Comparisons are made between the reflectivity $Z$, median volume diameter $D_0$, and rain rate $R$ from a dual-frequency profiler and the C-band polarimetric radar (C-POL), which are both located near Darwin, Australia. Examples from the premonsoon “buildup” regime and the monsoon (oceanic) regime are used to illustrate the excellent agreement between the dual-profiler retrievals and the polarimetric radar-based retrievals. This work builds on similar works that were limited in scope to shallow tropical showers and predominantly stratiform rain events. The dual-frequency profiler retrievals of $D_0$ and $R$ herein are based on ensemble statistics, whereas the polarimetric radar retrievals are based on algorithms derived by using one season of disdrometer data from Darwin along with scattering simulations. The latest drop shape versus $D$ relation is used as well as the canting angle distribution results obtained from the 80-m fall bridge experiment in the scattering simulations. The scatterplot of $D_0$ from dual-frequency profiler versus $Z_{dr}$ measurements from C-POL is shown to be consistent not only with the theoretical simulations and prior data but also within prior predicted error bars for both stratiform rain as well as convective rain.

Based on dual-frequency profiler–retrieved gamma drop size distribution parameters, a new smoothly varying “separator” indexing scheme has been developed that classifies between stratiform and convective rain types, including a continuous “transition” region between the two. This indexing technique has been applied on a number of low-elevation-angle plan position indicator (PPI) sweeps with the C-POL from the two regime examples, to construct “unconditioned” histograms of $D_0$ in stratiform and convective rain (to within the sensitivity of the radar). With reference to the latter, it is demonstrated that the distribution of $D_0$ is different in the buildup example than in the monsoon example, because of the differences in both the microphysical and kinematic features between the two regimes. In particular, (i) the mean $D_0$ is significantly larger in the buildup example than in the monsoon example, irrespective of rain type; (ii) the histogram width (or standard deviation) is much larger for the buildup example than the monsoon example, irrespective of rain type; and (iii) the histogram skewness is negative for the monsoon regime example because of a lack of larger $D_0$ values, whereas the buildup histogram is positively skewed irrespective of rain type.
1. Introduction

This article builds on prior work by May et al. (2001) and Williams and May (2008) related to joint observations and comparisons of the reflectivity \(Z\), median volume diameter \(D_0\), and rain rate \(R\) retrieved by the dual-polarized (5.5 GHz) C-band polarimetric radar (C-POL) and the dual-frequency-profiler, both located near Darwin, Australia. The latter three variables are related to the 6th, 3rd, and 3.67th moments of the drop size distribution (DSD). In May et al. (2001), the comparisons were preliminary and focused on shallow tropical showers, whereas in Williams and May (2008) three long-duration stratiform events that occurred during the monsoon season were analyzed. In this study, we focus on two example events from two different regimes that occurred prior and during the monsoon season in the Darwin area: (i) the 5 January 2006 “buildup” regime and (ii) the 19–20 January 2006 monsoon regime. Both examples were characterized by strong convection followed by long-duration stratiform rain with a bright band.

The principal assumptions and methods for the retrievals of \(D_0\) and \(R\) from dual-polarized radar, using reflectivity \(Z_h\) (at horizontal polarization), differential reflectivity \(Z_{dh}\), and specific differential phase \(K_{dp}\), are well covered in Bringi and Chandrasekar (2001, and references therein). Here, we use the latest drop shape versus \(D\) relation as well as the canting angle distribution results obtained from the 80-m fall bridge experiment described in Thurai et al. (2007) and Huang et al. (2008). To develop the retrieval algorithms, we use one season of Joss disdrometer data obtained from Darwin in 1999, which are fitted to a normalized gamma DSD (Testud et al. 2001; Illingworth and Blackman 2002) with parameters \(N_0\), \(D_0\), and \(\mu\), using the methodology in Bringi et al. (2003).

The dual-frequency profiler method uses the 50-MHz profiler for measuring the clear-air Doppler spectrum resulting from Bragg scattering, whereas the 920-MHz profiler is used to measure the Doppler spectrum of the falling precipitation (Currier et al. 1992; Maguire and Avery 1994).

