also centrally important in the determination of the electromagnetic scattering properties of precipitation media. The combination of data from the two channels, in principle, can provide more accurate estimates of DSD parameters than the TRMM PR. A number of dual-frequency retrieval approaches have been proposed (Meneghini et al., 1992, 1997; Mardiana et al., 2004; Iguchi, 2005; Rose and Chandrasekar, 2006a; Meneghini and Liao, 2009; Le et al., 2009).

Profile classification is an important module in the microphysical retrieval system for the GPM-DPR. The module has two functions: precipitation type classification, which classifies stratiform, convective, and other rain types; and hydrometeor profile characterization, which identifies the phase state of hydrometeors. The nature of microphysical models and equations to use in the DSD retrieval algorithm are determined by the precipitation type of each profile and the phase state of the hydrometeors. In the TRMM mission, the vertical profile of reflectivity (VPR) at Ku-band is the main information used to perform profile classification (Awaka et al., 1997). In the GPM era, the Ka- band channel enables the detection of light rain or snowfall in the mid- and high- latitudes compared to the TRMM PR (Ku- band only) (Iguchi et al., 2002). GPM-DPR offers dual-frequency observations (measured reflectivity at Ku- band: $Z_m(K_u)$ and measured reflectivity at Ka-band: $Z_m(K_a)$) along the vertical profile. This allows us to investigate the microphysical properties using the difference between two frequency observations (or $DFR_m =$

$Z_m(K_u) - Z_m(K_a)$). *DFRm* is also called the measured dual frequency ratio. Both the non-Rayleigh scattering effect and attenuation difference control the shape of the vertical profile of *DFRm*. Its pattern is influenced by both the rain and ice portions of precipitation and the forward scatter and back scatter of the scattering mechanism. Le and Chandrasekar (2012) have developed methods to perform profile classification for GPM-DPR using characterization of the *DFRm* profile and its range variability. The methods have been implemented into the GPM day one algorithm.

Ground validation is an integral part of all satellite precipitation missions. Ground validation helps to characterize errors, quantify measurement uncertainty, and, most importantly, provides insight into the physical basis of the retrieval algorithms. Similar to TRMM, the GPM validation falls in the general class of validation and integration of information from a variety of space-borne observing platforms with ground-based measurements. Dual polarization ground radar is a powerful tool that can be used to address a number of important questions that arise in the validation process, especially those associated with precipitation microphysics and algorithm development (Chandrasekar et al., 2008). Extensive research has been done regarding accurate rain DSD retrieval as well as attenuation correction for dual-polarization ground radar operating at S-, C- and X- band by using polarimetric measurements (Gorgucci et al., 2002a, 2008; Testud et al., 2000; Bringi and Chandrasekar, 2001; Anagnostou et al., 2008). However, polarimetric ground radar operating at a single frequency channel has limitations on DSD retrieval beyond the rain region. A dual frequency and dual polarization Doppler radar (D3R) operating at the same frequency channels as GPM-DPR has been built. A new DSD retrieval algorithm has been developed for this dual frequency and dual polarization ground radar, which will serve as GPM-

DPR ground validation (Le and Chandrasekar, 2011). Le and Chandrasekar (2011) presented an algorithm tested for the rain region, and the algorithm has potential application for melting and ice particle retrievals.

1.2 LITERATURE REVIEW

1.2.1 Space-based dual-frequency precipitation radar and microphysics retrieval

Unlike TRMM, GPM-DPR will provide two independent measurements of precipitation from two frequencies. Dual-frequency techniques will be used to improve the accuracy of the drop size distribution parameter as well as rainfall rate estimation. As mentioned earlier, there have been a number of dual-frequency methods proposed for GPM. They can be categorized into two types. One of the standard dual-frequency methods is based on the conversion of the differential attenuation to the rain rate (Eccles, 1979; Iguchi, 2005). This method requires one of the two assumptions to be valid: reflectivity at both channels are equal to Rayleigh scattering reflectivity or the rain is uniform. Either of these assumptions limits the application of the algorithm. Furthermore, the method is focused on the rain rate estimation rather than the drop size distribution parameters. Later, a two-scale DSD estimation procedure is generalized to dual-frequencies, thereby, providing a two-parameter estimation of DSD at each range gate. The concept underlying the second method is that dual-frequency ratio DFR (describing the difference of the radar reflectivity at two frequencies in decibels) is the key parameter in DSD retrieval, which is proportional to median drop diameter (D_0) when at least one of the frequencies falls into the non-Rayleigh scattering. This method has been widely used in dual-

frequency space or airborne radar retrieval (Meneghini et al., 1997; Kozu et al., 1991; Liao et al., 2008). According to the application of a downward looking space borne radar, the second method can be further divided into two approaches: the forward approach, where the DSDs are calculated at each radar bin starting from the top bin and moving down to the bottom; and the backward approach, where the algorithm begins at the bottom bin and moves upward to the top. The forward approach has limited application because of a tendency to diverge in regions of moderate-to-heavy rainfall (Liao and Meneghini, 2004). The backward approach (or surface reference technique, SRT) uses a backward calculation method that is more stable than the forward method but requires a priori knowledge of the total two-way path-integrated attenuation (PIA) for each ray or an ability to calculate it (Meneghini et al., 1997, 2002).

Mardiana et al. (2002) proposed a non-SRT algorithm, which is a self-consistent algorithm wherein the total PIA for each frequency channel is first estimated using an initial guess, then optimized through an iteration process. However, these DSD retrieval algorithms suffer from the bi-valued problem for the rain region. (i.e., the non-uniqueness of median volume diameter D_0 retrieval from the DFR parameter (Meneghini et al., 1997)). Rose and Chandrasekar (2006a) proposed a supplementary method, using linear assumption of vertical profiles for D_0 and N_w (equivalent intercept parameter (in log scale)) in the rain region to avoid the bi-valued problem. Later, a hybrid approach combining the advantages of the forward method and the recursive backward method was proposed by Le et al., (2009). The surface reference weak constraint (SRWC) method was proposed by Meneghini and Liao, (2009). This method belongs to the backward recursion with SRT approach, but uses a weak constraint by providing a group of possible combinations of solutions. Seto et al (2013) proposed an algorithm called HB-DFR

method combining the Hystchfeld-Bordan' attenuation correction method (Hystchfeld and Bordan, 1954) and the dual-frequency ratio method (Meneghini et al., 1997).

1.2.2 Stratiform/Convective rain type classification and melting region detection

In the TRMM era, where only the Ku- band channel is available, rain type classification and hydrometeor phase detection are mainly made based on a vertical profile of reflectivity (VPR) (Awaka, 1997) as well as temperature information. Stratiform and convective rain are the two main rain types in meteorology. Convective rain, in general, is defined as precipitation that has a strong vertical air motion and small (1-10 km horizontal dimension), intense, horizontally inhomogeneous radar reflectivity. In contrast to convective rain, stratiform rain is defined as precipitation that has a weak vertical air motion and produces a widespread, homogeneous layer of radar echo. Bright band (BB) is a radar signature and an indication of stratiform rain type. BB is denoted by a sharp increase of the vertical reflectivity profile caused by an increase of dielectric constant, and hence an increase in the backscattering cross section of melting particles. Extensive research has been done regarding the melting region detection using VPR. Tilford et al. (2001) used the gradient of reflectivity to detect the bright band top and bottom for stratiform rain type. The curvature of VPR was studied by Fabry and Zawadzki (1994) and was shown to be an indicator of melting region boundaries.

When vertical pointing ground radar is available, auxiliary information can be used for hydrometeor phase detection—ice, melting ice, and rain— of a vertical profile. Smyth and Illingworth (1998) and Bandera et al. (1998) pointed out that the linear depolarization ratio

(LDR) is an important signature in melting phase detection, with certain thresholds determined for different hydrometeor particles. Baldini and Gorgucci (2006) mentioned that the sudden change of the hydrometeor fall velocity is an implication of the melting layer. The curvature of velocity was used by Zrníc et al. (1994) in characterizing the melting boundaries. Klaassen (1988) found that the melting layer bottom can be detected by maximum of velocity.

In the GPM era, DPR on board the GPM satellite offers dual frequency observations along the vertical profiles that allow us to investigate the microphysics of precipitation using the difference between two frequency observations (or *DFRm*). There are two aspects that control the shape of the *DFRm* vertical profile: a) the non-Rayleigh scattering effect and b) the path integrated attenuation difference between two frequency channels. In the ice region, *DFRm* is mainly caused by the non-Rayleigh scattering effect while in the melting region; the change in dielectric constant due to the melting of the particles has different effects on Ku- and Ka- band (Bringi and Chandrasekar, 2001). Both non-Rayleigh scattering effects and attenuation difference play a role in the melting region. *DFRm* is strongly controlled by attenuation difference in the rain region. It was shown in Le and Chandrasekar (2012) that the shape of the *DFRm* profile is rich in information and its content is a good candidate for producing precipitation type classification and hydrometeor phase detection. Two models were developed based on *DFRm* for the GPM-DPR classification method. The first model is a precipitation type classification model (*PCM*) including stratiform, convective, and other rain types. The second model is the hydrometeor profile characterization (*HPC*) model which is used for melting region detection. Both models show good comparisons with TRMM-like algorithm and linear depolarization ratio (*LDR*) based

methods. The algorithm described in Le and Chandrasekar (2012) has been implemented in the GPM-DPR day one algorithm.

1.2.3 Dual-polarization ground-based radar and microphysics retrieval

Dual polarization ground radar is a very powerful tool in the space-borne radar validation system. Polarimetric radar provides accurate rain drop size distribution as well as rainfall rate estimation, and is capable of discriminating among phase-state and type of precipitation particles (Bringi and Chandrasekar 2001). The five basic polarimetric radar measurements are horizontal reflectivity (Z_h), differential reflectivity (Z_{dr}), specific differential phase (K_{dp}), linear depolarization ratio (LDR), and correlation coefficient (ρ_{hv}). Extensive research has been done regarding accurate rain DSD retrieval as well as attenuation correction using dual-polarization ground radar operating at S-, C- and X- band by using polarimetric measurements. One popular approach is the algorithm developed by Gorgucci et al. (2006b, 2008) that takes advantages of the self-consistency between the radar parameters of reflectivity factor, differential reflectivity, and specific differential phase. The self-consistency (SC) principle was applied for attenuation correction at X- band and later adapted to a fully self-consistent (FSC) method. The DSD parameters were retrieved in the literature (Gorgucci et al., 2008) based on the attenuation-corrected radar parameter using parameterization proposed earlier by Gorgucci et al. (2006b). The SC and FSC methods rely on an optimization procedure that constraints the estimated and observed differential phase.

However, polarimetric ground radar operating at a single frequency channel has limitations on DSD retrieval beyond the rain region. A dual frequency and dual polarization Doppler ground

radar operating at the same frequency channels as GPM-DPR has been built. A new DSD retrieval algorithm has been developed for this dual frequency and dual polarization ground radar that will serve as GPM DPR ground validation (Le and Chandrasekar, 2011). Although in Le and Chandrasekar (2011), the algorithm is tested only for the rain region, the algorithm has potential application to melting and ice particle retrievals, as has been shown in Le et al. (2009).

1.3 STATEMENT OF PROBLEM

Dual-frequency precipitation radar (DPR) on board a GPM core satellite will be the first dual frequency space-borne radar to make new Ka- band observations. The dual frequency observations from Ku- and Ka- band provide an opportunity to estimate drop size distribution parameters and hence rainfall rate estimation more accurately. Extensive research work on dual-frequency radar, including electromagnetic wave propagation characteristics from space and microphysics retrieval algorithms, are essential for system design and performance evaluation. Profile classification is an important module in the microphysical retrieval system for GPM-DPR. The nature of microphysical models and equations for use in the retrieval algorithm are determined by the precipitation type and phase state of each profile.

The GPM satellite won't be launched till 2014. The present research work is based on dual frequency observations from either simulated theoretical profiles or dual frequency airborne radar data. Although theoretical simulations with simple microphysical models cannot provide realistic vertical profiles, they are essential in developing and evaluating algorithms with known

microphysical information. A second generation airborne precipitation radar (APR-2 radar) operating at Ku- and Ka- band was designed to emulate GPM-DPR and was deployed in several experiments including the Wakasa Bay Experiment in 2003, the NASA African Monsoon Multidisciplinary Analysis (NAMMA) experiment in 2006, and the Genesis and Rapid Intensification Processes (GRIP) experiment in 2010. APR-2 radar provides realistic dual frequency observations that help improve modeling of precipitation microphysics.

Validation is an integral part of all satellite precipitation missions, and GPM validation falls in the general class of validation and integration of information from a variety of space-borne observing platforms with ground-based measurements. Dual polarization ground radar is a powerful tool that can be used to address a number of important questions arising in the validation process, especially those associated with precipitation microphysics and algorithm development. A dual frequency and dual polarization ground radar operating at the same frequency channels as DPR has been built to perform ground validation. Although extensive research work has focused on microphysical retrieval from dual polarization ground radar operating at single frequencies such as S-, C- and X-band, algorithms with higher accuracy and wider application are expected for the dual frequency and dual polarization ground radar.

This research attempts to address the unique and specific problems that exist in the field of space-borne radar observations. In particular, it focuses on the dual-frequency retrieval algorithms as well as profile classification modeling for GPM-DPR. For GPM ground validation purposes, development of retrieval algorithms for a dual frequency and dual polarization ground

radar is also an effective part of this research.

1.4 OBJECTIVE OF RESEARCH

The following items summarize the objects of this research.

- To develop a profile classification model for GPM-DPR.
 - Study GPM, its overall mission goals and subsystems.
 - Study stratiform / convective rain type.
 - Study profile classification method for TRMM PR.
 - Examine different criteria used for melting region detection based on vertical profile.
 - Develop a profile classification model for GPM-DPR using airborne radar data.
 - Evaluate model performance and compare results with existing algorithms.
 - Implement the profile classification method into the GPM-DPR day one algorithm.

- To develop microphysics retrieval algorithm for GPM-DPR.
 - Study drop size distribution parameters.
 - Examine principles of dual frequency retrieval algorithms for GPM-DPR.
 - Study the strengths and weaknesses of existing retrieval algorithms.

- Develop a hybrid dual frequency retrieval algorithm for GPM-DPR.
 - Evaluate the performance of the hybrid algorithm and compare it with existing algorithms.
 - Evaluate tropical storms using the hybrid method
- To develop a retrieval algorithm for a dual frequency and dual polarization ground radar that will serve as GPM ground validation.
 - Examine existing retrieval algorithms for dual-polarization ground radar operating at a single frequency channel.
 - Study fuzzy-logic algorithms to perform hydrometeor identification for dual-polarization ground radar at S band.
 - Simulate Ku- and Ka- band ground radar observations.
 - Develop a retrieval algorithm for the dual frequency and dual polarization ground radar.
 - Evaluate the performance of the retrieval algorithm.

CHAPTER 2

BACKGROUND

2.1 MICROPHYSICAL MODEL FOR PRECIPITATION: DROP SIZE DISTRIBUTION

Weather radar is an electromagnetic system for the detection of precipitation. It transmits energy into space and detects the echo signals reflected from the hydrometeor particles. Electromagnetic waves propagated through precipitation media and their scattering by precipitation particles are essential for understanding both space-borne and ground-based radar observations. The distribution of particle sizes drop size distribution as well as the particle scattering model are of central importance in determining the electromagnetic scattering properties of precipitation media. These effects, in turn, are embodied in radar parameters of interest here: the reflectivity factor (Z_h); differential reflectivity (Z_{dr}), which is the ratio of reflectivities at horizontal and vertical polarization states; specific attenuation (α_h) and specific differential attenuation (α_{dp}), which is the difference of specific attenuation between horizontal and vertical polarization.

Size distribution describes the probability density function of precipitation drop sizes. The estimation of the drop size distribution (DSD) parameters of precipitation particles helps to achieve more accurate estimation of precipitation rate. DSD is also centrally important in the determination of the electromagnetic scattering properties of precipitation media. The distribution of drop sizes contains a wide range of drop diameters and its evolution is determined by microphysical processes such as coalescence, collisional breakup, and evaporation. One of the scientific objectives of the dual frequency precipitation radar DPR on board the GPM core

satellite is to improve the accuracy of DSD parameters. Ulbrich (1983) showed that a gamma distribution model can adequately describe the natural variability in drop size distribution which can be expressed as

$$N(D) = n_c f_D(D) (m^{-3} mm^{-1}), \quad (2.1)$$

where $N(D)$ is the number of raindrops per unit volume per unit size interval (D to $D + \Delta D$), n_c is the number concentration, and $f_D(D)$ is the probability density function with the gamma form

$$f_D(D) = \frac{\Lambda^{\mu+1}}{\Gamma(\mu+1)} e^{-\Lambda D} D^{\mu}, \mu > -1, \quad (2.2)$$

where Λ and μ are the parameters of the gamma probability density function (Bringi and Chandrasekar, 2001). Any other gamma form, such as

$$N(D) = N_0 D^{\mu} e^{-\Lambda D}, \quad (2.3)$$

can be derived from the fundamental notion of raindrop size distribution. N_0 , μ , and Λ are three parameters and denote the intercept, the slope, and the shape of the gamma probability density function. The relation between D_0 , μ , and Λ is given by

$$\Lambda D_0 \cong 3.67 + \mu, \quad (2.4)$$

Where D_0 is the median drop diameter defined as precipitation particles up to size D_0 which contribute half the water content. Using (2.4), $f_D(D)$ in (2.2) can be expressed as

$$f_D(D) = \frac{(3.67 + \mu)^{\mu+1}}{\Gamma(\mu+1)D_0} \left(\frac{D}{D_0} \right)^\mu \exp \left[- (3.67 + \mu) \frac{D}{D_0} \right]. \quad (2.5)$$

In order to compare $f_D(D)$ in the presence of varying water contents, the concept of normalizing the DSD has been used by Testud et al. (2000). In this case, the normalized form of $N(D)$ can be expressed as

$$N(D) = N_w f(\mu) \left(\frac{D}{D_0} \right)^\mu \exp \left[- (3.67 + \mu) \frac{D}{D_0} \right], \quad (2.6)$$

Where N_w is the scaled version of N_0 defined in (2.3), which could be interpreted as the intercept of an equivalent exponential distribution with the same water content, and D_0 as the gamma DSD (Bringi and Chandrasekar, 2001).

$$N_w = \frac{N_0}{f(\mu)} D_0^\mu, \quad (2.7)$$

and

$$f(\mu) = \frac{6}{(3.67)^4} \frac{(3.67 + \mu)^{\mu+4}}{\Gamma(\mu+4)}. \quad (2.8)$$

when $\mu = 0$, $f(\mu) = 1$, $N(D)$ becomes an exponential form. Three critical parameters of the hydrometeor size distribution, N_w , D_0 , and μ , control the hydrometeor size distribution, and varying them over a wide range of naturally observed values yields a physically realistic simulation of derived parameters such as radar reflectivity and attenuation.

2.2 CONCEPT OF RADAR REFLECTIVITY AND ATTENUATION

The loss of energy that a radar beam suffers as it passes through an area of precipitation is called attenuation. Attenuation is determined by the extinction cross-section (σ_{ext}) of precipitation particles. The specific attenuation of a propagating wave through an area of precipitation can be expressed in an integral form of the extinction cross-section over DSD. The specific attenuation (α) at two polarizations horizontal polarization (h), and vertical polarization (v), is given by

$$\alpha_{h,v} = 4.343 \times 10^3 \int_D \sigma_{ext}(D) N(D) dD \quad \text{dB/km} \quad (2.9)$$

The specific differential attenuation α_{dp} is defined as the difference of α between horizontal and vertical polarization.

$$\alpha_{dp} = \alpha_h - \alpha_v \quad \text{dB/km} \quad (2.10)$$

Radar reflectivity factor Z is defined as:

$$Z = \frac{\lambda^4}{\pi^5 |K|^2} \int_D \sigma_{ext}(D) N(D) dD \quad (2.11)$$

where σ_b is the backscatter or radar cross-section. λ is the wavelength and K is the dielectric factor of the particle. It is a measure of the efficiency of a radar target in intercepting and returning radio energy. In Rayleigh scattering, the reflectivity factor is an approximation of the sixth moment of DSD, and (2.11) can be simplified as

$$Z = \int_D D^6 N(D) dD \quad (2.12)$$

However, in reality, radar measures the backscattered power from the precipitation, but not really sure what the hydrometeor type is, so the water equivalent radar reflectivity factor Z_e . Z_e is what we usually called radar reflectivity. The radar reflectivity at horizontal (h) and vertical polarizations (v) is given by

$$Z_{h,v} = \frac{\lambda^4}{\pi^5 |K_w|^2} \int_D \sigma_{ext}(D) N(D) dD \quad (2.13)$$

where K_w is the dielectric factor of water. When the precipitation is rain, the radar reflectivity is the same as the radar reflectivity factor. The differential reflectivity Z_{dr} in the dB sense is defined as the ratio between reflectivity (in linear sense) at horizontal and vertical polarization.

$$Z_{dr} = 10 \log_{10} \left(\frac{Z_h}{Z_v} \right) \quad (2.14)$$

The measured reflectivity at range r from radar is $Z_m(r)$. It can be expressed in terms of radar reflectivity and attenuation as

$$Z_m(r) = Z_e(r) \exp \left[-0.2 \ln 10 \int_0^r \alpha(s) ds \right] = Z_e(r) A(r) \quad (2.15)$$

$A(r)$ is the two-way path integrated attenuation factor from radar up to range r . Similarly, the measured differential reflectivity at range r can be expressed as:

$$Z_{drm}(r) = Z_{dr}(r) \exp \left[-0.2 \ln 10 \int_0^r \alpha_{dp}(s) ds \right] = Z_{dr}(r) A_{dp}(r) \quad (2.16)$$

where $A_{dp}(r)$ is the two-way differential path integrated attenuation factor.

2.3 STRATIFORM/CONVECTIVE RAIN TYPE

Stratiform and convective rain are the two main rain types defined in meteorology. Convective rain, in general, is defined as precipitation that has a strong vertical air motion, small (1-10 km horizontal dimension), and intense, horizontally inhomogeneous radar reflectivity. In contrast to convective rain, stratiform rain is defined as precipitation that has a weak vertical air motion and produces a widespread, homogeneous layer of radar echo. The characteristics of stratiform and convective rain have received significant attention since TRMM PR was launched in 1997. At that time, global evaluation of different rain types was achieved for the first time within a tropical area. Studies using TRMM PR have discovered that stratiform rain accounts for around 73% of the tropical area covered by rain and 40% of the total rain amount (Schumacher and House, 2003). However, the convective rain rate is around four times that of stratiform rain rate on average at TRMM PR horizontal resolution ($\sim 5\text{km}$).

The algorithm for classifying TRMM PR radar observations into convective and stratiform types was developed by Awaka et al. (1997). Two different methods are used for classifying rain type; one is the vertical profile method (V-method), and the other is the horizontal pattern method (H-method). Both methods classify rain into three categories: stratiform, convective, and other. The V-method detects the existence of bright band by peak search on a vertical profile of reflectivity. The H-method examines the horizontal pattern of Z at a given height. The “other” type is meant for cloud echoes and noisy observations. TRMM PR algorithms classify rain type using a combination of both the H- and V-methods.

2.4 SCATTERING MODEL FOR DIFFERENT PRECIPITATION TYPES

To simulate what radar will “see” often require two parts. One part is the scattering calculation from single precipitation particle (radar cross-section); the other part is the drop size distribution information ($N(D)$) for the precipitation media of interest. In order to calculate scattering properties from a single hydrometeor particle, a scattering model must describe the size, shape, components, density and orientation of the hydrometeor particle. Moreover, for a melting particle, the scattering model also needs to describe different components (different phases) of the particle and their distribution. Normally, besides the scattering model, a meteorological melting layer model is needed to calculate scattering properties for a melting particle. The meteorological melting layer model describes the melting fractions and fall velocity of hydrometeors as a function of distance from the 0 degree isotherm. The melting layer model involves the single scattering model into a vivid melting procedure and determines the melting fraction according to different melting status.

Table 2.1 lists some well-recognized scattering models and meteorological melting layer models for a single particle with different hydrometeor phases. The equilibrium shape of a raindrop can be regarded as an oblate spheroid (Green, 1975). Different raindrop models are represented by different relations between drop axis ratio (defined as b/a , with b being the semi-minor axis length and a the semi-major axis length) and volume-equivalent spherical drop diameter. The most popular raindrop shapes are the Beard and Chuang (BC) rain drop model (Beard and Chuang, 1987) and the Andsager and Beard Chuang (ABC) rain drop model (Andsager et al.,

1999). Other models such as a linear model (Pruppacher and Beard, 1970), as well as experimental models (Thurai et al., 2007), are used in some instances in the literature. In this research, the BC and ABC raindrop models are used in simulation and algorithm evaluation.

Hydrometeor types such as snow and graupel (densely-rimed snow (Zawadzki et al., 2005) are normally composed by two phases: air and ice. The shape of the snow varies greatly. Basically, there are several categories such as columns, plates, rosettes, and snowflakes. Although the exact shape of the snow is not easy to model, snow particles are prone to be aggregated when they fall and the aggregate is likely to be randomly oriented. Graupel is formed when water droplets condense on a snowflake, forming a ball of rime. Therefore, it is fair for both snow and graupel to be modeled as a sphere with the density of graupel larger than that of snow.

Because of the complex nature of the melting process and lack of experimental data, computations of the scattering properties of melting hydrometeors rely on models, including a scattering model and a melting layer model. A melting particle is normally composed of three phases—air, water and ice. Two types of scattering model often appear in the literature; one is the uniformly mixed sphere model where the water fraction is constant (uniform mixture) throughout the particle, and another is the two-layer concentric-sphere model where the water is confined to the outer shell and snow to the inner core. The most commonly used formulas to calculate an effective dielectric constant for uniformly melting snow are those of Maxwell Garnett (1904) and Bruggeman (1935). Liao and Meneghini, (2005) proposed a stratified sphere melting particle model. The melting particle is modeled as a nonuniform mixture with a water

fraction that decreases toward the particle center. Due to the lack of knowledge of the true melting processes, it is hard to judge which scattering model is preferable. For simplicity, the uniformly mixed sphere model is used in this research and Bruggeman's (1935) equation is applied to calculate the dielectric constant of the mixture. Besides the scattering model, a meteorological melting layer model is also important in calculating scattering properties of the melting layer. Some widely used melting layer models are found in Awaka et al. (2005), Yokoyama and Tanaka (1984), and Russchenberg and Ligthart (1996).

Table 2.1. Scattering model and meteorological melting layer model for single hydrometeor particle.

Hydrometeor Type		Rain	Snow/graupel	Melted particle
Scattering model	shape	Diameter VS axis ratio relations: BC , ABC, linear, experiment models etc.	Columns and plates; rosettes; sector snowflakes; dendrite snowflakes.	Sphere; two-layer sphere; stratified sphere etc.
	density (ρ)	1.0 g/cm ³	0.05-0.55 g/cm ³	Vary with water fraction
	components	water	Ice and air	Ice, water and air
Meteorological melting layer model		—	—	Awaka et al.(1985); Yokoyama and Tanaka (1984); Russchenberg and Ligthart (1996) etc.

2.5 SPACE-BORNE WEATHER RADAR

2.5.1 Introduction

Reliable global quantitative precipitation measurement is critically important for a variety of applications, including flood forecasting, numerical weather prediction, understanding the evolution of hurricanes and severe storms, and tracking long-term trends in global precipitation and water supply. Variability in the global distribution of precipitation is recognized as a key element in assessing the impact of climate change for life on earth. Before space-borne weather radar was available, the ground-based radar community including polarimetric radar, Doppler radar, and disdrometer measurements, played an important role in attempting to relate microphysical and resultant DSDs to local meteorological conditions. The Tropical Rainfall Measuring Mission Precipitation Radar (TRMM PR), launched in 1997, became the first space-borne weather radar to measure global precipitation within tropical areas. Although TRMM PR has successfully provided global precipitation information for more than 10 years, more coverage is needed both spatially and temporally. The Global Precipitation Measurement (GPM) mission is poised to be the next generation of observations from space after the TRMM mission, expected to be launched in 2014. One of its goals is to provide accurate precipitation measurement around the globe ($\pm 65^\circ$ latitude) every two to four hours. The GPM mission is centered on the deployment of a core observatory satellite with an active dual-frequency radar DPR, operating at Ku- and Ka- bands. The Ka- band channel was added to help achieve more sensitivity to light rain and ice compared to the TRMM PR, where little DSD information could be achieved at low and moderate rain rates (10 mm/h or less).

2.5.2 TRMM-PR

The Tropical Rainfall Measuring Mission (TRMM) was proposed as a joint project between the US National Aeronautics and Space Administration (NASA), Japan's National Space Development Agency (NASDA) and Communication Research Laboratory (CRL). The precipitation radar (PR) on the TRMM satellite was developed by Japan and is the world's first space borne precipitation radar. The TRMM satellite was launched in 1997 and has provided valuable global precipitation observations for more than 15 years. The TRMM-PR was designed to obtain three-dimensional maps of precipitation reflectivity. Such measurements yield information about the intensity and distribution of rain and its types, storm depth, and height of bright band, etc. This information contributes to investigations into climate systems, abnormal weather, and flood prediction to prevent disaster.

2.5.3 GPM-DPR

2.5.3.1 Introduction

The Global Precipitation Measurement (GPM) mission is an international network of satellites that will provide next-generation global observations of rain and snow. Building upon the success of the Tropical Rainfall Measuring Mission, the GPM concept centers on the deployment of a “core” satellite carrying an advanced radar / radiometer system to measure precipitation from space and serve as a reference standard to unify precipitation measurements from a constellation of research and operational satellites. Figure 2.1 is a graphical illustration of the GPM system. Through improved measurements of precipitation globally, the GPM mission will help to advance our understanding of the earth's water and energy cycle, improve forecasting of

extreme events that cause natural hazards and disasters, and extend current capabilities in using accurate and timely information of precipitation to directly benefit society. GPM, initiated by NASA and the Japan Aerospace Exploration Agency (JAXA) as a global successor to TRMM, comprises a consortium of international space agencies, including the Centre National d'Études Spatiales (CNES), the Indian Space Research Organization (ISRO), the National Oceanic and Atmospheric Administration (NOAA), the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT), and others. The GPM Core Observatory is scheduled for launch in early 2014.

The GPM mission objectives are:

- Advancing precipitation measurement capability from space
- Improving knowledge of precipitation systems, water cycle variability, and fresh water availability.
- Improving climate modeling and prediction.
- Improving weather prediction and 4-D climate reanalysis.
- Improving hydrometeorological modeling and prediction.

The GPM mission description is:

- A constellation of spacecraft provides global precipitation measurement coverage.

- NASA/JAXA core spacecraft provides a microwave radiometer (GMI) and dual-frequency precipitation radar (DPR) to cross-calibrate entire constellation – 65° inclination, 400 km altitude.
- Partner constellation spacecraft (JAXA, DoD, NOAA, etc.)

From (<http://pmm.nasa.gov/GPM>).



Figure 2.1. Illustration of GPM system.

2.5.3.2 GPM-DPR instrument

The DPR consists of the Ku-band precipitation radar (henceforth KuPR) and the Ka-band precipitation radar (henceforth KaPR). These earth-pointing KuPR and KaPR instruments will provide rain sensing over land and ocean both day and night. The KuPR and KaPR design specifications, with all active phased array elements functioning, are shown in table 2.2. Figure 2.2 shows the DPR scan pattern. KuPR's scan pattern is similar to that of the TRMM PR. It has 49 footprints in a scan and the footprint size is about 5 km in diameter. The scan swath is 245

km. The KaPR also has 49 footprints, but these are divided into two types of scan. In the first type of scan (Ka_MA), the beams are matched to the central 25 beams of KuPR, providing a swath of 120 km. In the second type of scan (Ka_HS), the KaPR is operated in the high-sensitivity mode to detect light rain and snow; in this case, its beams are interlaced within the scan pattern of the matched beams as shown in figure. 2.2. The KuPR and KaPR for the Ka_MA scan have the same range resolution (250 m), while the range resolution of data in Ka_HS is 500m. In both cases, radar echoes are over-sampled at twice the rate of the corresponding resolution: 125 m for the matched beams and 250 m for the Ka_HS. Figure 2.3 shows the observation range. The DPR's echo sampling is designed to cover a range that, at minimum, extends from the surface to 19 km above sea level (or from the ellipsoid). The pulse repetition interval is adjusted according to the satellite altitude and the angle of observation. As a result, the number of independent samples changes slightly as a function of the scan angle (from GPM-DPR level 2 algorithm theoretical basis document (ATBD)).

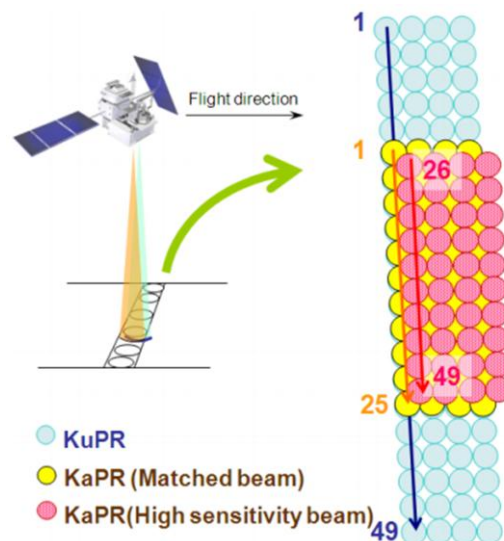


Figure 2.2. DPR scan pattern (from GPM-DPR level 2 algorithm theoretical basis document (ATBD)).

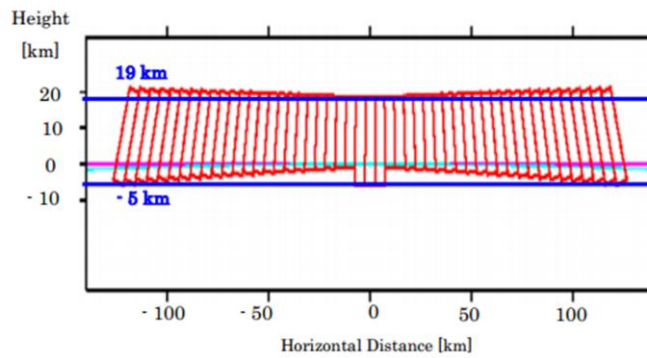


Figure 2.3. DPR's data sampling range (from GPM-DPR level 2 algorithm theoretical basis document (ATBD)).

2.6 GPM GROUND VALIDATION SYSTEM

2.6.1 Introduction

Over all, the GPM mission has defined a series of scientific objectives, including improvement in predicting terrestrial weather, climate, and hydrometeorology through a better observational understanding of the global water cycle. The purpose of the Global Precipitation Measurement (GPM) mission Ground Validation System (GVS) is rooted in the need for independent and objective evaluation of the precipitation products generated by the GPM mission. For its part, the GVS provides an independent means of evaluation, diagnosis, and ultimately improvement of the GPM space borne measurements and precipitation retrievals. These goals are more completely defined as follows:

- Evaluation—Quantify the uncertainties in GPM standard precipitation retrieval algorithms.

Table 2.2. DPR design specifications (from GPM-DPR level 2 algorithm theoretical basis document (ATBD)).

Item	KuPR	KaPR
Swatch width	245 kilometers (km)	120 kilometers (km)
Range resolution	250 meters (m)	250/500 meters (m)
Spatial resolution	5.2 km (nadir at 407 km)	5.2 km (nadir at 407 km)
Beam width	0.71 degree (center beam)	0.71 degree (center beam)
Transmitter	128 solid state amplifiers	128 solid state amplifiers
Peak transmitter power	1012.0 Watts (W)	146.5 Watts (W)
Pulse repetition frequency	4000-4500 Hertz (Hz)	4000-4500 Hertz (Hz)
Pulse width	two 1.6 microseconds (μ s) pulses	two 1.6 microseconds (μ s) pulses in matched beams two 3.2 microseconds (μ s) pulses in interlaced scans
Beam number	49	49 (25 in matched beams and 24 in interlaced scans)
Minimum measurable rain rate	0.5 mm/hr	0.2 mm/hr
Beam matching error	Under 100 m	Under 100 m
Observable range	19 km to surface	19 km to surface
Dynamic range	From -5dB below the system noise level to +5dB above the nominal maximum surface echo level	From -5dB below the system noise level to +5dB above the nominal maximum surface echo level
Receiver power accuracy	+/- 1dB	+/- 1dB
Scan angle	$\pm 17^\circ$ Cross Track	$\pm 8.5^\circ$ Cross Track
Frequencies	13.597 and 13.603 GHz	35.547 and 35.553 GHz
Bandwidth	14 MHz	14 MHz
Max. mass	472 kilograms (kg)	336 kilograms (kg)
Power (max)	446 W (orbit average)	344 W (orbit average)
Science data rate max	109 kilobits per second (kbps) (The Total of KuPR and KaPR is 190 kbps)	81 kilobits per second (kbps) (The Total of KuPR and KaPR is 190 kbps)
Housekeeping data rate	1 kilobits per second (kbps)	1 kilobits per second (kbps)

- Diagnosis—Understand the time and space error characteristics of GPM precipitation products generated by these algorithms.
- Improvement—Contribute to the improvement of GPM precipitation retrieval algorithms throughout the mission.

A Ground Validation System (GVS) consists of several system elements employed in the independent validation of the instruments on the GPM core satellite and the associated data products generated from them. The high-level roles within the GPM mission, and the GVS portions of them, are illustrated in figure 2.4 (Schwaller et al, 2006).

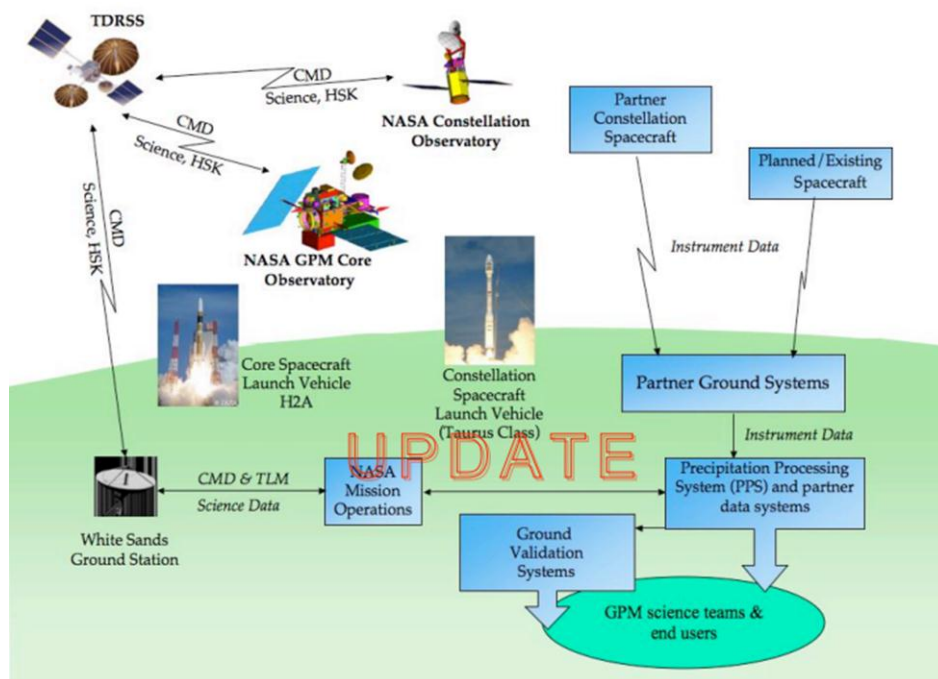


Figure 2.4. GPM mission architecture (Schwaller et al, 2006).

2.6.2 D3R radar overview

A dual-frequency dual-polarized Doppler radar (D3R) was developed with funding from NASA's Global Precipitation Measurement (GPM) Project. The D3R is a fully polarimetric, scanning weather radar system operating at the nominal frequencies of 13.91 GHz and 35.56 GHz covering a maximum range of 30 km. The frequencies chosen allow close compatibility with the GPM Dual-frequency Precipitation Radar system. The D3R is the part of GPM ground validation activities. These activities support GPM pre-launch algorithm development and contribute to post-launch precipitation product validation. Pre-launch, the D3R provides an independent estimation of hydrometeor classification and drop size distribution retrievals. The radar thus offers an insight into the microphysical processes that dominate the retrieval (and associated measurement error) of precipitation types and rates from satellite data. While the GPM DPR radar presents a global picture of precipitation through observations at Ku- and Ka-band, the ground-based D3R yields detailed, fine-scale local statistics for the microphysical interpretation.

The D3R, a relative compact, transportable system, takes advantage of several innovative technologies to achieve its design goals. Chief among these are the use of solid-state power amplifiers and a novel waveform composed of three consecutive, frequency modulated, frequency separated pulses. Using these methods, blind ranges and range side lobes are minimized, and the radar meets its sensitivity requirement of -10 dBZ at 15 km (clear air, single pulse, with 150 m range resolution). The design specifications and data products of D3R radar are shown in table 2.3

Table 2.3. Design specifications and data products of D3R radar.

SYSTEM	
Frequency	Ku: 13.91GHz±25MHz Ka: 35.56 GHz±25MHz
Minimal detectable signal (Ku,Ka)	-10 dBZ at 15 km for a single pulse at 150m range resolution
Minimal operational range	450 m
Operational range resolution	150 m (nominal)
Maximum range	30km
Angular coverage	0-360° Az, -0.5-90° EI (full hemisphere)
ANTENNA	
Parabolic reflector (diameter)	6ft/72in (Ku), 28in (Ka)
Gain	44.5 dB (Ku, Ka)
HPBW	~1° (Ku, Ka)
Polarization	Dual linear simultaneous and alternate (H and V) (Ku, Ka)
Maximum side lobe level	~-25 dB (Ku, Ka)
Cross-polarization isolation	<-32 dB (on axis)
Ka-Ku beam alignment	Within 0.2°
Scan capability	0-24°/s Az, 0-12°/s EI
Scan types	PPI sector, RHI, Surveillance, Vertical pointing
TRANSMITTER/RECEIVER	
Transmitter architecture	Solid state power amplifier modules
Peak power/Duty cycle	160W (Ku), 40W (Ka) per H and V channel, Max duty cycle 30%
Receiver noise figure	4.6 (Ku), 5.5 (Ka)
Receiver dynamic range	90 dB (Ku, Ka)
Clutter suppression	GMAP
DATA PRODUCTS	
Standard products	Equivalent reflectivity factor Zh (Ku, Ka), Doppler velocity (unambiguous : 25 m/s)
Dual-polarization products (Ku, Ka) (LDR only in alternate transmit mode)	Differential reflectivity Zdr Differential propagation phase ϕ_{dp} Copolar correlation coefficient ρ_{hv} Linear depolarization ratios LDRh, LDRv
Data format	NetCDF

Source: <http://pmm.nasa.gov/science/ground-validation/D3R>.

2.7 SIMULATION METHOD FOR ALGORITHM EVALUATION

For the purpose of radar system design and algorithm evaluation, it's very useful to have true microphysics information. One effective way to develop a dataset is through theoretical simulation. By coupling information about the particle scattering model, the melting layer model, and drop size distributions, the backscattering intensities and attenuation coefficients can be computed from any location within the radar echo. An electromagnetic scattering method such as the T-matrix method (Waterman, 1965, 1971) or the DDA (discrete dipole approximation) method (Draine and Flatau, 1994) is used to calculate scattering properties. In conjunction with a gamma drop size distribution, radar observations can be simulated. A schematic plot of the simulation procedure is shown in Figure 2.5. In this study, the drop size distributions used in the simulations are retrieved from real radar observations. The main reason for using this approach is to maintain the natural distribution of precipitation particles rather than base it on rough assumptions.

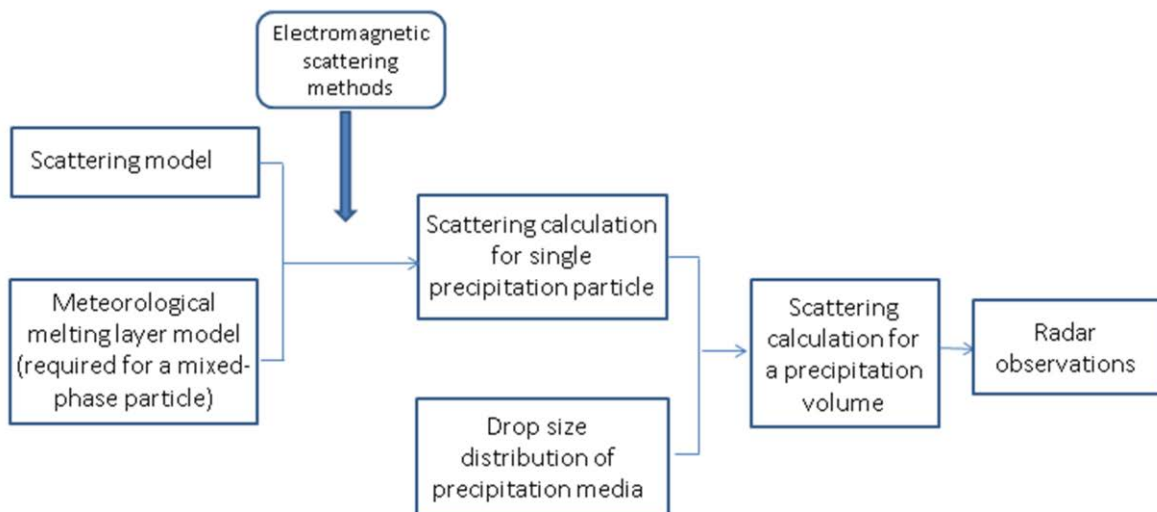


Figure 2.5. Schematic plot of radar simulation procedure.

Although the simulation concept and procedure are the same for space-borne and ground-based radar, they are based on different radar observations and the methods for preparing drop size distributions are not the same. In the sections below, the simulation steps are described separately for space-borne and ground-based radar.