Validation of dual-polarized radar DSD retrievals using dual-profiler DSD methods have several advantages, such as matching the vertical extent of the resolution volume and the height above ground, when comparing the two measurements and the corresponding retrievals. The height resolution of the 50-MHz profiler is 315 m, and we average the 920-MHz sampling to match this. This also matches approximately the C-POL resolution volume at the range of the profiler. However, the differences resulting from dwell time remain with the radar being essentially instantaneous, whereas the profiler is a 45-s average. In principle, one can reduce, for example, the large “representativeness” errors of single-point ground-based instruments, especially in convective rain, when comparing against the active remote sensors. The dual-frequency profiler offers a distinctive advantage as opposed to single profiler methods, especially in strong convective rain, where the clear-air signal is “washed out” from the 920-MHz Doppler spectrum of the falling precipitation. However, even dual-frequency profiler methods have some limitations in strong convective rain, where turbulence and wind shear cause an increase in the retrieval errors [see Schafer et al. (2002) for an example and discussion of other error sources]. In contrast, the dual-polarized radar retrieval methods are based on assumptions regarding the use of measured DSDs at the ground using disdrometers, the possible alteration of the drop shapes resulting from collisions in heavy rain, and variations in the canting angle distribution resulting from strong wind shear and turbulence. The dual-profiler DSD retrievals are known to be accurate in steady stratiform rain (with a minimum resolvable \(D\sim0.7\) mm), with vertical resolution of the order of 100 m (Schafer et al. 2002), whereas dual-polarized radars have decreasing accuracy when drops are small and poorer vertical resolution at long ranges (>60 km for a 1° beam). On the other hand, in heavier convective rain where large drops are more frequent, the dual-polarized retrievals have higher accuracy. Because of the scarcity of comparisons between dual-profiler and dual-polarized radar thus far, it is important to have more intercomparison studies in a variety of rain regimes, as described in this paper.

The primary goals of this paper are (i) comparison of \(Z\), \(D_0\), and \(R\) from the C-POL and the dual-frequency profiler on a case study basis; (ii) use of the profiler-based DSD retrievals to develop a smoothly varying index value representing the likelihood of stratiform or convective rain type, including a continuous “transition” region between the two; and (iii) using this indexing technique on a number of low-elevation-angle plan position indicator (PPI) sweeps with the C-POL from the two regime examples to construct “unconditioned” histograms of \(D_0\) in stratiform and convective rain (to within the sensitivity of the radar). An example of this will be shown comparing convective DSDs in a continental (buildup) regime with an oceanic monsoon squall, where warm rain processes are expected to be more important.

2. Data sources and retrievals

a. C-POL

The dual-polarized (5.5 GHz) C-POL is located near Darwin. A full description of the radar system is given by...
Keenan et al. (1998). Briefly, the radar transmits alternating horizontal (H) and vertical (V) polarized pulses with 1-μs pulse widths and with pulse repetition times of 1 ms using a high-power ferrite-switched circulator. The received copolar signals are processed, in essence, by using the same receiver, which enables the measurements of H-polarized equivalent reflectivity factor \(Z_h\), the differential reflectivity \(Z_{dr}\), the differential propagation phase \(\Phi_{dp}\), and the copolar correlation coefficient \(\rho_{hv}\) using the algorithms of Zahrai and Zrnić (1993). The radar also measures the mean Doppler velocity and spectrum width. Here, we use only the radar measurements of \(Z_h\), \(Z_{dr}\), and \(\Phi_{dp}\); from the latter, we derive the specific differential specific phase \(K_{dp}\) by using the finite impulse response (FIR) range filter described in Hubbert and Bringi (1995). The radar data used herein were collected in the range–height indicator (RHI) mode, with range samples spaced 150 m apart, and in PPI mode, where the spacing was 300 m.