2.7.1 Simulation of space-borne radar observations

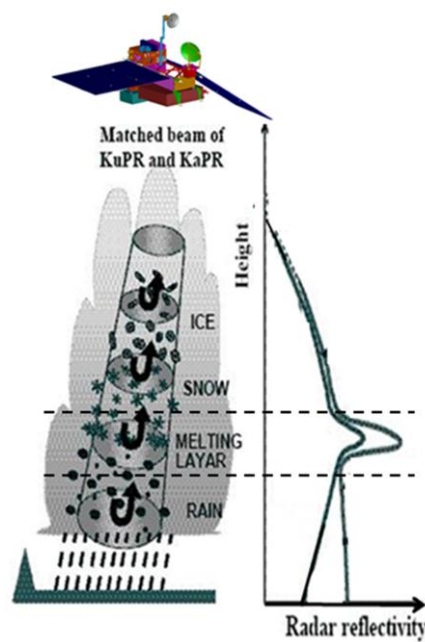


Figure 2.6. A depiction of a downward-looking Dual-frequency precipitation radar on board GPM satellite. Dash lines represent the melting layer boundaries and solid lines are vertical profiles of radar reflectivity at Ku- and Ka- band. (Senbokuya et al. (2004))

Since the DPR on board the GPM core satellite will be the first dual-frequency space precipitation radar operating at high frequencies, a simulation-based study is important for system design and algorithm development. In order to support the study of DPR observations, a

down-looking second-generation airborne precipitation radar (APR2) with the same frequencies channels (Ku and Ka band) was developed by NASA and JPL to emulate the DPR before it is launched. APR2 data has good range resolution, which provides a powerful means for improving our understanding of microphysical properties of vertical precipitation structure. In this study, DPR simulation is based on the observations of APR2 data. The scanning geometry of the APR2 radar on the NASA DC-8 aircraft is shown in figure 2.7. The radar looks downward and scans its beams cross-track, with each scan beginning at 25 degree left of nadir and ending at 25 degrees right of nadir. The characteristics are shown in Table 2.4.

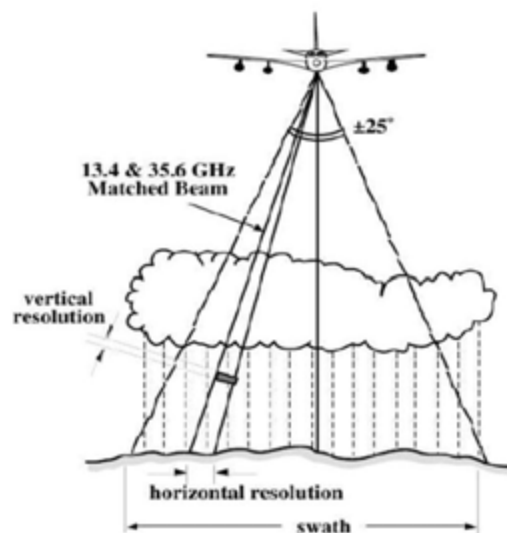


Figure 2.7. APR-2 scanning geometry on the NASA DC-8 aircraft.

Similar to figure 2.5, figure 2.8 shows the detailed procedure for DPR simulation based on airborne radar data. APR2 radar observations are from several field experiments such as the Wakasa Bay Experiment in 2003; the NASA African Monsoon Multidisciplinary Analysis

Table 2.4. APR-2 radar characteristics (Tanelli et al., 2004).

Airborne Precipitation radar (APR2) characteristics		
Frequency	13.4 GHz	35.6 GHz
Polarization	HH,HV	HH,HV
Antenna diameter	0.4m	0.14m
Antenna gain	34dBi	33dBi
Antenna side lobe level	-30dB	-30dB
Peak power	200W	100W
Pulse width	10-40 μ s	10-40 μ s
PRF	5 KHz	5 KHz
Range bin spacing	30 m	30 m
Horizontal resolution	400 m	500 m
Ground swath	4.5 km	4.5 km
Noise equivalent Ze	5 dB	5 dB
Doppler precision	0.4 m/s	1 m/s

(NAMMA) experiment in 2006, and the Genesis and Rapid Intensification Processes (GRIP) experiment in 2010. Figure 2.9 shows an example of the APR2 data at nadir during the NAMMA experiment. Two typical profiles of stratiform and convective rain are shown in figure 2.10, marked as A and B in figure 2.9. With a vertical resolution of around 30m, APR2 profiles keep all detailed information especially within the melting layer. The linear depolarization ratio

(LDR) as well velocity profile available for the APR2 radar helps determine the boundaries of rain, melting and ice regions.

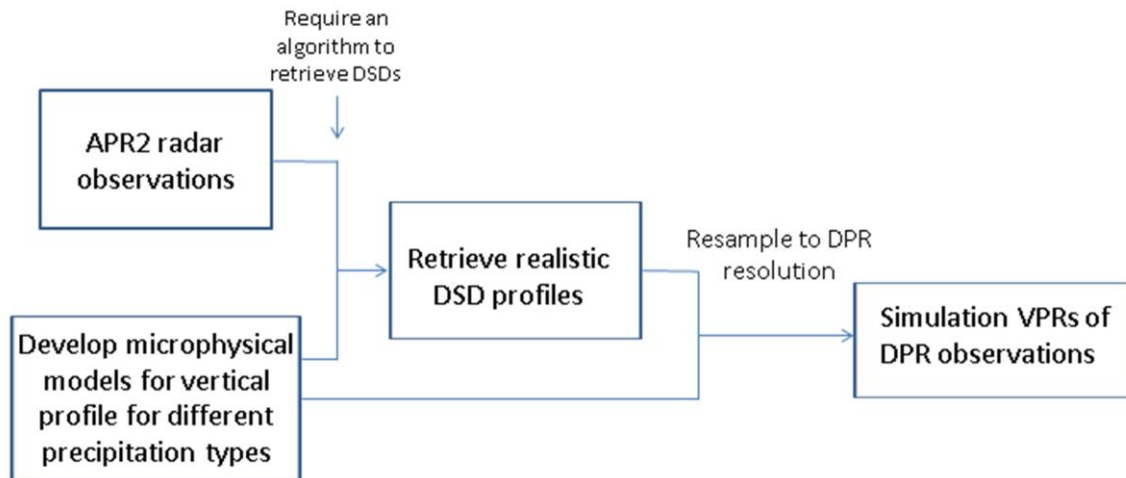


Figure 2.8. A schematic plot of simulation procedure for DPR observations from APR2 radar.

For a stratiform rain profile, as shown in figure 2.10 (a), there is a clear enhancement of reflectivity associated with particle melting (or bright band). The primary cause of enhancement is a rapid increase of dielectric constant associated with melting snow. After reaching a maximum, the reflectivity decreases because of an increase in particle velocities and a decrease in the effective particle size.

Compared to a stratiform rain profile, a convective rain profile is characterized by stronger vertical motion. Updrafts take water drops above the melting layer and these drops condense on

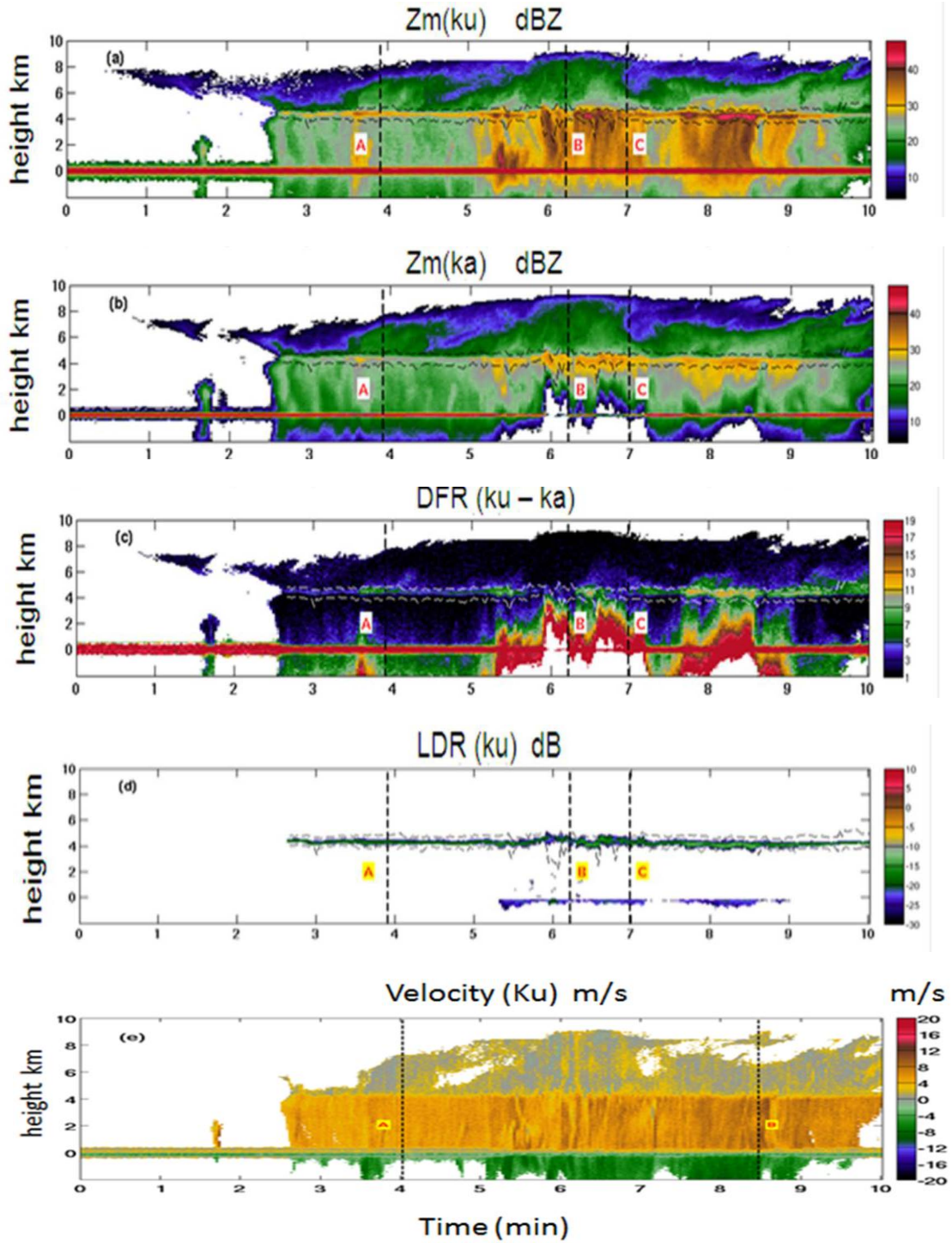


Figure 2.9. Along-track observations at nadir of the APR2 radar in the NAMMA experiment (20060903_142134). (a) panel is reflectivity at Ku- band; the (b) panel is reflectivity at Ka- band; the (c) panel is the difference between reflectivity at Ku- and Ka-band; the (d) is LDR at Ku- band; the (e) panel is fall velocity at Ku- band.

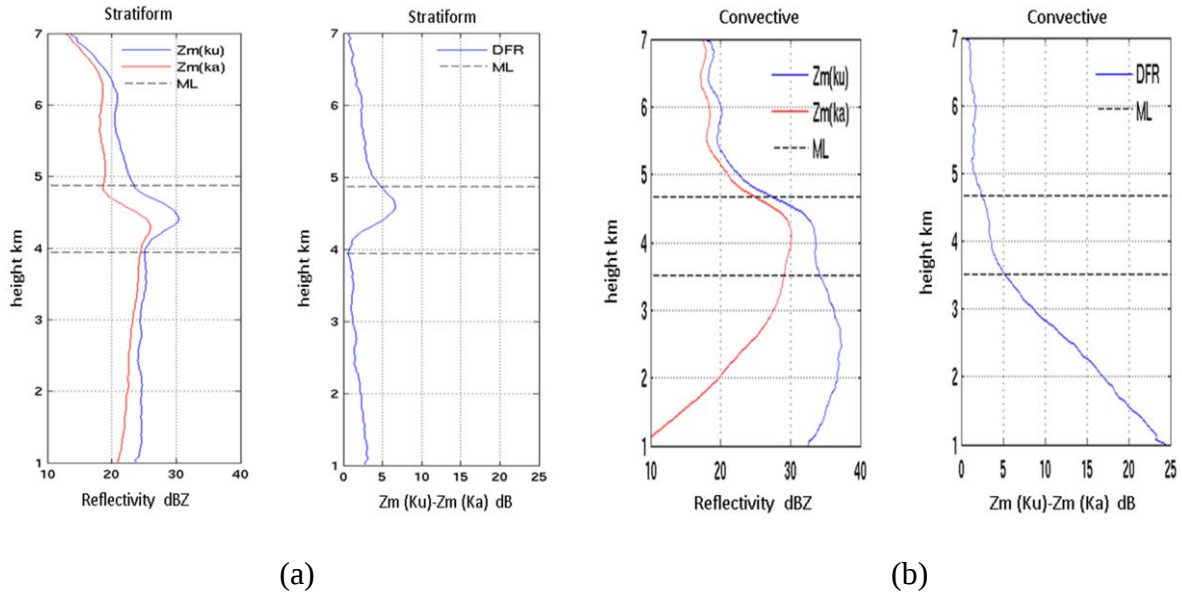


Figure 2.10. (a) typical vertical profile of reflectivities (Ku- and Ka- band) and their difference (measured dual frequency ratio) for stratiform rain marked as A in figure 2.9. (b) typical vertical profile of reflectivities and their difference for convective rain marked as B in figure 2.9.

Snowflakes, forming a ball of riming. Therefore, for convective rain, there exist high-density particles such as graupel. When high-density particles begin to melt, the shape and density do not change significantly, in other words, the melting procedure is slower. As a result, there is no large and obvious increase of reflectivity and the reflectivity remains close to peak value below the melting layer, as can be seen in figure 2.10 (b) (Zawadzki et al., 2005). Due to the different formation of stratiform and convective rain, two vertical scattering models are built for the simulation of stratiform and convective rain. The schematics of the models are shown in figure 2.11.

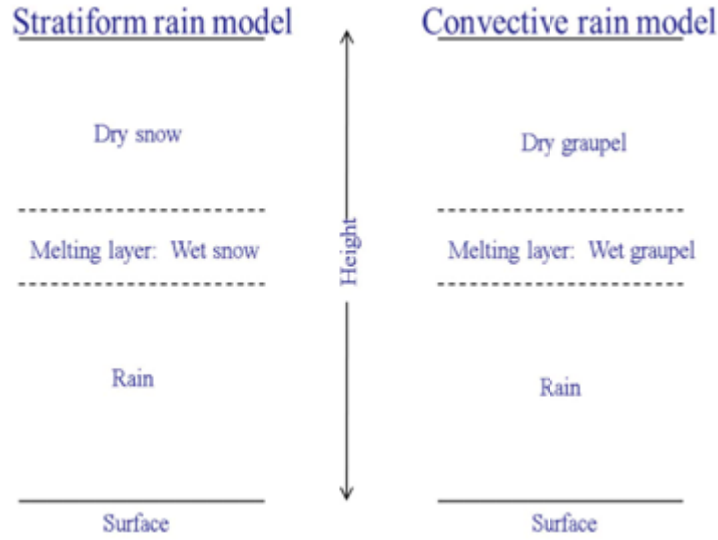


Figure 2.11. Microphysical model developed for stratiform (left) and convective (right) rain simulation.

In order to prepare realistic DSDs for the DPR simulation, DSD profiles are retrieved using a combination of the forward method (Meneghini et al. 1992) and the DAD (difference of attenuation difference) method described in Iguchi, (2005). Although the method used to retrieve DSDs has some limitations such as the assumption of uniform rain, it provides a way to prepare realistic DSD information along the vertical profile for simulation purposes. Different microphysical models, as shown in figure 2.11, are applied in the DSD retrieval for stratiform and convective rain, respectively. The retrieved DSD profiles are used to simulate radar observations. It needs to be pointed out that these DSDs are regarded as “true” DSDs used for algorithm evaluation in Chapter 4. Considering the range resolution difference between APR2 radar data (30m) and the DPR radar (250m), the simulated radar observations need to be re-sampled to DPR resolution. Figure 2.12 (a) and (c) show the simulated DPR profile for the

stratiform and convective rain profile from APR2 data as illustrated in figure 2.10 (a) and (b), respectively. Through the comparison between figure 2.10 and 2.12, the simulation procedure can capture the main characteristics of airborne observations and make the simulation data more realistic. Although simulation of DPR observations is the focus of this section, this simulation approach can be applied to other space-borne radars if needed.

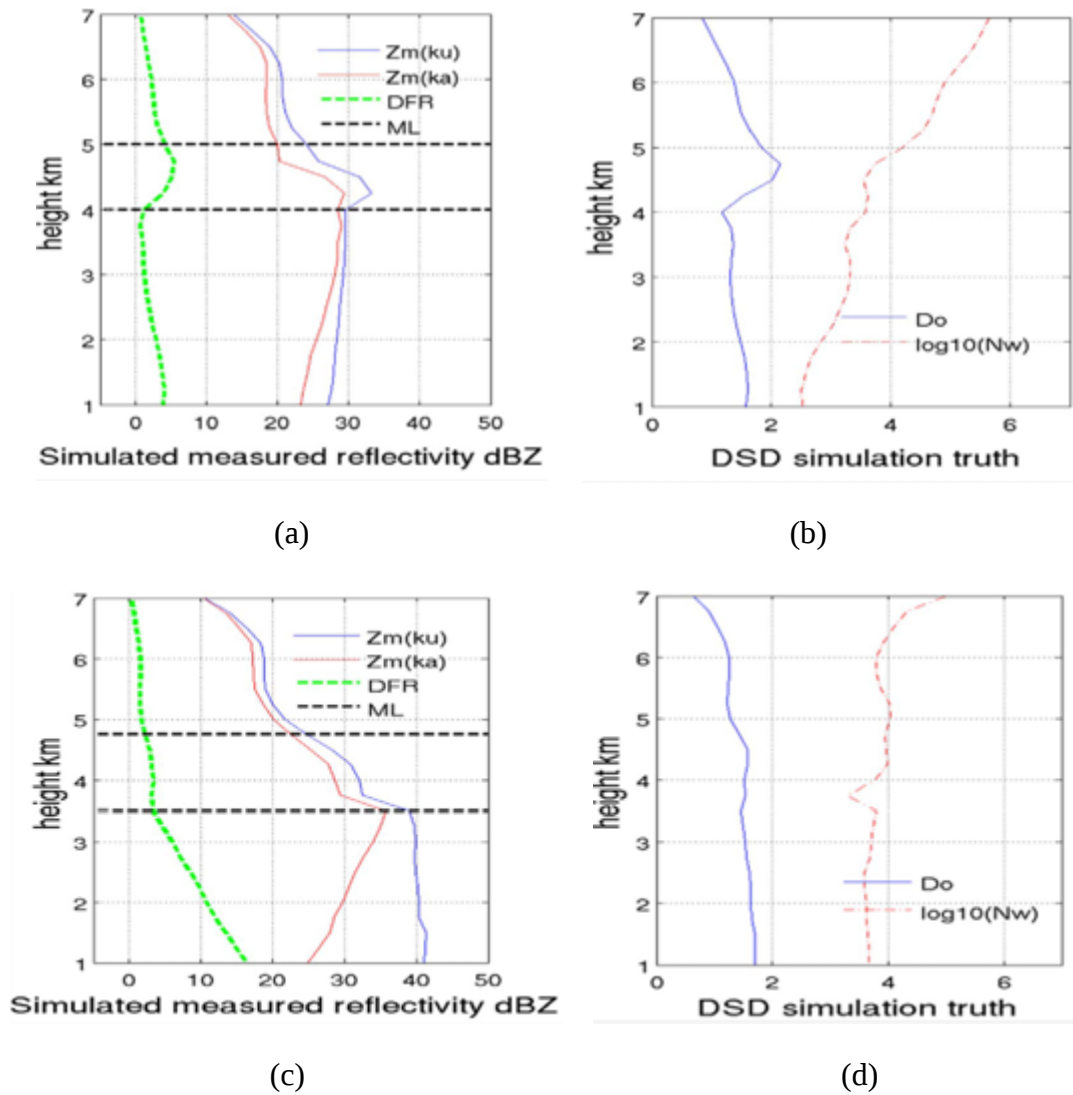


Figure 2.12. Profiles of reflectivity and the measured dual frequency ratio for stratiform rain simulated from airborne radar profile marked as A in figure 4.6;(b) True DSD profiles for (a); (c) Same profiles for convective rain simulated from airborne radar profile marked as B in figure 4.6; (d) True DSD profiles for (c).

2.7.2 Simulation of ground-based radar observations

2.7.2.1 Simulation of Ku- and Ka- band observations from S-band dual-polarization radar observations.

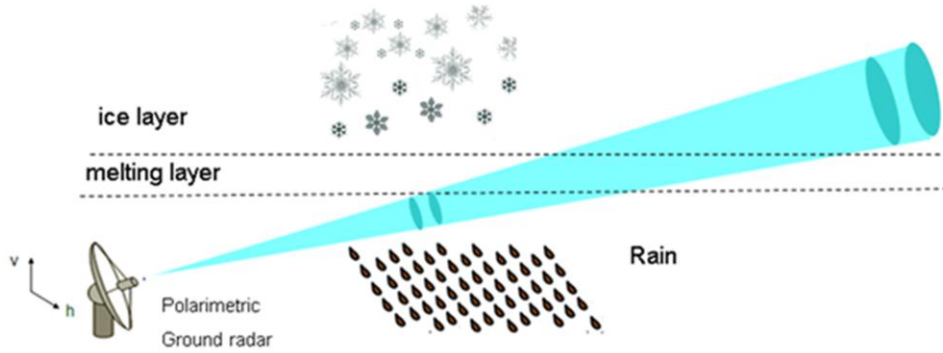


Figure 2.13. Schematic of ground radar propagation through precipitation media.

A dual-frequency dual-polarization ground radar has been built to perform ground validation with DPR on board the GPM satellite. Similar to DPR, this is the first ground radar designed to operate at Ku- and Ka- band. For system design and algorithm evaluation purpose, simulation plays a crucial role. Figure 2.13 is a schematic plot showing ground radar propagation through precipitation media. Unlike DPR simulation, the ground radar observations are simulated based on S-band dual-polarization ground radar. The reason to choose S-band (3GHz) dual-polarization radar observation is because 1) there have been algorithms in the literatures to retrieve rain DSD information from polarimetric parameters (Gorgucci et al., 2002, 2008; Testud et al., 2000) and 2) S-band observations are not affected by attenuation effects. Figure 2.14 shows a schematic plot of a simulation procedure for rain and simulation details are described by Chandrasekar et al. (2006).

Figure 2.15 is an example of the simulated Ku- and Ka- band PPI observation for rain based on the ground radar data collected by the CSU-CHILL radar during the Severe Thunderstorm Electrification and Precipitation Study (STEPS) project. The data used was collected June 20, 2000. In the figure, (a), (c), and (e) are the simulated intrinsic reflectivity at Ku-, Ka- band, and intrinsic differential reflectivity at Ku- band while (b), (d), and (f) are the corresponding attenuated values. It is obvious that attenuation at Ka- band is higher compared to Ku band. The data from the second column are regarded as the “true” observations in the microphysical retrieval algorithm evaluation; they are discussed in detail in Chapter 5.

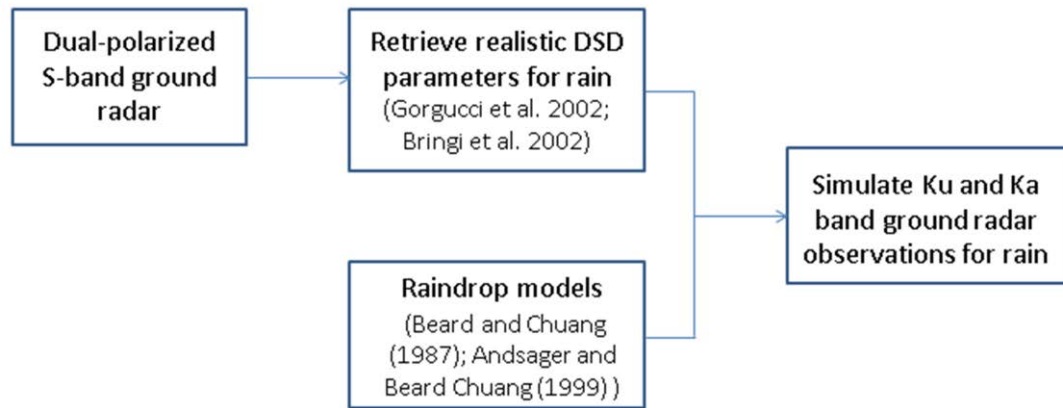


Figure 2.14. Schematic plot of the simulation procedure for ground radar observation within rain region.

For regions beyond rain, there are no decent algorithms for retrieving DSD parameters from a dual-polarizations ground radar operating at a single frequency. An alternative approach, simulating an RHI scan of ground based radar operating at Ku- and Ka- band, is discussed in the next section.

2.7.2.2 Simulation of Ku- and Ka- band observations from airborne radar observations.

Data from airborne precipitation radar (APR-2) provides us an approach for achieving more accurate 3D DSDs for rain, melting ice, and ice using dual frequency retrieval algorithms (Iguchi, 2005; Meneghini et al, 1997). However, simulating RHI observations of a ground radar requires a cartesian coordinate (APR-2 coordinate) to radar coordinate transition. The simulation procedure can be described briefly as follows: 1) 3D APR-2 radar data is interpolated to a finer resolution in order to meet the resolution requirement of the ground radar; 2) a virtual radar location is decided close to precipitation observed by APR-2 radar; 3) elevation and azimuthal angle are decided to calculate the Cartesian coordinate of each radar resolution volume center and radius. Finally, calculate the average value of Cartesian DSDs that drop into each radar resolution volume. Figure 2.16 shows a schematic plot of the setup for this simulation approach. Scattering models and a T-matrix method are applied to generate radar observations. Figure 2.17 shows some sample RHI scans that are simulated from the APR-2 NAMMA 20060903-142134 overpass using the method described above.

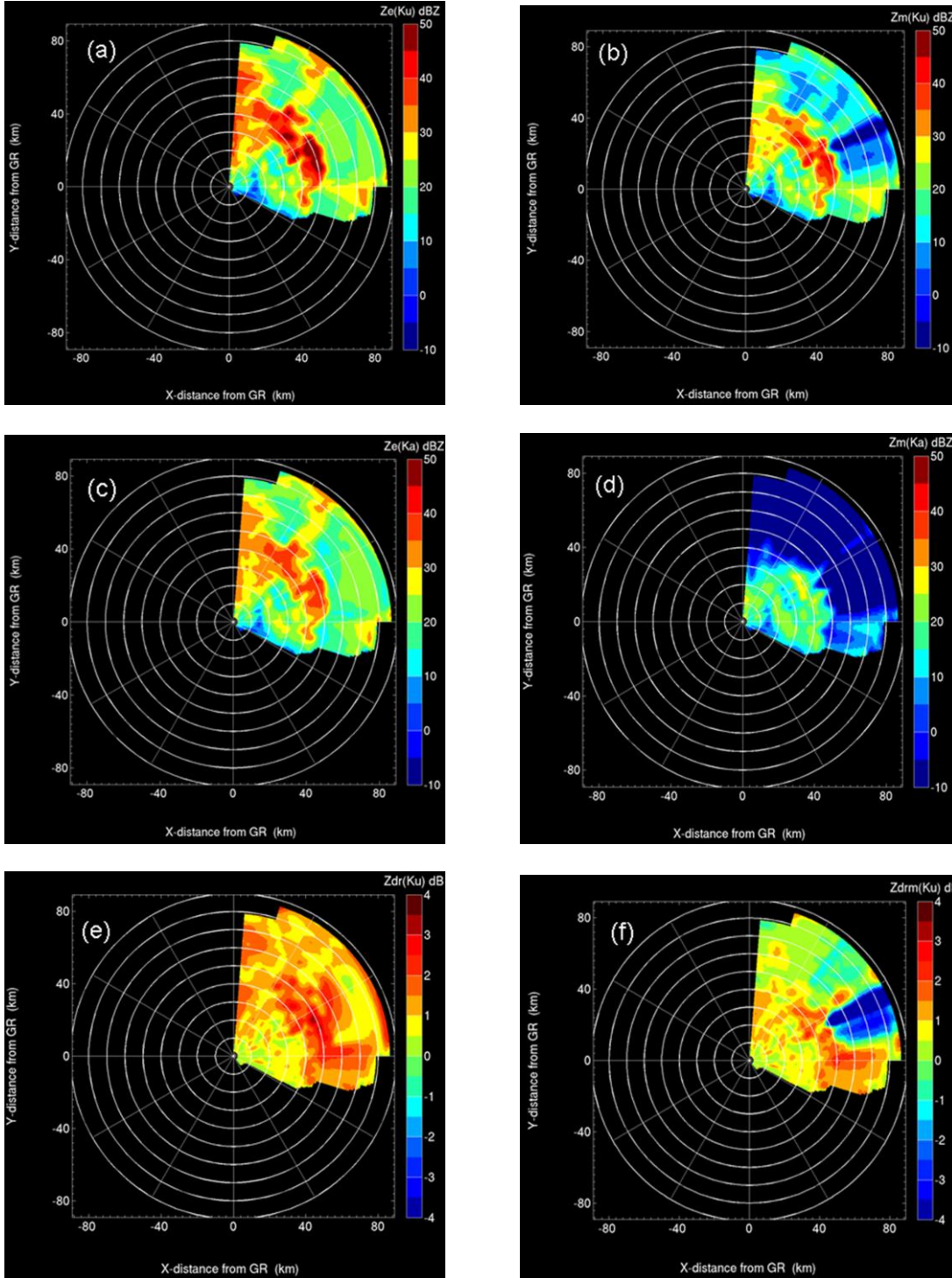


Figure 2.15. Simulated PPI scan of Ku- and Ka- band observations from S- band radar during STEPS project (20000620_012145 case). (a), (c), and (e): intrinsic reflectivity at Ku-, Ka- band and intrinsic differential reflectivity at Ku- band. (b), (d), and (f): attenuated reflectivity at Ku-, Ka- band and attenuated differential reflectivity at Ku- band.

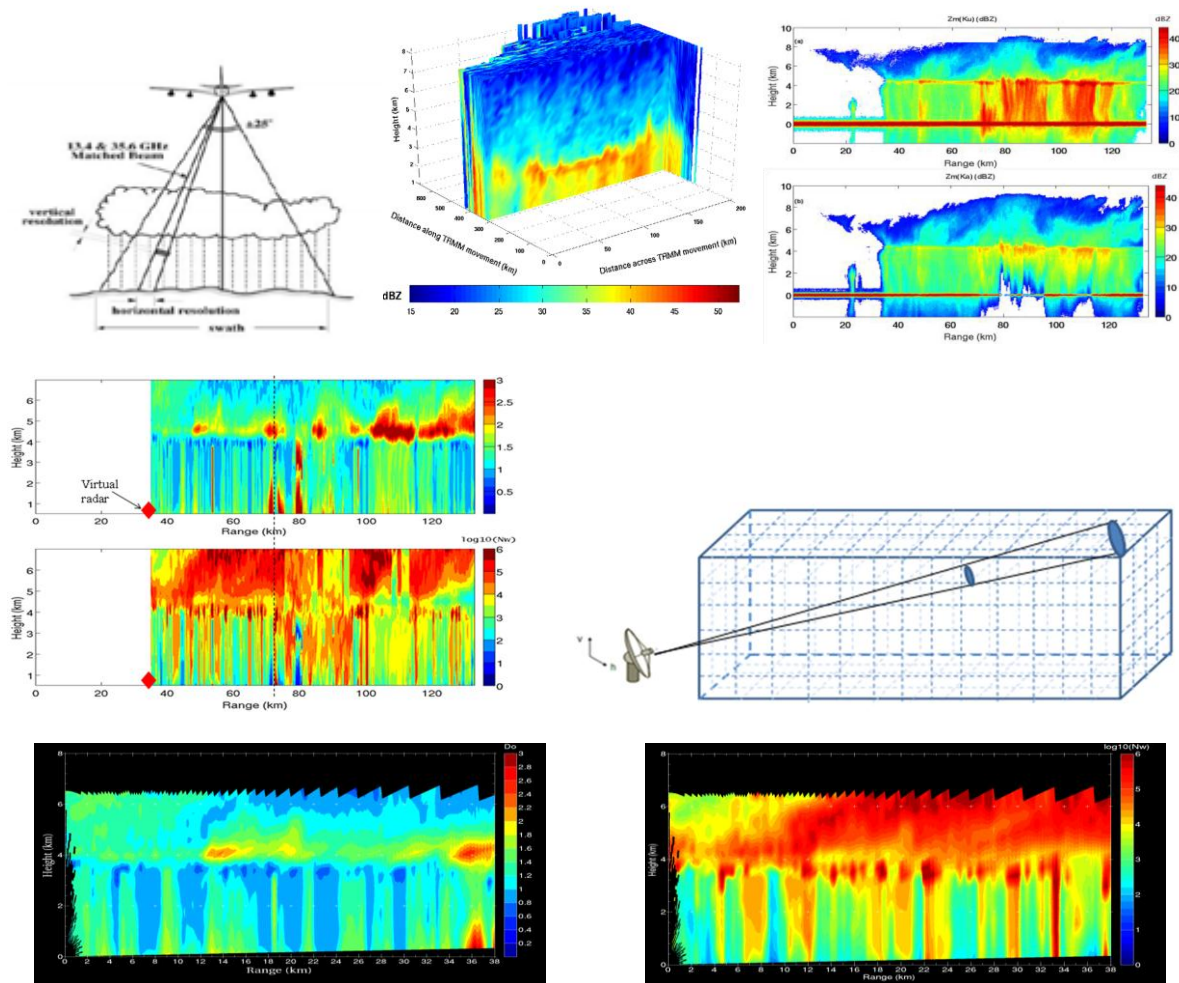


Figure 2.16. Top row (from left): schematic plot of APR-2 radar; 3D data structure of APR-2 radar; sample observations at Ku- and Ka- band at nadir angle. Middle row (from left): retrieved DSDs using dual frequency algorithm; virtual radar setup and coordinate transfer illustration. Bottom row (from left): DSDs mapped from Cartesian coordinate to radar coordinate.

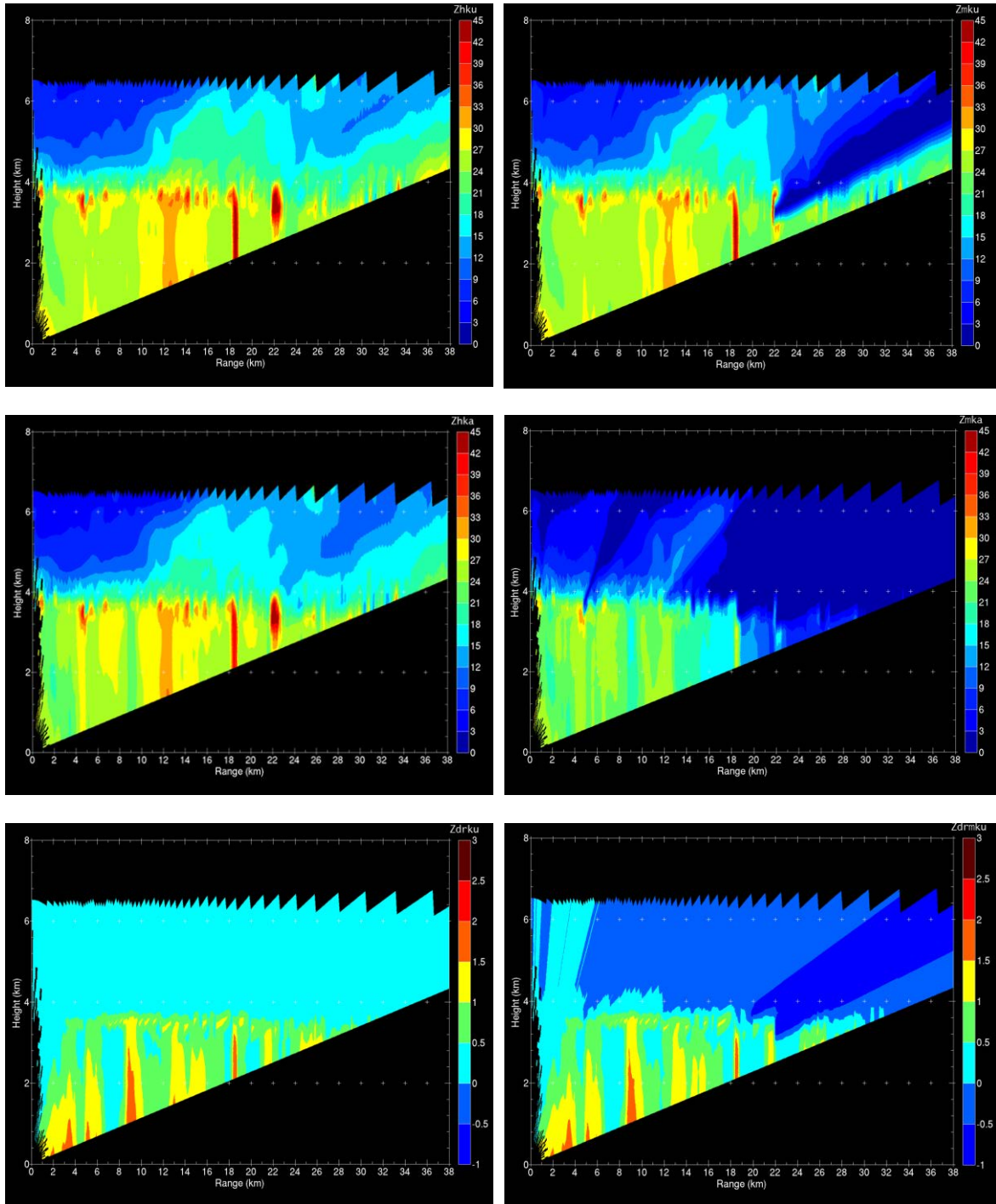


Figure 2.17. Simulated RHI scan from APR-2 NAMMA 20060903-142134 overpass. Top row (from left): Zh(Ku); Zm(Ku). Middle row (from left): Zh(Ka); Zm(Ka). Bottom row (from left): Zdr(Ku); Zmdr(Ku).

CHAPTER 3

PROFILE CLASSIFICATION METHOD FOR GPM-DPR

3.1 INTRODUCTION

Profile classification is an important module in the microphysical retrieval system for space precipitation radar. It classifies the storm type by looking at the existence of a bright band, the vertical profile and the horizontal distribution pattern of precipitation echoes in the vicinity of the pixel in question. The nature of microphysical models and equations to use in the retrieval algorithm are determined by the precipitation type and phase state of each profile. Profile classification module for the GPM-DPR includes two parts: 1) classification of precipitation type such as stratiform, convective, and other rain type; and 2) detection of the melting layer top and bottom boundaries. Figure 3.1 illustrates the basic structure of the GPM-DPR level 2 algorithm.

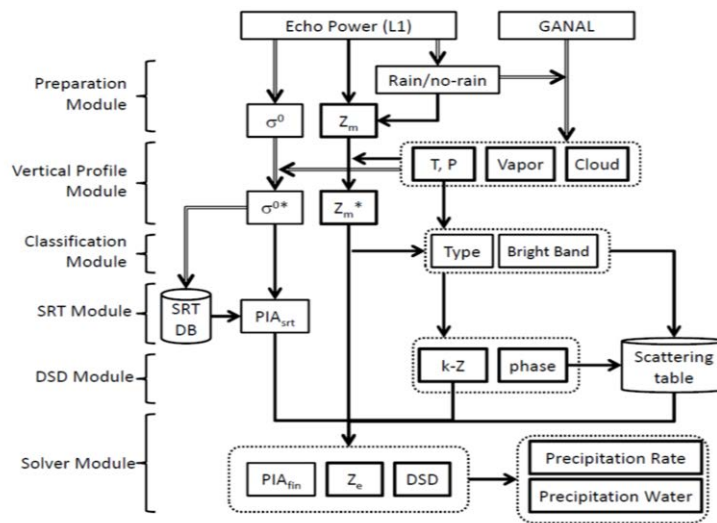


Figure 3.1. Basic structure of GPM-DPR level algorithm (Iguchi et al. 2013).

This chapter starts with an introduction of the profile classification method used for TRMM-PR and its limitations. The characteristics of *DFRm* profile and its advantages in profile classification are described. Then, the profile classification method based on *DFRm* is developed for GPM-DPR using airborne radar data. The melting layer boundaries detected from the *DFRm* profile are compared to existing criteria in the literature. Off-nadir and smoothing effects for the method are described in detail. This chapter ends with the current status for implementing the method to the GPM-DPR day one algorithm.

3.2 PROFILE CLASSIFICATION METHOD FOR TRMM-PR

In the TRMM era, there is only one frequency observation available for TRMM-PR. TRMM-PR uses the vertical profile method (V-method) and the horizontal pattern method (H-method) to perform profile classification. Both methods classify rain into three categories: stratiform, convective, and other. The V-method classifies rain type by detecting the existence of bright band in the vertical profile. The H-method examines the horizontal pattern of the maximum reflectivity along the range for each antenna angle below freezing height. The results from both methods are combined to give the final rain type decision (Awaka et al. 1998). After rain type is classified, the melting layer region (top and bottom height) is defined as two range bins above and below the bright band peak if it is stratiform rain and three range bins above and below the 0 degree isotherm if it is convective rain. Figure 3.2 illustrates the profile classification approach of TRMM-PR. The limited information determining the profile classification method for TRMM-PR is relatively rough.

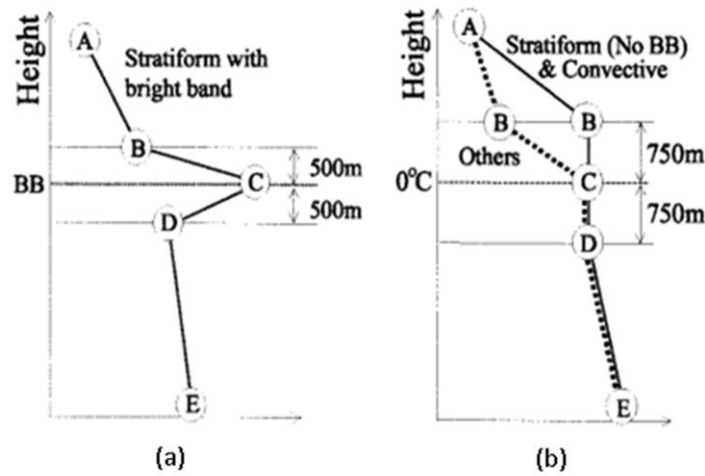


Figure 3.2. Schematic presentation of the profile classification approach in TRMM-PR (Iguchi et al. 2000).

3.3 AIRBORNE RADAR OBSERVATIONS

As described in section 2.7, in support the NASA GPM mission, NASA JPL developed the second-generation Airborne Precipitation Radar (APR-2) as a prototype of an advanced dual-frequency space radar which emulates DPR on board the GPM core satellite. APR-2 has collected data in several field campaigns that are used in this study. They are: 1) the NAMMA campaign (NASA African Monsoon Multidisciplinary Analysis), located 350 miles off the coast of Senegal in West Africa; 2) the Wakasa Bay campaign located in the sea of Japan, a region famous for very shallow rain; 3) the GRIP campaign located in the Gulf of Mexico and the Caribbean Sea with a major goal of being able to better understand tropical storms and hurricanes. GRIP is the most recent campaign of the three; It was conducted in the year 2010. Figure 2.9 shows a sample of APR-2 measurements at nadir during the NAMMA campaign and the characteristics of the APR-2 radar are summarized in table 2.4. Figure 3.3 shows the

geolocations of the three field experiments. A sample plot of GRIP and Wakasa Bay data are shown in Figure 3.4. From top to bottom, the panels are measured reflectivity at Ku-, Ka- band and the measured dual-frequency ratio (DFR_m). Due to the fine vertical resolution ($\sim 30\text{m}$), the melting layer can be seen clearly in the reflectivity measurements. From figure 3.4 (a) and (b), melting layers are obvious at around 5 km and 2 km for GRIP and Wakasa Bay experiment areas.

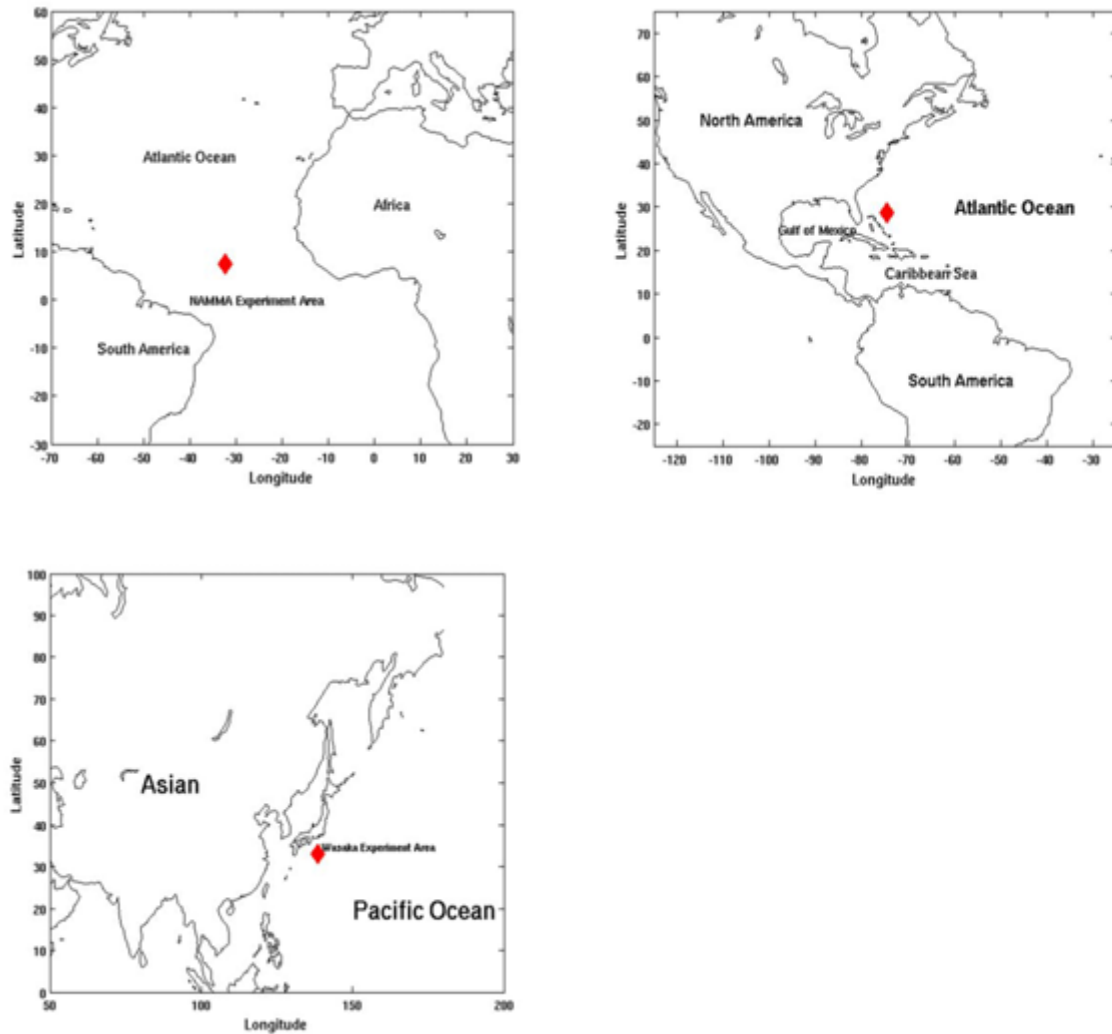


Figure 3.3. Top left: Geolocation of NAMMA field experiment. Top right: Geolocation of GRIP field experiment. Bottom left: Geolocation of Wakasa Bay field experiment.