At C band, the effect of attenuation and differential attenuation resulting from rain along the path must be corrected for, especially in strong convective cores. The measured \(Z_h\) is corrected by using the so-called iterative ZPHI method, described by Bringi et al. (2001) and Testud et al. (2000). The \(Z_{dr}\) is corrected using the method described by Tan et al. (1995). The latter is a gate-by-gate correction method based on a nonlinear relation between specific differential attenuation \(A_{dp}\) and \(K_{dp}\): \(A_{dp} = a(K_{dp})^{0.5}\). After correction for attenuation, the system offsets in \(Z_h\) and \(Z_{dr}\) were determined using the methodologies described in Bringi et al. (2006), and they were found to be \(-4\) and \(-0.4\) dB, respectively. Because the \(Z_{dr}\) data were “noisy,” we used the same FIR range filter alluded to earlier to reduce the high-frequency gate-to-gate fluctuations in \(Z_{dr}\) while still retaining the “physical” trends in the data. For each beam, a data mask was generated to classify precipitation from nonprecipitation echoes using the standard deviation of \(\Phi_{dp}\) over a 10-gate moving window. The classification was based on using a threshold of \(15\)° for the C-POL based on prior analysis. Drop size distribution and rain-rate retrievals described later were only done for precipitation echoes.

To develop the retrieval algorithms, we have analyzed 6 months of disdrometer (RD-69; Joss and Waldvogel 1967) data from Darwin collected during the 1999 wet season. A total of 2160 1-min averaged \(N(D)\) were fitted to a normalized gamma distribution with parameters \(N_0\), \(D_0\), and \(\mu\), following the method described in Bringi et al. (2003). Next, T-matrix scattering calculations were performed assuming the following: (i) drop shapes based on the most recent 80-m fall bridge experiments [Eq. (1) of Thurai et al. (2007)] for \(D > 1.5\) mm and the Beard and Kubesh (1991) fit for \(0.7 < D < 1.5\) mm, as given in Eq. (3) of Thurai et al. (2007)]; (ii) Gaussian canting angle distribution with mean of \(0\)° and standard deviation of \(7.5\)°, again based on the recent 80-m fall bridge experiment (Huang et al. 2008); (iii) upper integration diameter of \(3.5D_0\) or 8 mm, whichever is less; and (iv) temperature of \(20^\circ\)C and elevation angle of \(0^\circ\). (The elevation angle dependence between \(0^\circ\) and \(5^\circ\) is negligible, with the latter being the elevation angle of the C-POL observations used herein for comparison with the profiler estimates.) The T-matrix scattering calculations outputs, for each fitted DSD (with parameters \(N_0\), \(D_0\), and \(\mu\)), the values of \(Z_h\), \(Z_{dr}\), \(K_{dp}\), specific attenuation, and specific differential attenuation \(A_{dp}\).

For deriving the \(A_{dp} - K_{dp}\) relation, we used nonlinear least squares fit to arrive at \(A_{dp} = 0.016K_{dp}^{1.27}\). The units for \(A_{dp}\) and \(K_{dp}\) are in dB km\(^{-1}\) and degrees km\(^{-1}\), respectively. For the retrieval of \(D_0\) from \(Z_{dr}\), we first added Gaussian noise to the simulated \(Z_{dr}\) values with mean of \(0\) dB and standard deviation of \(0.2\) dB. This was done to extend the retrieval for low values of \(D_0 \sim 0.5\) mm in the presence of statistical fluctuations, which cause the \(Z_{dr}\) to fluctuate around its mean with both positive and negative excursions. Our polynomial fits to estimate \(D_0\) (in mm) from \(Z_{dr}\) are given:

\[
D_0 = 0.0203 Z_{dr}^3 - 0.1488 Z_{dr}^2 + 0.2209 Z_{dr} + 0.5571 Z_{dr} + 0.801; \quad -0.5 \leq Z_{dr} < 1.25 \text{ dB.} \tag{1a}
\]

\[
D_0 = 0.0355 Z_{dr}^3 - 0.3021 Z_{dr}^2 + 1.0556 Z_{dr} + 0.6844; \quad 1.25 \leq Z_{dr} < 5 \text{ dB.} \tag{1b}
\]

Figure 1 shows the \(D_0\) versus \(Z_{dr}\) scatter points along with the mean fit in (1). Note how the \(D_0\) values reach a lower bound of around \(0.5\) mm as \(Z_{dr}\) tends to \(-0.5\) dB. Also, note that the frequency of occurrence of \(D_0 > 2\) mm is very sparse in the disdrometer dataset. The scatter about the mean fit is mainly due to the variability.
in the shape parameter $\mu$, although some of the variability may be due to instrumental errors (Ulbrich and Atlas 1998). The parameterization error in the retrieval of $D_0$ has a 1σ value of around 0.116 mm for $Z_{dr}$ values in the most frequently occurring range of 0.5–2.5 dB. As mentioned earlier, Gaussian noise has already been added to the simulated $Z_{dr}$ prior to the fitting. Because the mean $D_0$ is around 1.35 mm, the fractional standard error in the estimate of $D_0$ is around 9%, which is similar to that obtained via theoretical simulations by Gorgucci et al. (2002).

The estimation of $N_w$ follows Bringi et al. (2002), who use a power law of the form $Z_h/N_w = c(D_0)^d$ but adapted herein for C band. The scatter (not shown) is minimal and due to $\mu$ variations. For the Darwin DSD data, $R(K_{dp})$, $R(Z_h, Z_{dr})$, or $R(Z_h)$, which is used in the flowchart in Fig. 2:

$$R(K_{dp}) = -0.1335K_{dp}^4 + 2.0887K_{dp}^3 - 10.663K_{dp}^2$$
$$+ 37.512K_{dp}^{-1}Z_{linear}^{10^x},$$

$$R(Z_h, Z_{dr}) = Z_{linear}^{x} + 0.056 D_0^{35};$$

where the units for $Z_h$, $N_w$, and $D_0$ are mm$^6$ m$^{-3}$, mm$^{-1}$ m$^{-3}$, and mm, respectively.

The rain-rate estimator is based on a variant of the approach described by Ryzhkov et al. (2005) but adapted for C band and using the scattering simulations alluded to earlier. A climatological $Z$–$R$ relation ($R = 0.017Z_h^{0.72}$) was derived from the Joss disdrometer data for the Darwin wet season. The synthetic algorithm uses $R(K_{dp})$, $R(Z_h, Z_{dr})$, or $R(Z_h)$, which is used in the flowchart in Fig. 2:

$$R(Z_h, Z_{dr}) = Z_{linear}^{x} + 0.056 D_0^{35};$$

The flowchart given in Fig. 2 summarizes the conditions where each of the rain-rate equations [Eqs. (3)–(5)] is used. The thresholds for $K_{dp}$ and $Z_{dr}$ were based on considering the standard deviations of these measureables by using FIR range-filtered data in homogeneous (uniform reflectivity) regions of rain. Figure 3 shows the scatterplot of the retrieved $R$ (using the algorithm in Fig. 2) versus the disdrometer-measured $R$ for the Darwin dataset in order to illustrate the performance of the algorithm under ideal conditions with the scatter...
about the 1:1 line reflecting the model or parameterization error.

Note that our retrievals of $D_0$ and $R$ are different from the more commonly used power laws for $D_0(Z_{dr})$, $R(K_{dp})$, or $R(Z_{h}, Z_{dr})$ (e.g., Bringi and Chandrasekar 2001, and references therein). There is no real theoretical basis for a power-law form for the retrieval of $D_0$ from $Z_{dr}$ as opposed to, say, polynomial fits. For $R(K_{dp})$, most authors have used power-law forms, but the inherent assumption here is that the terminal fall speed and the integrand for $K_{dp}$, which is proportional to $\Re(f_h - f_o)$, are both expressible as power-law functions of $D$ ($f_h$ and $f_o$ are the forward scattering amplitudes). The latter assumption is not strictly valid at C band and because nonlinear least squares fits are used anyway we have used a 4th-order polynomial fit, as in (3), primarily to minimize the bias. For $R(Z_{h}, Z_{dr})$, our form is different from the commonly used $R/Z_{h} = f(Z_{dr})$, where $f(Z_{dr})$ is either a polynomial or a power law. Our form is nevertheless monotonic; the practical purpose of this form was to reduce the scatter between the “true” $R$ and the $R$ from (4). We have not attempted to estimate the variance of the $D_0$ or $R$ because of the measurement variances of $Z_{dr}$, $K_{dp}$, or $Z_{h}$ (however, see Bringi et al. 2006). However, we will partly address this issue when we compare our retrievals with those from the dual-frequency profiler.

b. Dual-frequency profilers

The dual-frequency profilers used in this study are VHF and UHF profilers operating at 50 and 920 MHz, respectively, which are collocated 23.8 km southwest of the C-POL. We refer to prior work for technical specifications regarding these profilers (e.g., Rajopadhyaya et al. 1998; May et al. 2001; Cifelli et al. 2000). These key technical specifications include beamwidth (VHF: 3°, UHF: 9°), vertical resolution (VHF: 315 m, UHF: 105 m), height coverage (VHF: 1.5–20 km, UHF: 0.2–12 km), and dwell time (45 s, with each starting at the beginning of every minute). However, some details need to be discussed herein because they impact the underlying assumption with dual-frequency profiler DSD retrievals (e.g., both radars are observing the same portion of the atmosphere at the same time).