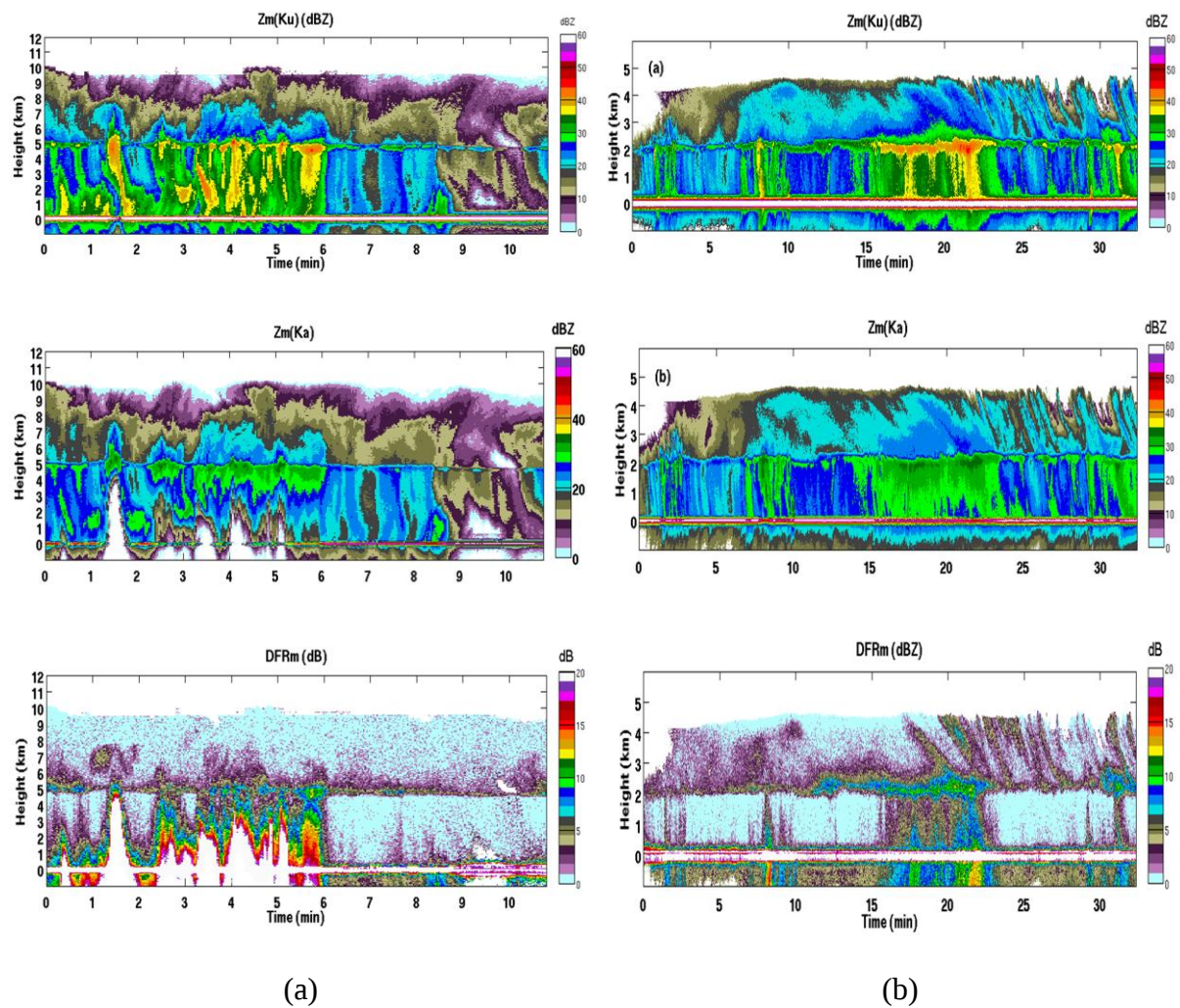


Figure 3.4. (a) Overpass of GRIP data (100901_202048). Top: Zm(Ku); Middle: Zm(Ka); Bottom: *DFRm*. (b) Overpass of Wakasa Bay data (030123-075827). Top: Zm(Ku); Middle: Zm(Ka); Bottom: *DFRm*.

3.4 CHARACTERISTICS OF MEASURED DUAL-FREQUENCY RATIO (DFR_m)

GPM-DPR offers two independent observations at two frequency bands. The Ka- band observation of precipitation particles is in the non-Rayleigh scattering region. Measurements from both Ku- and Ka- band suffer from attenuation when a radar beam propagates through precipitation such as melting layer and medium to heavy rain (Bringi and Chandrasekar, 2001). However, attenuation from Ka- band is larger from Ku- band. This makes the difference between two DPR measurements a viable parameter to make inferences about the profile. DFR_m (in dB scale) is defined as

$$DFR_m = 10\log_{10}(Z_m(K_u)) - 10\log_{10}(Z_m(K_a)) \quad (3.1)$$

Z_m is the measured equivalent radar reflectivity factor in linear scale. Z_m can be related to equivalent radar reflectivity factor Z_e through

$$\begin{aligned} Z_m &= Z_e \times A \\ &= Z_e \exp[-0.2\ln(10) \int_0^r k(s)ds] \end{aligned} \quad (3.2)$$

where A is the cumulative attenuation factor from radar to the bin of interest. Z_e is related to the drop size distribution $N(D)$ and the backscatter cross section σ_b of the hydrometeors for a given wavelength λ as

$$Z_e = \frac{\lambda^4}{\pi^5 |K_w|^2} \int_0^\infty N(D) \sigma_b(D, \lambda) dD \quad (3.3)$$

K_w is the dielectric constant of water and $|K_w|^2 \cong 0.93$ (Battan,1973). The Natural variation of drop size distribution $N(D)$ can be approximated by a gamma model (Ulbrich,1983) as

$$N(D) = N_w f(\mu) \left(\frac{D}{D_0} \right)^\mu \exp \left[- (3.67 + \mu) \frac{D}{D_0} \right],$$

$$f(\mu) = \frac{6}{(3.67)^4} \frac{(3.67 + \mu)^{\mu+4}}{\Gamma(\mu+4)} \quad (3.4)$$

where D_0 (mm) is the medium volume diameter, μ is a measurement of shape of drop size distribution and N_w ($\text{mm}^{-1} \text{m}^{-3}$) is the normalized intercept parameter of an equivalent exponential distribution with the same water content and D_0 .

Take three log scale of both sides, (3.2) can be expressed as

$$10 \log_{10}(Z_m) = 10 \log_{10}(Z_e) - \log_{10}(\exp[0.2 \ln(10) \int_0^r k(s) ds]) = 10 \log_{10}(Z_e) - PIA \quad (3.5)$$

where $PIA = -10 \log_{10}(A) \quad (3.6)$

PIA (in dB) is a positive number and denotes the two-way attenuation from radar to the bin of interest. k is specific attenuation in dB per kilometer. It is related to drop size distribution $N(D)$ and extinction cross section σ_{ext} of the hydrometeors

$$k = 4.343 \times 10^3 \int_0^\infty N(D) \sigma_{ext}(D, \lambda) dD \quad (3.7)$$

Radar dual-frequency ratio (*DFR*) in dB, describing the difference of reflectivity factor between two frequency channels, is defined as

$$DFR = 10\log_{10}(Z_e(K_u)) - 10\log_{10}(Z_e(K_a)) \quad (3.8)$$

Substituting (3.5) in (3.8) results in

$$DFR_m = 10\log_{10}(Z_m(K_u)) - 10\log_{10}(Z_m(K_a)) = DFR + \delta PIA \quad (3.9)$$

δPIA is the attenuation difference between Ku- and Ka- band expressed in dB scale. It is a positive number since Ka- band attenuation is larger than Ku- band attenuation. From (3.9), it is clear that DFR_m is composed of two parts. The DFR part is caused by the non-Rayleigh scattering of precipitation particles; and δPIA is responsible for the difference due to attenuation.

Figure 3.5 shows a typical vertical profile of reflectivity and DFR_m for stratiform and convective rain from APR-2 observation. The DFR_m profiles for different rain types, as shown in figure 3.5 (b) and (d), have some common features. At altitudes above about 5 km, DFR_m values are small and increase slightly with the decrease of height. This can be explained through the non-Rayleigh scattering effect on snow particles. Figure 3.6 (a) shows a theoretical simulation between DFR and median drop diameter (D_0) for ice crystal distributions as a function of fixed densities. Figure 3.6 (b) shows similar relations with ice density as a function of size (Hogan et

al., 2002; Holroyd, 1973; Heymsfield et al., 2002). Although in recent years, research work has shown that “sphere model” is not accurate enough to model ice crystals (Petty and Huang, 2010; Tyynelä et al., 2011), for illustration purpose only, the spherical model is used in the theoretical simulation of figure 3.6 with volume equivalent diameters of snow particles following an

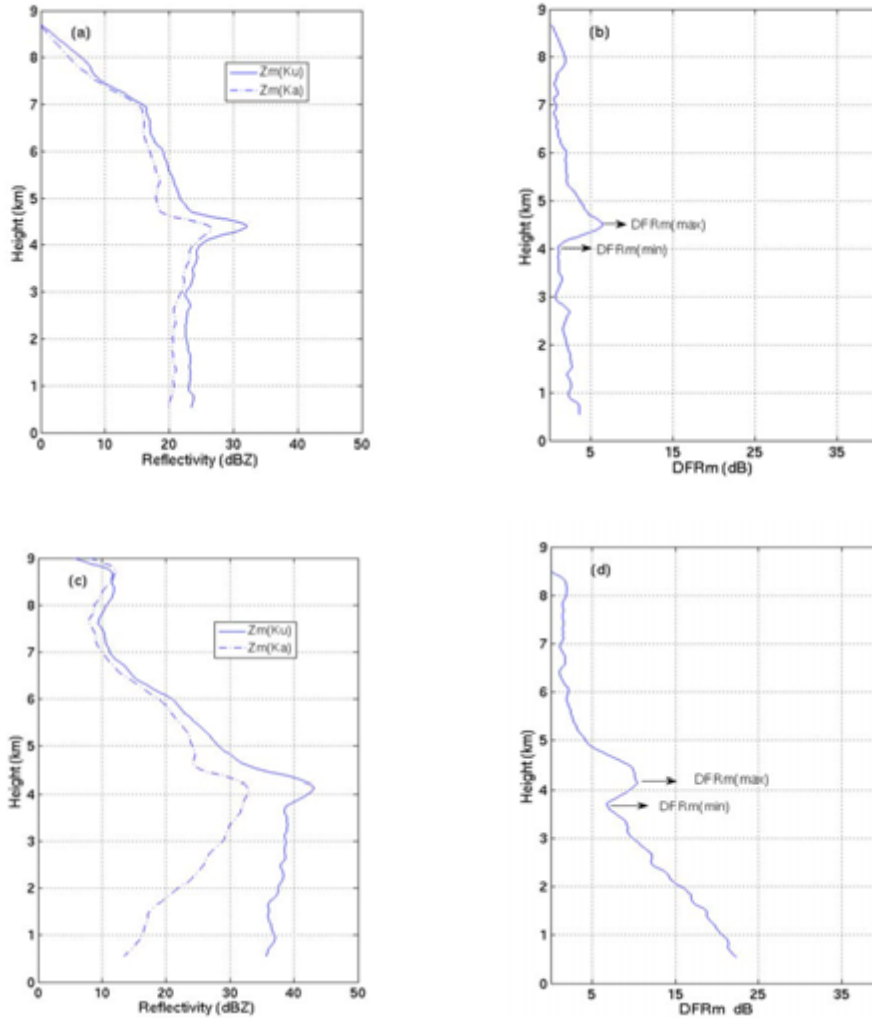


Figure 3.5. Typical vertical profile for stratiform (a)(b) and convective (c)(d) rain from NAMMA APR-2 data; (a)(c) Measured reflectivity at Ku- and Ka- band; (b)(d) DFRm. $DFRm(max)$ and $DFRm(min)$ marked on (b) and (d) are local max and min value.

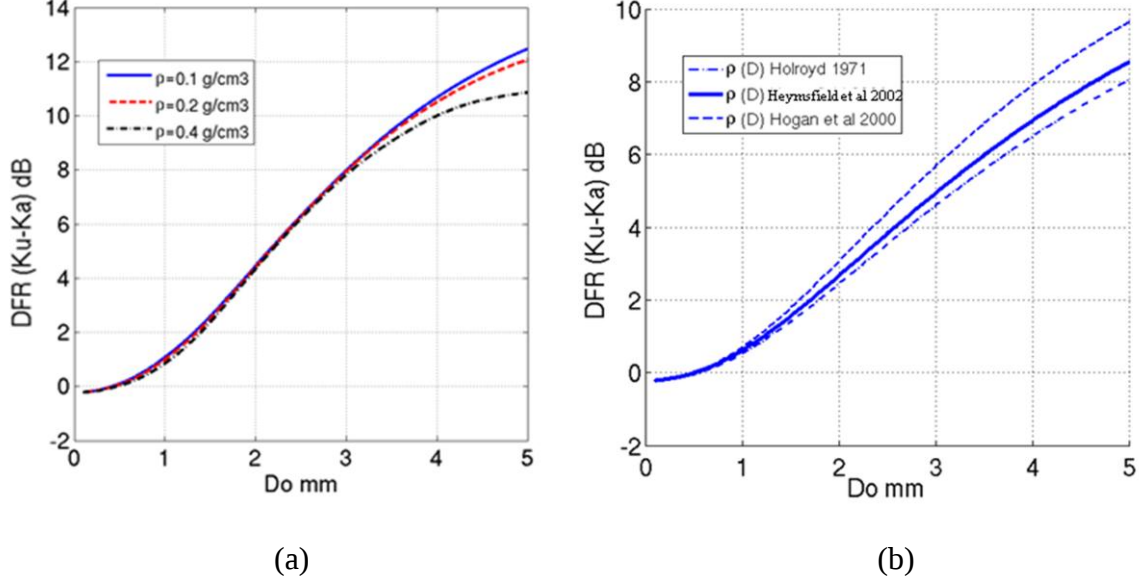


Figure 3.6. (a) DFR versus D_0 for dry snow with snow density of 0.1, 0.2 and 0.4 g/cm^3 . (b) DFR versus D_0 for snow using different density versus size relations.

exponential distribution ranging between 0.03 to 10 cm. The large value of D_0 indicates there are more particles with large sizes. It can be seen from both plots that the DFR is a monotonically increasing function of D_0 within a 0 to 5 mm range, which covers most of the snow particle sizes. The small values of $DFRm$ at top bins, as shown in Figure 3.5 (b) and (d), indicate that the snow particles are relatively small. The particles start to aggregate when they fall and this explains the slight increase of $DFRm$ with decrease of height. It should be noted that in the ice region, the attenuation difference δPIA is negligible compared with DFR . Therefore, the shape of $DFRm$ is controlled by DFR in the ice region.

Below 5 km, as in Figure 3.5 (b) and (d), the $DFRm$ increases sharply until it hits a local maximum value, then it decreases with decreasing height until it reaches a local minimum value. This shape is associated with the precipitation process in the melting layer. For convenience of description, Figure 3.7 shows a schematic plot of a typical $DFRm$ profile with key points A, B, C, and D marked. These key points are $DFRm$ slope peak where the gradient of the $DFRm$ profile reaches its maximum magnitude (point A); $DFRm$ local maximum (point B); $DFRm$ local minimum (point C); and $DFRm$ value toward surface (point D). Within the melting layer, both DFR and δPIA control the shape of the $DFRm$ profile. In order to explain the shape of the $DFRm$ within the melting layer, figure 3.8 (a) shows the theoretical relation of DFR versus Do for melting particles with three melting states. A spherical model is applied to the melting particles, which are composed of water, ice and air. There are other melting layer models such as two-layer coated model (Hardaker et al., 1995; Meneghini and Kozu, 1990) and a stratified sphere melting particle model proposed by Liao and Meneghini, (2005). Due to the lack of knowledge of true melting processes, it is hard to judge which scattering model is preferable. For simplicity of analysis, a uniformly mixed sphere model is used in this study and the Bruggeman (1935) equation is applied to calculate the dielectric constant of the mixture. Gamma distribution is applied for melting particle sizes, with shape factor μ assumed to be 0. Different water fractions indicate different melting statuses within a melting process, and a bulk-averaged water fraction is used in this study. The solid line shows the relation of melting particles with a water fraction of 0.01, which is the state very close to the dry snow particle. If we assume that the height of point A is where the melting layer starts, a water fraction of 0.01 could represent the melting status at point A. The dash-dot line shows the relation for melting particles with water fraction of 0.2. A

water fraction of 0.2 is associated with the melting state at point B in figure 3.8 (a) using Awaka et al.'s (1985) melting layer model. Figure 3.8 (b) shows the relation between water fraction and

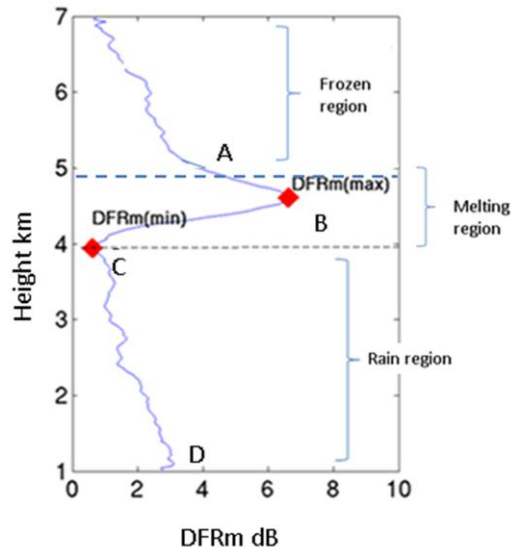
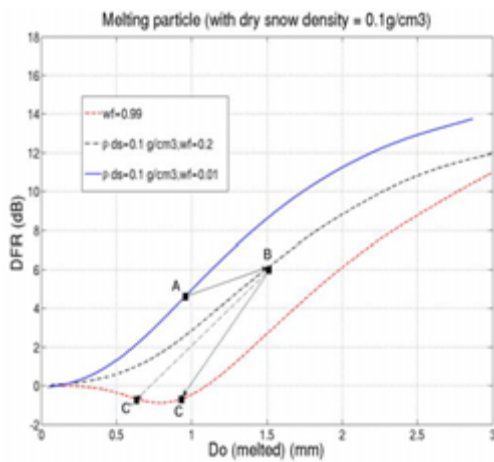
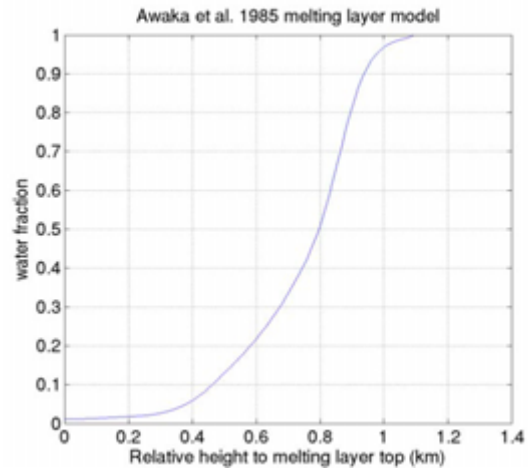


Figure 3.7. Schematic plot of DFRm profile with key points A, B, C, and D. Point A: slope of DFRm has peak value. Point B: local maximum of DFRm. Point C: local minimum of DFRm. Point D: DFRm value near surface.



(a)



(b)

Figure 3.8. (a) DFR versus D_0 for melting particles of dry snow density of 0.1 g/cm^3 and bulk averaged water fraction of 0.01, 0.2 and 0.99. Points A, B, and C (C') correspond to the A, B, and C points in Figure 3.7. (b) Bulk averaged water fraction versus relative height to melting layer top (km) using Awaka et al. (1985) melting layer model.

relative height to the melting layer top applied in Awaka et al.'s model. The dashed line illustrates the same relation for melting particles with a water fraction of 0.99, and this is the state where the melting process ends (height of point C). To estimate ΔPIA , ΔDo is assumed to be 0.5 dB and 1 dB at points B and C, respectively, which is a reasonable value for a stratiform profile. The corresponding ΔDo retrieved from DFR from point A to B is increased from around 1 mm to 1.5 mm. From point B to point C, ΔDo decreases from 1.5 mm to either 0.6 mm or 0.9 mm (marked as point C and C' in figure 3.8(a) where a double solution exists (Liao et al., 2003; Meneghini et al., 2002), possibly due to the “breakup” process. Melted ΔDo is used in the simulation of figure 3.8(a).

From around 4 km and below in figure 3.5 (b) and (d), the $DFRm$ profile continues to increase with decreasing height and this is the rain region. The DFR value doesn't change much in the stratiform rain region due to balance in the various precipitation processes (Yokoyama and Tanaka, 1984). The increase of $DFRm$ below 4 km is mainly due to the attenuation difference. A theoretical relation of DFR versus ΔDo using the Beard and Chuang (1987) rain drop model is shown in figure 3.9 (a). For convective rain, ΔDo normally won't exceed 2~3mm. It can be seen from figure 3.9 (a), that the contribution to the DFR value from ΔDo is about 10 dB or less. Any $DFRm$ value beyond 10 dB, as shown in figure 3.5(d), is due to the attenuation difference ΔPIA accumulated from the storm top to the range of interest. The increase of the $DFRm$ value in rain is obvious for both stratiform and convective rain. The slope of $DFRm$ with respect to the height is much larger for convective than for stratiform rain. Figure 3.9(b) shows the theoretical relation of specific attenuation at Ku- ($k(ku)$) and Ka- ($k(ka)$) band as well as the specific attenuation difference Δk ($=k(ka) - k(ku)$) versus the rain rate. From the figure, a higher rain rate, which

is commonly associated with convective rain, corresponds to a larger specific attenuation difference. Since DFR_m is directly proportional to δPIA , it will be larger in convective than in stratiform rain. Based on the analysis above, signatures on the DFR_m profile such as DFR_m local max and min value as well as the slope of DFR_m profile imply hydrometeor phase transition from the frozen to the liquid region. These signatures, though they might be different in values, are common for different rain types.

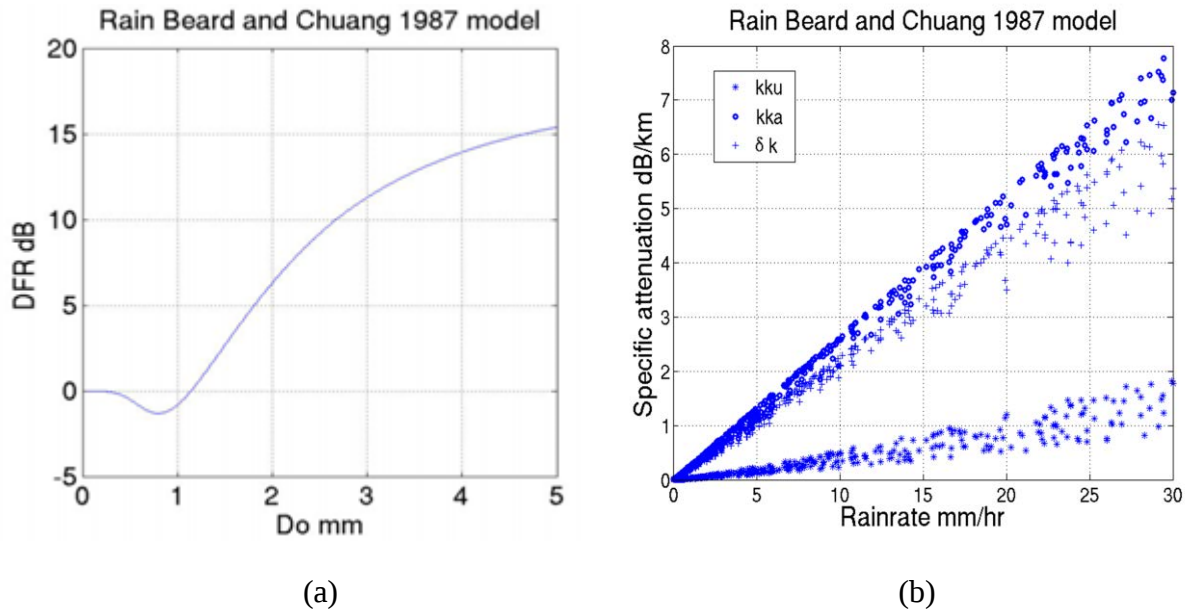


Figure 3.9. (a) Theoretical relation of DFR versus D_0 for rain using Beard and Chuang rain drop model with $\mu=0$ and temperature of 10 °C. (b) Theoretical relation of specific attenuation at Ku- and Ka- band versus rain rate using the same rain model as in (a). δk is the differential specific attenuation.

3.5 PROFILE CLASSIFICATION METHOD FOR GPM-DPR

3.5.1 Precipitation type classification method (*PCM*)

As discussed in section 3.4, a *DFRm* profile holds rich information for precipitation type classification. In order to quantify the features of *DFRm*, a set of *DFRm* indices are defined. Let $V1$ be

$$V1 = \frac{DFR_m(max) - DFR_m(min)}{DFR_m(max) + DFR_m(min)} \quad (3.10)$$

$DFR_m(max)$ and $DFR_m(min)$ are shown in figure 3.5. Let $V2$ be the absolute value of the mean slope for *DFRm* below the local minimum point. The first several range bins above the surface are eliminated to avoid surface clutter contamination.

$$V2 = abs(mean(DFR_m slope)) \quad (3.11)$$

Both $V1$ and $V2$ are normalized values and not dependent on the height or depth of the melting layer. As discussed in section 3.4, $V1$ values are normally larger for stratiform than for convective rain and $V2$ values are larger for convective than for stratiform rain. To further enlarge the difference between stratiform and convective rain types, a third *DFRm* index $V3$ is defined as

$$V3 = \frac{V1}{V2} \quad (3.12)$$

The *DFRm* index V3 can be an effective parameter and provide a separable threshold for performing precipitation type classifications.

To explore the capability of the *DFRm* index V3 in *PCM*, airborne radar data were used. In the analysis of *PCM*, all good datasets from the field experiments of NAMMA, GRIP, and Wakasa Bay were separated into model and test data. Then, both the TRMM-like method (Awaka et al., 1997) and the Doppler velocity information were combined to separate APR-2 model data into stratiform, convective and other rain types. The logic for combining the classification type decisions from the TRMM-like method and the velocity information is shown in table 3.1. If updrafts could be found from the Doppler velocity profile with the threshold of mean absolute value larger than 1.5 *m/s*, then this profile was classified as convective rain in this study. Otherwise, the rain type as decided by TRMM-like method was used. After the stratiform and convective rain model datasets were prepared, the *DFRm* index V3 was calculated for each vertical profile.

Table 3.1. Combined decision from TRMM-like method and velocity information. ‘S’, ‘C’, ‘O’ represent stratiform, convective and other rain type. ‘U’ and ‘no’ represent whether updraft exists or not respectively.

TRMM-like	Velocity	Decision
‘S’	‘U’	‘C’
‘C’	‘U’	‘C’
‘O’	‘U’	‘C’
‘S’	‘no’	‘S’
‘C’	‘no’	‘C’
‘O’	‘no’	‘O’

Figures 3.10 and 3.11 show histogram plots of the $V3$ value for stratiform and convective rain database, respectively, collected from the NAMMA campaign. The CDF (cumulative density function) of the $V3$ value is calculated for convective rain and the 90% confidence line gives the $V3$ value of $C1$. This means that 90% of the $V3$ values are smaller than $C1$ for convective rain. For stratiform rain, $CDF' (=1-CDF)$ is calculated and the 90% confidence line hits the value of $C2$, which indicates that 90% of stratiform rain has a $V3$ value larger than $C2$. The $C1$ and $C2$ variables are 0.09 and 0.201, respectively. $C1$ value is smaller than $C2$. In other words, based on the 90% confidence line, The $DFRm$ index $V3$ can separate stratiform and convective rain. Therefore, statistical evaluation of NAMMA data indicates there exists thresholds for PCM which can be summarized as follows: Stratiform: $V3 > C2$; Convective: $V3 < C1$; Transition type: $C1 \leq V3 \leq C2$. “Transition” type is neither a stratiform, nor a convective rain type, but a type transitioning from stratiform to convective rain. The criteria above were applied to the test data and compared with the combined decision made from TRMM-like as well as velocity criteria. The percentage of the profiles with common classification is 83 % and 71 % for stratiform and convective rain, respectively. The evaluation procedure for PCM is shown in a block diagram in figure 3.12.

A similar analysis was performed using GRIP and Wakasa Bay data, and table 3.2 shows the corresponding $C1$ and $C2$ values for all three campaigns. Table 3.2 illustrates that the $DFRm$ index $V3$ can separate stratiform and convective rain, and the $C2$ values from three campaigns are very close. Considering that the NAMMA, Wakasa Bay, and GRIP campaigns were located in different geographic locations and conducted over a six year span of time, the robustness of this decision procedure is very good. The $DFRm$ index $V3$, defined in (3.12) yields normalized

values that are not dependent on the depth of the melting layer and the height of the melting layer top. This means that C2 might be a stable value for stratiform rain among different geographic locations around the globe. The index V3 carries important information and might be applied to perform precipitation type classification for DPR. The variability of C2 is fairly tight compared to C1 from different datasets.

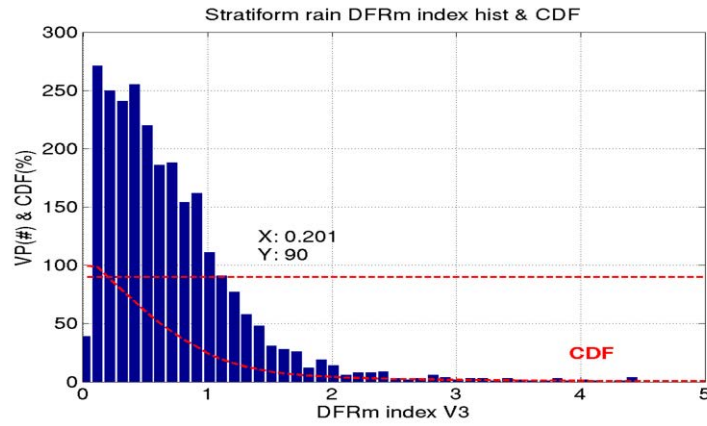


Figure 3.10. Histogram of *DFRm* for stratiform rain database of NAMMA experiment.

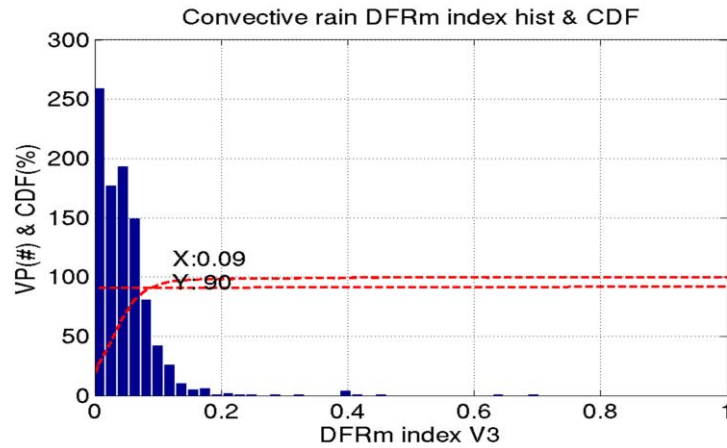


Figure 3.11. Histogram of *DFRm* for convective rain database of NAMMA experiment.

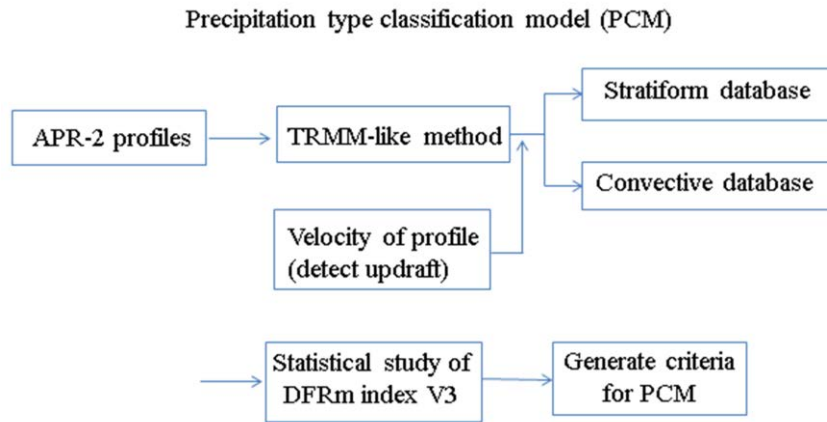


Figure 3.12. Flow chart of *PCM* analysis.

Table 3.2. PCM criteria for NAMMA, GRIP and Wakasa Bay campaigns with 90% CDF threshold.

90% CDF	NAMMA	GRIP	Wakasa Bay
C1	0.09	0.120	0.101
C2	0.201	0.216	0.192

3.5.2 Hydrometeor profile characterization (*HPC*) method

The hydrometeor profile characterization model (*HPC*) is used in profile classification for GPM-DPR. It determines the phase state of the different sections of the range profile. It decides the melting layer top and bottom height of each vertical profile. Microphysical retrieval algorithms (solver module in Figure 3.1) rely on the *HPC* to decide what theoretical relations to apply. The vertical profile of the *DFRm* carries rich information on the hydrometeor phase state, including ice, melting ice, and rain, as discussed in section 3.4. To evaluate the capability of the *DFRm* to detect the hydrometeor phase, airborne radar data from APR-2 were used.

The main parameter used in the *HPC* is the *DFRm* profile and its range variability. The criteria for the melting layer top in the *HPC* is defined as the height at which the slope of the *DFRm* profile hits a peak value. Similarly, the melting layer bottom is defined as the height at which the *DFRm* profile has a local minimum value. Figure 3.12 illustrates a sample APR-2 overpass from NAMMA experiment. The data details are discussed in Chapter 2. Figure 3.13 shows two sample profiles indicated as “A” and “B” in Figure 3.12. The “A” profile shows typical stratiform rain and “B” typical convective rain. The dashed lines in both cases are the melting layer top and bottom as defined in the *HPC*.

To test whether the measured dual-frequency ratio (*DFRm*) vertical profile can be applied to detect the phase state of hydrometeors, we compared the criteria of *HPC* with other existing criteria. Different criteria are available in the literature regarding the melting region detection

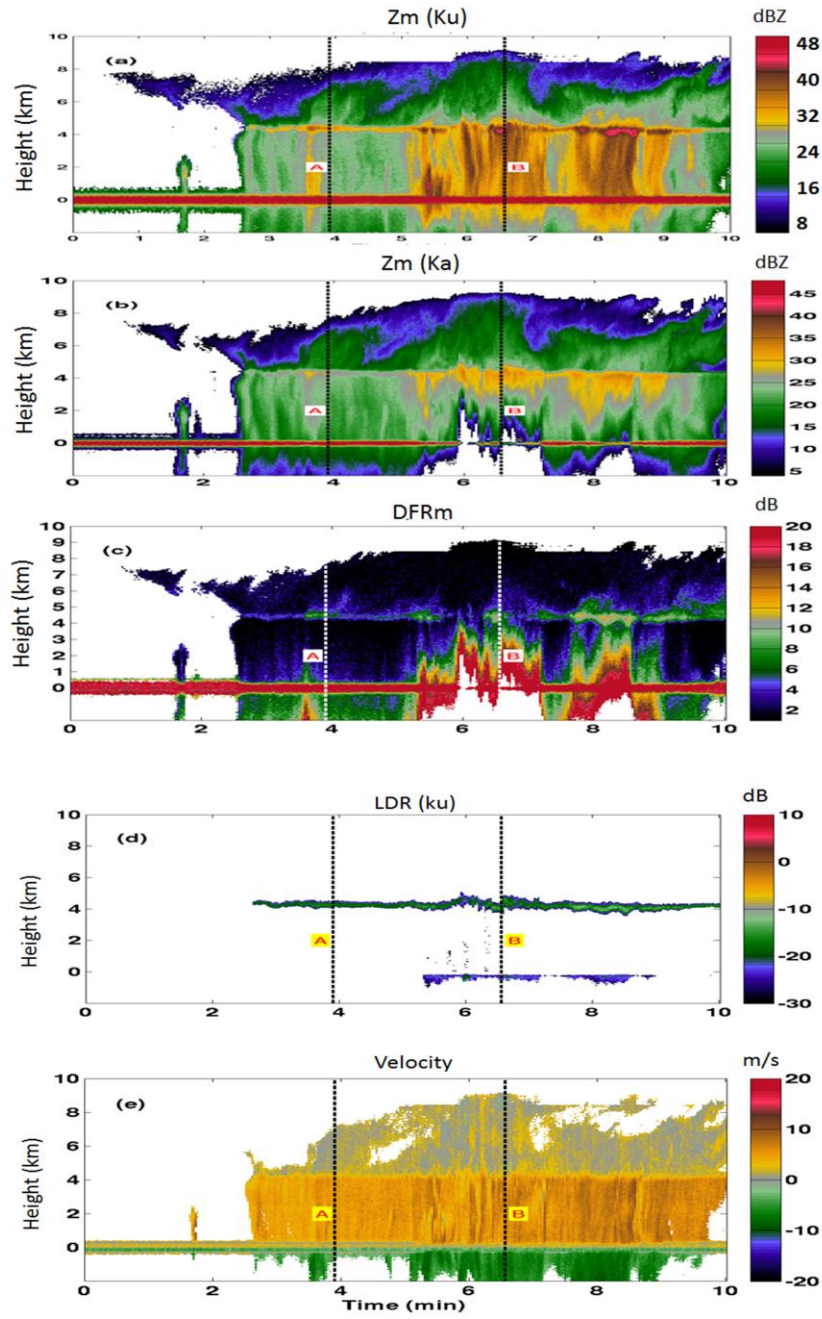


Figure 3.13. Measurements of APR-2 NAMMA data at nadir. (a) Measured reflectivity at Ku band; (b) measured reflectivity at Ka- band; (c) measured dual-frequency ratio (*DFRm*); (d) linear depolarization ratio (LDR) at Ku- band; (e) Doppler velocity at Ku-band.

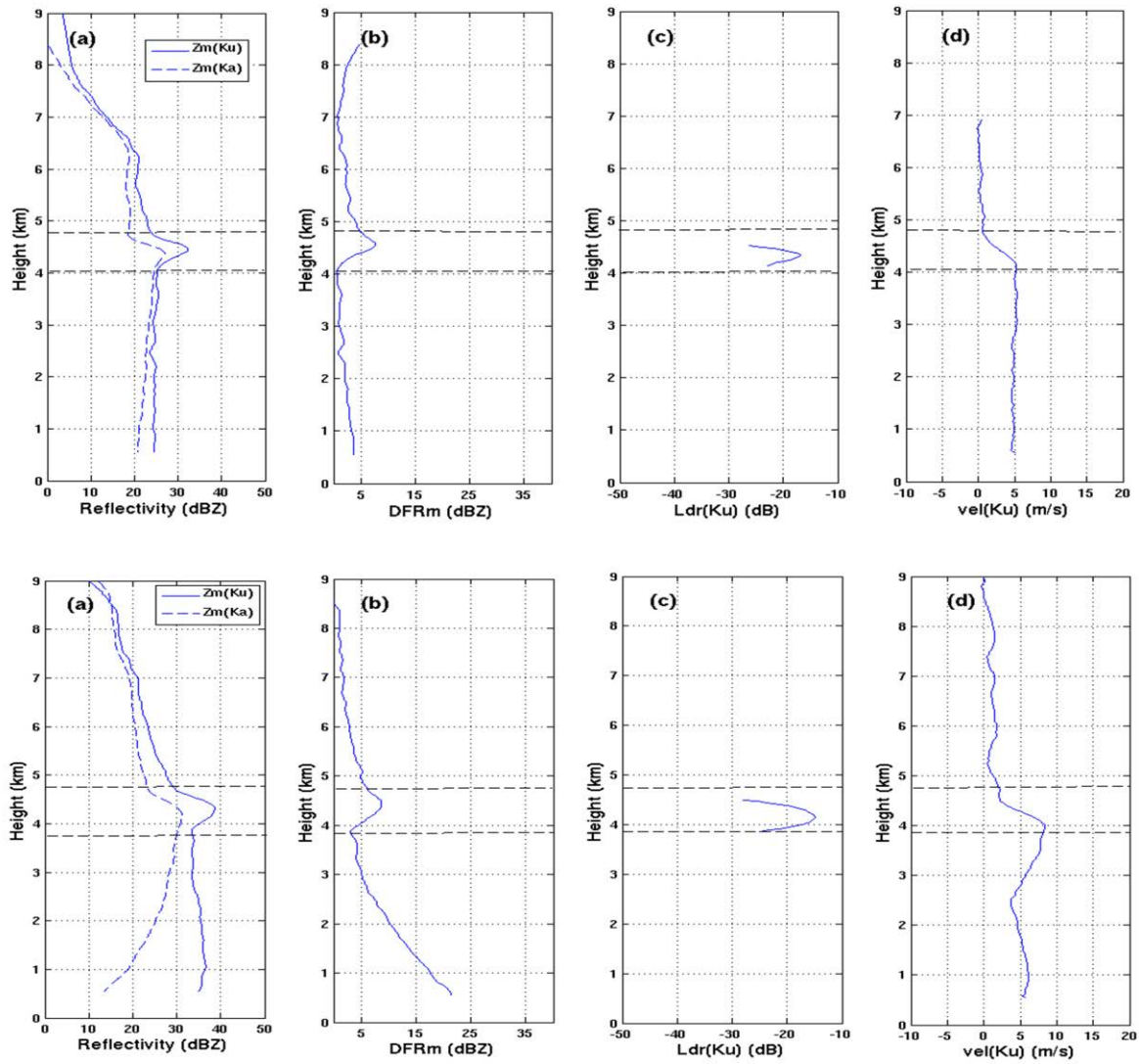


Figure 3.14. Top row: Profile (A) shown in figure 7. (a) $Z_m(Ku)$ and $Z_m(Ka)$; (b) DFR_m ; (c) LDR; (d) Velocity; Dashed lines are melting layer top and bottom decided by *HPC*. Bottom row: Profile (B) shown in figure 3.13. (a) to (d) are the same as in top row.

using different radar parameters. Tilford et al. (2001) used the gradient of reflectivity (Z_m) to detect the bright band top and bottom for stratiform rain type. The linear depolarization ratio (LDR) has been pointed out by many researchers as an important signature in melting phase detection, with certain thresholds determined for different hydrometeor particles (Smyth et al., 1998; Bandera et al., 1998; Tan and Goddard, 1995; Hines, 1983). Typical vertical profiles of reflectivity as well as the corresponding velocity for stratiform and convective type were extensively studied by Fabry and Zawadzki, (1994). Baldini and Gorgucci (2006) mentioned that the rapid change of the hydrometeor fall velocity is an implication of the melting layer. The curvature of velocity was used by Zrnica et al. (1994) in characterizing the melting boundaries. Klaassen (1988) found that the melting bottom can be detected by maximum of velocity.

The APR-2 collected simultaneous measurements of the linear depolarization ratio (LDR) and Doppler velocity, which are valuable for cross-validation of the *HPC*. A schematic diagram of the comparisons between the criteria used in *HPC* and the criteria mentioned above is shown in Figure 3.15 for both melting layer top and bottom. The data applied for comparison are profiles classified as stratiform rain using both a TRMM-like method and Doppler velocity information. Figure 3.16 shows the comparisons for the melting layer top between *HPC* criteria and the four methods listed in figure 3.15 (a) using NAMMA data. Normalized bias (NB) is defined as the difference between the mean estimate from one of the four criteria and the *HPC* criteria normalized to the *HPC* criteria, while normalized standard error (NSE) is the root-mean-square error normalized with respect to the *HPC* criteria. From figure 3.16 (a) and (b), it can be seen that the estimation from the *HPC* criteria is in between the Z_m gradient estimation and the

Z_m curvature estimation. The height of the melting layer top estimated by the *HPC* criteria is higher than the height detected by the Z_m gradient method; normalized bias (NB) equals -2.6%.

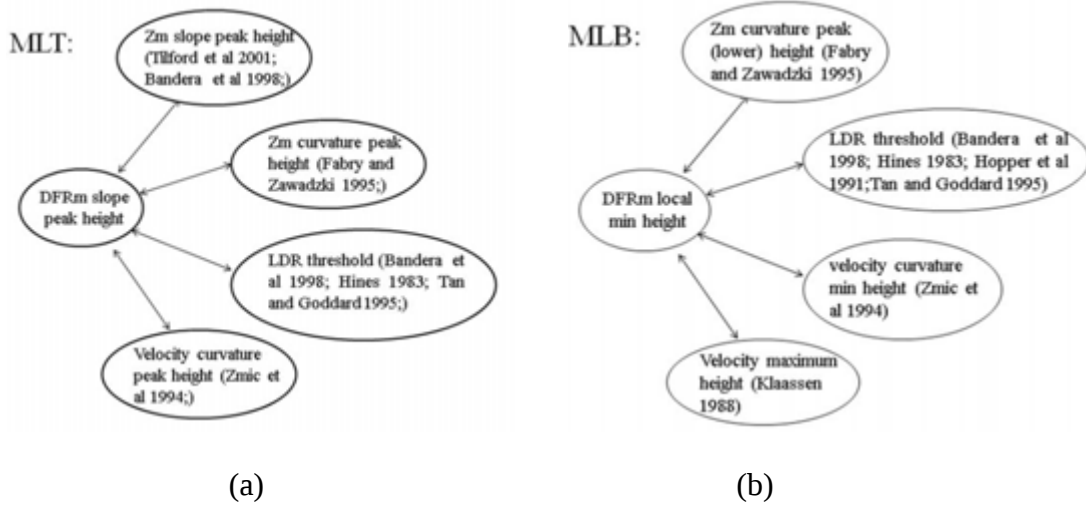


Figure 3.15. Schematic plots of some current criteria for melting layer boundaries detection and their possible relations with *HPC* criteria: (a) melting layer top criteria; (b) melting layer bottom criteria.

It agrees with the statement made by Fabry and Zawadzki (1994) that Z_m gradient maximum height underestimates where the bright band starts. In figure 3.16 (c), the *HPC* criteria match best with the velocity curvature estimation showing normalized bias (NB) as small as -1.3%. Vertical Doppler velocity is not available for GPM-DPR, but it is an important parameter that indicates microphysics properties. The *HPC* criteria compare well with the LDR criteria, using a -28dB threshold for melting layer top estimation in figure 3.16 (d), and the bias between these two criteria is around -2.8%. A similar comparison for the melting layer bottom is summarized in table 3.3. Among the four comparisons of melting layer bottom, the *HPC* criteria show best matches with velocity curvature and velocity maximum estimations. The NB is as small as 2.2%

and 1.6% respectively. Both Z_m curvature and LDR estimations show slightly higher melting layer bottom than the *HPC* or the velocity curvature method.

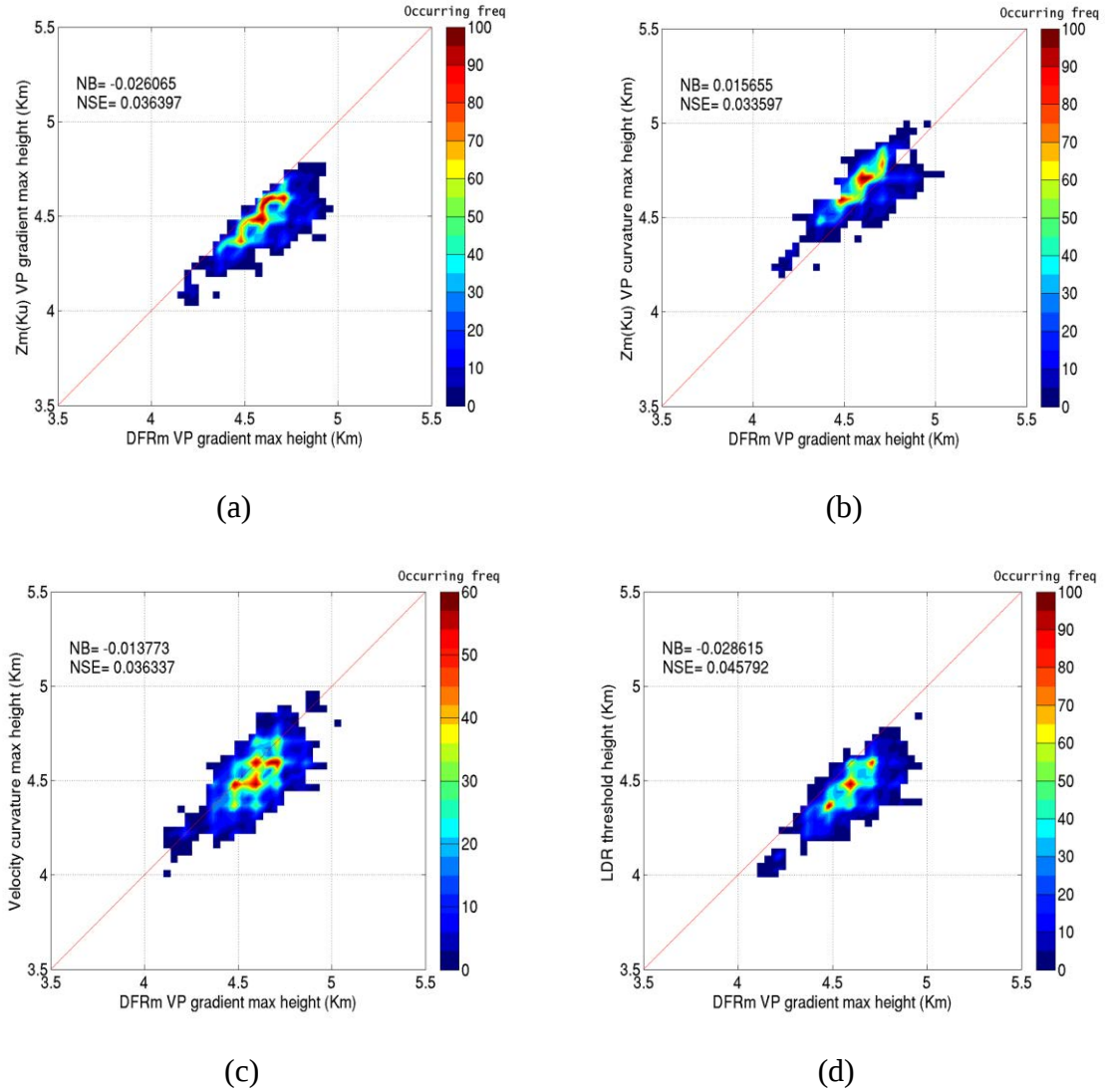


Figure 3.16. Comparisons of the melting layer top between *DFRm* criteria and four existing criteria listed in figure 3.15(a). (a) *DFRm* versus Z_m gradient maximum; (b) *DFRm* versus Z_m curvature maximum; (c) *DFRm* versus velocity curvature maximum; (d) *DFRm* versus LDR threshold.

Table 3.3. Comparisons of melting layer boundaries between different criteria for NAMMA, GRIP and Wakasa Bay data. Only stratiform profiles classified by TRMM-like method and Doppler velocity information are used in the comparisons.

	Criteria	DFRm slope peak (NAMMA)	DFRm slope peak (GRIP)	DFRm slope peak (Wakasa Bay)
Melting layer top comparison	Zm slope peak	NB= -2.6%; NSE= 3.6%	NB= -2.5%; NSE= 3.6%	NB= -4.9%; NSE= 6.6%
	Zm curvature peak	NB= 1.6%; NSE= 3.3%	NB= 1.5%; NSE= 3.0%	NB= 2.8%; NSE= 5.2%
	LDR	NB= -2.8%; NSE= 4.5%	NB= -3.3%; NSE= 4.2%	NB= -6.0%; NSE= 7.2%
	Velocity curvature peak	NB= -1.3%; NSE= 3.6%	NB= -1.4%; NSE= 3.7%	NB= -1.9%; NSE= 5.6%
	Criteria	DFRm local min (NAMMA)	DFRm local min (GRIP)	DFRm local min (Wakasa Bay)
Melting layer bottom comparison	Zm curvature peak	NB= 4.3%; NSE= 5.5%	NB= 3.7%; NSE= 5.0%	NB= 4.3%; NSE= 6.9%
	LDR	NB= 4.5%; NSE= 5.9%	NB= 4.0%; NSE= 5.4%	NB= 5.4%; NSE= 11.2%
	Velocity curvature min	NB= 2.2%; NSE= 4.9%	NB= 1.7%; NSE= 4.4%	NB= -0.08%; NSE=7.0%
	Velocity max	NB= 1.6%; NSE= 5.9%	NB= 1.9%; NSE= 4.3%	NB= -2.6%; NSE= 13.9%

Overall, the *HPC* method shows good agreement with velocity criteria for the estimation of both the melting layer top and bottom. Since GPM-DPR will not have Doppler velocity, the *DFRm* profile could be a good substitute to help with hydrometeor identification. LDR is also an effective parameter for detecting phase state since the increase of LDR is associated with melting particles. In the comparison, LDR with a threshold of -28 dB shows a narrower melting region than the *DFRm* detector, with NBs of -2.8% and 4.5% for melting layer top and bottom estimations. This might be caused by using a hard threshold of LDR or data quality. The same

analysis was performed using GRIP and Wakasa Bay data. Table 3.3 illustrates the results for all three campaigns and it is easy to see that similar conclusions can be made in each case.

Although the comparisons shown above are based on stratiform rain profiles, *DFRm* criteria used in *HPC* can be applied to profiles beyond stratiform rain as long as the *DFRm* local max and min are detectable. Here, we define the difference between max and min of the *DFRm* within an estimated melting height window larger than 1 dB ($DFRm \text{ (max)} - DFRm \text{ (min)} > 1 \text{ dB}$) as detectable. Table 3.4 shows the estimates between the *HPC* criteria and LDR as well as velocity criteria based on all *DFRm* profiles with detectable melting layer signatures. Except for a relatively larger NSE, the NB values shown in table 3.4 are very close to those shown in table 3.3. Furthermore, it should be pointed out that, for NAMMA, GRIP and Wakasa Bay data, around 77.5%, 73.33%, and 88%, respectively, of convective and other type rain classified using a TRMM-like method and Doppler velocity information have a detectable melting layer signature on the *DFRm* profile. This means the *HPC* criteria are independent of stratiform and convective rain types.

Table 3.4. Comparisons between *DFRm* criteria and LDR, velocity criteria based on APR-2 data with detectable *DFRm* local max and min values along *DFRm* profile.

Criteria	DFRm criteria (NAMMA)	DFRm criteria (GRIP)	DFRm criteria (Wakasa Bay)
LDR	MLT: NB= -2.1%; NSE= 5.6%	MLT: NB= -2.9%; NSE= 4.5%	MLT: NB= -4.9%; NSE= 9.8%
	MLB: NB= 3.1%; NSE= 5.7%	MLB: NB= 2.9%; NSE= 5.6%	MLB: NB= 6.9%; NSE= 19.5%
Velocity curvature	MLT: NB= -1.2%; NSE= 4.3%	MLT: NB= -1.4%; NSE= 4.3%	MLT: NB= -1.6%; NSE= 9.5%
	MLB: NB= 1.9%; NSE= 5.6%	MLB: NB= 1.5%; NSE= 5.2%	MLB: NB= -0.5%; NSE= 13.0%
Velocity max	MLB: NB= 1.0%; NSE= 6.4%	MLB: NB= 1.5%; NSE= 6.0%	MLB: NB= -3.6%; NSE= 16.4%

3.5.3 Availability of the method to the DPR resolution

In GPM/DPR Level 2 ATBD, DPR will have a Ku-/Ka- band matched beam vertical resolution of 250m. DPR echoes will also be oversampled at twice the rate of the matched beam: 125m. As mentioned in previous sections, APR-2 data has fine vertical resolution of around 30m. In order to evaluate the availability of a precipitation type classification model developed from APR-2 data to DPR resolutions, APR-2 data were resampled to 250m and 125m vertical resolution. Similar classification procedures as discussed in sections 3.5.1 and 3.5.2, were performed on both the NAMMA and GRIP datasets. Table 3.5 shows the *PCM* criteria based on resampled data. C1 and C2 values for both resampled cases are just slightly different as compared to the results before resampling. In both cases, C1 and C2 values can separate stratiform and convective rain based on 90% CDF, and the C2 value is very close for the NAMMA and GRIP cases indicating there might exist a common threshold for stratiform rain on the *DFRm* index V3

in different geographic locations. From the analysis above, it is evident that the profile classification method developed from the APR-2 data is applicable to GPM-DPR observations.

Table 3.5 *PCM* criteria for resampled NAMMA and GRIP data (DPR resolution) with 90% CDF threshold.

90% CDF	NAMMA (resample to 250m)	NAMMA (resample to 125m)	GRIP (resample to 250m)	GRIP (resample to 125m)
C1	0.093	0.092	0.13	0.13
C2	0.210	0.20	0.20	0.199

The horizontal resolution difference between satellite radar and airborne radar is also a concern although it is not as critical as the vertical resolution difference. Nevertheless, in order to confirm this, that is, how well the algorithm performs for GPM-DPR horizontal resolution, APR-2 data within a ~5km (DPR horizontal resolution) was averaged and processed through the same algorithm and the results are summarized in table 3.6. Only profiles at nadir are considered in the analysis in this section. Comparing the results in table 3.6 and table 3.2, C1 and C2 values are stable for all three campaigns. C2 values for a coarser horizontal resolution are slightly smaller than the values for finer resolution, which might be caused by the averaging of vertical profiles.

Table 3.6. *PCM* criteria for NAMMA, GRIP and Wakasa Bay campaigns with 90% CDF threshold using DPR horizontal resolution.

90% CDF	NAMMA	GRIP	Wakasa Bay
C1	0.09	0.112	0.10
C2	0.194	0.201	0.17

In order to evaluate the suitability of the hydrometeor profile characterization model developed from the APR-2 data for the DPR resolution, the *HPC* criteria were applied to the under-sampled APR-2 profiles to detect the melting layer top and bottom height. Since the resolution of DPR is coarse compared to APR-2 data resolution, the under-sampled data are not ideal for calculating curvature estimations, as shown in figure 3.15. The comparison in figure 3.17 is between the *HPC* criteria estimation before and after resampling using the NAMMA data. The occurring frequency in figure 3.17 shows the data points are well aligned with NB: 0.8% and -2.3% for melting layer top and bottom estimation, respectively, using 250m resolution. Similar values can be found for the 125m resolution comparison. Both normalized bias and normalized standard error come from the resolution difference. The same conclusions could be made for the GRIP data. From the above analysis, it is evident that the *HPC* developed from the APR-2 data is applicable to GPM-DPR observations.

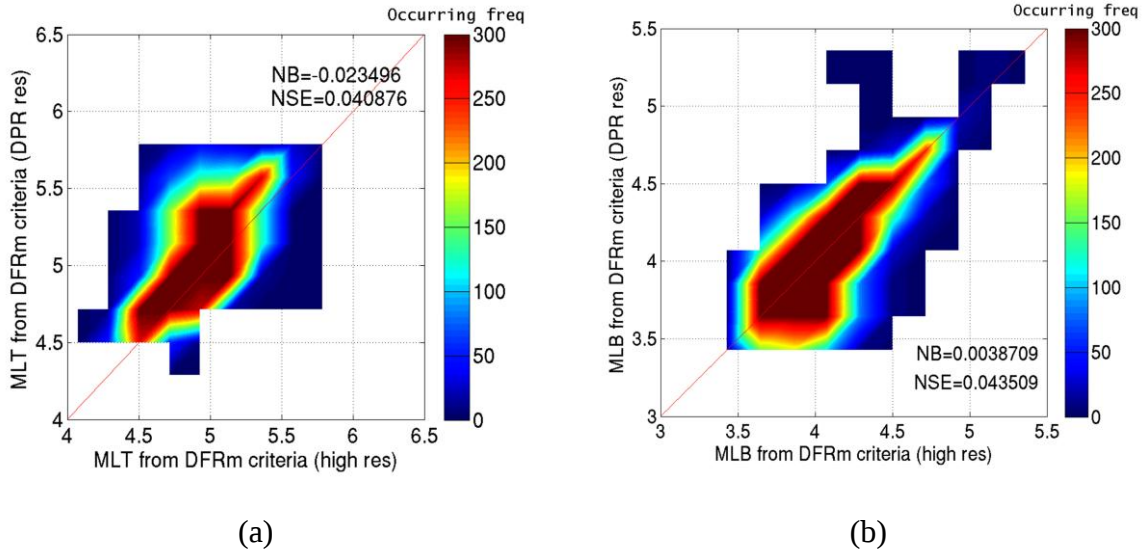


Figure 3.17. Scatter plots of melting layer top (a) and bottom (b) height detected by *DFRm* criteria before and after resampling to GPM-DPR resolution.

One major advantage of this profile classification method is its straightforwardness. It is based on radar observations and doesn't require attenuation correction beforehand, a procedure that might involve some errors. In the next section, the performance of the analysis is evaluated for profiles that are off nadir in the next section.

3.5.4 Availability of the method to off-nadir observations

The DPR on board the GPM satellite will scan cross-track up to a ~ 245 km swath. Those off-nadir beams will also provide useful information about precipitation. It is meaningful to check the availability of the *PCM* to off-nadir observations. Figure 3.18 shows a sample cross-track plot for a stratiform rain event. During the analysis, the off-nadir observation angle effect is

corrected when calculating the DFR_m index C1 and C2. Off-nadir observations at 6, 12, 18 and 22 degrees deviated from nadir are taken.

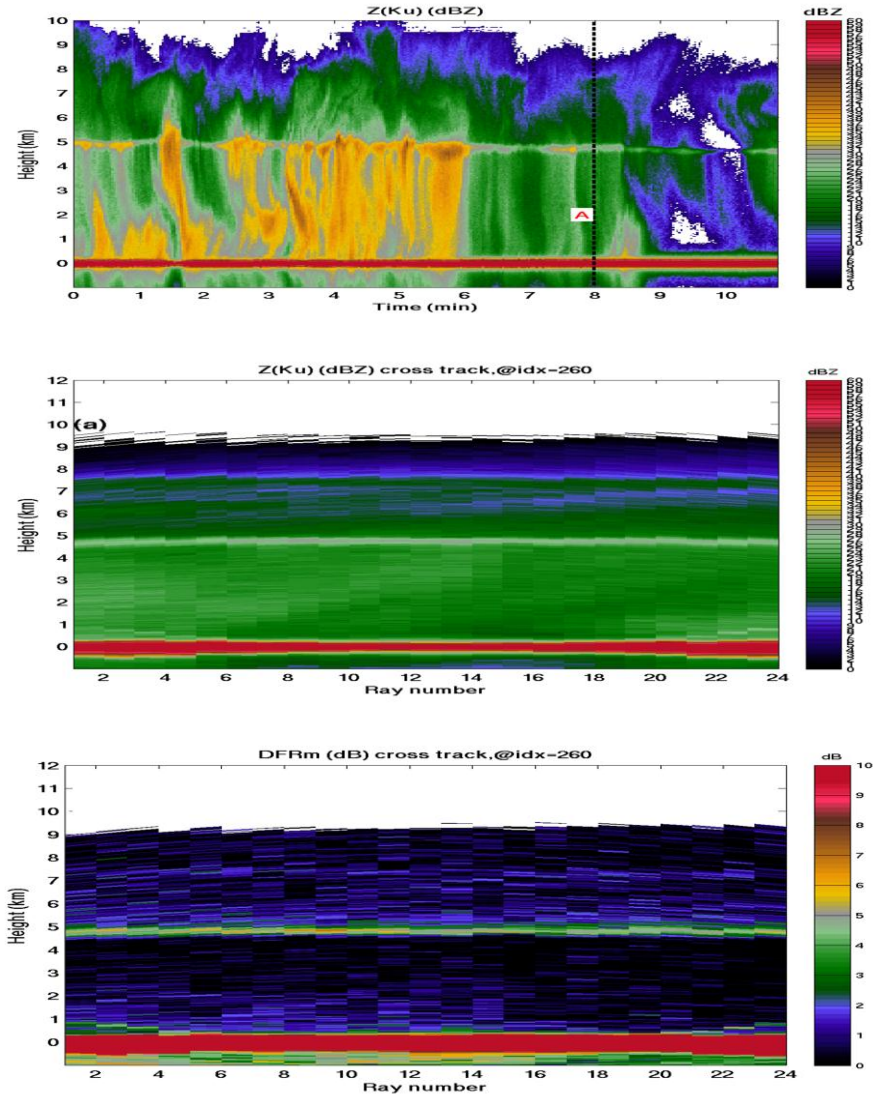


Figure 3.18. Top: Overpass of GRIP data 100901.202048 at nadir. Middle: Cross-track (Ray # 1 to 24 corresponds to off-nadir angle $\pm 25^\circ$) plot of $Z_m(Ku)$ at “A” profile shown in the top plot. Bottom: Cross-track plot of DFR_m at “A” profile.

Table 3.7. *PCM* criteria for off-nadir analysis using NAMMA, GRIP and Wakasa Bay data with 90% CDF threshold.

	NAMMA	GRIP	Wakasa Bay
@ nadir	C1=0.090 C2=0.201	C1=0.120 C2=0.216	C1=0.101 C2=0.192
Off- nadir 6 degree	C1=0.109 C2=0.204	C1=0.113 C2=0.223	C1=0.112 C2=0.215
Off- nadir 12 degree	C1=0.120 C2=0.220	C1=0.106 C2=0.221	C1=0.111 C2=0.225
Off- nadir 18 degree	N/A	C1=0.100 C2=0.210	C1=0.105 C2=0.250
Off- nadir 22 degree	N/A	C1=0.009 C2=0.220	C1=0.108 C2=0.225

Table 3.7 illustrates the *PCM* thresholds for different off-nadir observations. For observations within 6 degree off-nadir angle, C1 and C2 value biases are within 12.5% and 5.6%, respectively. It is not hard to identify that, in general, the more the observation is off-nadir, the more the C1 and C2 thresholds deviate from at nadir values. The main reason is due to the off-nadir data quality and it is not appropriate to give useful conclusions when the analysis is based on an unconvincing dataset. More detailed analysis will be performed after the off-nadir APR-2 data are re-analyzed, which is part of our future work.

3.5.5 Effect of data smoothing

Both the *PCM* and *HPC* models are based on the detection of the *DFRm* local max and min values as well as the slope and derivatives. This requires a certain degree of data-smoothing to avoid the mis-catching of local max and min values. From equations (3.10) to (3.12), the *DFRm*

index V1 is affected by the data-smoothing effect. The more the smoothing is performed, the smaller the $DFRm(\max)-DFRm(\min)$ value becomes. The V2 index is not affected by smoothing since it is an average value itself. Therefore, $DFRm$ index V3 is affected by the smoothing of data. All the analyses shown in the previous sections are based on the moving average with window length of 5. The reason for choosing a window length of 5 is the height resolution of the DPR. If we take a window length of 5 as a reference, figure 3.19 shows the effect of data-smoothing to C1 and C2 in a bias sense. As expected, both C1 and C2 values decrease when the smoothing window length increases. The HPC model detects the heights (melting layer top and bottom) where $DFRm$ profile holds certain characteristics but not the $DFRm$ value itself. Therefore, HPC won't be affected much by the data smoothing.

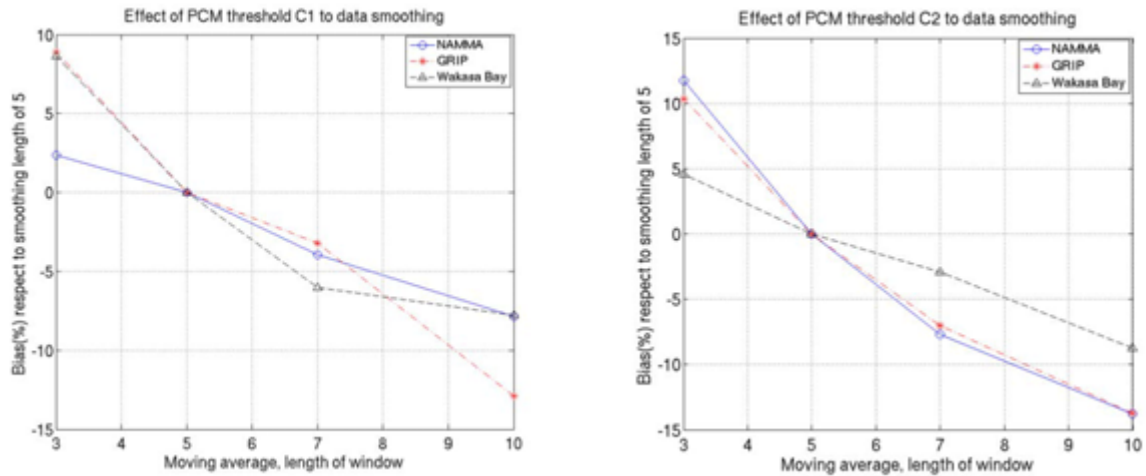


Figure 3.19. Bias of C1 and C2 thresholds for PCM due to the effect of data-smoothing.

3.5.6 Comparison with other approaches

The profile classification method described in previous sections has been compared to other methods: 1) the Z-DFR plane analysis by Liao and Meneghini (2010); and 2) the classification method used by JPL (Jet Propulsion Laboratory) through the Bayesian approach for cross-validation purpose.

Liao and Meneghini (2010) presented a pixel-based method for classifying hydrometeor types for GPM-DPR using the $Z_{ku} - DFR$ theoretical plane, assuming that snow follows the Gunn-Marshall size distribution (1958) and rain follows the Marshall-Palmer size distribution (1948). Both Z_{dr} and DFR are attenuation corrected values, which indicate that this method needs attenuation correction in advance and it might misclassify if the attenuation correction method is not proper. To verify the simulated results, Liao and Meneghini (2010) applied the method to an APR2 dataset from the Wakasa Bay experiment. The melting layer is detected by LDR in their study and from the results they concluded that snow can be easily distinguished from rain and mixed phase media. Rain, however, is not always separable from mixed phase in the $Z_{ku} - DFR$ theoretical plane. In order to make comparison, in this study, we map the attenuation-corrected NAMMA overpass data to the same simulated $Z_{ku} - DFR$ plane to study whether similar conclusions could be made using a different dataset. The melting region used for the NAMMA data is detected by the *HPC*.

Figure 3.20 indicates the mapping results, with the left top subplot the theoretical $Z_{ku} - DFR$ plane for rain (solid blue line) and snow with several fixed densities. The right top subplot shows

the 2D PDF contours of snow (left upper cluster) and rain (right lower cluster), which are completely separable according to the plot. For rain and melting snow, as shown in the right bottom subplot of figure 3.20, it is hard to separate the two since the trailing part of the melting layer yields a similar magnitude of DFR and reflectivity. This point was also concluded by Liao and Meneghini (2010). From the left bottom subplot, snow and melting snow have small overlaps, while Liao and Meneghini (2010) concluded that it is separable in the Wakasa Bay dataset. One possible reason for this difference is that the melting region top decided by the DFR_m criteria is slightly higher than that using the LDR parameter which can be seen from figure 3.16 (d). Thus a part of the snow data is classified into the mixed-phase dataset and causes the overlap. Meanwhile, both Z_{dr} and DFR used in the comparisons are all attenuation-corrected values; thus a different attenuation correction procedure may be responsible for the difference.

The results of the *HPC* have been compared to the results from melting layer detection developed by JPL (Simone et al., 2004). The algorithm details can be described as below: the method operates iteratively as a 1-D (range) multi-parametric algorithm (ML1) and a 2-D (along-track and azimuth) contiguity check (ML2). In ML1 the range profile of each parameter (down to the last range bin not affected by surface clutter) is first reduced into a piecewise linear curve (linearity is interrupted at the local maxima of the second derivative of the smoothed profile). The decision tree shown in figure 3.21 is applied to detect the presence of a melting layer of precipitation and its upper and lower boundaries. In the ML2 algorithm the result of ML1 for each radar beam is compared with the estimates for adjacent radar beams and with the general statistics of the melting layer boundaries. The result of ML2 for each radar beam is either a confirmation of ML1 estimates or a flag to discard that result and reprocess it.

The comparison is shown in figure 3.22 based on an NAMMA overpass (060903-142134) data. The melting top from both methods agree well. The melting bottoms estimated by JPL are higher on average based on the testing overpass. Scatter plots are shown in figure 3.23 with normalized bias NB =0.06 for the melting layer bottom comparison.

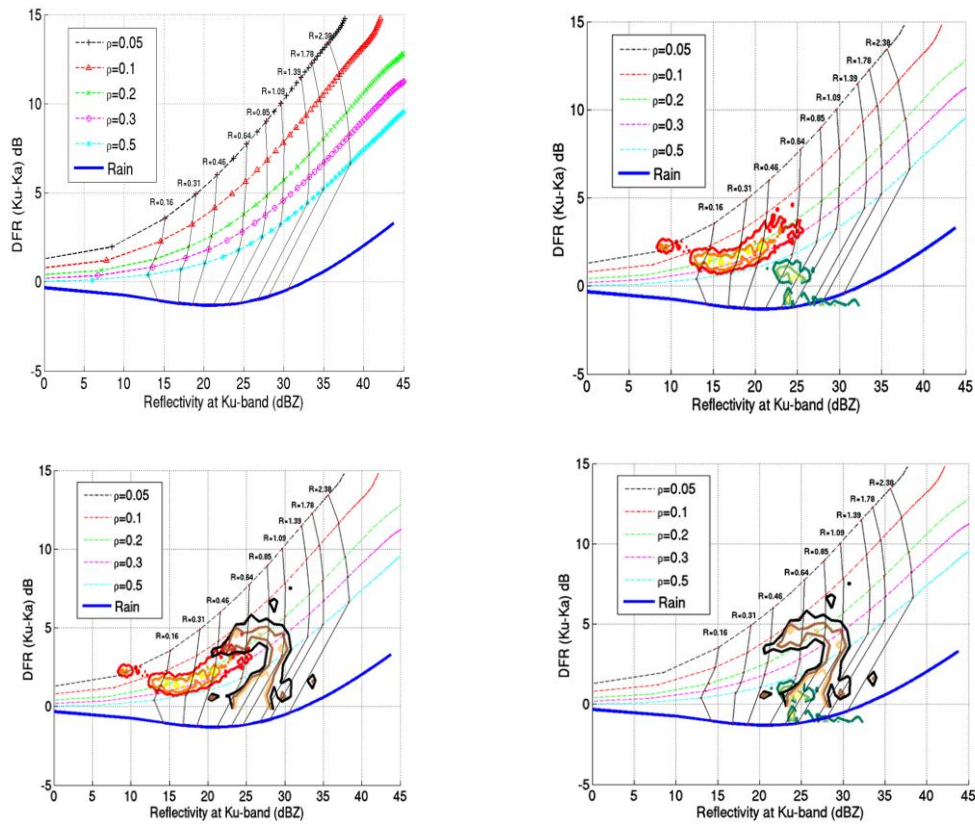


Figure 3.20. Left top: theoretical relationships between DFR and reflectivity at Ku band for snow and rain (solid line). Right top: 2D PDF contours for snow (left upper cluster) and rain (right lower cluster); left bottom: contours for snow (left cluster) and melting snow (right cluster); right bottom: contours for rain (bottom cluster) and melting snow (upper cluster).

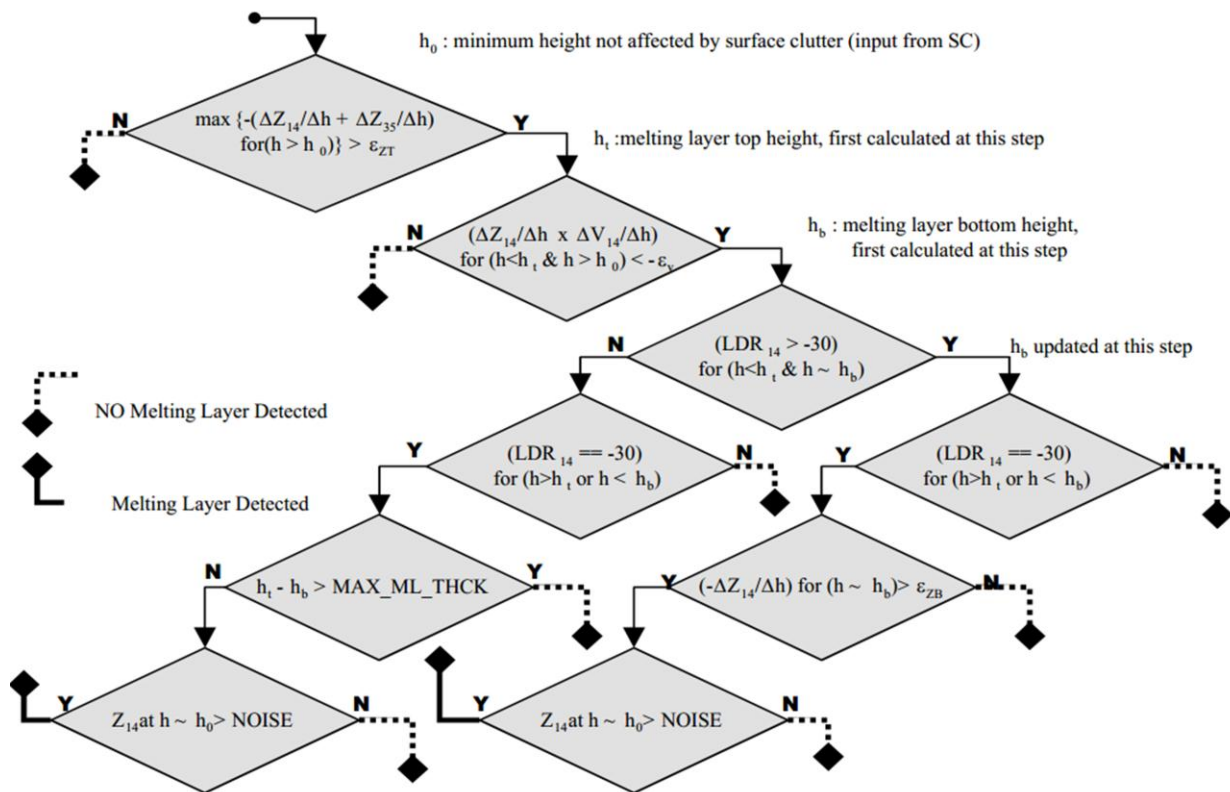


Figure 3.21 Diagram of decision tree used in the ML1 algorithm by JPL.

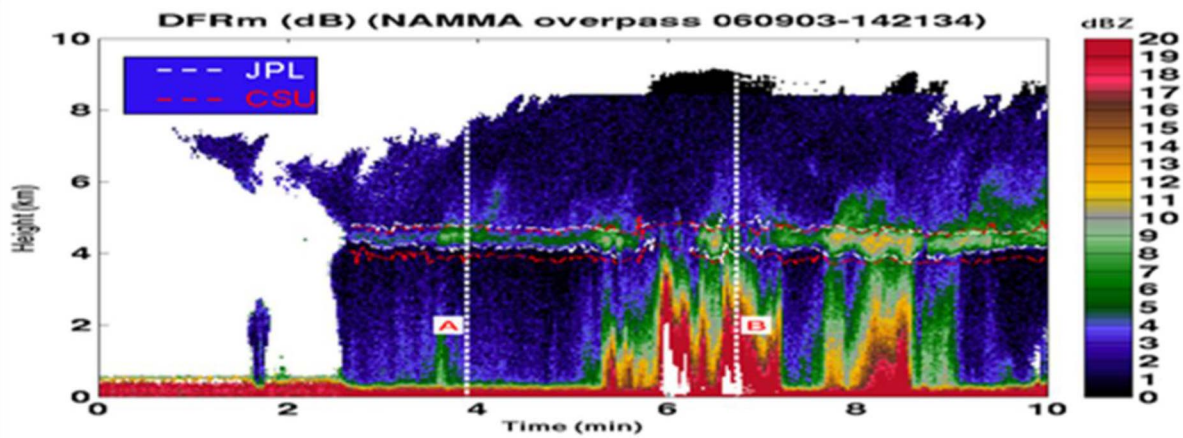
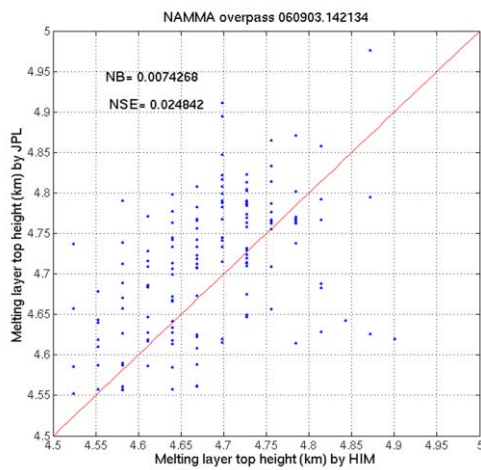
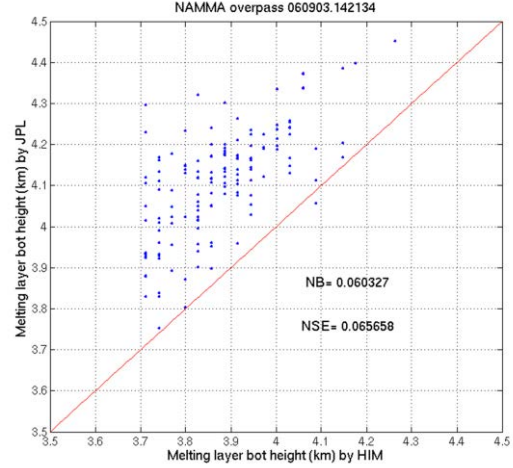


Figure 3.22. NAMMA DFRm overpass (060903-142134) with melting layer top and bottom height detected by HIM criteria and JPL results.



(a)



(b)

Figure 3.23. Scatter plot of melting layer top (a) and bottom (b) height between *HPC* criteria and JPL results.

3.6 Implementation of GPM-DPR day one algorithm

The proposed profile classification method including precipitation type classification module (*PCM*) and hydrometeor profile characterization (*HPC*) module are being tested for the GPM-DPR day one algorithm (Le and Chandrasekar, 2012). JAXA/NASA and CSU are working together to implement and test the algorithm. The profile classification method is being tested using synthetic DPR overpasses generated from TRMM overpasses through a Ka sampling experiment (Seto et al. 2013). Figure 3.24 illustrates the first orbit of synthetic DPR data (GPM DPR Level 2 ATBD). For robustness, constraint of *DFRm* V2 is added in *PCM* in order to avoid misclassification when “*DFRm* bump” is not due to melting process. The threshold of V2 are

generated based on 90% CDF of *DFRm* V2 database from the three APR-2 campaign datasets. Figure 3.25 illustrates a block diagram of *PCM* algorithm used in GPM day one algorithm. Figure 3.26 shows a sample plot of the preliminary test results using the data shown in figure 3.24. The first column of figure 3.26 shows the classification results by PCM for over land and over ocean case. The second column shows the precipitation type with the “Transition” category, introduced by the DPR algorithm, merged into the large classification categories of “Stratiform”, “Convective”, and “Other” types in order to follow TRMM legacy. However, the precipitation type details will be kept in the DPR classification numbering system. The third column of figure 3.26 shows the classification results by TRMM-like method. A comparison of figure 3.26 (b) and (c) show overall good agreement between the classification methodology. The profile classification algorithm is undergoing comprehensive testing and the final version is expected to be submitted around September of 2013.

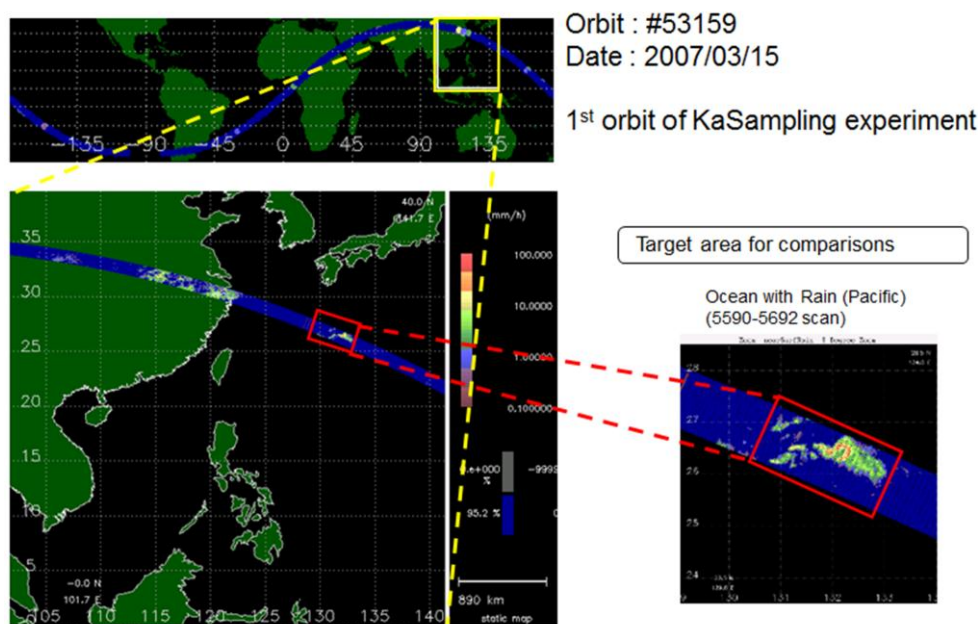


Figure 3.24. Synthetic DPR overpass generated using TRMM Ka sampling experiment.

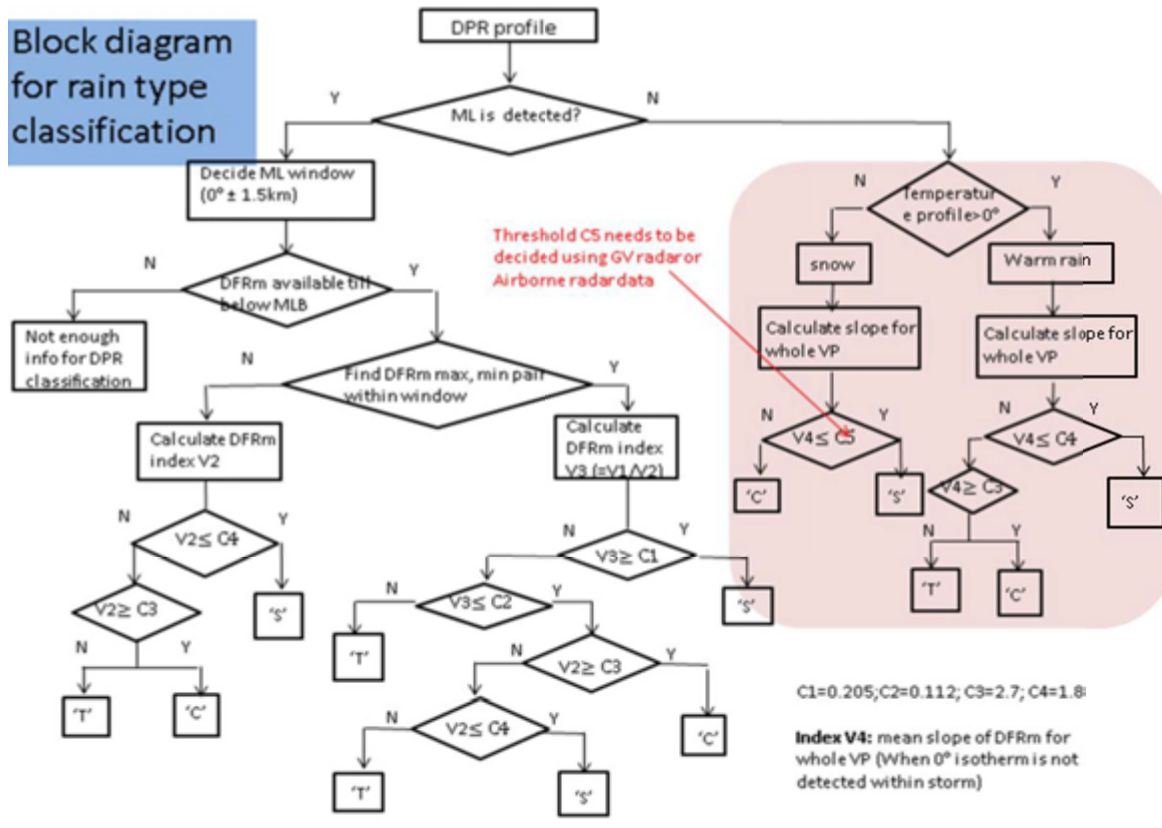


Figure 3.25. Block diagram of precipitation type classification model (PCM). Part with shadow is not implemented to the day one algorithm but will be included after the satellite is launched.

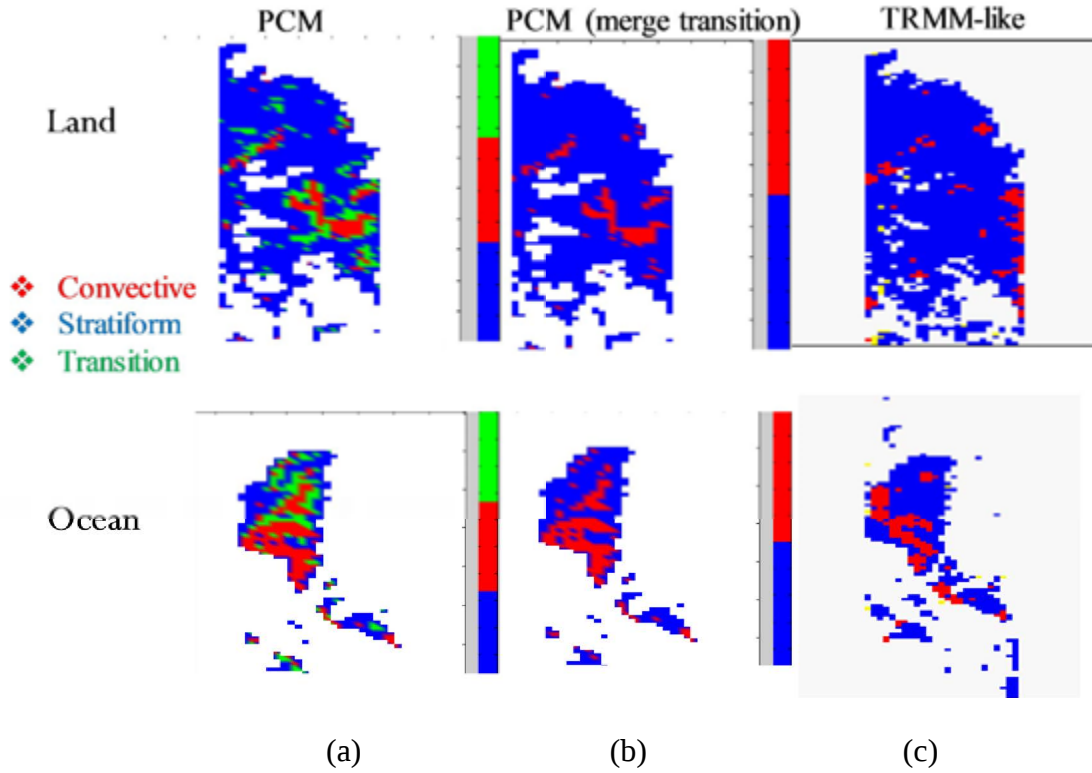


Figure 3.26. A preliminary comparison of DPR classification method (Le and Chandrasekar, 2012) and Ku-only method (Awaka et al., 1997) using the DPR synthetic data shown in figure 3.24. Column (a) Classification results by PCM criteria for over land and over ocean case. Column (b) PCM results merge into stratiform rain when H-method classification is stratiform. Column (c) Classification results by TRMM-like method.

CHAPTER 4

PRINCIPLE OF SPACE-BORNE RADAR DUAL FREQUENCY RETRIEVAL ALGORITHM

4.1 INTRODUCTION

The TRMM-PR algorithms rely on the surface-reference technique (SRT) to estimate path attenuation and correct the measured Ku-band reflectivity measurements. With the attenuation-corrected reflectivities, a modified Hitschfeld-Bordan method (Hitschfeld and Bordan, 1954) is then used to retrieve limited drop-size-distribution (DSD) information and the rain rate (Iguchi et al., 2000). One major disadvantage of single-frequency space radar like TRMM-PR is that only one of the three drop-size-distribution (DSD) parameters D_0 , can be retrieved, with two others N_w , and μ , being assumed. Therefore, k - Z and Z - R relationships, with their inherent assumptions, are used to estimate rain rate. In contrast, the proposed dual-frequency precipitation radar (DPR) on board the GPM core satellite will be equipped with two independent frequency channels. Two of the three parameters, D_0 and N_w , can be retrieved, with μ assumed. Using the DSD parameters directly is potentially a more accurate method for estimating rain rate than that used in TRMM-PR.