A smaller VHF profiler beamwidth implies that, if both profilers could observe the Bragg scattering signal at the same altitude, then the VHF profiler spectral broadening would be smaller than the UHF profiler estimate. To account for the different beam widths and for the UHF profiler not observing Bragg scattering at the altitudes of interest, the VHF estimated spectral broadening was increased by 10% and used in the DSD retrievals. The larger VHF profiler distance between range gates implies that the vertical air motion and spectral broadening estimates are representative of larger vertical extents in the atmosphere than the UHF observations. To account for the mismatch in vertical resolution, the lower-vertical-resolution VHF estimates are interpolated to the higher-vertical-resolution UHF observations, with the lowest DSD retrieval occurring at the lowest VHF range gate of 1.5 km. Finally, to reduce the errors associated with temporal mismatch between the observations, great effort was made to make both profilers start sampling in the vertical beam at the beginning of each minute and dwell for the same duration of 45 s.

Doppler weather radars have been used in vertically pointing mode to retrieve the drop size distribution for many decades (e.g., Rogers 1967; Atlas et al. 1973). The use of VHF radars for simultaneously measuring the clear-air Doppler velocity spectrum due to Bragg scattering and the Doppler velocity spectrum due to Rayleigh scattering from falling precipitation is more recent and has been ongoing since the seminal work of Wakasugi et al. (1986) and Gossard (1988). The addition of a colocated 920-MHz vertically pointing profiler, which is used in essence as a weather radar, allows for much more sensitivity to Rayleigh scattering from falling precipitation and more accurate retrieval of the drop size distribution (Currier et al. 1992; Maguire and Avery 1994; Rajopadhyaya et al. 1999). The dual-frequency approach thus allows for the estimation of the mean vertical air motion as well as the spectral width from the 50-MHz profiler, which are then used to correct the 920-MHz Doppler spectrum of precipitation for updrafts/downdrafts and spectral broadening resulting from turbulence and
wind shear. The DSD can then be estimated at each UHF range gate using two steps. First, each downward motion velocity bin is assigned a raindrop diameter by using an air-density-adjusted terminal fall speed relationship (i.e., Atlas et al. 1973; Brandes et al. 2002). Errors associated with the air-density adjustment are presented in Kanofsky and Chilson (2008). The second step estimates the number of raindrops at each diameter size by dividing the observed reflectivity factor in each velocity bin by its corresponding diameter taken to the sixth power.

Although the two-step procedure seems like a simple task, the actual retrieval process contains many assumptions, complex computational techniques, and measurement uncertainties that lead to the conceptual view that each retrieved DSD is a single member of a family of possible solutions. Given the substantial prior work addressing the various factors affecting the final accuracy of dual-frequency profiler–retrieved \( D_0 \) and \( R \), our intent is to outline the retrieval method used in this study and refer to prior work as needed. In section 3, we build on relevant work that compared C-POL and dual-frequency profiler DSD retrievals from Darwin (Williams and May 2008) and another comparison using the C-band COBRA radar and a 400-MHz profiler in Okinawa, Japan (Bringer et al. 2006).

The dual-frequency retrievals of the DSD parameters, namely \( D_0 \) and \( R \), used in this study are based on the idea of ensemble statistics by Williams and Gage (2009). The main purpose of that work was to quantify the errors in dual-frequency retrievals of \( D_0 \) and \( R \) by generating a family of solutions where each solution is as plausible as any other solution due to the assumptions made for that retrieval. The dual-frequency profiler–retrieved \( D_0 \) and \( R \) used in this study are the mean values estimated from an ensemble of 36 different retrieval models. These 36 separate models were generated by choosing a functional form of the DSD (6 options), a numerical inversion technique to correct the Doppler spectrum for updraft/downdraft and spectral broadening (2 options), and a cost function to determine the “best” solution for the DSD (3 options). The possible options are outlined in this paper, with more details provided in Williams and Gage (2009).