This chapter begins with an introduction of the principles of the current dual-frequency retrieval algorithms. The advantages and disadvantages of these algorithms are discussed. The hybrid method, which could avoid the bi-valued problem in retrieval, is described and evaluated in

detail. Then the comparisons of the hybrid method to the SWRC and HB-DFR methods are performed. The chapter ends with an evaluation of Hurricane Earl using the hybrid method.

4.2 PRINCIPLE OF EXISTING DUAL-FREQUENCY RETRIEVAL ALGORITHM

Generally, there are two main types of dual-frequency algorithms that can be used within a downward-looking space radar: 1) the forward method, where the DSDs are calculated at each bin starting from the top bin and moving down to the bottom; and 2) the backward method, where the algorithm begins at the bottom bin and moves upward to the top (Rose and Chandrasekar, 2005). Figure 4.1 depicts the downward-looking GPM satellite and illustrates the forward and backward retrieval directions. The two types are summarized in Figure 4.2. The forward method has limited application because of a tendency to diverge in regions of moderate-to-heavy attenuation or moderate-to-heavy rainfall (Meneghini et al., 2002). Backward algorithms can be divided into three groups: 1) standard dual-wavelength (or DAD); 2) surface-reference technique (SRT); and 3) iterative non-SRT.

The basic principle of the standard dual-wavelength approach is to estimate the path attenuation and rain rate using the radar equation and the ratio of the returned power of both wavelengths. This method requires one of two assumptions: the rain rate must be uniform over the measurement interval; or the reflectivity factor must be wavelength independent, meaning Rayleigh scattering at both frequencies (Iguchi, 2005). The SRT method uses a backward calculation method that is more stable than the forward method but requires a priori knowledge of the total two-way path-integrated attenuation (PIA) for each ray, or an ability to calculate it

(Meneghini et al., 1997, 2002). The third method, the non-SRT algorithm, is a self-consistent algorithm wherein the total PIA for each frequency channel is first estimated using an initial guess then optimized through an iteration process (Mardiana et al., 2004).

Except for the DAD method, which retrieves rain rate instead of DSDs, most of the dual-frequency retrieval algorithms mentioned above rely on the DFR-Do (dual frequency ratio versus medium drop diameter) relation. However, the forward and backward methods both suffer from a bi-valued solution when retrieving median volume diameter Do from DFR for rain, as described in detail by Liao, L. (2003); Mardiana et al. (2004); and Meneghini et al. (2002). Rose and Chandrasekar (2005) pointed out that a backward-iteration algorithm is unable to correctly estimate DSD profiles for a significant portion of Do and N_w combinations in rain because of the bi-value solution space. A boundary line was given by Rose and Chandrasekar (2006) to quantitatively describe the correct and incorrect convergence regions. A supplementary method was proposed using a linear assumption of vertical profiles for Do and N_w (in log scale) in the rain region, which is a reasonable assumption for avoiding the bi-valued problem. (Chandrasekar et al., 2003a).

Since the DFR versus Do relation is fundamental in dual-frequency retrieval, it deserves more detailed description. Figure 4.3 (a) shows a theoretical DFR versus Do relation for snow particles with fixed density. Snow particles are composed of ice and air. Figure 4.3 (b) shows similar relations with snow density as a function of size (Hogan et al., 2002; Holroyd, 1973; Heymsfield et al., 2002). A spherical model is used with volume-equivalent diameters of snow particles following an exponential distribution ranging between 0.03 to 10 cm in a theoretical simulation.

The large value of the medium volume diameter indicates there are more particles with large sizes. It can be seen from both plots that the DFR is a monotonically increasing function of D_o within a 0 to 5 mm range, which covers most of the snow particle sizes. The sphere model is used in simulation for simplicity purpose. It is obvious that the relation is slightly sensitive to snow density changes. Figure 4.3 (c) illustrates the DFR versus D_o relation for melting snow particle. A spherical model is applied to the melting particle, which is composed of water, ice and air. The Bruggeman (1935) mixing formula is used to calculate the dielectric constant of the mixture. Gamma distribution is applied for melting particle sizes, with shape factor μ assumed to be 0. Different water fractions indicate different melting statuses within a melting process, and a bulk-averaged water fraction is used in this study. The density of the melting snow is calculated using equation (4.1) with water fraction decided by the Awaka et al. (1985) model and ice fraction from the assumed snow density. The relation between bulk averaged water fraction and its relative height to the melting top, described by Awaka et al. (1985), is shown in Figure 4.3 (d).

$$\rho_m = \rho_w * f_w + (1 - f_w) * f_i * \rho_i \quad (4.1)$$

ρ_m represents density of a melting particle. ρ_w and ρ_i are density of water and ice. f_w and f_i are water fraction and ice fraction within a mixed phase particle. A theoretical relation of DFR- D_o for rain is shown in Figure 4.3 (e). The Beard and Chuang (1987) rain drop model is used in simulation. When DFR is a negative value, D_o cannot be unambiguously retrieved; this is the “bi-value” problem indicated early in this section. The bi-value phenomenon exists for most rain-drop models, including the Andsager et al. (1999); the Pruppacher and Beard, (1970) models.

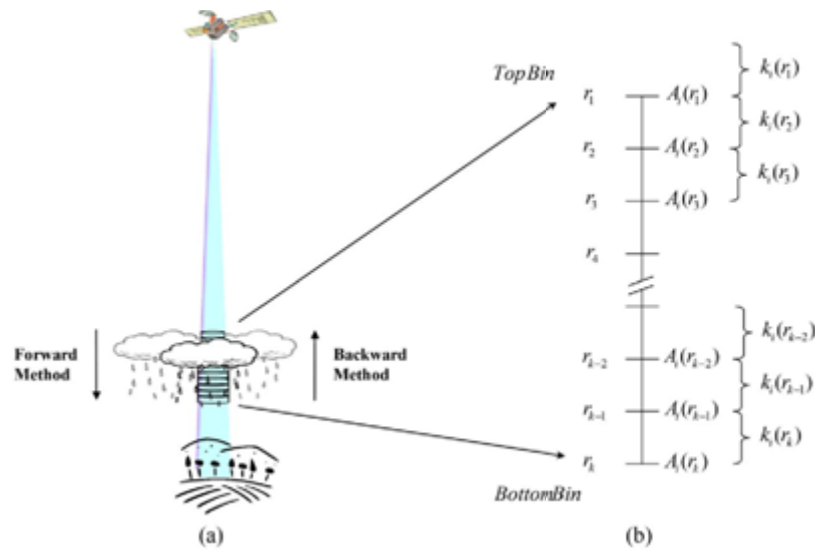


Figure 4.1. Part (a) shows a downward-looking GPM satellite. The discs represent sampling volumes. The forward method calculates DSD values starting at the top and moving to the bottom. The backward method calculates from the bottom to the top. Part (b) shows how the bin nomenclature and specific attenuation are defined (Rose and Chandrasekar, 2005).

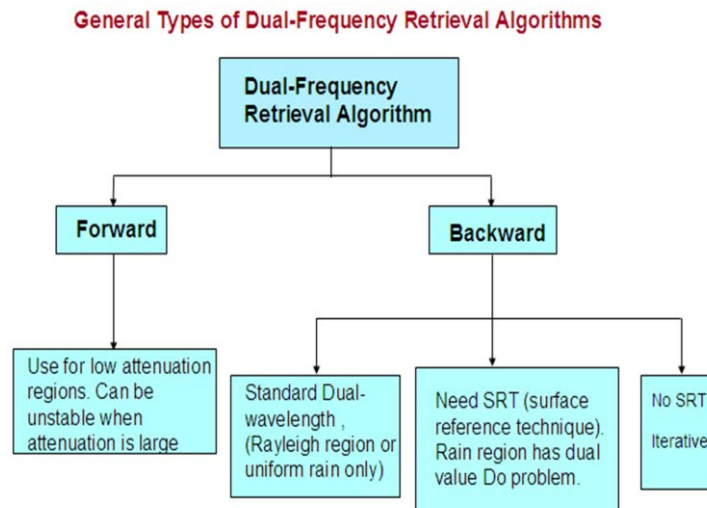
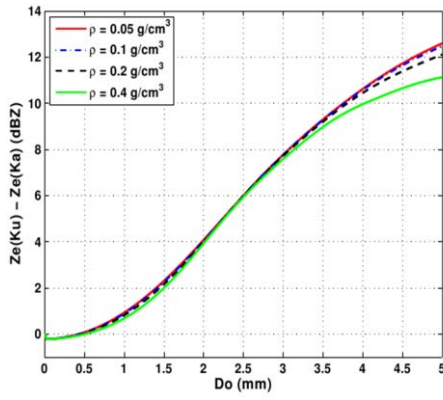
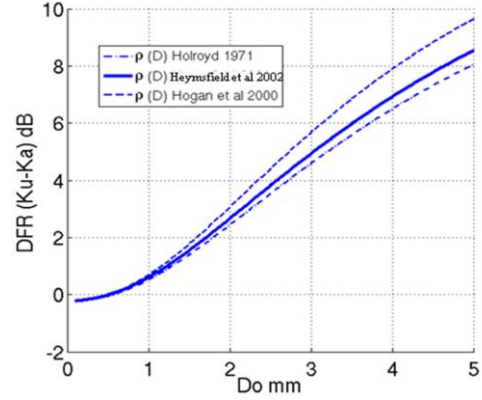


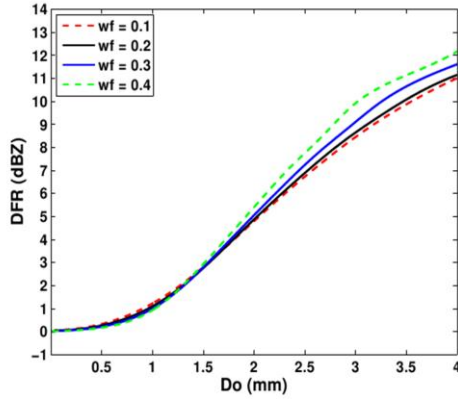
Figure 4.2. General types of dual-frequency retrieval algorithm (Rose and Chandrasekar, 2005).



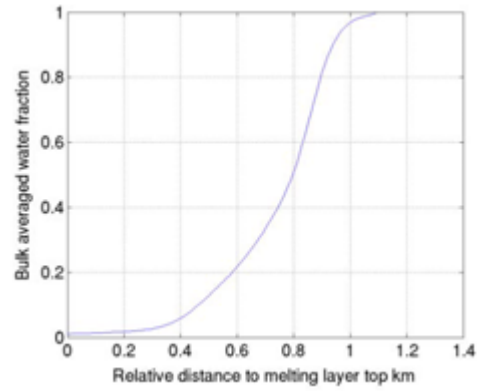
(a)



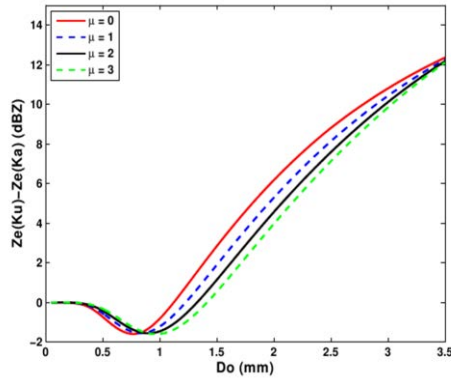
(b)



(c)



(d)



(e)

Figure 4.3. (a) DFR versus Do relation for snow particle at fixed density of 0.05, 0.1, 0.2, 0.4 g/cm^3 . (b) Same relation for snow particle with density as a function of size. (c) DFR versus Do relation for melting particle with water fraction of 0.1, 0.2, 0.3 and 0.4. (d) Bulk averaged water fraction as a function of relative distance to melting layer top (Awaka et al. 1985). (e) DFR versus Do relation for rain particle with shape model of Beard and Chuang (1987).

4.3 HYBRID METHOD

4.3.1 Algorithm description

The word “hybrid” comes from the combination of the forward method and the linear constraints on D_0 and N_w (in log scale) profile for rain. The forward method is applied to the frozen and melting regions while the linear DSD assumption is applied to rain. As mentioned in section 4.2, two DSD parameters of the gamma distribution can be retrieved in each radar resolution, leaving the shape factor μ assumed to be a fixed number ($\mu=0$ is used in this study for simplicity purposes). It needs to be pointed out that DSD parameters in the retrieval are the un-melted DSDs if not explicitly explained.

The hybrid method is a profile-based optimization procedure that can be described in three steps. First, estimate DSD from vertical profile using the hybrid method. Second, reconstruct Z_m (refer to estimated $\tilde{Z}_m$) based on estimated DSD and the assumed scattering models. Third, optimize the residual of the difference between reconstructed and observed reflectivity measurements till it is minimized. The state vectors for the optimization process are D_0 and $\log(N_w)$ at surface. Following commonly used notations in the literature (Meneghini et al., 1997; Bringi and Chandrasekar, 2001), the governing equations of the hybrid algorithm can be written as follows: Let $\tilde{Z}_{mi}(r)$ be the estimated measured reflectivity. A tilde ($\sim$) indicates it is an algorithm-derived value. The subscript $i(i=1,2)$ represents the particular frequency (13.6 and 35.5 GHz, respectively). Z_{ei} is intrinsic reflectivity, while A_i is a two-way path-integrated attenuation factor. The measured reflectivity can be written in term of the intrinsic values and attenuation as:

$$\tilde{Z}_{mi}(r) = \tilde{Z}_{ei}(r) \tilde{A}_i(r) \quad (4.2)$$

where the intrinsic reflectivity can be related to the DSD parameters as

$$\tilde{Z}_{ei}(r) = \tilde{N}_w(r) f(\mu) D_0^{-\mu} I_{bi}(\tilde{D}_0), \quad (4.3)$$

$$\tilde{A}_i(r) = \exp[-0.2 \ln(10) h \sum_{n=1}^j \tilde{\alpha}_i(r_n)], \quad (4.4)$$

I_{bi} is a function of D_0 , which can be expressed as

$$I_{bi}(\tilde{D}_0) = C_{zi} \int_D \sigma_{bi}(D) D^\mu e^{-\Lambda D} dD, \quad (4.5)$$

$$C_{zi} = \frac{\lambda_i^4}{\pi^5 |K_w|^2}, \quad (4.6)$$

σ_{bi} is the backward-scattering cross section and λ represents wavelength. K_w is defined as

$$K_w = \frac{m^2 - 1}{m^2 + 1}, \quad (4.7)$$

where m is a complex refraction index of water. The specific attenuation $\tilde{\alpha}_i$ in (4.4) is defined as

$$\tilde{\alpha}_i(r) = \tilde{N}_w f(\mu) D_0^{-\mu} I_{ii}(\tilde{D}_0) \quad (4.8)$$

where

$$I_{ii}(\tilde{D}_0) = C_{ki} \int_D \sigma_{ii}(D) D^\mu e^{-\Lambda D} dD, \quad (4.9)$$

$$C_{ki} = 4.343 \times 10^{-3}. \quad (4.10)$$

The estimated $\tilde{D}_0$ and $\tilde{N}_w$ used in (4.3) are derived using the hybrid method described in (4.11), (4.12), and (4.13) for the ice and melting ice regions. The dual-frequency ratio DFR in decibels has been defined in previous sections, but here the reflectivities are intrinsic values with attenuation corrected. The definition is shown in (4.11), describing the difference of radar reflectivity (in dB) between two frequencies. The linear constraints of the DSD profile are shown in (4.14) and (4.15) for the rain region.

$$DFR(r) = \log_{10}(Z_{e1}(r) / Z_{e2}(r)), \quad (4.11)$$

$$\tilde{D}_0(r) = F^{-1}(DFR(r)), \quad (4.12)$$

$$\tilde{N}_w(r) = \frac{Z_{mi}(r)}{f(u) \tilde{D}_0^{-u}(r) I_{bi}(\tilde{D}_0(r)) A_i} \quad (4.13)$$

$$\tilde{D}_0(r_j) = \frac{D_{0mlb} - D_{0surf}}{length_{rain}} * bin\# + D_{0mlb}; \quad (4.14)$$

$$\tilde{N}_w(r_j) = 10^{\left[\frac{\log N_{wmlb} - \log N_{wsurf} * bin\# + \log N_{wmlb}}{length_{rain}} \right]}; \quad (4.15)$$

“mlb” and “surf” in (4.14) and (4.15) represent melting layer bottom and surface, respectively. The function F in (4.12) represents the DFR versus D_0 relations for snow and melting snow particles, which are shown in figure 4.3 (a) and (c). This relation is fundamental to the dual-frequency retrieval.

The residual of the difference between reconstructed and true observation is expressed as

$$CF = \sum_{j=1}^{r_N} [\tilde{Z}_{m1}(r_j) - Z_{m1}(r_j)]^2 + [\tilde{Z}_{m2}(r_j) - Z_{m2}(r_j)]^2 \quad (4.16)$$

The initial guesses of $D_{0_{surf}}$ and $\log(N_{w_{surf}})$ are adjusted until the cost function (4.16) is minimized. Therefore, the DSD profiles are optimized, and concurrently, attenuations are corrected. The diagram of the hybrid method is shown in figure 4.4. The diamond block in figure 4.4 classifies profiles, and its output is needed for DSD retrievals. The classification method developed in Chapter 3 could be one of the algorithms. In order to achieve simplicity, in a simulation-oriented evaluation, the threshold of LDR is used for the melting layer detection.

4.3.2 Algorithm evaluation using APR-2 data

The performance of the hybrid method is evaluated using simulated DPR profiles from airborne radar data obtained during the NAMMA experiment (20060903_142134). The plot of the NAMMA overpass is shown in figure 4.5 (same as the plot shown in figure 2.9). The reasons for using simulation data and the details of the simulation procedure are discussed in Chapter 2.

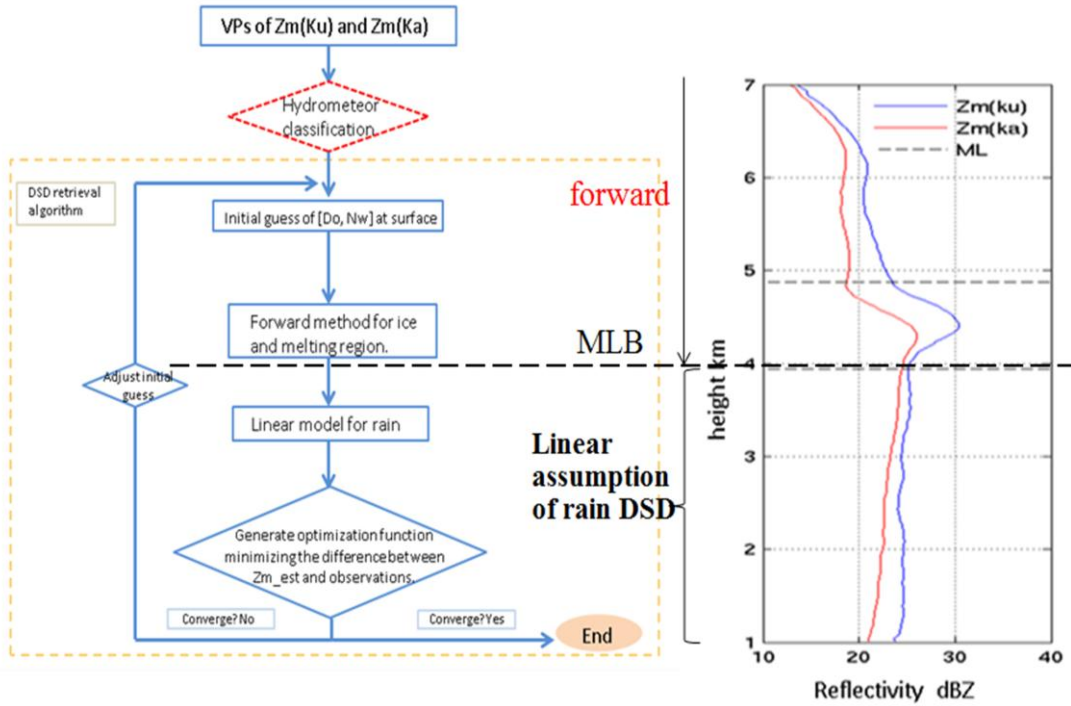


Figure 4.4. Diagram of the hybrid DSD retrieval algorithm for GPM-DPR.

Figure 4.6 (same as figure 2.10) shows typical stratiform and convective profiles from NAMMA data, marked as A and B in figure 4.5. Figure 4.7 (same as figure 2.12) shows the corresponding simulated DPR profile. Figure 4.7 (a) is the stratiform profile simulated from figure 4.6 (a) and figure 4.7 (b) shows the true DSD profile used in the simulation. Figure 4.7(c) is the convective profile simulated from figure 4.6 (b) and figure 4.7 (d) illustrates the true DSD used in simulation. Comparing figure 4.6 and 4.7, the simulated profiles can capture the characteristics of the airborne radar profile. The two profiles in figure 4.7 are used to estimate the hybrid method as a representative of stratiform and convective rain profiles. An LDR with a threshold

of -28 dB is used to separate regions with different hydrometeor phase state. The initial guess for Do and $\log(N_w)$ is [3,3] in the retrieval.

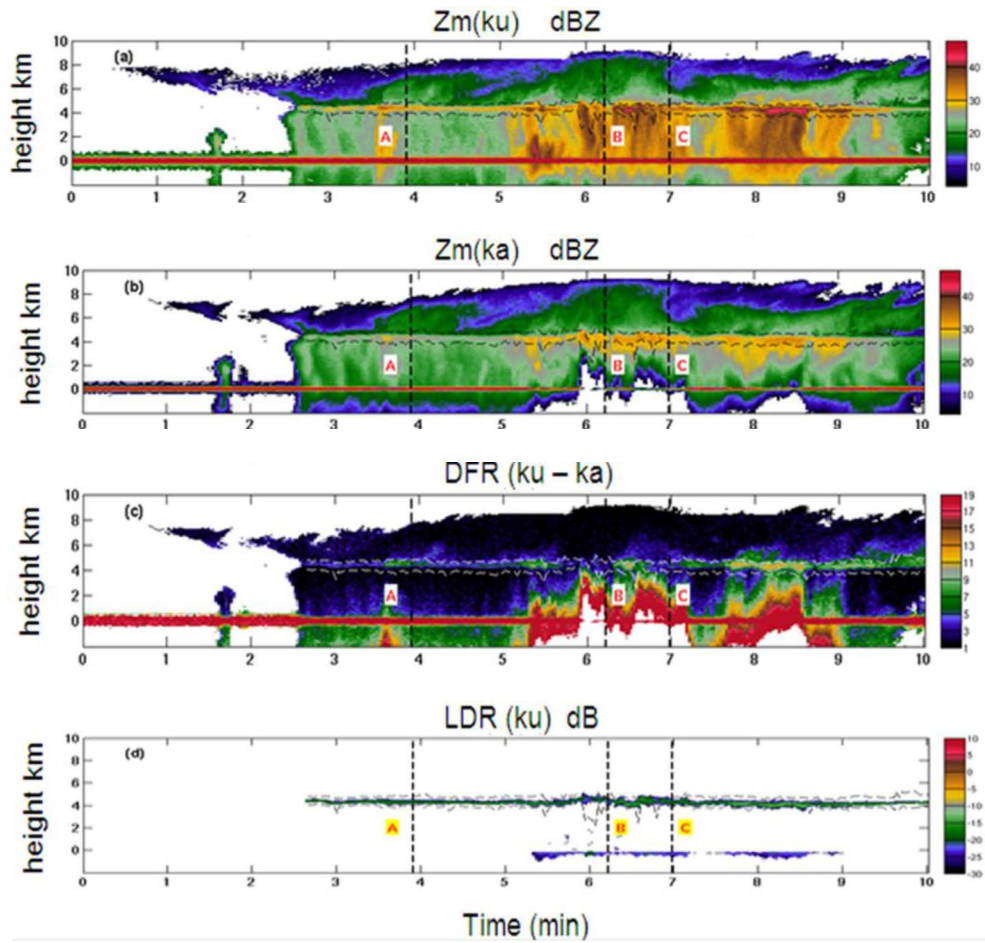


Figure 4.5. Along-track observations at nadir of the APR2 radar in the NAMMA experiment. The (a) panel is reflectivity at Ku- band; the (b) panel is reflectivity at Ka- band; the (c) panel is the difference between reflectivity at Ku- and Ka- band; the (d) panel is LDR at Ku- band; the (e) panel is fall velocity at Ku- band.

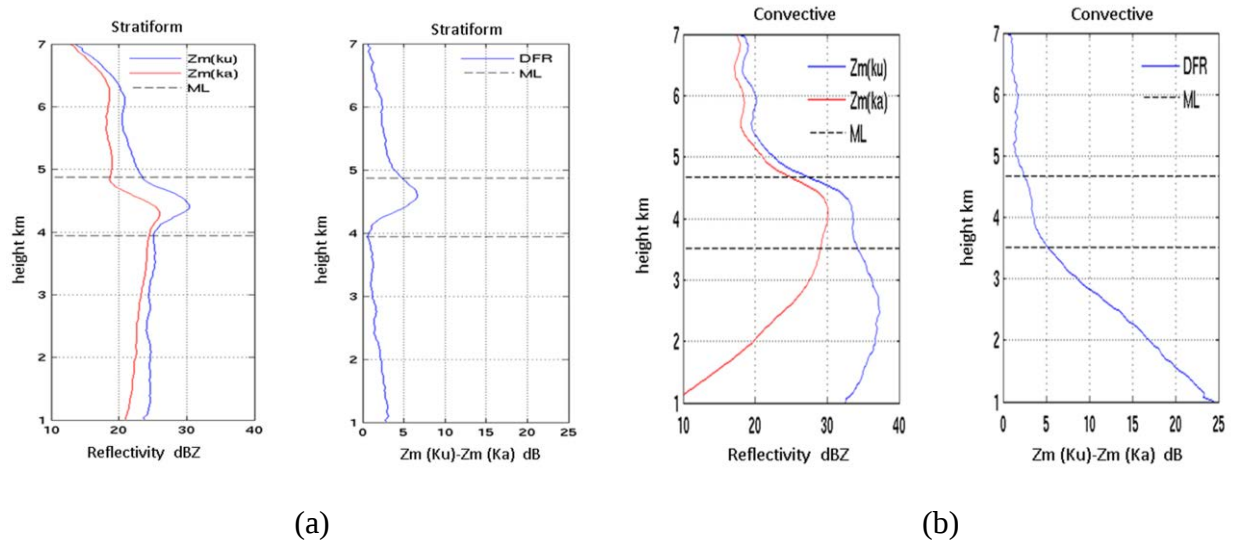
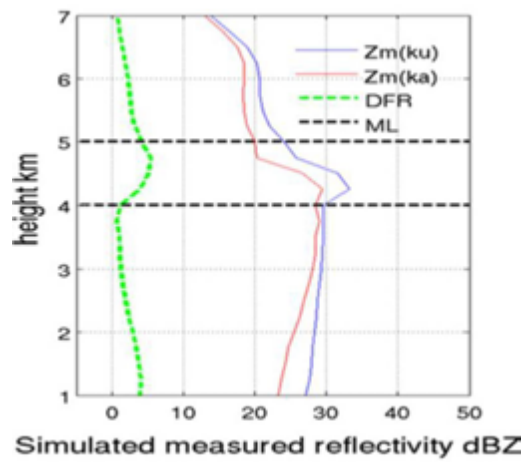
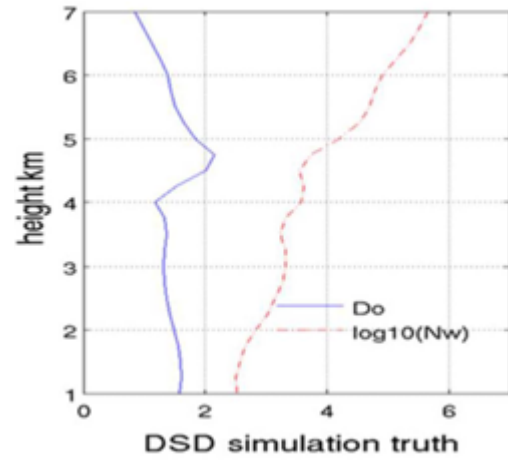


Figure 4.6. (a) Typical vertical profile of reflectivities and the measured dual-frequency ratio for stratiform rain marked as A in figure 4.5. (b) Typical vertical profile of reflectivities and the measured dual frequency ratio of convective rain marked as B in figure 4.5.

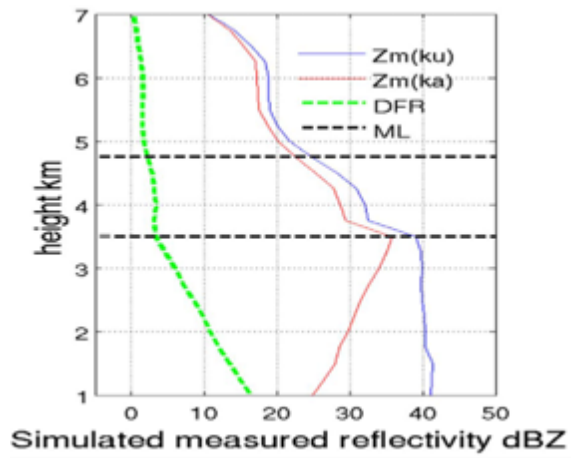
Figure 4.8 illustrates the evaluation of the retrieval using the same microphysical model in simulation as in retrieval. For both cases, as shown in figure 4.8 (a) and (c), the hybrid method illustrates good performance in the retrieval. Within the ice and melting ice regions, the forward method retrieves DSDs that match well with true DSDs. The difference in the rain region is caused by the deviation from the true DSDs to the linear assumption.



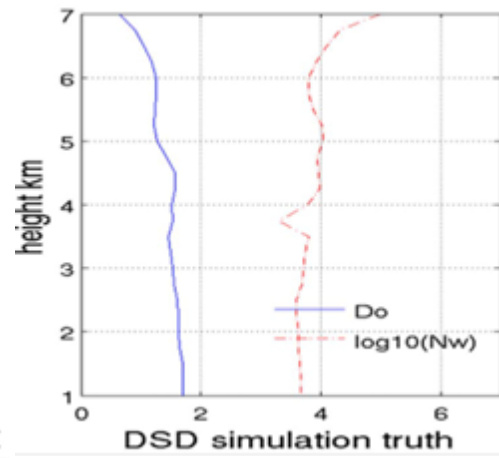
(a)



(b)

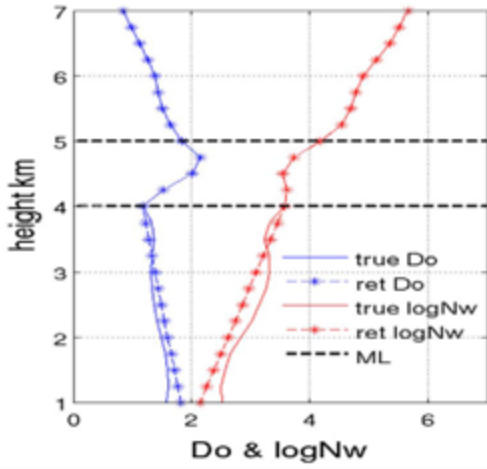


(c)

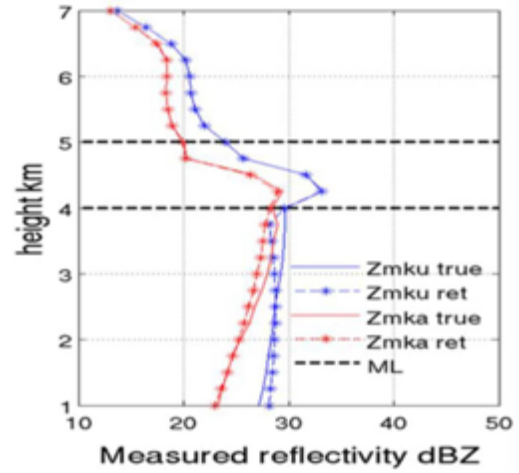


(d)

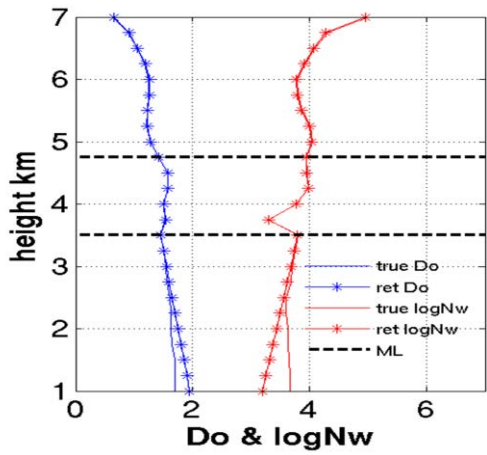
Figure 4.7. (a) Profiles of reflectivities and the measured dual frequency ratio for stratiform rain simulated from airborne radar profile shown in figure 4.5 at profile “A”; (b) true DSD profiles for (a); (c) Same profiles for convective rain simulated from airborne radar profile shown in figure 4.5 at profile “B”; (d) true DSD profiles for (c).



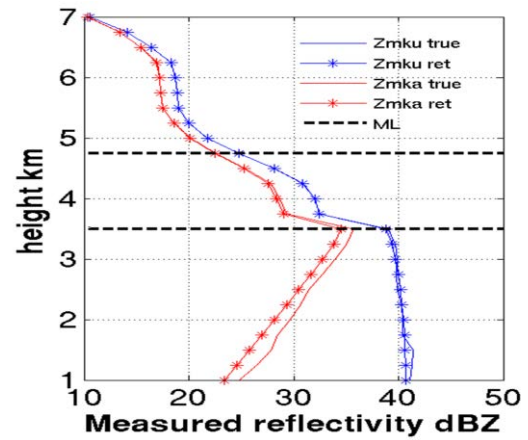
(a)



(b)



(c)



(d)

Figure 4.8. (a) Comparison between retrieved DSDs and simulation truth for stratiform rain. (b) Comparison between estimated reflectivity profiles and true observations. (c) and (d) are the same as (a) and (b), but for convective rain.

Figure 4.8 (b) and (d) are the estimated and the true reflectivities for the stratiform and convective profiles. The differences between the estimation and the observations are minimized to get optimized DSD retrievals.

The hybrid method is applied to the entire overpass of the NAMMA data illustrated in figure 4.5. The retrieved DSDs are shown in figure 4.9. The blank regions in the figure represent either no data or the Ka- band signal becoming extinct at high altitude.

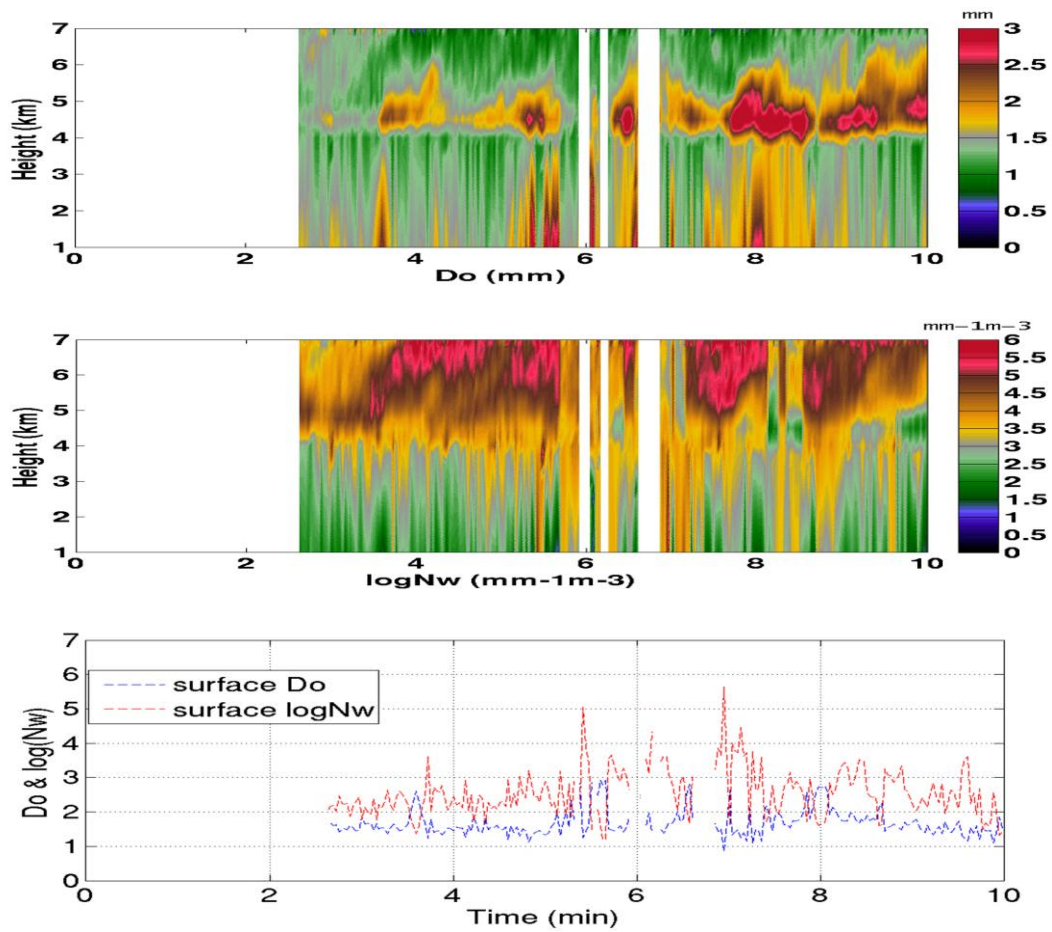


Figure 4.9. Top panel: retrieved overpass of Do ; middle panel: retrieved overpass of N_w in log scale; bottom panel: retrieved DSD parameters at surface.

4.3.3 Stability test

Although the density of snow is assumed in simulation, in reality, snow density is an unknown parameter that could involve error if the true value is different from the assumed value. Therefore, the sensitivity of the hybrid method to snow density change is worth studying. In order to test the sensitivity in simulation, the density of a snow particle is assumed as 0.1 g/cm^3 and 0.4 g/cm^3 for stratiform and convective profiles respectively. In retrieval, snow densities of 0.2 g/cm^3 and 0.3 g/cm^3 are used. The performance of the sensitivity test is shown in figure 4.10 (a) and (b) for the stratiform and convective profiles. Both cases indicate that Do is not sensitive to the snow density change while $\log(Nw)$ is more sensitive. It shows around a 12% underestimation of $\log(Nw)$ in the frozen region for the stratiform profile.

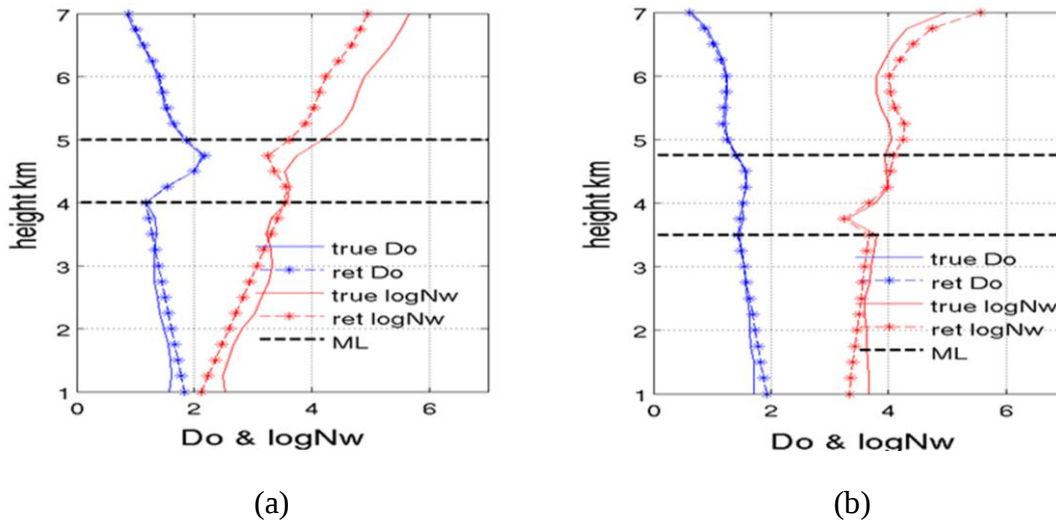
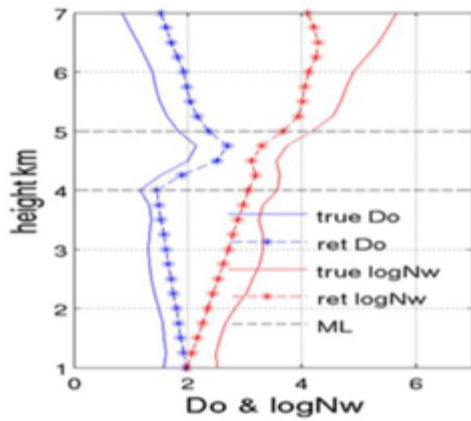


Figure 4.10. (a) Comparison between retrieved DSDs and simulation truth for stratiform rain profile using snow density of 0.1 g/cm^3 in simulation while 0.2 g/cm^3 is used in retrieval. (b) Same comparison for convective rain profile using snow density of 0.4 g/cm^3 , while 0.3 g/cm^3 is used in retrieval.

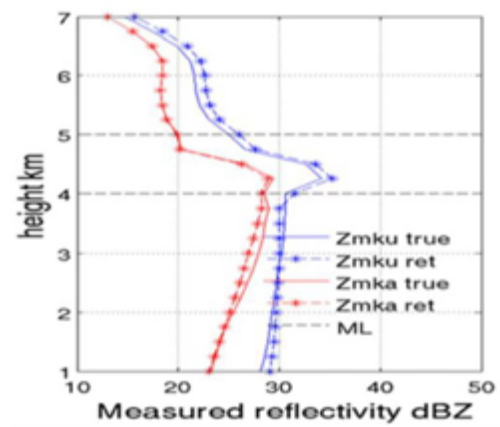
Since the algorithm compares the estimates with true measurements, it is subject to system bias. Two bias scenarios are tested. One is [1,0] with the first number to be the bias (in dB) of the Ku-band channel and second value to be the bias of the Ka-band channel. Figure 4.11 (a) and (b) show the retrieved DSDs versus true DSDs based on this bias scenario. As expected, D_0 is overestimated because of the bias. Correspondingly, N_w is underestimated in order to match estimated measurements. The second bias scenario of [1,1] is applied to vertical profiles and the estimation is shown in Figure 4.11 (c) and (d). From the figure, D_0 is not affected much from the system bias since the biases for both reflectivity channels are the same while N_w is affected. The reason is that D_0 is retrieved by DFR, where bias from the two channels cancels out, but N_w is retrieved using both retrieved D_0 and the reflectivity measurements.

4.3.4 Considering attenuation from non-precipitation particles

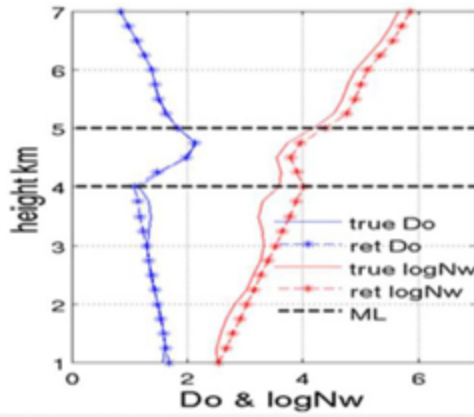
The analysis in the above sections uses the forward method with the assumption that there is no attenuation from non-precipitating particles. In other words, the evaluation doesn't include the attenuation from cloud liquid water, water vapor, and oxygen. However, attenuations from non-precipitating particles exist in the real environment and cannot be ignored. Therefore, it is useful to evaluate the impact of attenuation profiles from non-precipitating particles on the hybrid method. Figure 4.12 shows the same flow chart as figure 4.4, but considering attenuation profiles from non-precipitating particles.



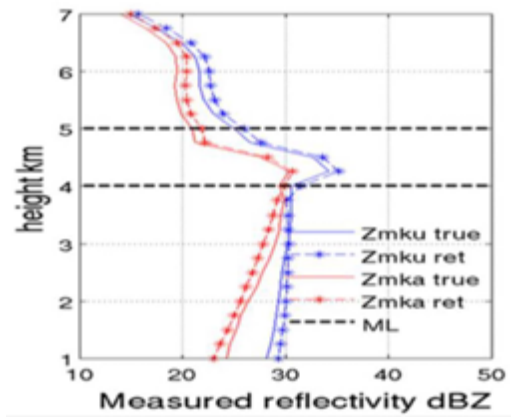
(a)



(b)



(c)



(d)

Figure 4.11. (a) Comparison between retrieved DSDs and simulation truth for stratiform rain profile considering system bias scenario of [1,0]. (b) Comparison between estimated measurement and observations considering system bias scenario of [1,0]. (c) and (d) Same comparisons as (a) and (c) with system bias scenario of [1,1].

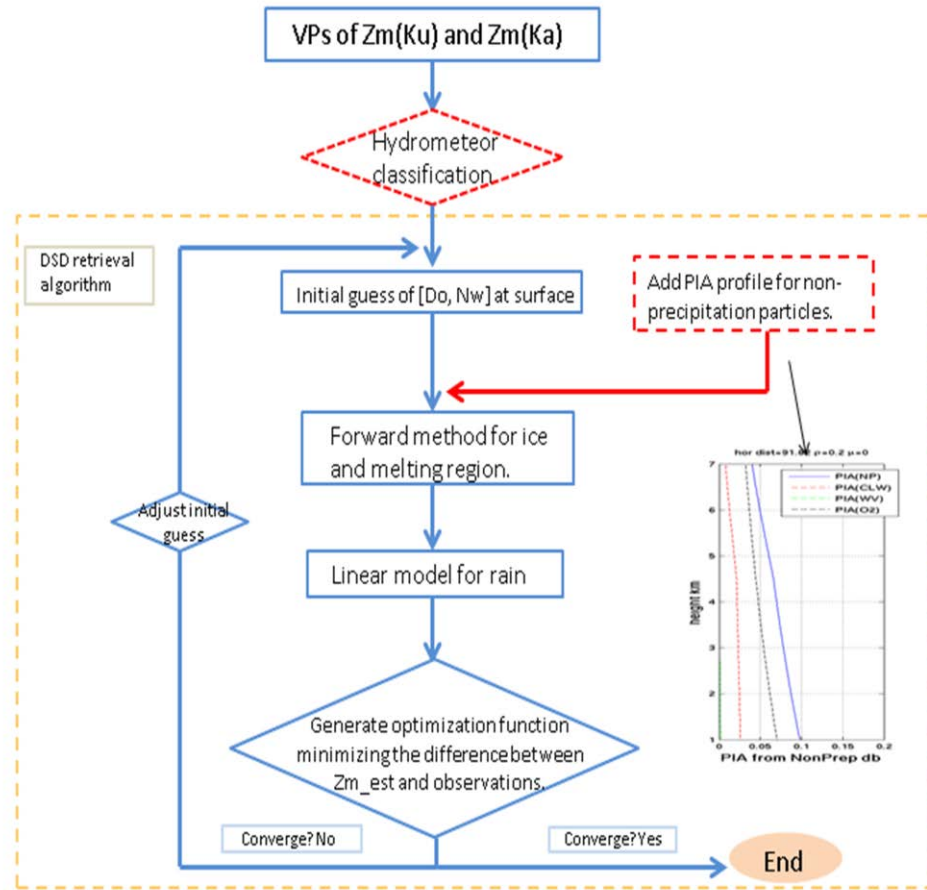


Figure 4.12. Flowchart of the hybrid method considering attenuation from non-precipitating particles.

The evaluation procedure is the same as described in previous sections; the only difference is that attenuation profiles from non-precipitating particles are subtracted from the simulated measurements using true DSDs. Then, the retrieved DSDs are compared to the true DSDs to evaluate their influence.

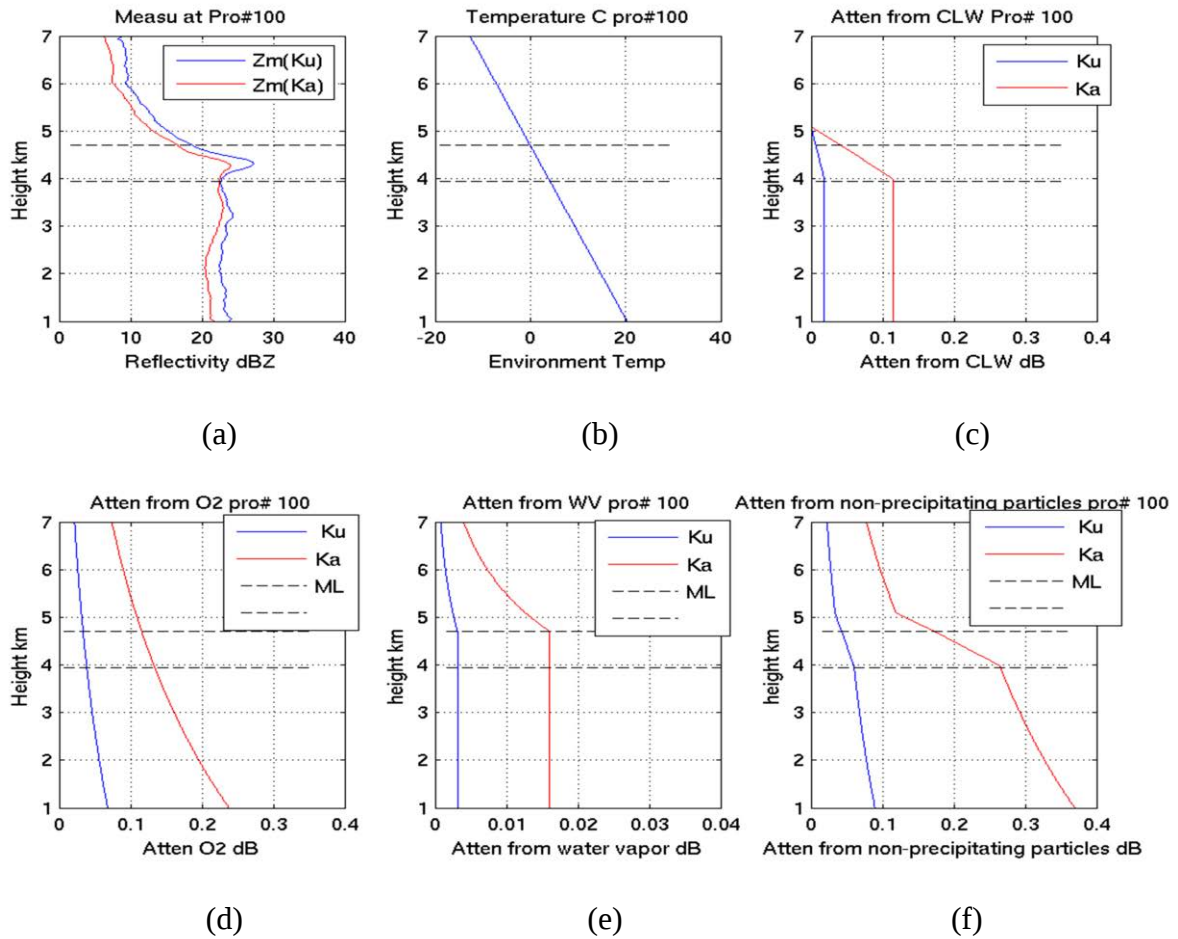


Figure 4.13. Attenuation profile from non-precipitating particles. (a) Sample profile of measured reflectivity. (b) Temperature profile (°C). (c) Attenuation profile from cloud liquid water. (d) Attenuation profile from oxygen. (e) Attenuation profile from water vapor. (f) Total attenuation profile from cloud liquid water, oxygen and water vapor.

The model from Gunn and East (1954) is used to calculate attenuation from cloud liquid water. Gaseous attenuations, including oxygen and water vapor, are calculated based on the model described in ITU-R (in ITU-R P.676-6 "Attenuation by Atmospheric Gases"). A sample plot of the attenuation profile from non-precipitating particles is shown in figure 4.13. Figure 4.13 (a) is

a vertical profile of stratiform rain with the dash line representing the melting layer top and bottom detected by the method described in Chapter 3. The temperature profile is shown in figure 4.13 (b) with 0 °C at melting layer top and 6 °C / km lapse applied. In Figure 4.13 (c), (d), and (e), the attenuation profile from cloud liquid water, water vapor, and oxygen are illustrated, respectively. Attenuation from cloud liquid water is only applied around the melting layer region and attenuations from oxygen and water vapor are applied for the whole profile. Figure 4.13 (f) is the attenuation profile at Ku- and Ka- band from the three non-precipitation sources and the one used in evaluation.

The same vertical profile shown in Figure 4.7 (a) was tested considering the attenuation shown in figure 4.13 (f). The retrieved DSD profile was compared to the true DSDs. Figures 4.14 and 4.15 show the results of comparison for each case. In order to show the impact from non-precipitating attenuation, the top and middle row in figures 4.14 and 4.15 indicate the comparison without and with the attenuation from non-precipitating particles. From the comparison, except for a slight increase of retrieved D_0 and corresponding N_w , no obvious difference can be found. This indicates that the hybrid method can handle the non-precipitating attenuation. The bottom row in Figure 4.14 shows the attenuation from non-precipitating particles and from precipitation. At Ka-band, attenuation from non-precipitating particles is only around 10% of the attenuation from precipitation. Figure 4.15 shows the same comparison, but for the convective rain from Figure 4.7 (b) and similar conclusions can be made.

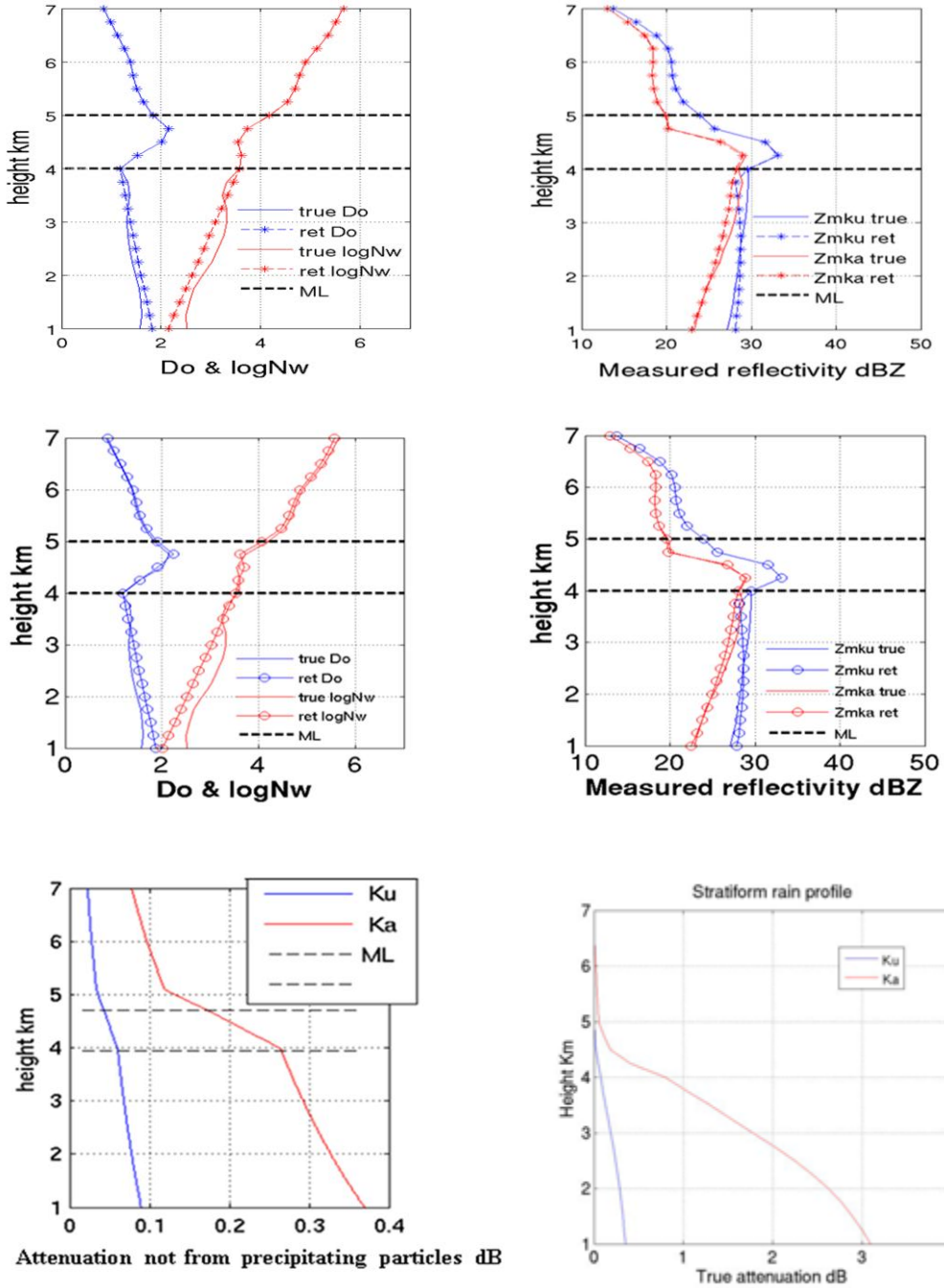


Figure 4.14. Top row: Comparison between retrieved DSDs and simulation truth for stratiform rain profile with no attenuation from non-precipitating particles (same as top row of figure 4.8) Middle row: Same comparison as in Top row with attenuation from non-precipitating particles added. Bottom row: Attenuation profile from non-precipitation particles used in retrieval (left); and true attenuation profile from precipitation in retrieval (right).

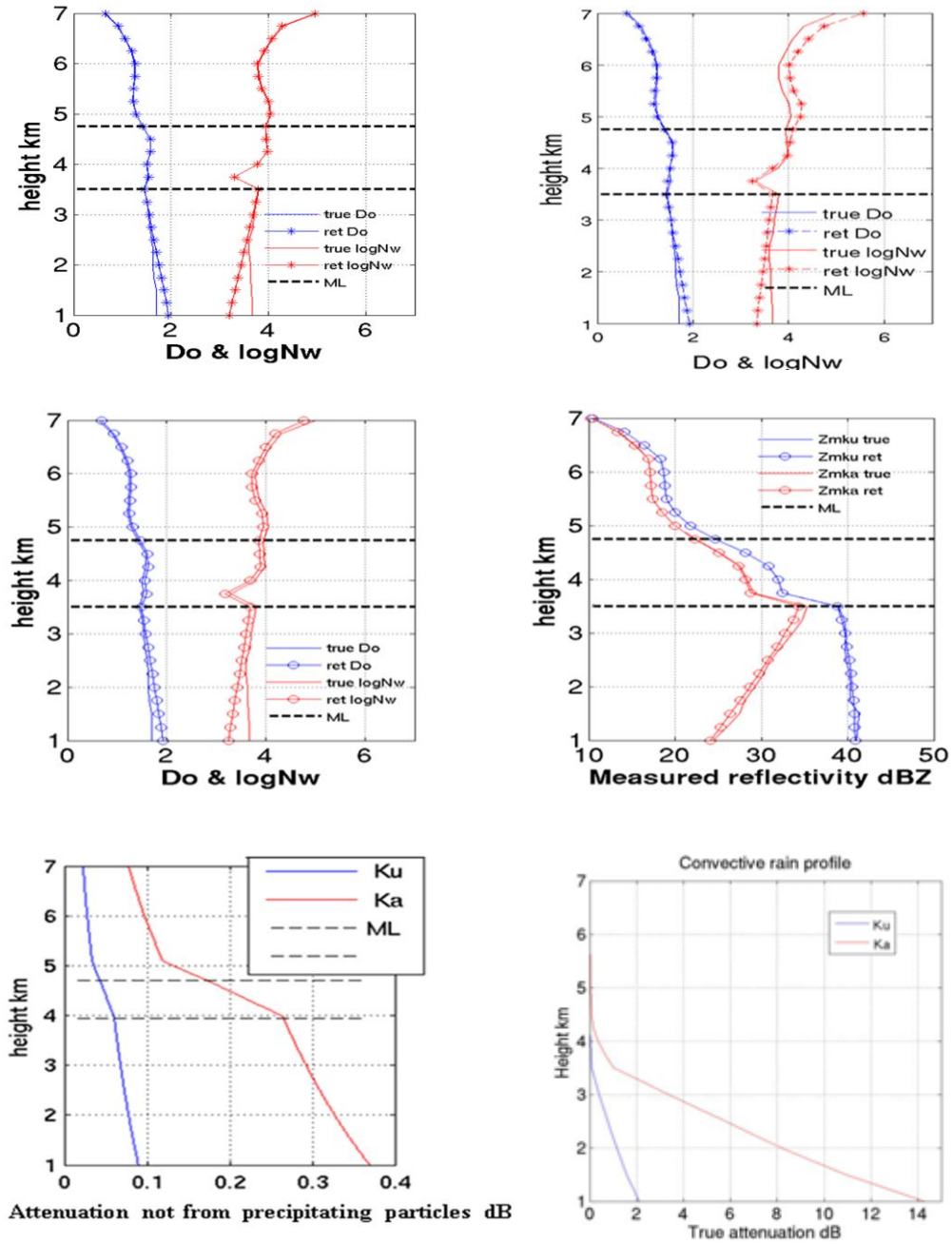


Figure 4.15. Top row: Comparison between retrieved DSDs and simulation truth for convective rain profile with no attenuation from non-precipitating particles (same as bottom row of figure 4.8) Middle row: Same comparison as in Top row with attenuation from non-precipitating particles added. Bottom row: Attenuation profile from non-precipitation particles used in retrieval (left); and true attenuation profile from precipitation in retrieval (right).

4.3.5 Comparison with the SRWC method

The hybrid method described above falls into the general class of non-SRT (surface reference technique) iterative process. Meneghini and Liao (2009) proposed an algorithm for GPM-DPR called surface reference with weak constraint (SRWC). This method belongs to the backward recursion with SRT, but using a weak constraint. In this section, a comparison is performed between the hybrid method and the SRWC method.

The advantage of the hybrid method is that the iterative process picks the optimized DSD values at the surface and avoids the ambiguity problem in the rain region. The limitation depends on to what extent the actual vertical profiles of DSD parameters for rain deviate from the linear model, although Chandrasekar et al. (2003a) pointed out that the profiles of both D_0 (drop median diameter) and $\log(N_w)$ (scaled number concentration in log scale) could be approximated in rain by a linear function. The SRWC method suggests an alternative to the SRT using the difference in the measured radar reflectivity DFR_m near the surface. This difference, however, is a weak constraint in the sense that it is a function of one of the unknowns. Therefore, there are multiple solutions consistent with the constraint in the SRWC method. Some preliminary comparisons are made between these two DSD retrieval algorithms based on the same APR-2 NAMMA overpass data shown in figure 4.16. The markers A, B, and C show the location of the three vertical profiles used in the comparison.

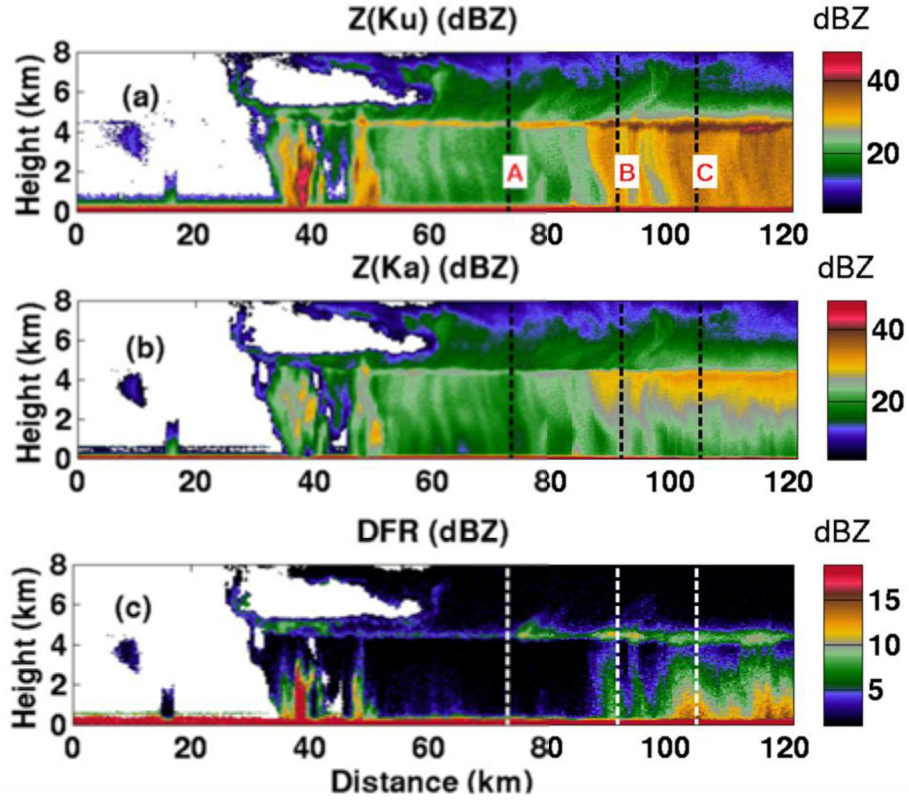


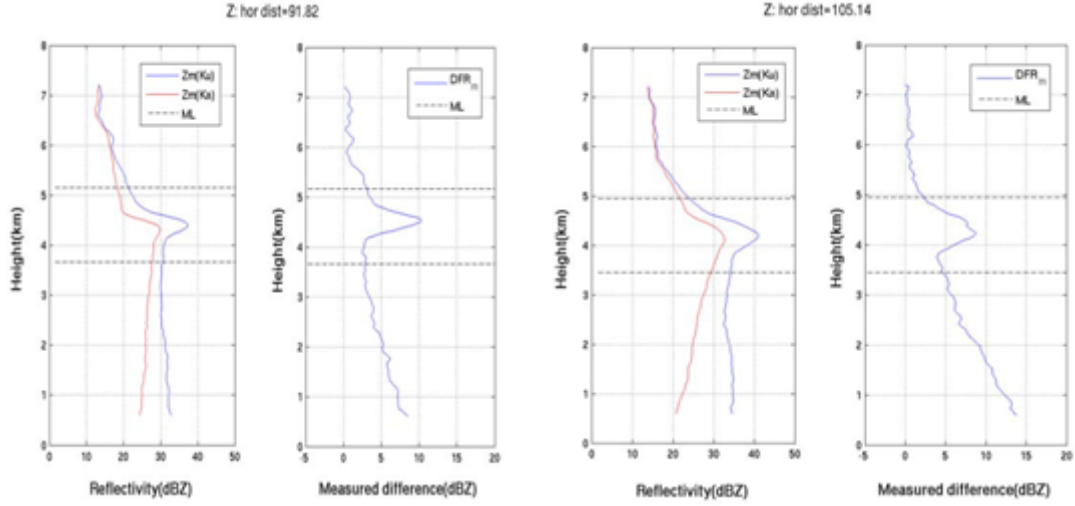
Figure 4.16. Overpass of NAMMA experiment at 20060901-142310. A, B, C indicate the location of the profiles for comparison purposes.

The convention of drop size distribution parameters follows the definition in Meneghini and Liao (2009), where D_o is defined as melted drop diameter (all D_o outside of section 4.3.5 is un-melted D_o) and N_t is the number concentration and can be connected to N_w , D_o , and μ as

$$N_T = \frac{N_w f(\mu) D_o^{\mu+1}}{3.67} \quad (4.17)$$

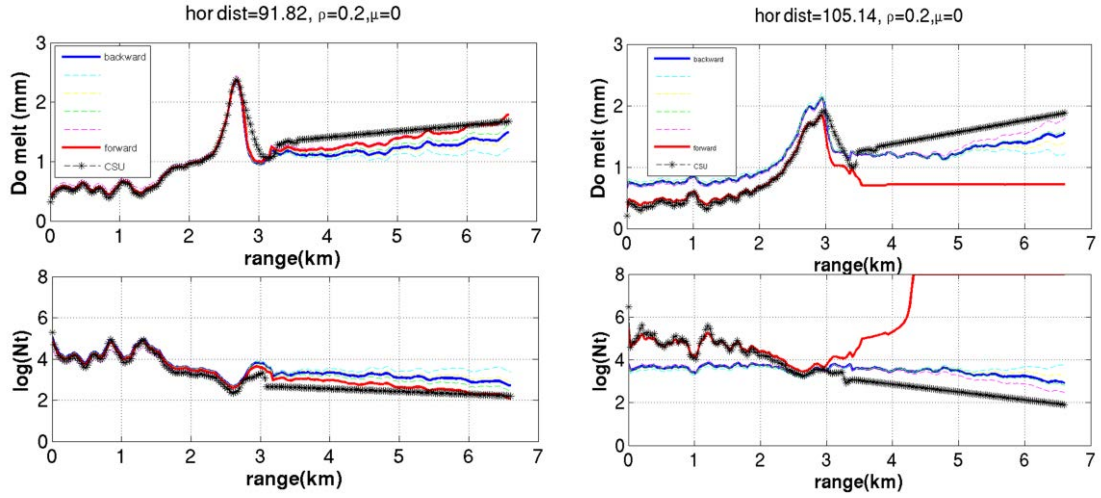
At markers B, and C in figure 4.16, where the stratiform profiles tend to be moderate to strong, the comparisons between the two methods are shown in figure 4.17, with the left column for the profile at marker B and the right column at marker C. The profile at marker B is a moderate stratiform profile. From the comparison shown in the left bottom subplot of figure 4.17, the black starred line, which is the result of the hybrid method, is close to at least one of the outputs of the SRWC methods and it tends to match with the larger branch of D_o in the rain region. The profile at marker C is a strong stratiform profile; the deviation of the black starred line to the solutions of the SRWC method in the frozen and melting regions can easily be seen. The explanation could be that the hybrid method follows the forward method in these two regions, matching the red line, while the SRWC method applies backward recursion to the profile top; thus, errors in the retrieval might accumulate to the top. Furthermore, the mixed-phase particle microphysical models used in the comparison are different, which might cause the mismatch in the melting region comparison.

At marker A in figure 4.16, which shows a very weak stratiform case, the hybrid method (black starred line) estimates a smaller D_o than the outputs of the SRWC method in the rain region, as indicated in figure 4.18. One possible reason is that either the forward or the backward recursion method always picks the larger branch of D_o in the rain region when a bi-valued problem occurs (Liao, L., 2003; Mardiana et al., 2004 and Meneghini et al., 2002). However, in the hybrid method, the iterative procedure automatically chooses the D_o value that minimizes the difference between the estimates and the observations. In other words, the black starred line might reflect the truth although it deviates from other SRWC solutions.



(a)

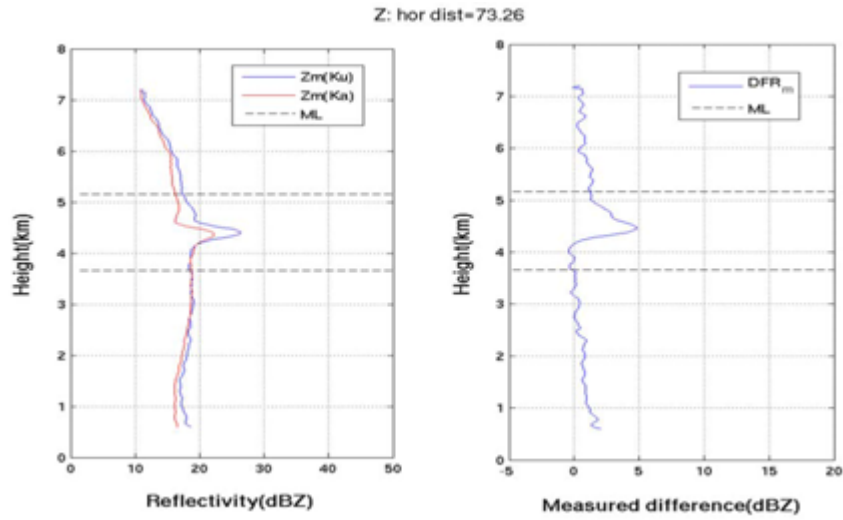
(b)



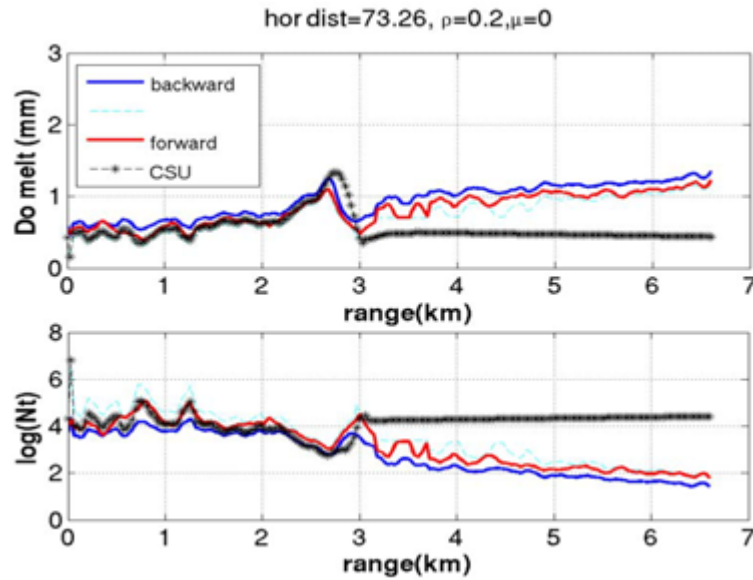
(c)

(d)

Figure 4.17. (a)(c): Vertical profile at marker B in figure 4.16 and the comparison between hybrid method and the SRWC method. (b)(d): Vertical profile at marker C in figure 4.16 with the same comparison. Black star line indicates the hybrid method. Red solid line indicates the forward method. Other lines in the plot indicate the outputs of the SRWC method. X-axis in the figure is defined as the relative distance to the profile top in km.



(a)



(b)

Figure 4.18. (a) Vertical profile at marker A in figure 4.16. (b) the comparison between hybrid method and the SRWC method. Black star line indicates the hybrid method. Red solid line indicates forward method. Other lines in the plot indicate SRWC method. X-axis in the figure is defined as the relative distance to the profile top in km.

4.3.6 Comparison with HB-DFR method

Seto et al. (2013) proposed an algorithm for GPM-DPR retrieval called the HB-DFR method, combining the Hitschfeld-Bordan attenuation correction method (Hitschfeld and Bordan, 1954) and the dual-frequency ratio method (Meneghini et al., 1997). HB-DFR is a profile based optimization algorithm, with the initial guess of k -adjustment coefficient ϵ , DSD parameters are first estimated and updated coefficient ϵ is generated at each range bin and each frequency. When difference between updated ϵ and initial ϵ are minimized, optimized DSDs are achieved. Algorithm details are in Seto et al. (2013). HB-DFR has the advantage of the consistency between single and dual-frequency algorithms which is desired for the DPR to produce a seamless three-dimensional field of the precipitation rate estimates. The HB-DFR algorithm is part of a baseline algorithm for the DPR standard algorithm. The potential disadvantage of HB-DFR method is that Hitschfeld-Bordan attenuation algorithm is forwardly estimated and could be unstable for retrievals in strong precipitation, especially for Ka- band.

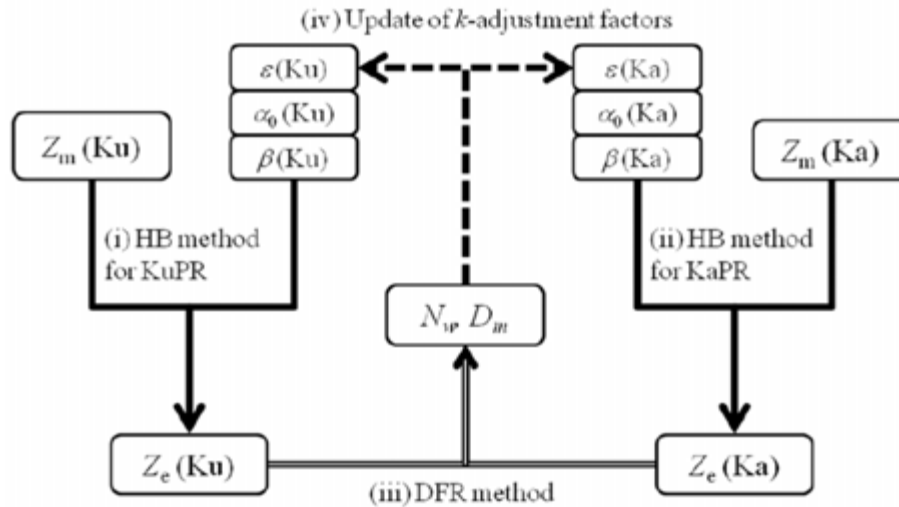
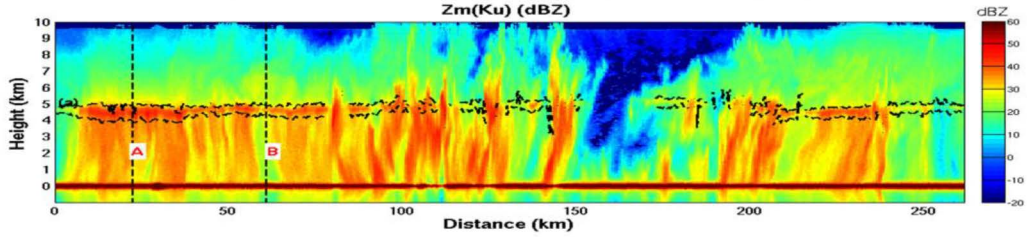
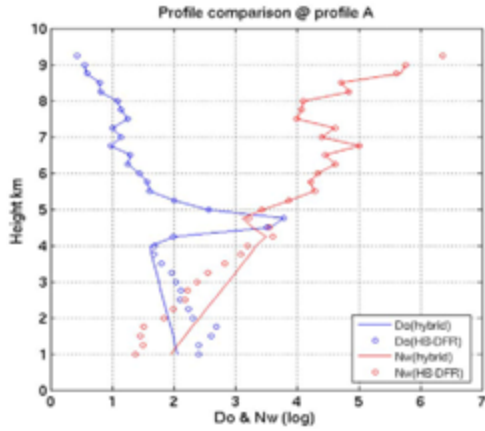


Figure 4.19. Flowchart of HB-DFR algorithm (Seto et al., 2013).

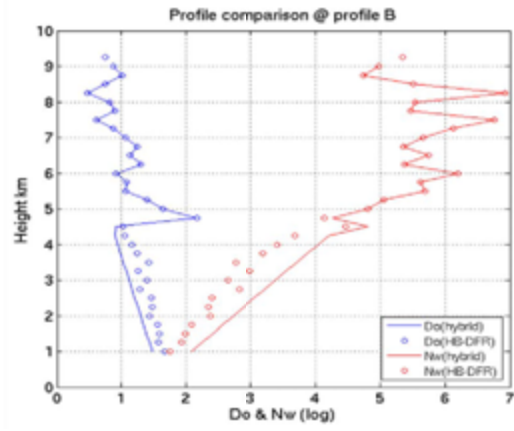
GRIP overpass of 100829-201850 collected by APR-2 on Aug 29, 2010



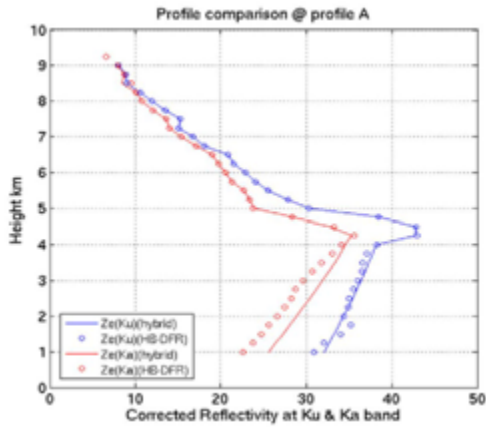
(a)



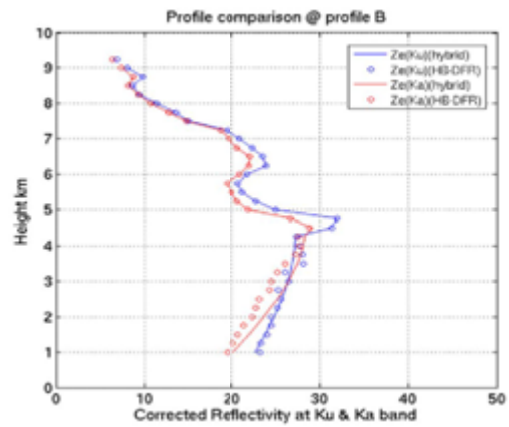
(b)



(c)



(d)



(e)

Figure 4.20 (a) GRIP overpass 100829-201850. (b) Comparison of DSDs between HB-DFR method and the hybrid method using profile (A) and (B) from (a). (c) Comparison of intrinsic reflectivity retrieved from HB-DFR method and the hybrid method based on the same profiles as in (b).

In order to deal with that, a HB-DFR-SRT (HB-DFR-Surface reference technique) method is being developed. Figure 4.19 shows the flowchart of the HB-DFR method. In this section, the HB-DFR method is compared with the hybrid method using APR-2 observation. Two profiles are chosen from a GRIP overpass 100829-201850 during hurricane Earl as shown in figure 4.20 (a). The details about Hurricane Earl are described in section 4.4.1. Figure 4.20 (b) shows the comparisons between DSDs retrieved from HB-DFR method and the hybrid method. In ice and melting regions, two methods match very well. In rain, HB-DFR method shows larger D_0 than hybrid method for both profile (A) and (B). Since HB-DFR method still picks larger value of D_0 when it suffers from dual-value problem in rain retrieval (Meneghini et al. 1997), it is very possible that HB-DFR method overestimates D_0 and underestimates corresponding N_w values in rain. Figure 4.20 (d) (e) show the comparison between intrinsic reflectivity at Ku- and Ka- band retrieved from HB-DFR method and hybrid method. The profile compares well including the rain region. More comprehensive study is needed and is a part of future work.

4.4 EVALUATION FOR TROPICAL STORM

4.4.1 Hurricane Earl

Hurricane Earl developed out of a tropical wave west of Cape Verde Island on August 25, 2010. It strengthened into a tropical storm intensity when it continued across the Atlantic on August 29, and later a major hurricane on August 30. APR-2 participated in the GRIP experiment in August and September of 2010 and captured Earl from August 29 to September 2. Figure 4.21 illustrates

the geographic location of Earl and the GRIP experiment. Figure 4.22 shows the GRIP overpass of 100829.201850 on August 29, 2010. In order to study the microphysics of Earl, the hybrid method described in section 4.3 was applied to the storm to perform a DSD retrieval. As mentioned in the previous section, the height of the melting layer should be known or assumed in advance. The hydrometeor profile characterization (*HPC*) method described in Le and Chandrasekar (2011) (see also in Chapter 3) is applied to detect the melting layer for Earl.

Figure 4.23 (a) shows the same plot as in figure 4.22 (a) but with the black dashed line representing the melting layer top and bottom using the *HPC* method. Figure 4.23 (b) shows the LDR (linear depolarization ratio), available for APR-2 data, of the overpass which is a good indicator of the melting layer. The melting region detected by the *HPC* method shows a good match with the LDR with a threshold of -28 dB. The melting regions, where not detectable, are assigned a fixed value of melting top and bottom. Figure 4.23 (c) and (d) shows the retrieved Do and Nw (in log scale) values for Hurricane Earl using the hybrid method. The blank regions in the plots are either bad data or Ka- band signals extinct at high altitudes in convections. From figure 4.23 (c), Do values are small at high altitudes due to the small size of ice crystals and Do increases with the decreasing height since ice crystals aggregate when they fall. When entering the melting layer, Do values have the trend to increase in the early state of melting and then decrease in the bottom half of the melting layer. The shrinking of the particle is due to the increase of the density. In the rain region that is far from the storm's eye, Do profiles are more constant along the height while entering the convection area adjacent to the storm eye, more variation can be seen from the retrieval. Accordingly, retrieved Nw (in log scale) values show complementary trends to Do which is reasonable. In figure 4.23 (c) and (d), retrieval is

performed only in regions with altitude above 1km in order to avoid clutter. The limitation of the hybrid method is that it doesn't work when Ka- band reflectivity is extinct according to strong attenuation. The retrieval might not be accurate when the melting region cannot be detected properly, which happens in strong convections.

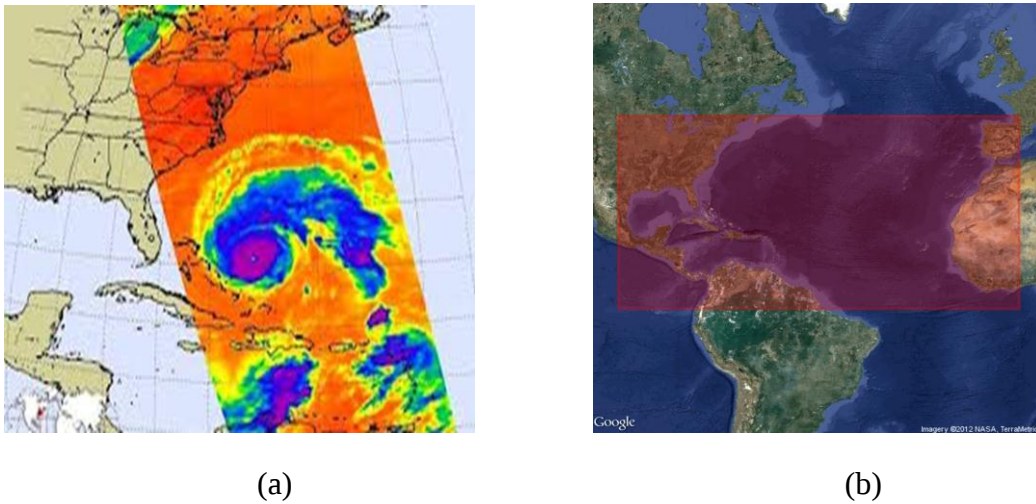


Figure 4.21. (a) Geographic location of Hurricane Earl. (b) Geographic location of APR-2 field experiment of GRIP.

Retrieval details of two sample profiles marked at “A” and “B” of GRIP overpass 100829-201850 are shown in Figure 4.24. The four left subplots in figure 4.24 belong to profile A, which is a convective rain with a reflectivity peak value around 44 dBZ. “Retrieved measurement” indicates how well the optimization procedure works since the difference between “retrieved” and “real” measurements should be minimized in the hybrid method. “Intrinsic measurement” corrects the attenuation at Ku- and Ka- band, respectively. Attenuation correction is done within same optimization procedure as in the hybrid method. The four right subplots belong to profile

B, which is a typical stratiform rain with bright band peak value smaller than 35 dBZ. A larger value of D_0 is retrieved for profile A than profile B; the corresponding N_w value is slightly smaller for profile A than for profile B.

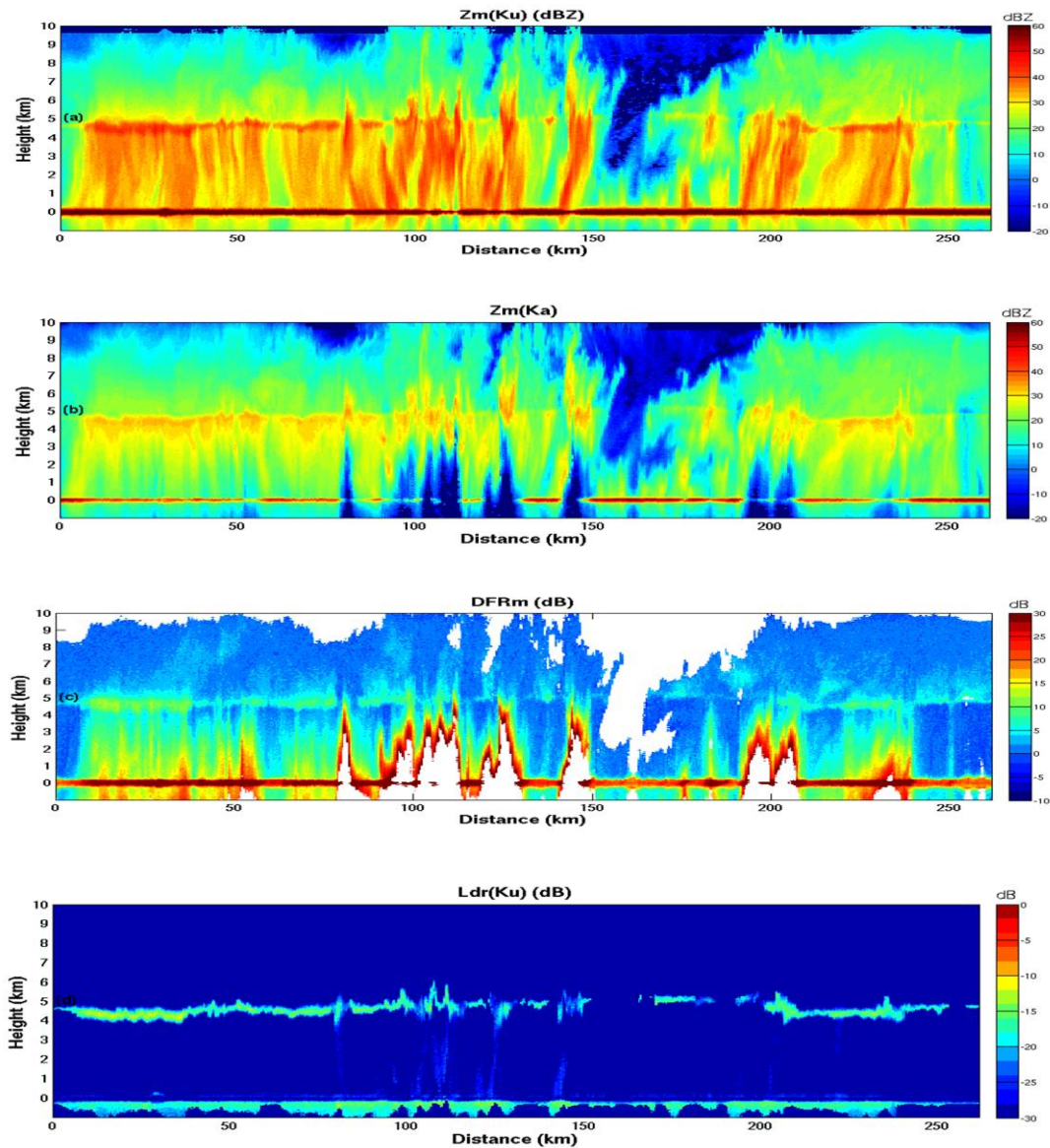


Figure 4.22. GRIP overpass of 100829-201850 collected by APR-2 on August 29, 2010. Top to bottom panels are: Reflectivity at Ku- band; reflectivity at Ka- band; measured dual frequency ratio; linear depolarization ratio at Ku- band.