Six different functional forms of the DSD were used in this study. Five of these functional forms are commonly used forms and are based on the unnormalized three-parameter gamma form (intercept parameter \( N_0 \), mass-weighted mean diameter \( D_m \), and shape parameter \( \mu \)) introduced by Ulbrich (1983). Subsets of this three-parameter gamma form include the exponential (\( \mu = 0 \)); the constant shape parameter (\( \mu = 2.5 \) and \( \mu = 5 \)); and the constrained gamma form, which assumes a priori a fixed nonlinear relation between \( D_m \) and \( \mu \) (Brandes et al. 2003; Zhang et al. 2003). For completeness, the sixth functional form of the DSD followed the three-parameter lognormal distribution described in Feingold and Levin (1986). One advantage of using a functional form of the DSD is that, after the three DSD parameters are determined, any other moment of the DSD can be estimated, including normalized parameters \( N_w \) and \( D_0 \) (e.g., Bringer and Chandrasekar 2001).

Two numerical inversion techniques were used to correct the Doppler velocity spectrum from precipitation: (i) the convolution-fitting method described in many prior works (e.g., Wakasugi et al. 1986; Rajopadhyaya et al. 1999) and (ii) the deconvolution method described in Schafer et al. (2002) and Lucas et al. (2004). The convolution-fitting method projects estimated DSDs from diameter space to radar Doppler velocity–reflectivity space, with the best solution determined by comparing the original spectrum with the transformed model spectrum. In contrast, the deconvolution method removes the air motion shift and spectrum broadening effects from the original spectrum before comparing with the estimated model DSD spectrum in the raindrop diameter–reflectivity space. The work by Schafer et al. (2002) describes both methods in detail by using simulations as well as dual-frequency profiler data.

Three cost functions were used to determine the best solution. These cost functions were the conventional sum of squares of the differences in each velocity bin; the sum of absolute differences, which is less sensitive to outliers; and a moment cost function involving the sum of the absolute differences between the first three spectral moments.

Thus, the ensemble statistic methodology uses the same dual-frequency profiler observations to generate 36 different \( D_0 \) and \( R \) estimates (6 DSD models, 2 inversion methods, and 3 cost functions) from which the mean values \( \langle D_0 \rangle \) and \( \langle R \rangle \) are compared with the C-POL retrievals. The normalized intercept parameter \( N_w \) is estimated from the ensemble mean \( D_0 \) and liquid water content by using Eq. (7.61) in Bringer and Chandrasekar (2001). Note that the ensemble statistic methodology used by Williams and Gage (2009) to estimate the \( \langle D_0 \rangle \) and \( \langle R \rangle \) retrieval accuracies only account for model and retrieval procedure errors but does not account for other errors related to measurement, sampling, or spatiotemporal inhomogeneity of the precipitation within the resolution volume during the observational dwell time (45 s for this dual-frequency dataset).

3. Comparisons between C-POL and dual-frequency radar

Examples from two different regimes from Darwin have been chosen for the comparison: (i) the 5 January
2006 monsoon buildup and (ii) the 19–20 January 2006 monsoon regimes. Storms in the buildup tend to be strongly forced and contain intense convection with large electrical activity, whereas monsoon conditions tend to support widespread but weaker convection of oceanic character (e.g., Keenan and Carbone 1992; May and Ballinger 2007). There is an abrupt transition between these two regimes characterized by a reversal of the low-level winds (Drosdowsky 1996). These regimes are characterized by similar amounts of convective available potential energy (CAPE; McBride and Frank 1999), but there are significant differences in boundary layer structure that may affect storm characteristics. For example, the widespread convection, extensive cloud cover, and low-level westerlies from the ocean during the monsoon tend to limit boundary layer depth to ~500 m, whereas the buildup has boundary layers over the continent in excess of 1.5 km deep. The midlevels are also significantly moister during the monsoon period, which also has an effect on storm dynamics (May and Ballinger 2007). There are also marked variations in aerosol content with the premonsoon period characterized by moderate aerosol concentration and the monsoon being extremely clean (Allen et al. 2008). However, the buildup event discussed here was only just prior to the onset, so the low-level aerosol content is likely to have been relatively low compared with early in the season. Figure 4 shows the time–height reflectivity plot for the 5 January 2006 event using the 1-min-resolution 920-MHz profiler data. The strong convection (with the ~30 dBZ contour extending to nearly 13 km) followed by the longer duration stratiform rain with bright band is clearly evident.