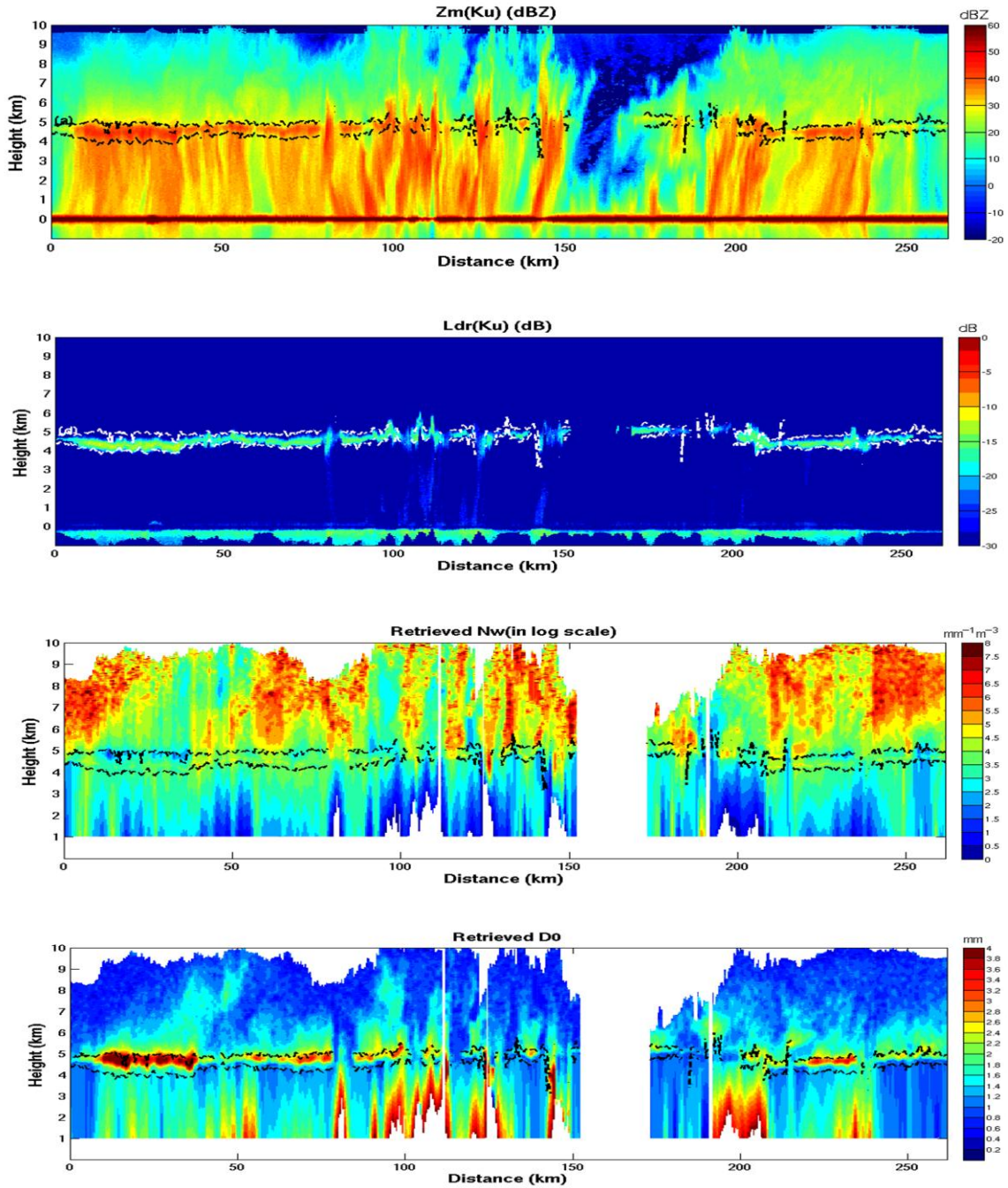


Figure 4.23. Top to bottom panels are: GRIP overpass of 100829-201850, reflectivity of Ku-band (Black dashed lines are melting layer top and bottom detected using *HPC* method); LDR at Ku-band with white dashed line being the melting layer top and bottom detected using *HPC* method; retrieved N_w (in log scale) using the hybrid method; retrieved D_0 using the hybrid method.

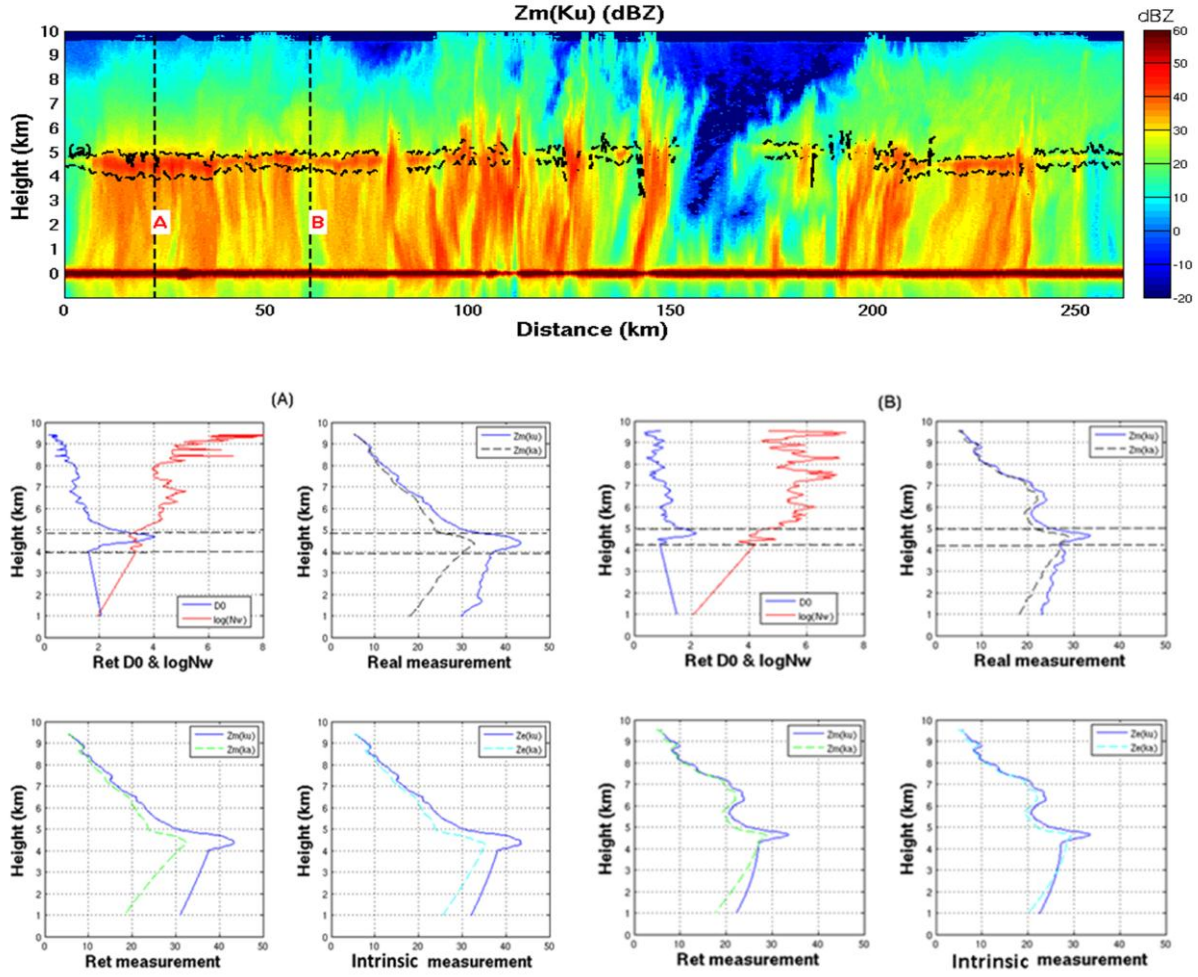


Figure 4.24. Top panel: Same GRIP overpass of reflectivity at Ku-band with black dashed lines indicating melting layers and location of vertical profile “A” and “B”. Left bottom four subplots: real measurements and retrievals of profile “A”. Right bottom four subplots: real measurements and retrievals of profile “B”.

4.4.2 Self-consistency check

The true microphysics of Hurricane Earl are unknown. However, a self-consistency check provides an effective way to look into the rationality of the retrievals. Figure 4.25 (a) shows the

scatter plot between D_0 and $\log(N_w)$. As expected, these two DSD parameters show complementary relations, with most D_0 values falling into 1~2.5mm and $\log(N_w)$ in between 2~4. These are reasonable values. In figure 4.25 (b), the relation between $\log(D_0)$ and $\log(\frac{Z_{ku}}{N_w})$ is plotted and the fitting equation is calculated. The coefficients of the fitting curve show good agreement with the theoretical relation, as shown in (14) in Chandrasekar et al. (2005). Histograms of D_0 and $\log(N_w)$ are shown in Figure 4.25 (c) and (d).

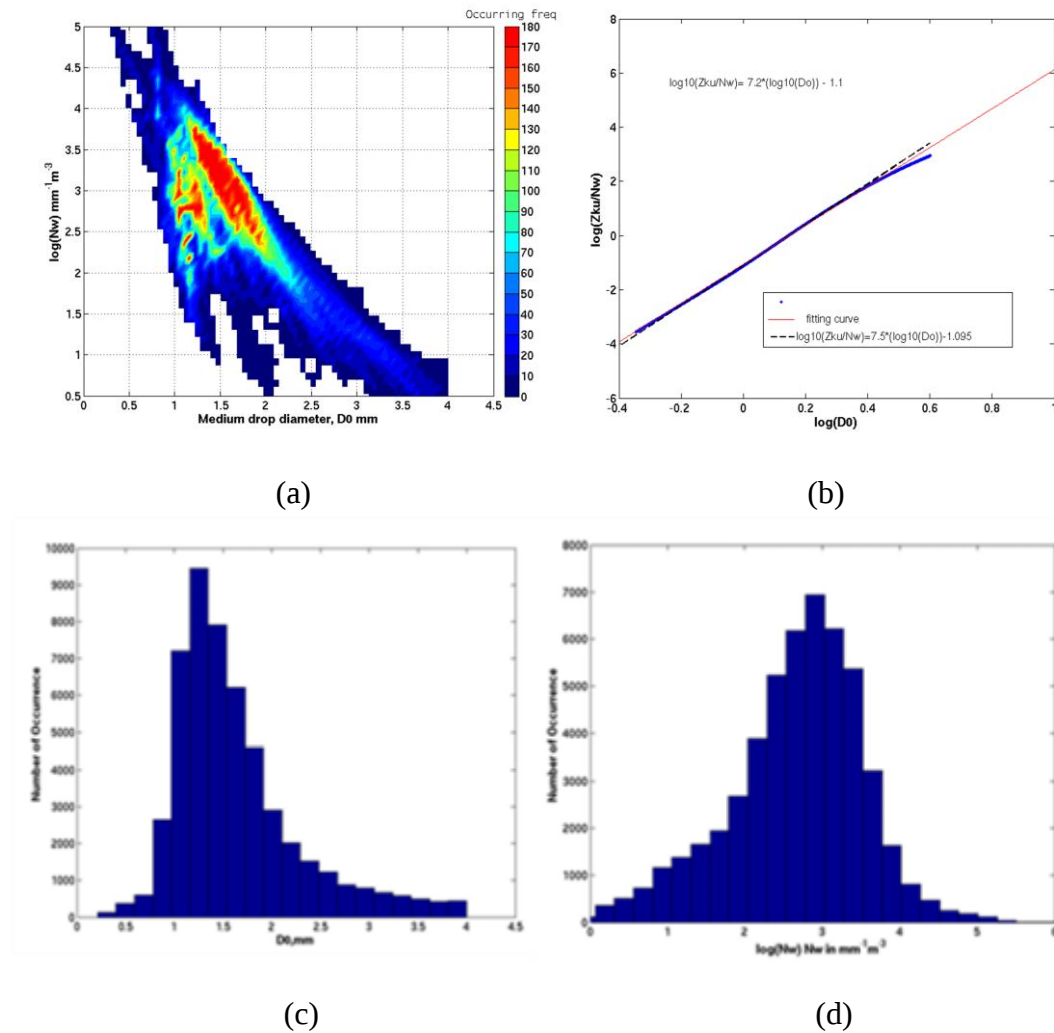


Figure 4.25. (a) Scatter plot of D_0 versus $\log(N_w)$ with occurring frequency shown in color scale. (b) Relation of $\log(D_0)$ versus $\log(\frac{Z_{ku}}{N_w})$. (c) Histogram of D_0 . (d) Histogram of $\log(N_w)$.

Stratiform and convective rain can be separated using the *PCM* method described in Chapter 3. Their corresponding DSDs are plotted in figure 4.26. Stratiform rain shows smaller D_0 than convective rain with the mean value around 1.3 mm. The corresponding mean value of $\log(N_w)$ for stratiform rain is around 3. Convective rain has a larger D_0 and smaller N_w in general.

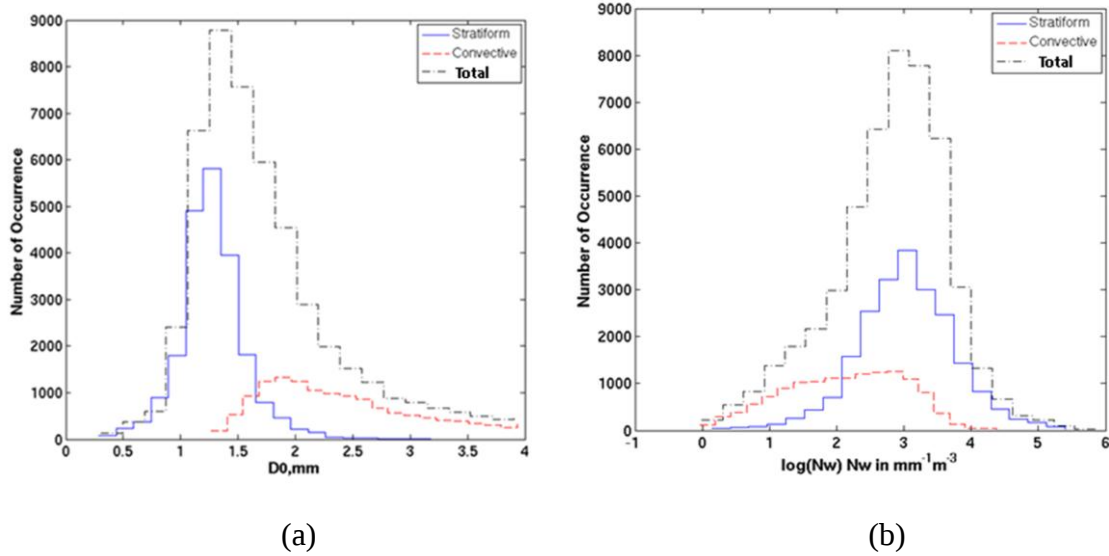


Figure 4.26. (a) Histogram of D_0 for stratiform, convective and total rain analyzed from GRIP 100829-201850 overpass. (b) Same analysis for $\log(N_w)$.

CHAPTER 5

DROP SIZE DISTRIBUTION RETRIEVAL ALGORITHM FOR DUAL FREQUENCY AND DUAL POLARIZATION DOPPLER (D3R) RADAR

5.1 INTRODUCTION

Ground validation is an integral part of all satellite precipitation missions. Ground validation helps to characterize errors, quantify measurement uncertainty, and, most importantly, provides insight into the physical basis of the retrieval algorithms. GPM validation falls in the general class of validation and integration of information from a variety of space-borne observing platforms with ground-based measurements. Dual-polarization ground radar is a powerful tool that can be used to address a number of important questions that arise in the validation process, especially those associated with precipitation microphysics and algorithm development (Chandrasekar et al. 2008).

Estimation of the drop size distribution (DSD) parameters of precipitation particles helps to achieve more accurate estimations of precipitation rate. Simplified models have been used to obtain DSD from both space-borne radar and ground dual polarization radar (Meneghini et al., 1992, 1997; Chandrasekar et al., 2005; Mardiana et al., 2004; Gorgucci et al., 2002a, 2008; Bringi et al., 2002). However, no retrieval algorithms currently exist for a dual-frequency, dual-polarization ground radar, which is the main focus of this chapter. The DSD retrieval algorithm developed in this chapter is applied to the Ku-/Ka- band dual-frequency and dual-polarization

Doppler (D3R) radar, which will serve as the GPM-DPR ground validation. Figure 5.1 shows a sketch of ground validation of the GPM-DPR with D3R radar.

This chapter starts with a discussion of the principle of dual-frequency and dual-polarization retrieval. The DSD retrieval algorithm developed for D3R radar forms the main part of the chapter. Evaluations are focused on rain and some preliminary evaluations are performed for regions beyond rain.

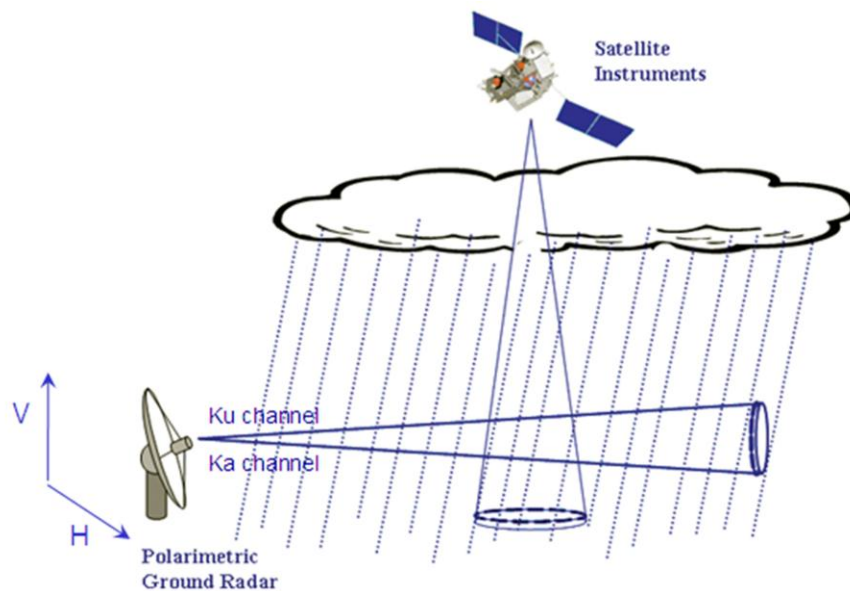


Figure 5.1. Illustration of ground validation of GPM-DPR with D3R radar.

5.2 PRINCIPLES OF DUAL-FREQUENCY AND DUAL-POLARIZATION RETRIEVAL ALGORITHM

One of the standard dual-frequency methods used for space radar is based on the conversion of differential attenuation to the rain rate (Eccles, 1979; Iguchi, 2005). However, this method requires one of two assumptions to be valid: reflectivity at both channels is equal to Rayleigh scattering reflectivity or the rain is uniform. Either of these assumptions limits the application of the algorithm. Meanwhile, the method is focused on the rain rate estimation rather than the drop size distribution parameters. Then, a two-scale DSD estimation procedure is generalized to dual-frequencies, thereby providing a two-parameter estimation of DSD at each range gate. This method has been widely used in dual-frequency space and airborne radar retrievals (Meneghini et al., 1997; Koze et al., 1991; Liao et al., 2008). The common concept within the second approach that has been proposed for dual-frequency radar is that the dual-frequency ratio DFR (describing the difference of the radar reflectivity at two frequencies in decibels) is the key parameter in DSD retrieval and is proportional to median drop diameter when at least one of the frequencies falls into non-Rayleigh scattering.

However, these DSD retrieval algorithms suffer from the bi-valued problem for the rain region. (i.e., the non-uniqueness of median volume diameter D_0 retrieval from DFR parameter (Meneghini et al. 1997)). Chapter 4 contains a detailed discussion of dual-frequency retrievals. Extensive research has been done regarding accurate DSD retrieval as well as attenuation correction for dual-polarization ground radar operating at S-, C- and X- band using polarimetric measurements (Testud et al., 2000; Gorgucci et al., 2002a, 2008; Bringi and Chandrasekar,

2001). The five basic polarimetric radar measurements are: horizontal reflectivity (Z_h), differential reflectivity (Z_{dr}), specific differential phase (K_{dp}), linear depolarization ratio (LDR), and correlation coefficient (ρ_{hv}). One of the popular approaches is the algorithm developed by Gorgucci et al. (2006b, 2008), which takes advantage of the self-consistency between the radar parameters of reflectivity factor, differential reflectivity, and specific differential phase. The self-consistency (SC) principle is applied for attenuation correction at X- band and later adapted to a fully self-consistent (FSC) method. The DSD parameters are retrieved (Gorgucci et al., 2008) based on the attenuation-corrected radar parameter using parameterization proposed earlier by Gorgucci et al. (2002a). The SC and FSC methods rely on an optimization procedure that constraints the estimated and observed differential phases.

In this chapter, a new DSD retrieval algorithm is presented with the retrieval philosophy based on combining the attributes of DFR, historically used in space-borne radar techniques, and dual-polarization approach Z_{dr} used in ground radar algorithms. As mentioned in Chapter 4, retrieval of Do from DFR suffers from a bi-valued solution for rain, as can be seen in figure 5.2 (a). The DSD retrieval algorithm introduced in this chapter mitigates this problem by adding a constraint to the Do retrieval from differential reflectivity (Z_{dr}). Figure 5.2 shows theoretical simulation of DFR versus Do and Z_{dr} versus Do relation for rain drop using the Andsager et al. (1999) model. The widely varying DSDs used in the simulation are generated by randomly varying N_w , Do, and μ over the following ranges:

$$10^3 \leq N_w \leq 10^5 \text{ (mm}^{-1}\text{m}^{-3}\text{)}$$

$$0.5 \leq D_0 \leq 3.5 \text{ (mm)}$$

$$-1 \leq \mu \leq 5 \quad (5.1)$$

These two relations are fundamental to the retrieval and will be discussed in detail in the following section.

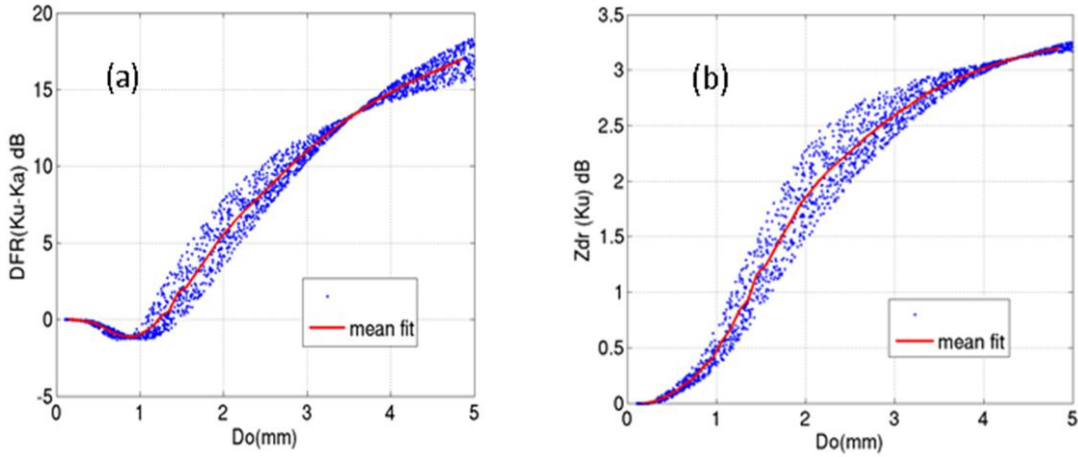


Figure 5.2. (a) DFR versus D_0 for rain, with $-1 < \mu < 5$, using the Andsager et al. (1999) rain drop model. (b) Z_{dr} versus D_0 for rain using the same rain drop model. The curves in both plots are the mean fit.

5.3 DROP SIZE DISTRIBUTION RETRIEVAL ALGORITHM FOR D3R

5.3.1 Algorithm description

The dual-frequency and dual-polarization retrieval algorithm developed for D3R radar is a ray-based, self-consistent optimization procedure. The two frequencies considered for the dual-frequency radar are Ku- and Ka- band. The method adjusts the estimates of the cumulative

attenuations at Ku- and Ka- band and cumulative differential attenuation at Ku- band at the farthest range of each beam iteratively until these estimates retrieve the reflectivity and differential reflectivity factors that best match the measurements. The state vectors are optimized when the retrievals converge within a given tolerance; concurrently with the DSD values at each bin. Attenuation correction is achieved within the same optimization process.

Following commonly used notations in the literature (Bringi and Chandrasekar, 2001) the governing equations of dual-polarization, dual-frequency observations from precipitation can be written as follows: Let $Z_{m,i}(r)$ and $Z_{drm,i}(r)$ be the measured reflectivity and differential reflectivity in linear sense at a specified range r . The subscript $i(i = 1, 2)$ represents the particular frequency (13.6 (Ku) and 35.5 (Ka) GHz, respectively). $Z_{e,i}(r)$ and $Z_{dr,i}(r)$ are the intrinsic reflectivity and differential reflectivity in a linear sense while $A_i(r)$ and $A_{dp,i}(r)$ are the two-way path-integrated attenuation and differential attenuation factors from the radar to range r . When these variables are used with a tilde ($\sim$), it implies these are algorithm-estimated values. The attenuated reflectivity and differential reflectivity in rain can be written in term of the intrinsic values and attenuation as

$$Z_{m,i}(r) = Z_{e,i}(r)A_i(r), \quad (5.2)$$

$$Z_{drm,i}(r) = Z_{dr,i}(r)A_{dp,i}(r), \quad (5.3)$$

where the intrinsic values can be related to the DSD parameters as

$$Z_{e,i}(r) = N_w(r)f(\mu)D_0^{-\mu}I_{hb,i}(D_0), \quad (5.4)$$

$$Z_{dr,i}(r) = I_{db,i}(D_0). \quad (5.5)$$

$I_{hb,i}$ and $I_{db,i}$ are both function of D_0 which can be expressed in the form of

$$I_{hb,i}(D_0) = C_{zi} \int_D \sigma_{b,i}(D) D^\mu e^{-\Lambda D} dD, \quad (5.6)$$

$$C_{zi} = \frac{\lambda_i^4}{\pi^5 |K_w|^2}, \quad (5.7)$$

$$I_{db,i}(D_0) = I_{hb,i}(D_0) / I_{vb,i}(D_0). \quad (5.8)$$

σ_b is the backward scattering cross section and λ represents wavelength. K_w is defined as

$$K_w = \frac{m^2 - 1}{m^2 + 1}, \quad (5.9)$$

with m representing the complex index of refraction of water. $I_{hb,i}$ represents the integrated scattering parameter at horizontal polarization, while $I_{vb,i}$ has the same definition as (5.6), but with σ_b at the vertical polarization. The two-way attenuation factor and differential attenuation factor can be expressed using specific attenuations as

$$A_i(r) = \exp[-0.2 \ln(10) h \sum_{n=1}^j \alpha_{h,i}(r_n)], \quad (5.10)$$

$$A_{dp,i}(r) = \exp[-0.2 \ln(10) h \sum_{n=1}^j \alpha_{dp,i}(r_n)], \quad (5.11)$$

where specific attenuation $\alpha_{h,i}$ and specific differential attenuation $\alpha_{dp,i}$ are related to DSD parameters as

$$\alpha_{h,i}(r) = N_w f(\mu) D_0^{-\mu} I_{ht,i}(D_0) , \quad (5.12)$$

$$\alpha_{dp,i}(r) = N_w f(\mu) D_0^{-\mu} I_{dt,i}(D_0) , \quad (5.13)$$

where

$$I_{ht,i}(D_0) = C_{ki} \int_D \sigma_{t,i}(D) D^{-\mu} e^{-\Lambda D} dD , \quad (5.14)$$

$$I_{dt,i}(D_0) = I_{ht,i}(D_0) - I_{vt,i}(D_0) , \quad (5.15)$$

$$C_{ki} = 4.343 \times 10^{-3} . \quad (5.16)$$

σ_t is the extinction cross section. $I_{ht,i}$ represents the integrated scattering parameter at horizontal polarization while $I_{vt,i}$ has the same definition as in (5.14), but with σ_t at the vertical polarization. j in (5.10) and (5.11) represents the number of gates and h is the range resolution of the radar beam. The radar dual frequency ratio (DFR) in decibels, describing the difference of the radar reflectivity at two frequencies, is defined as

$$DFR = 10 \log_{10}(Z_{e,1} / Z_{e,2}) . \quad (5.17)$$

The proposed retrieval algorithm falls into the general class of self-consistent optimization procedures. Within each iteration, this radar beam-based DSD retrieval algorithm can be separated into two steps. The first step is the backward retrieval. The “backward” direction means starting from the farthest detectable bin of each beam and moving closer to the radar. In this step, the DSD parameters D_0 and N_w are retrieved bin by bin using the combined estimate.

The combination comes from the parameter of DFR and attenuation-corrected Z_{dr} at Ku- band.

The combined estimate can be expressed as

$$\tilde{D}_0 = f(DFR, Z_{dr,1}) \quad (5.18)$$

Figure 5.2 (a) and (b) shows the simulated theoretical relation of DFR versus Do and Z_{dr} (in decibels) versus Do for rain. When the DFR versus Do relation falls into the bi-solution region, where Do is approximately smaller than 1.2 mm according to the mean fit curve in figure 5.2 (a),

the $Z_{dr,1}$ versus Do relation is used to get $\tilde{D}_0$. Otherwise, the mean value of estimated Do from

(a) and (b) is taken as $\tilde{D}_0$. Then, N_w at the same bin is calculated based on

$$N_w = \frac{Z_{m,i}}{f(\mu)D_0^{-\mu}I_{b,i}(D_0)A_i}, \quad (5.19)$$

where $Z_{m,i}$ represents the observation of reflectivity. Since DFR and Z_{dr} used in retrieving Do are both attenuation-corrected values, the backward retrieval corrects attenuation concurrently with the initial guess of the cumulative two-way attenuations A_H and differential attenuation A_{dp} at the farthest detectable bin, also known as state vectors. Then the attenuation corrected for the second farthest bin is calculated based on the DSD parameters retrieved at the farthest bin described in (5.10)-(5.16). This process continues bin by bin until it reaches the closest bin to radar. A_H and A_{DP} are related to the attenuation factors described in (5.10) and (5.11) by

$$A_{H,i} = -10\log_{10} A_i(r_N), \quad (5.20)$$

$$A_{DP,1} = -10\log_{10} A_{dp,1}(r_N), \quad (5.21)$$

where r_N represents the farthest detectable bin from radar. The initial guesses of $A_{H,1}$ and $A_{dp,1}$ are from the approximately linear relation between differential phase ϕ_{dp} versus $A_{H,1}$ and ϕ_{dp} versus $A_{DP,1}$ for rain (Bringi and Chandrasekar, 2001). These relations are calculated with widely varying DSDs using the Andsager et al. (1999) rain model. The widely varying DSDs are generated by randomly varying N_w , D_0 , and μ over the ranges in (5.1). The initial guess of $A_{H,2}$ is calculated from its approximately linear relation with DAD (difference of attenuation differences) (Iguchi, 2005).

The second step is the forward estimation. The “forward” direction means starting from the bin closest to the radar and moving away until it reaches the farthest detectable one. In this step, $Z_{m,1}$, $Z_{m,2}$ and $Z_{drm,1}$ at each bin are estimated based on the DSD parameters retrieved in the first step using (5.2)-(5.16). The measurements for the first bin are estimated without attenuation correction. Then the two-way attenuations at the second bin are estimated based on the DSD parameters retrieved in the first one and are subtracted from the estimated intrinsic values to get the estimated measurements. This process continues until it reaches the farthest detectable bin. Figure 5.3 shows the schematics of the backward and forward directions in the proposed D3R DSD retrieval algorithm.

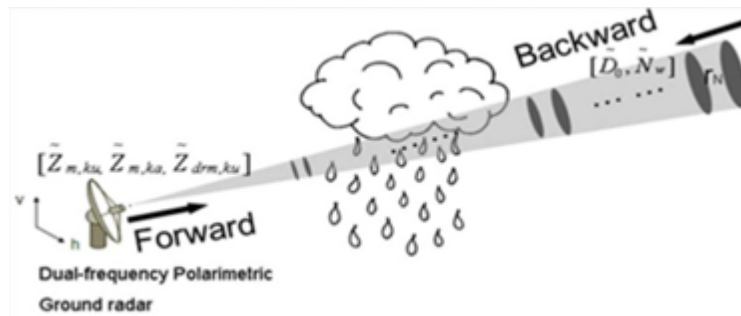


Figure 5.3. Schematics of forward and backward steps in the D3R DSD retrieval.

Then, the minimization function is formulated using the estimated measurements from step two and the observations as

$$C = \sum_{n=1}^j [(Z_{m,1}^{\sim}(r_n) - Z_{m,1}(r_n)) \times W_1(r_n)]^2 + \sum_{n=1}^j [(Z_{m,2}^{\sim}(r_n) - Z_{m,2}(r_n)) \times W_2(r_n)]^2 + \sum_{n=1}^j [(Z_{drm,1}^{\sim}(r_n) - Z_{drm,1}(r_n)) \times W_3(r_n)]^2 \quad (5.22)$$

for the complete beam. W_1, W_2, W_3 represent the weighting function of each term calculated based on the normalized ratio defined as

$$W_1(r_n) = \frac{Z_{e,1}(r_n)}{\sum_{n=1}^j Z_{e,1}(r_n) \times \overline{Z_{e,1}}},$$

$$W_2(r_n) = \frac{Z_{e,2}(r_n)}{\sum_{n=1}^j Z_{e,2}(r_n) \times \overline{Z_{e,2}}},$$

$$W_3(r_n) = \frac{Z_{dr,1}(r_n)}{\sum_{n=1}^j Z_{dr,1}(r_n) \times \overline{Z_{dr,1}}} \quad (5.23)$$

Reflectivity and differential reflectivity in (5.23) are intrinsic values in decibels calculated from (5.4) and (5.5). The symbol “ $\overline{}$ ” in (5.23) indicates the mean value.

The state vectors are adjusted until the difference between the estimations and observations are minimized within the given tolerance. Therefore, the optimized Do and N_w are achieved at each bin and the attenuations are corrected within the same procedure. The flow diagram of the algorithm is summarized in figure 5.4.

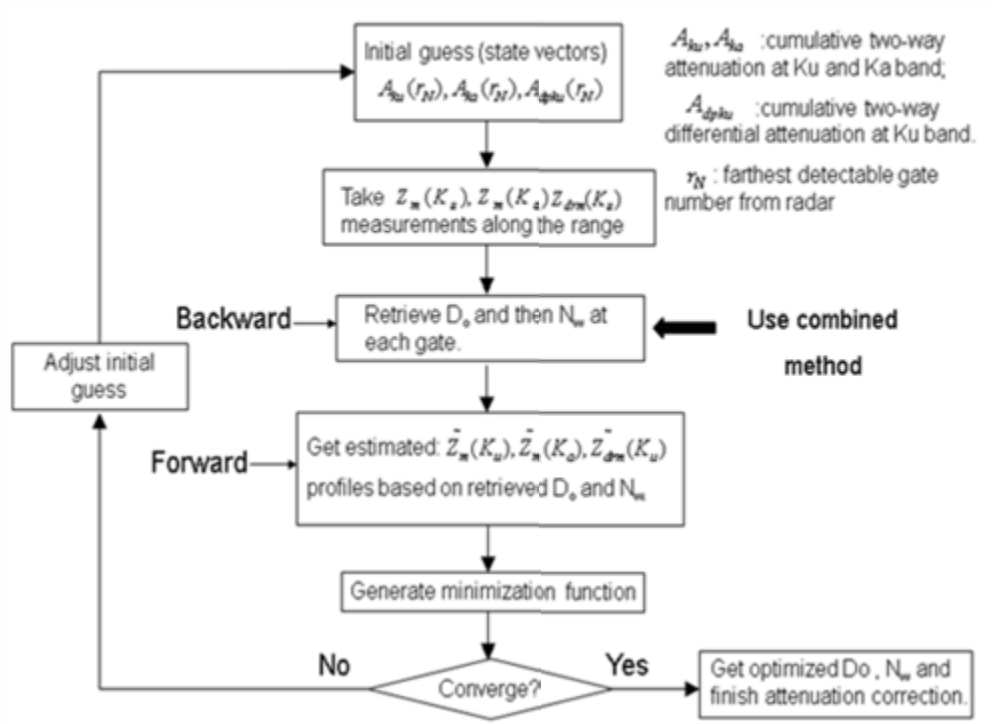


Figure 5.4. Flowchart of DSD retrieval algorithm for D3R radar.

5.3.2 Algorithm evaluation for rain observation

The DSD retrieval algorithm described in the previous section is evaluated for rain observation based on simulation data. S-band (3 GHz) PPI (Plan Position Indicator) scan observations from the Severe Thunderstorm Electrification and Precipitation Study (STEPS) project collected by CSU-CHILL radar in 2000 (www.nssl.noaa.gov/observations/projects/steps.html) are used to generate Ku- and Ka- band observations for algorithm evaluation. A low elevation angle (1.4 degrees) PPI scan of S band data is chosen to make sure the region of interest is dominated by rain. The reason and the procedure for using simulation data are discussed in Chapter 2.

Figure 5.5 shows the evaluated DSD parameters from the S- band dual-polarization radar observations (Gorgucci et al., 2002a; Bringi et al., 2002). Figure 5.6 illustrates the simulation data at Ku- and Ka- band using the DSDs shown in Figure 5.5. Figure 5.6 (a), (c) and (e) are the simulated intrinsic reflectivity at Ku-, Ka- band and intrinsic differential reflectivity at Ku- band while (b), (d), and (f) are the corresponding attenuated values. It is obvious that attenuation at Ka- band is higher compared to Ku- band. The data from the second column will be regarded as the true observations in the algorithm evaluation. Figure 5.6 was shown in chapter 2 (figure 2.15) and is shown in this chapter for ease of reference.

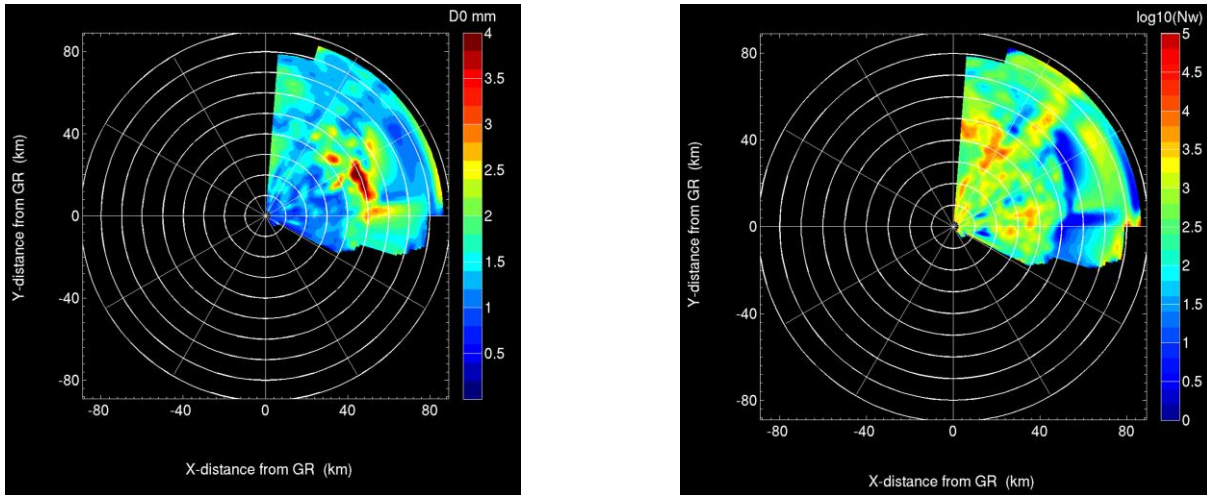


Figure 5.5. Retrieved D_0 and N_w (in log scale) from S band dual-polarization ground radar observations during STEPS project (20000620_012145).

The performance of the retrieval algorithm is illustrated in the scatter plot in figure 5.7 using the same raindrop model in simulation as in the retrieval. The algorithm retrieved D_0 and N_w (in log scale) parameters are compared to the simulation “truth”. Normalized bias (NB) is defined as the difference between the mean estimated and true values normalized to the mean true, while

normalized standard error (NSE) is the root-mean-square error normalized with respect to the mean true value. Good agreement can be found with an NB of -0.35%, NSE of 1% for D_0 comparison and NB of 0.74%, NSE of 1.47% for $\log_{10} N_w$ comparison as shown in (a) and (b) of figure 5.7. The evaluation shown in (a) and (b) of figure 5.7 doesn't include the impact of backscatter differential phase (δ). However, the backscatter differential phase is not negligible for large rain drop volume at Ku- band. In order to evaluate that, the backscatter differential phase simulations were included in the Φ_{dp} profiles that were used in the calculation of the state vectors. The corresponding retrievals are shown in figure 5.7 (c) and (d). The NB and NSE are -0.37% and 1.2% for D_0 comparison, and 0.71% and 1.5% for N_w comparison. It is clear that the backscatter differential phase doesn't affect the performance of the algorithm since it only affects the values of the initial guess, which could be automatically adjusted within an iterative process.

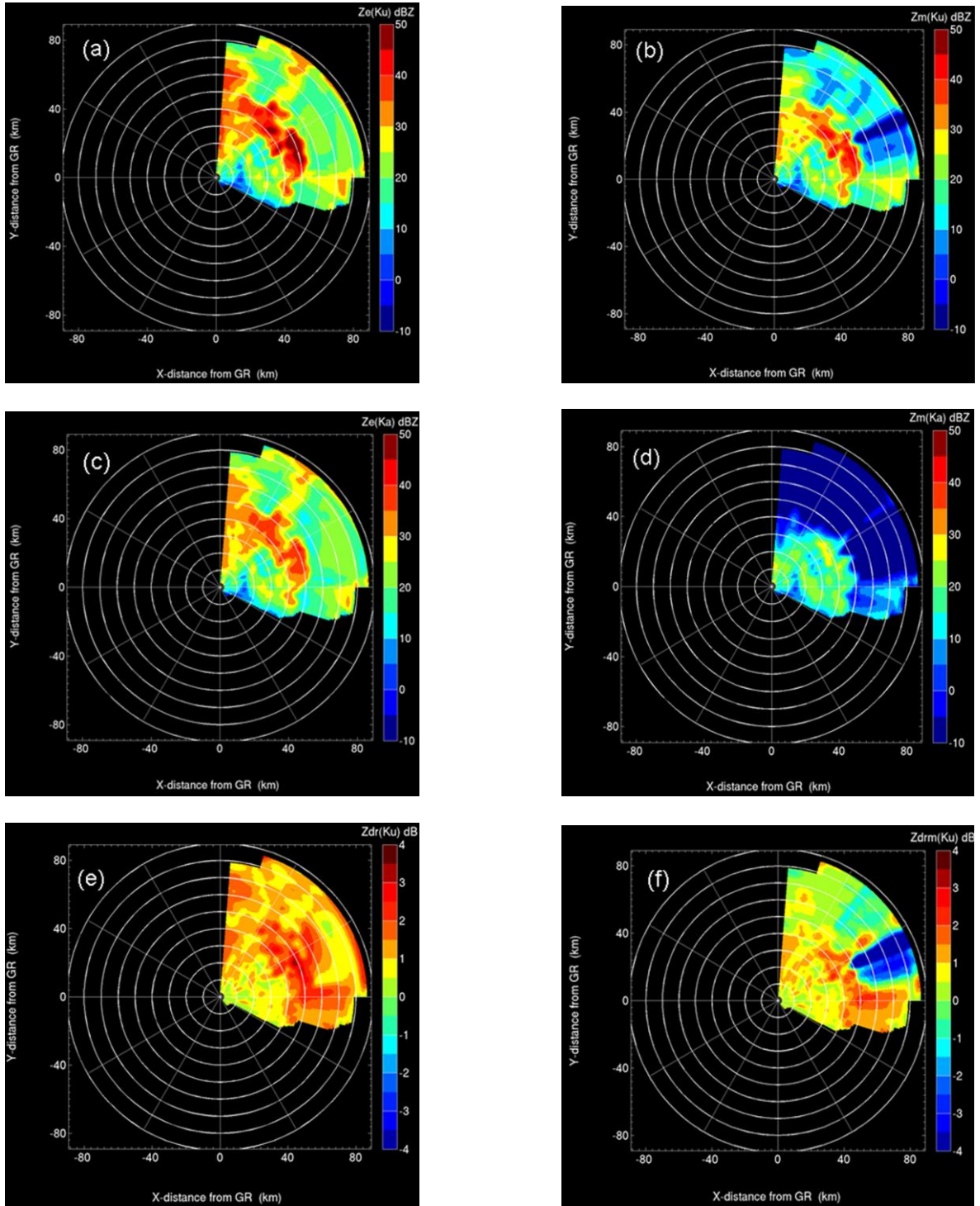


Figure 5.6. Simulated PPI scan from S- band observations during STEPS project (20000620_012145 case). (a), (c) and (e): intrinsic reflectivity at Ku-, Ka- band and intrinsic differential reflectivity at Ku- band. (b), (d) and (f): attenuated reflectivity at Ku-, Ka- band and attenuated differential reflectivity at Ku- band.

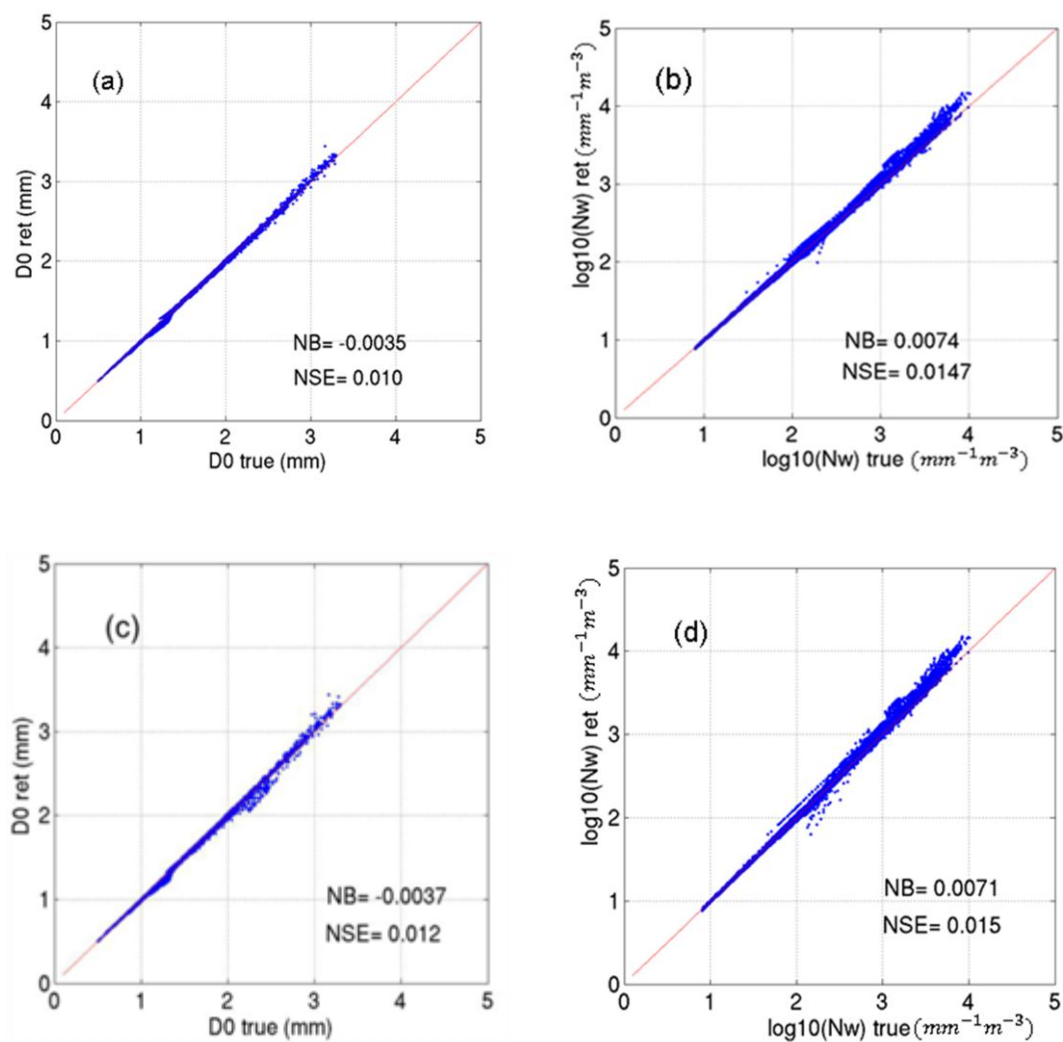


Figure 5.7. Scatter plot of the algorithm retrieved D_0 and $\log_{10} N_w$ versus the simulation truth using the same raindrop model in simulation as in retrieval. (a) and (b): no backscatter differential phase is added. (c) and (d): backscatter differential phase is added.