Figure 5 shows time series comparisons of equivalent reflectivity factor, $D_0$ and $R$. The 1-min time-resolution profiler data are averages of 3 gates centered at 2-km height (vertical extent of 315 m). Recall that the profiler retrievals of $D_0$ and $R$ from each gate are based on an ensemble average. The C-POL performed RHI scans over the profiler location every 10 min. The $Z_h$ and retrieved $D_0$ and $R$ are averaged over 3 gates (150-m spacing) around the profiler site (23.8 km) and then the height profiles are constructed. Then, data from the height closest to 2 km are used for the comparison. Note that the vertical extent of the C-POL resolution volume at the range of 23.8 km is approximately 400 m, so it is reasonably well matched with the profiler. However, the C-POL data are nearly instantaneously processed with a dwell time of 128 ms compared with the profiler dwell time of 45 s.

The reflectivity comparison in Fig. 5a is in very good qualitative agreement between C-POL and 920-MHz profiler with deviations well within the expected uncertainties from the two radars ($\pm 1$ dB). Note that the C-POL measures $Z_h$ at low elevation angles, whereas the profiler measures $Z$ at vertical incidence. In regions of large $Z_{dr}$, one might expect the comparisons to deviate more than shown. However, for vertical incidence, the wave “sees” the circular equator of the oblate drop whose $Z$ is very close to $Z_h$ (see Bringi and Chandrasekar 2001, chapter 7). Hence, the profiler and C-POL reflectivity comparisons are, as mentioned before, in good agreement, in spite of the different viewing angles. The $D_0$ comparison is also in good qualitative agreement, except near the beginning (leading edge) of the intense convection, where large spatial gradients are to be expected (more scatter in the profiler data). As described later (see Fig. 8 in the context of stratiform/convective-rain-type separation), the convective time interval has large updrafts at midlevels and moderate
downdrafts within the main precipitation shaft. Similar comments also apply to the $R$ comparisons (i.e., larger scatter in the convective region and less scatter in the more steady stratiform rain). It is well known that it is more difficult to deconvolve the 920-MHz Doppler spectrum for the spectral broadening because of wind shear and turbulence in strong convection than with stratiform rain (Schafer et al. 2002). However, considering various factors, the qualitative agreement between the profiler and the C-POL is surprisingly good and better than similar past comparisons, which have been limited in scope (May et al. 2001 in tropical showers). Although $N_w$ comparisons have not been shown, for gamma DSD assumptions, it follows from the good comparison of $Z$, $D_0$, and $R$ that $N_w$ would also show similar good agreement.

To better quantify the $D_0$–$Z_{dr}$ retrieval [in a manner similar to Williams and May (2008), whose focus, however, was stratiform rain only], we show in Fig. 6 a scatterplot of $D_0$ (as estimated from the profiler using ensemble averaging) versus the C-POL-measured $Z_{dr}$. Because the profiler data were available every 1 min versus every 10 min for C-POL, cubic spline interpolation over a 4-min window was used for the profiler $D_0$ data.

**Fig. 5.** Time series intercomparison between C-POL and dual-frequency profiler (top) reflectivity, (middle) $D_0$, and (bottom) rain rate. The $x$ axis is UTC time. The C-POL retrievals of $D_0$ and $R$ are based on Eq. (1) and the flowchart in Fig. 2. The profiler retrievals are based on ensemble averaging (Williams and Gage 2009). The data are from the buildup regime on 5 Jan 2006.
and then the closest match to the C-POL time sample of $Z_{dr}$ was used.