5.3.3 Error analysis

The error structure of the proposed algorithm depends on many aspects such as prevailing raindrop model, measurement error, as well as the uncertainties of temperature and shape factor μ . The self-consistency algorithm imposes the internal consistency of the reflectivity and differential reflectivity estimates with respect to variability in DSD as well as variability in raindrop shape model. In the literature, there are many raindrop models besides the Beard and Chuang (1987) rain model (the BC model) such as the linear model, the Andsager et al. (1999) model (ABC model), and other raindrop models from experiments (Pruppacher and Beard 1970; Thurai et al. 2007). However, the variability of shape model within a storm is not clearly known. To evaluate the error due to drop shape variability, Ku- and Ka- band data generated from S-band are based on the raindrop model given by the BC model, while the ABC model was used in the algorithm retrieval. Figure 5.8 shows a scatter plot of the comparison between the algorithm retrieved D_0 , N_w and the simulation truth using the BC rain drop model in simulation but the ABC model in retrieval. The influence of the model change can be seen in the corresponding NB values for D_0 and N_w which equal 8.77% and -7.35% while the corresponding NSE values are 9.68% and 7.74% respectively. These results indicate that the algorithm is sensitive to the raindrop model change. A reasonable explanation is that the dual polarized parameter Z_{dr} is the parameter affected by different drop axis ratio versus drop size relations. However, the NB and NSE values for both D_0 and N_w are still good for these two commonly recognized raindrop models.

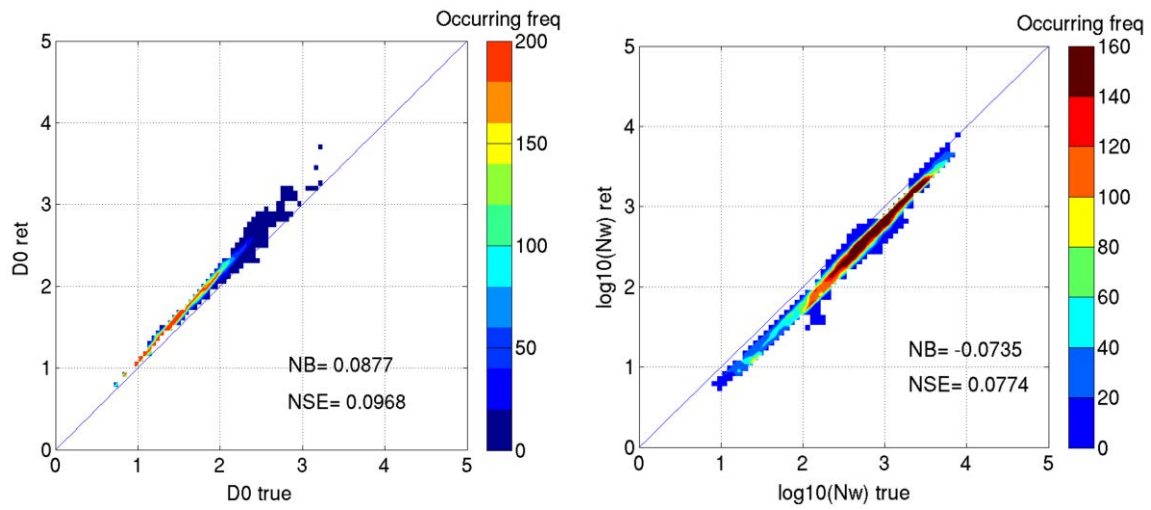


Figure 5.8. Scatter plot with the occurrence frequency shown in the color bar. Comparison between the algorithm retrieved Do, Nw and the simulation truth using the BC rain drop model in simulation but the ABC model in retrieval.

The impacts of the measurement errors, including measurement fluctuation and radar system bias to the algorithm, were tested. Random signal fluctuation was generated that reflectivity and differential reflectivity measurement errors correspond to 1 dB and 0.2 dB, respectively. Figure 5.9 shows the scatter plot of the comparison between the algorithm retrieved Do, Nw and the simulation truth when only system noise is considered. The analysis illustrates a good agreement for Do comparison with a small NB of 1.70% and an NSE of 11.3%. Similar conclusions are true for Nw comparison with an NB of -1.11% and an NSE of 15.1%. The scatter plot clearly indicates that most of the points are well aligned with true values.

Since the proposed algorithm compares estimated measurements to the observations, it is subject to bias errors in reflectivity and differential reflectivity. Assuming the bias errors in reflectivity and differential reflectivity are within 1 and 0.2 dB, respectively, table 5.1 lists the four system

bias types applied in the test. Bias type 1 corresponds to [1,1,0] and the three values in order are the biases in reflectivity measurements at Ku-, Ka- band and the bias in differential reflectivity measurement at Ku- band. Bias types 2,3,4 are [1,-1,0], [1,1,0.2], and [1,-1,-0.2], as shown in table 5.1. The effects from bias errors are tested based on the four bias types, and the NB and NSE are calculated and summarized in table 5.2. It is not difficult to see that the attribute of the combined method helps balance the biases from different parameters. For example, comparing the results with noise only and bias type 2 ([1,-1,0]) in table 5.2, the bias caused by DFR overestimates D_o with NB increases from 1.70% to 4.82%. However, in bias type 4 ([1,-1,-0.2]), the same value decreases to -1.44% since the negative bias applied to Z_{dr} measurement helps balance out the positive bias in DFR. The backscatter differential phase and noise are also added to the measurements in the bias test.

Table 5.1. System bias scenario for the two-frequency formulation test.

Bias scenario:	Zm(Ku) dBZ	Zm(Ka) dBZ	Zdrm(Ku) dB
Type 1	1	1	0
Type 2	1	-1	0
Type 3	1	1	0.2
Type 4	1	-1	-0.2

The shape factor μ in the gamma distribution could extend over a wide range; most of the literature studied the variability in the -0.99 to 5 (Ulbrich 1983). The variability of μ affects the performance of the algorithm. In order to quantify the error caused by this parameter, $\mu=3$ is used in the simulation, while $\mu=0, 1, 2, 3, 4, 5, 6$ is applied in the algorithm retrieval, respectively. Other error sources are not included in this evaluation. Figure 5.10 shows normalized bias of Do and Nw in the algorithm evaluation with respect to different μ values assumed in retrieval. It is shown that the performance of the algorithm is affected by different shape factor μ . If exponential distribution is assumed in retrieval, NB is around -17% and 15% for Do and Nw estimation. However, the magnitude of NBs for both parameters decrease when the μ assumed in retrieval increases from 0 to 3. Both NB values approach 0 when μ used in retrieval is the same as in the simulation ($=3$). The magnitude of NBs starts to increase when retrieved deviates μ from 3. It needs to be pointed out that the NBs with retrieved μ around its true value have opposite signs. In reality, shape factor μ is not a fixed number but within a range. In order to test the algorithm in a varying μ condition, μ is randomized between 0 to 5 for each gate in the retrieval and $\mu=3$ is kept in the simulation. The bias is around -2.28% and 2.66% for Do and Nw estimation. These values are small indicating that randomized μ s average the biases with opposite signs. Therefore, the proposed algorithm is not significantly affected by the sensitivity of the shape factor μ considered in realistic situations. Temperature is another variability source in the error analysis. The sensitivity of temperature affects the initial guess of state vectors, which cannot be ignored. However, the optimization procedure can adjust the state vectors within the iterative process.

Table 5.2. Normalized bias and normalized standard error in the comparison of the retrieved DSD and the truth for two-frequency formulation test.

Case	D_0		$\log_{10}(N_w)$	
	NB	NSE	NB	NSE
	(%)	(%)	(%)	(%)
noise only	1.70	11.3	-1.11	15.1
noise+bias(type1)	4.53	12.4	-2.52	15.4
noise+bias(type2)	4.82	12.9	-2.87	16.1
noise+bias(type3)	14.9	18.9	-12.2	17.8
noise+bias(type4)	-1.44	13.6	3.80	19.9

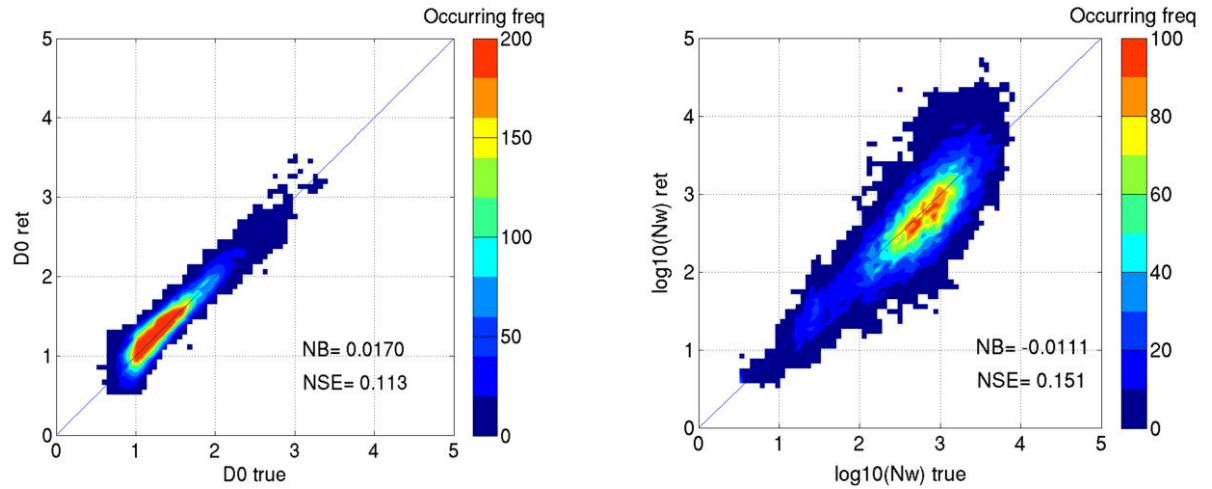


Figure 5.9. Scatter plot with occurrence frequency shown in the color bar. Comparison between the algorithm retrieved D_0 and the simulation truth considering system noise.

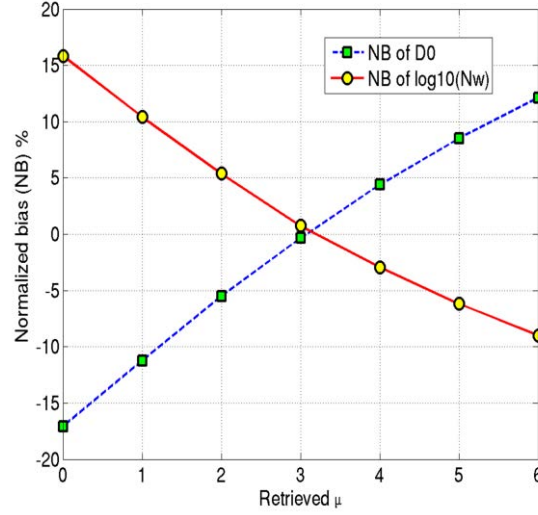


Figure 5.10. Normalized bias NB (%) of Do and Nw in the evaluation with respect to different μ values in retrieval when $\mu=3$ is used in simulation.

5.3.4 Applicability of the algorithm when Ka- band signal is extinct

Weather radar operating at Ku- and Ka- band suffers from attenuation when propagating through precipitation media like medium to heavy rain (Bringi and Chandrasekar, 2001). Compared to the Ku- band channel, the Ka- band channel suffers larger attenuation, and has a greater chance of becoming extinct. Under this condition, a dual frequency procedure is not useful and a Ku- band only retrieval is presented. The DSD retrieval algorithm proposed in previous sections is referred to as a two-frequency formulation in this section.

The Ku- band formulation retrieves Do from attenuation-corrected differential reflectivity $Z_{dr,1}$

$$\tilde{D}_0 = f(Z_{dr,1}) . \quad (5.27)$$

After estimating Do and Nw at each bin backwardly, attenuated reflectivity and differential reflectivity at Ku- band are estimated in the forward direction. The minimization function is formed as

$$C = \sum_{n=1}^j [(Z_{m,1}^{\sim}(r_n) - Z_{m,1}(r_n)) \times W_1(r_n)]^2 + \sum_{n=1}^j [(Z_{drm,1}^{\sim}(r_n) - Z_{drm,1}(r_n)) \times W_3(r_n)]^2 . \quad (5.28)$$

Compared to (5.25) and (5.26), all the symbols and the interpretations are the same but with the Ka- band information removed. The state vectors become cumulative attenuation and cumulative differential attenuation at Ku- band. Although Do is retrieved from $Z_{dr,1}$, cumulative attenuation at Ku- band is needed to estimate Nw which can be seen from (5.21).

Figure 5.11 shows the performance of the Ku- band only retrieval when the same raindrop model was used and the backscatter differential phase was included. The NB and NSE of both Do and Nw estimations illustrate good performance with similar orders of the performance for the two frequency formulations, as described in detail in section 5.3.1. The impact of the raindrop model is studied in this section. In order to do that, the BC model is applied in the simulation while the ABC model is used in the algorithm retrieval. Figure 5.12 shows a scatter plot of the comparison between the algorithm retrieved Do, Nw and the simulation truth using the BC rain drop model in simulation but the ABC model in retrieval. As expected, the performance of the Ku- band only retrieval is affected by the raindrop model change. Figure 5.13 shows the sensitivity of the $Z_{dr} - Do$ curve to different raindrop model. Comparing the results from figures 5.11 and 5.12,

NB of Do estimate increases from negative to positive value because the curve of $Z_{dr} - Do$ using ABC model overestimates the Do value in the retrieval. However, the NB and NSE values give similar orders as in the same sensitivity test for the two-frequency formulations which is satisfactory.

Figure 5.14 shows a scatter plot of the comparison between the algorithm retrieved Do, Nw and the simulation truth with random error. The performance is characterized by the following quantitative parameters: NB of 1.31%, NSE of 12.2% for Do estimation, and NB of 0.281%, NSE of 15.8% for Nw estimation, which is fairly good. When adding system biases, the mean value of NSE for Do and Nw estimations using Ku band only retrieval are approximately 6% and 3% worse than the two frequency formulation, while the NBs are about 1%-4% worse. The values for each bias scenario can be found in tables 5.3 and 5.4. The combined method used in the two-frequency formulation helps to balance the biases and performs better than Ku- band only retrievals.

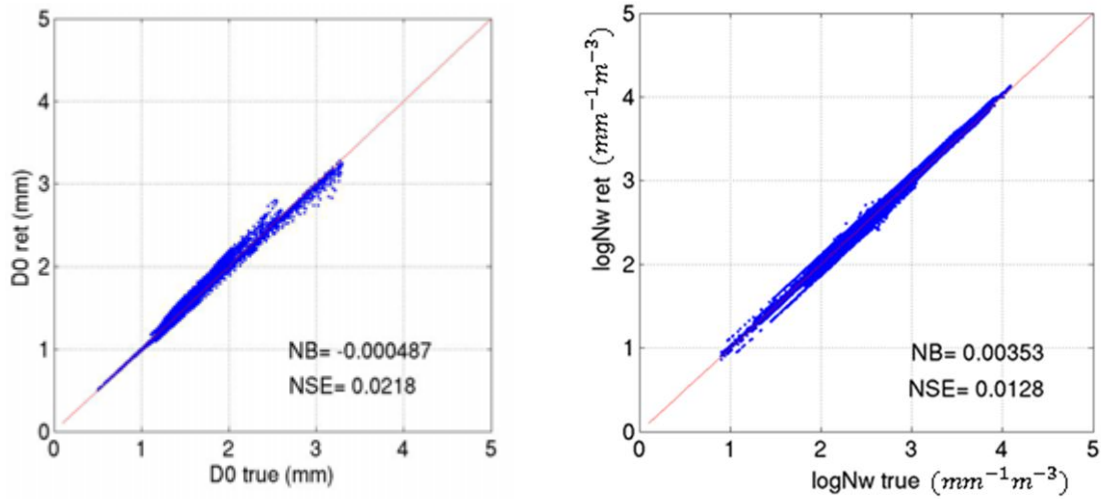


Figure 5.11. Scatter plot of the algorithm retrieved Do and Nw versus the simulation truth using the same raindrop model in simulation as in retrieval considering backscatter differential phase based on Ku- band formulation.

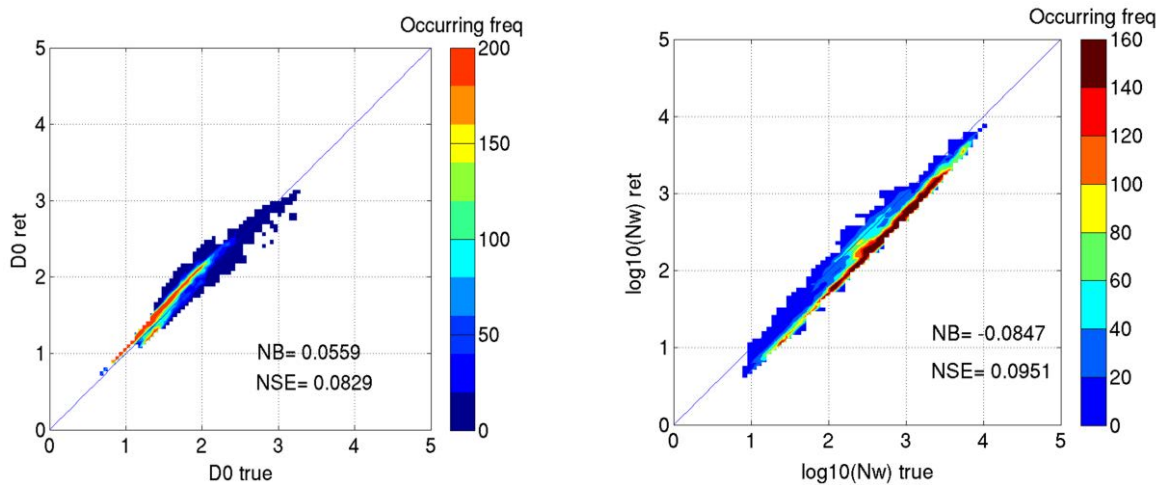


Figure 5.12. Scatter plot of the algorithm retrieved Do and Nw versus the simulation truth using the BC model in simulation but the ABC model in retrieval based on Ku- band formulation.

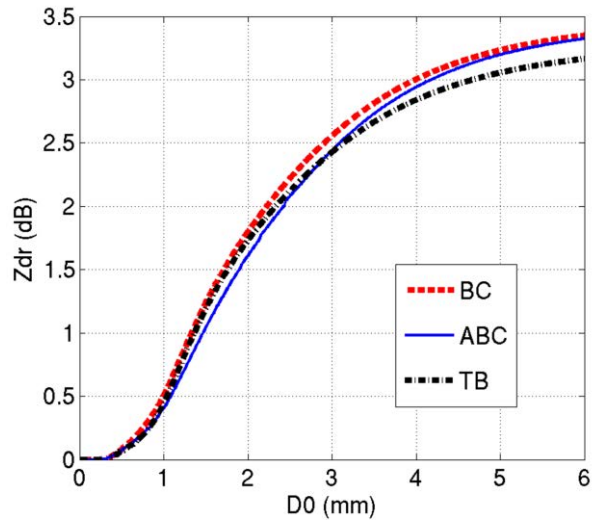


Figure 5.13. Z_{dr} versus D_0 relation for three commonly recognized rain drop models with shape factor μ fixed at 3 and temperature fixed at 20 degrees. ABC refers to the Andsager and Beard Chuang raindrop model; BC refer to the Beard and Chuang rain drop model; TB refer to the rain drop model developed by Thurai et al. (2007).

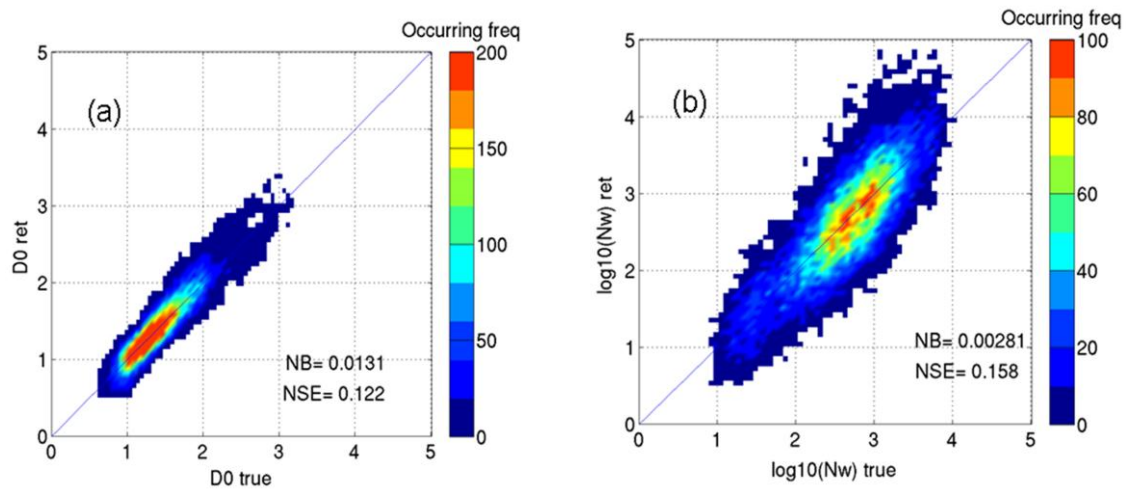


Figure 5.14. Scatter plot with occurrence frequency shown in the color bar. Comparison between the algorithm retrieved DSD parameters $D0$ and Nw and the simulation truth using Ku- band formulation. Radar system noise is considered.

Table 5.3. System bias scenario for Ku- band only retrieval test.

Bias scenario:	$Z_m(\text{Ku})$ (dBZ)	$Z_{\text{drm}}(\text{Ku})$ (dB)
Type 1	1	0
Type 2	0	0.2
Type 3	1	0.2
Type 4	1	-0.2

Table 5.4. Normalized bias and normalized standard error in the comparison of the retrieved DSD and the truth for Ku- band only retrieval test.

Case	D_0		$\log_{10}(N_w)$	
	NB (%)	NSE (%)	NB (%)	NSE (%)
noise only	1.31	12.2	0.28	15.8
noise+bias(type1)	6.69	18.5	-0.11	17.1
noise+bias(type2)	8.51	15.6	-12.5	19.5
noise+bias(type3)	14.9	21.4	-12.5	19.6
noise+bias(type4)	1.31	25.8	11.7	24.1

5.3.5 Algorithm evaluation for a complete region including rain, melting layer and ice

The algorithm described and evaluated in the previous sections can also be applied to observations beyond the rain region, say the melting and frozen regions. The simulation data preparation is described in section 2.7.2.2. From figure 5.3, we know that the DFR is a monotonically increasing function of D_0 for melting and ice particles. In the evaluation of the complete region, for each ray beyond rain, only DFR- D_0 is used in retrieval. The initial guess of the farthest bin should include the attenuation from melting and ice region. However, there are no decent algorithms available for accurate evaluation of the attenuation from the melting layer and ice, although the attenuation from the latter part can be ignored. In this section, the initial

guess of attenuations A_H and differential attenuation A_{dp} still come from (5.20) and (5.21).

Figure 5.15 shows the simulated RHI scan from APR-2 data NAMMA 20060903-142134 (same plot of figure 2.17 (b)) with circled “1” and “2” representing the profiles to perform DSD retrieval.

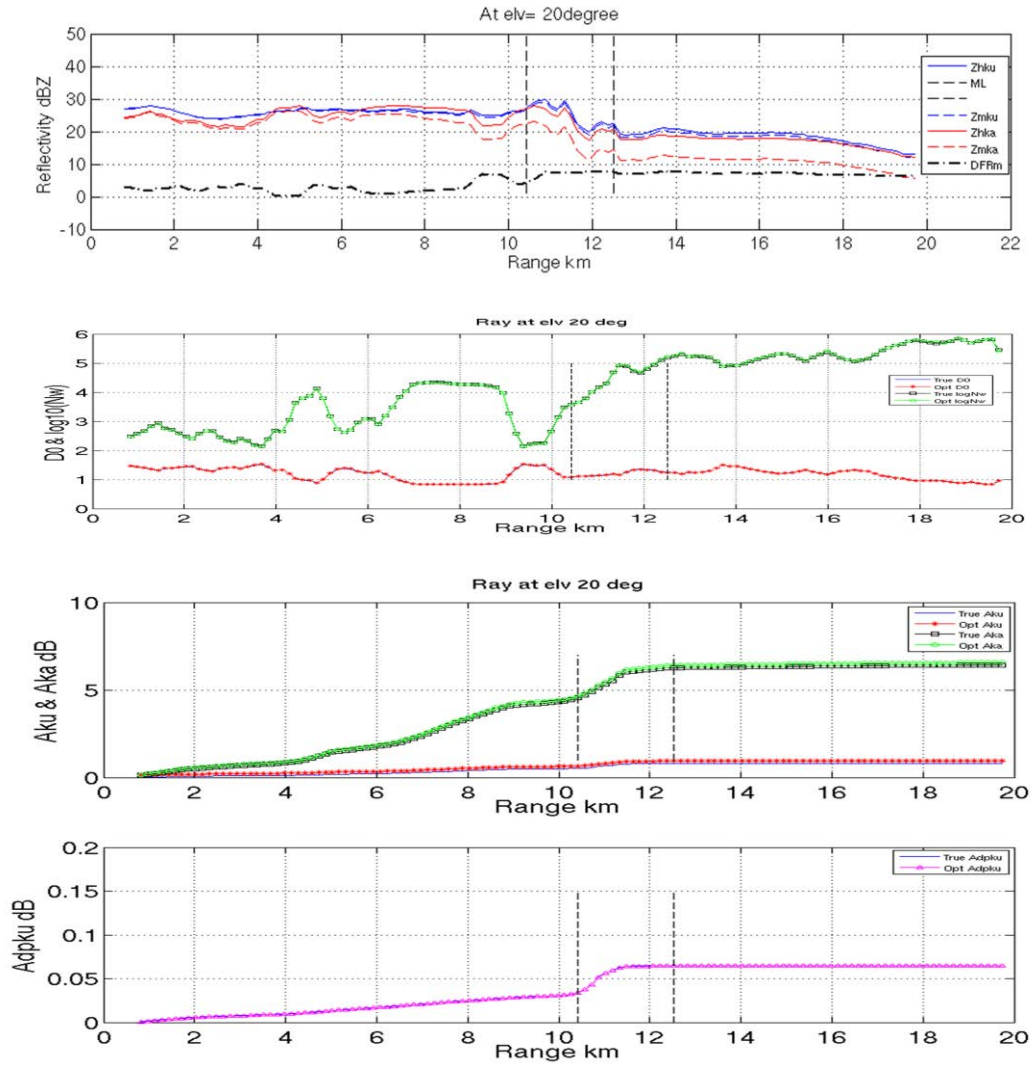


Figure 5.16. Profile at “1” with elevation of 20 degrees. Top panel: range profile of reflectivity measurements, measured dual frequency ratio, and attenuation-corrected reflectivity. The dot-dash line represents the melting layer boundary decided using the *HPC* method. Second panel: retrieved DSDs with true DSDs. Third panel: retrieved attenuation at Ku- and Ka- band with simulation truth. Bottom panel: retrieved differential attenuation at Ku- band with simulation truth.

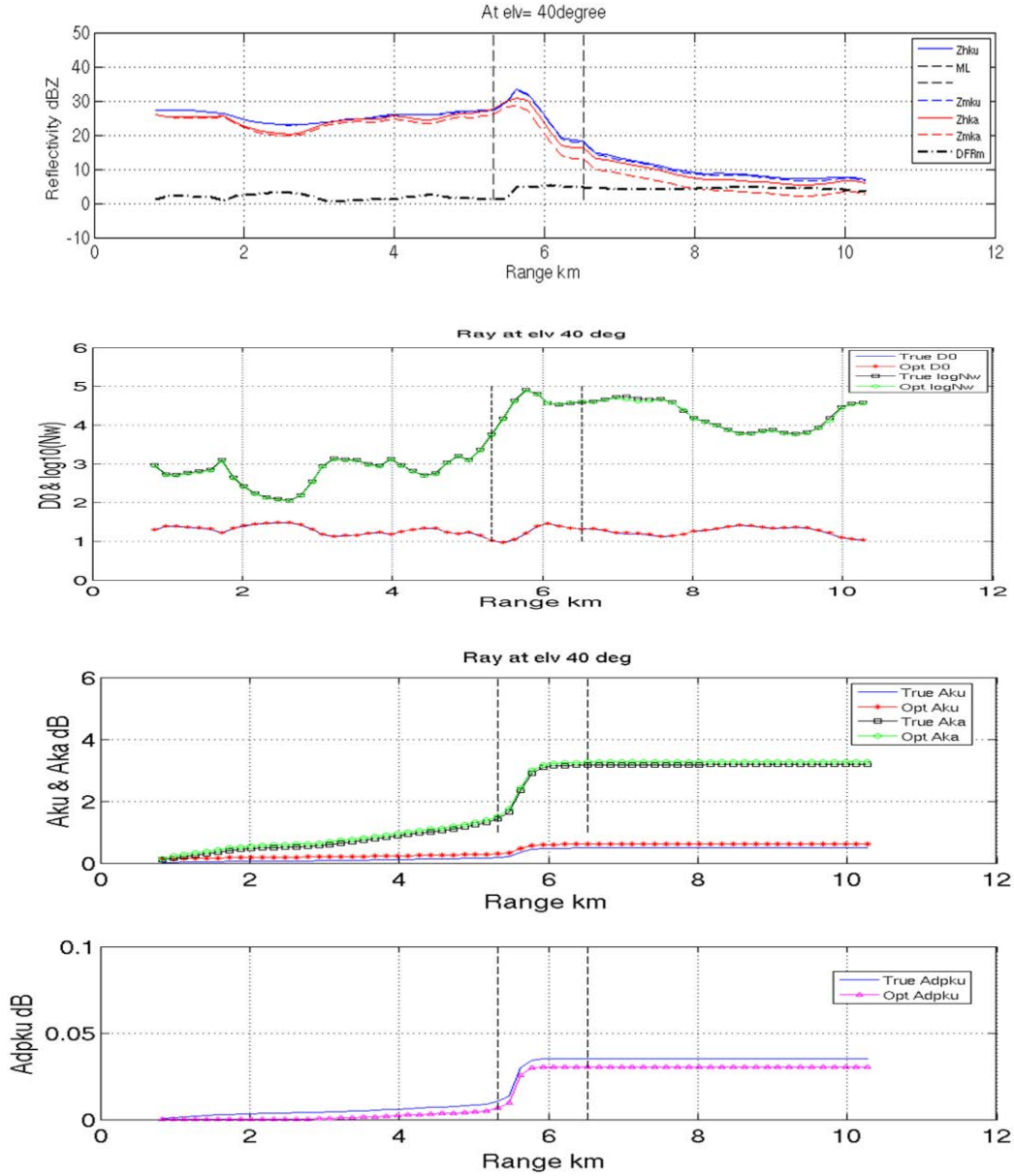


Figure 5.17. Profile at “2” with elevation of 40 degree. Top panel: range profile of reflectivity measurements, measured dual frequency ratio, and attenuation corrected reflectivity. The dot dash line represents the melting layer boundary decided using the *HPC* method. Second panel: retrieved DSDs with true DSDs. Third panel: retrieved attenuation at Ku- and Ka- band with simulation truth. Bottom panel: retrieved differential attenuation at Ku- band with simulation truth.

Figures 5.16 and 5.17 show the details in retrieval for profile at circled “1” and “2” in Figure 5.15. The top panel of figure 5.16 illustrates reflectivity measurements and retrievals of attenuation corrected reflectivity. The dot-dashed lines are the measured dual-frequency ratio retrievals rely on. The vertical dashed lines indicate the melting layer boundary detected using the *HPC* method. Retrieved DSDs and true DSDs are shown in the second panel. As expected, they match perfectly since the microphysical model is the same in retrieval as in simulation. The bottom two panels are the comparison of retrieved attenuation and the true attenuation at Ku- and Ka- band. They all match well.

Sensitivity of snow density to algorithm is tested using snow density of 0.1 g/cm^3 in simulation but 0.2 g/cm^3 in retrieval. Figure 5.18 shows the effect of the retrieval caused by the density change. We find that, for both profile “1” and “2”, D_0 is a parameter that is not very sensitive to snow density change, while N_w is more sensitive. N_w in log scale shows about 20% underestimation for profile “1” and slightly more than 20% for profile “2”. Figure 5.19 shows the effect of snow density change on the attenuation retrieval. Both attenuation and differential attenuation are affected by the snow density change. Differential attenuation is affected more since they have small values. Comparing profiles “1” and “2”, profile “2” is more affected by the snow density change in a general sense. This is because of the reflectivity of profile “2” is lighter compared to profile “1”, especially in the melting and ice region, which indicates that the retrieval algorithm might be more stable for a heavy storm case. More extensive study is needed before confident conclusions can be made. Another point that needs to be clarified is that only snow density is changed (melting particle density changes accordingly), which is why divergence can only been seen in the melting and ice regions. The rain model is the same in

retrieval as in simulation in this preliminary study since the sensitivity test of the rain model was studied in figure 5.8 of section 5.3.3.

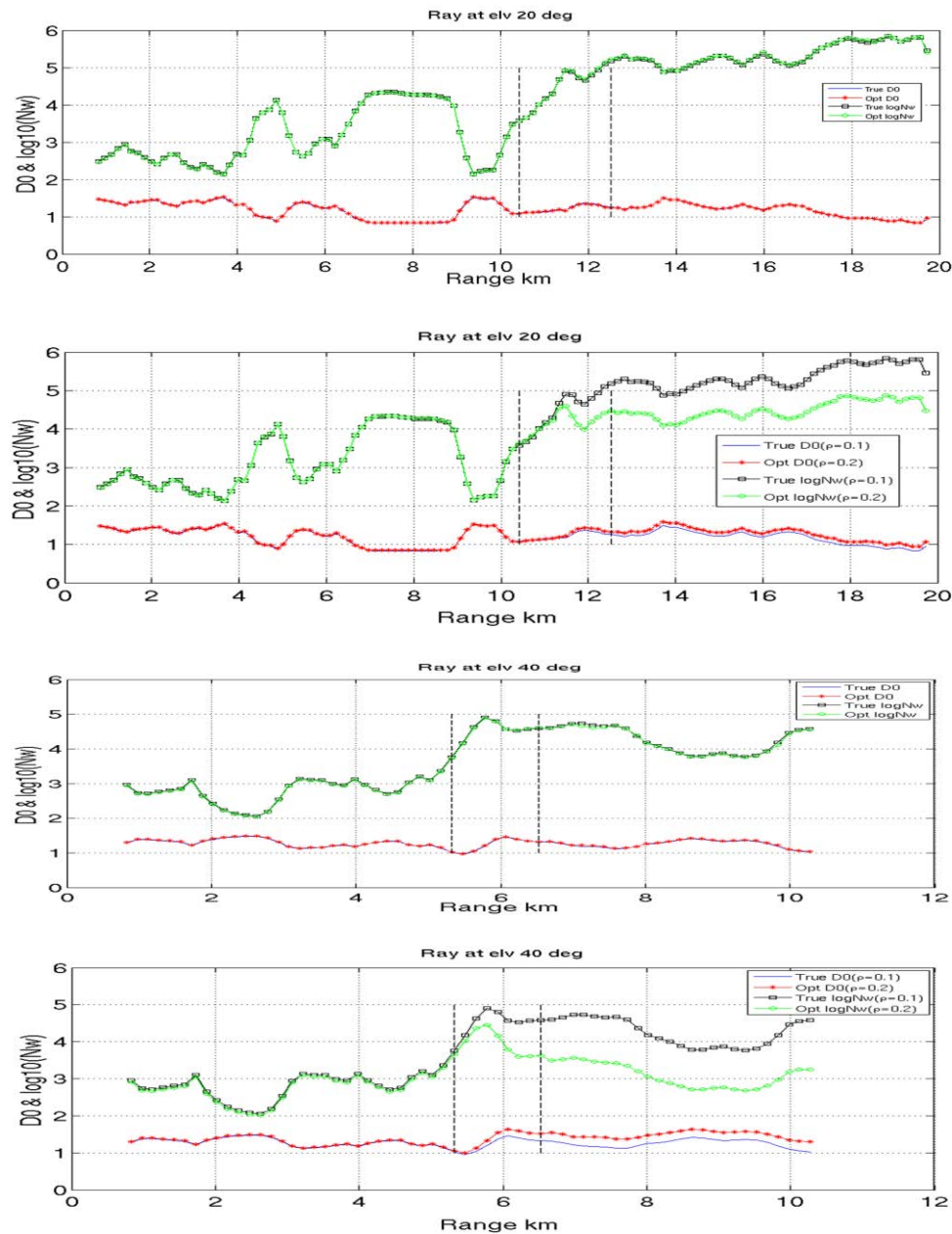


Figure 5.18. Top two panels: profile “1” in figure 5.15 with elevation of 20 degree. Comparison of retrieved DSDs and true DSDs using the same microphysical model in retrieval as in simulation. Same DSD comparison with snow density of 0.1 g/cm³ in simulation while 0.2 g/cm³ in retrieval. Bottom two panels: same comparison for profile “2” in figure 5.15 with elevation of 40 degree.

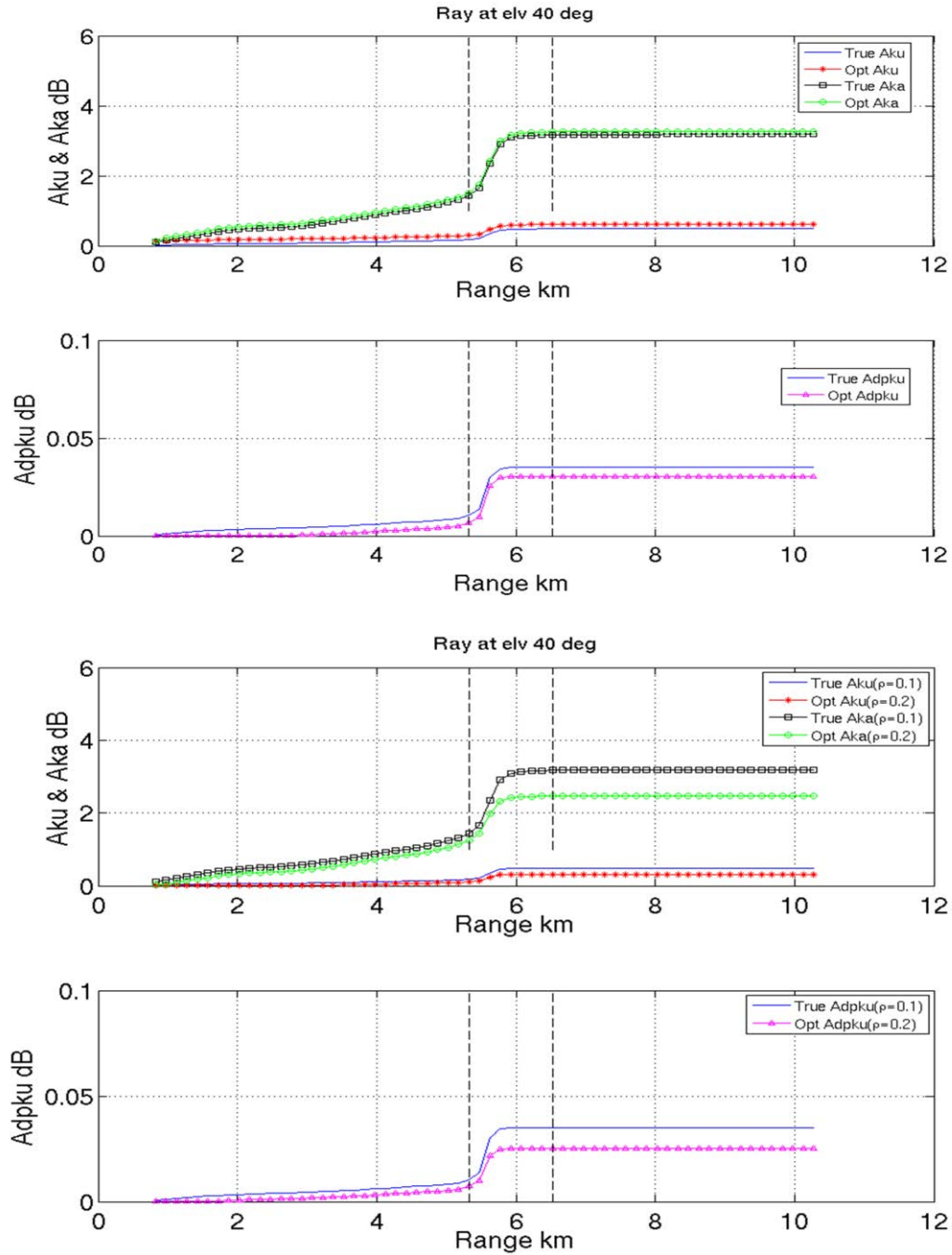


Figure 5.19. Top two panels: profile “1” in Figure 5.15 with elevation of 20 degrees. Comparison of retrieved attenuation and true attenuation using the same microphysical model in retrieval as in simulation. Same attenuation comparison with snow density of 0.1 g/cm^3 in simulation, while 0.2 g/cm^3 in retrieval. Bottom two panels: same comparison for profile “2” in figure 5.15 with elevation of 40 degrees.

CHAPTER 6

SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS FOR FUTURE WORK

6.1 SUMMARY AND CONCLUSIONS

The primary goal of this research is to develop algorithms to perform microphysics retrieval and profile classification for GPM-DPR and the ground validation D3R radar. The profile classification method developed in this work is being implemented as the day one algorithm for DPR classification and implementation into the level two DPR algorithm. The DSD retrieval algorithms for DPR and D3R are candidate algorithms that have a direct impact on the evaluation and development of dual-frequency retrievals that are designed for DPR and D3R. In this study, an array of relevant results has been obtained toward this goal.

The profile classification method developed here classifies precipitation type and identifies hydrometeor phase state through the precipitation type classification (*PCM*) model and the hydrometeor profile characterization (*HPC*) model. The measured dual-frequency ratio *DFR_m* profile and its range variability are used to generate criteria for both models. Airborne radar observations, which can emulate what the DPR will “see”, are used for validation purposes. Studies show that a *DFR_m* index exists and can effectively separate stratiform and convective rain types. In particular, the melting layer boundaries detected from *HPC* are compared to other criteria such as LDR and velocity widely used in the literature. Good agreement is found, especially from comparisons with velocity criteria. The profile classification algorithm developed in this study illustrates reasonable comparisons with the pixel- based algorithm

developed by Liao and Meneghini (2010) and the bayesian approach by JPL. The algorithm was also evaluated for GPM-DPR vertical resolution. The results show that the method is stable for data resolution change from 30m to 250m (125m). Off-nadir and smoothing effects are also studied. Considering that *DFRm* criteria are based on measurements and no attenuation correction is required in advance, this approach is straightforward and efficient.

The algorithm developed in Chapter 4 is a candidate algorithm for obtaining DSD retrieval and attenuation correction using dual-frequency observations from GPM-DPR. The hybrid method combines the forward method and the linear assumption to avoid the dual-valued problem in the dual-frequency retrieval. The optimization procedure minimizes the difference between estimated reflectivity measurements and true observations based on a cost function formulated as a determined non-linear least square problem. The estimation of the algorithm is based on the simulated DPR observations using airborne radar. The limitation of the algorithm comes from the discrepancy between true profiles and linear assumptions in rain, although it is a reasonable assumption (Rose and Chandrasekar 2006). For cross validation purposes, the proposed retrieval algorithm is compared to the SRWC (surface reference with weak constraint) method proposed by Meneghini and Liao (2009) and the standard DPR level 2 algorithm developed by Seto et al. (2013). Profiles in heavy rain tend to show better agreement while for very light rain, the hybrid method tends to choose a smaller D_0 compared to the SRWC method, and the latter method always chooses the larger D_0 in rain if retrieval falls into the dual-valued region. The proposed algorithm is evaluated adding the impact of attenuation from non-precipitation media such as cloud liquid water, water vapor, and oxygen. The results show that the hybrid method can handle the attenuation from non-precipitating particles well.

A DSD retrieval algorithm for a dual-polarization, dual-frequency Doppler ground radar (D3R) operating at Ku- and Ka- band is proposed in Chapter 5. This ground radar has been built to perform ground validation with the GPM-DPR after it is launched. The retrieval philosophy is to combine attributes of the dual-frequency ratio (*DFR*) normally applied in space radar retrieval and the dual-polarization parameter (Z_{dr}) commonly used for dual-polarization ground radar. The algorithm is evaluated for rain region and shows promising results. Errors from rain drop shape, μ , and measurement errors are analyzed separately. In particular, the combined method can easily be adapted to Ku- band retrieval in case Ka- band signal is extinct during moderate to heavy rain. The evaluation for the complete profile including rain and ice is performed using simulated data obtained based on airborne radar observations. Melting boundaries are detected using the *HPC* method described in Chapter 3. Preliminary results show the N_w retrieval is sensitive to snow density change while D_0 is more stable.

6.2 RECOMMENDATIONS FOR FUTURE WORK

When the GPM satellite is launched, there will no doubt be various aspects of the system that will require fine-tuning. Within that content the following is a list of some specific suggestions.

- **Profile classification method for GPM-DPR classification module**

---Extensive testing of the *PCM* is needed for various storm types and geographic regions. *PCM* and *HPC* models need to be compared to TRMM-like results using synthetic data.

---Off-nadir observations from APR-2 experiments need to be further studied when data quality is improved after re-processing.

--- Adjustments of the thresholds for the *PCM* model might be necessary when more global observations are available.

- **DSD retrieval algorithm for GPM-DPR**

---Detailed comparison of the hybrid method to the HB-DFR standard method is needed, especially after the HB-DFR-SRT method is developed.

---Assumptions for non-precipitation particles such as cloud liquid water, water vapor and oxygen need to be evaluated using realistic profiles from TMI (TRMM Microwave Imager).

- **DSD retrieval algorithm for dual frequency and dual polarization Doppler ground radar for GPM-DPR validation**

---This technique has not been evaluated with in-situ verification. Such a study is very important and should be pursued.

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