The data from convective and stratiform rain have been separately plotted (for the 5 January 2006 event, see Fig. 4; the time intervals for convective and stratiform are prior to 1030 UTC and after 1100 UTC, respectively). The smaller variability in the $D_0-Z_{dr}$ relation for stratiform rain versus the much larger variability in convective rain is clear. The C-POL retrieval of $D_0$ is based on (1), which is also shown. Note that each data point is an average of gates between 2–3 km in height and includes data from two regimes: (a) the 5 January 2006 buildup and (b) the 19–20 January 2006 monsoon regime (which also had a similar convective time interval followed by long-duration stratiform rain with bright band). The $\pm 1\sigma$ error bars are from Williams and May (2008), who showed via theoretical calculations that the measurement standard deviation of C-POL $Z_{dr}$ is between 0.25 and 0.34 dB. For three stratiform rain events, they obtained a mean $D_0 = 1.43Z_{dr}^{0.4}$ relation (plotted in Fig. 6), which is close to (1) (i.e., within a few tenths of a decibel). Considering that their mean relation was a power-law fit to $D_0$ from profiler and $Z_{dr}$ from C-POL, it is rather remarkable that it lies so close to (1), which is based on Joss disdrometer DSDs and scattering simulations. From Fig. 6, we note that our stratiform rain data fall largely within their error bars but a larger subset of convective rain points fall outside their error bars. This is not unexpected because their error bars were derived from stratiform rain only. Schafer et al. (2002) show that the simulated standard deviation in the retrieval of $D_0$ using the dual-frequency profiler method would be around 0.5 mm for a clear-air spectral width of 3 m s$^{-1}$. Excluding a few outliers and assuming that most of the scatter in $D_0$ in convective rain is largely due to the profiler retrieval errors, the data in Fig. 6 are generally consistent with the Schafer et al. (2002) simulations, especially considering that the clear-air standard deviation for the buildup case within the convective rain shaft was estimated to be $3 \pm 0.9$ m s$^{-1}$. The corresponding value for the monsoon event was $2.6 \pm 1$ m s$^{-1}$. These values far exceed those found in the stratiform rain ($0.6$ m s$^{-1}$, typically).

4. Analysis of buildup and monsoon events

a. Separating convective and stratiform rain types

There are a large number of prior works dealing with classification of rain types, mainly using ground-based disdrometers, scanning radars and profilers (e.g., Tokay and Short 1996; Tokay et al. 1999; Ulbrich and Atlas 2007; Williams et al. 1995; Steiner et al. 1995). The main classification in these prior works has been convective versus stratiform as the microphysics and dynamics that control the DSD are vastly different. A more elaborate classification has been also been used (e.g., convective, transition, and stratiform; Ulbrich and Atlas 2007). Tokay and Short (1996) used a disdrometer-based $N_w-R$ relation ($N_w$ is the intercept parameter for an unnormalized gamma DSD; Ulbrich 1983) to separate convective versus stratiform rain types. More DSD-based separation has been done by Testud et al. (2001), Bringi et al. (2003), and Ulbrich and Atlas (2008). Ulbrich and Atlas (2008) proposed the use of different $Z-R$ relationships in different types. Here, our motivation to develop an “automated” radar-based procedure for convective/stratiform separation to better understand the variability of $D_0$ in these rain types, independent of $Z$, $R$, or $N_w$. For example, if $D_0$ tends to a near-constant value in strong convective rain, then it can imply an “equilibrium like” DSD (Hu and Srivastava 1995); if the $D_0$ is highly variable, then it may indicate a more complex microphysical process of rain formation and drop breakup [see Uijlenhoet et al. (2003) for a more detailed description of “concentration controlled” or “size controlled” DSDs]. The probability distribution function (pdf) of $D_0$—without rain-rate thresholding—is also important for satellite-based radar and/or radiometer algorithm development (e.g., Masunaga and Kummerow 2005).

Herein, a more in-depth analysis of profiler data has indicated that convective and stratiform rain types can be separated by utilizing the variation between the two main parameters defining the DSD: namely, $N_w$ and $D_0$. To illustrate this, the $N_w$ and $D_0$ variations for the buildup and monsoon cases are shown in Fig. 7. The data points are averages in the height interval 1.5–3 km.
both cases, stratiform and convective rain periods were separated based on visual inspection of the time–height profiles of $Z$; for example, for the buildup case shown in Fig. 4, stratiform rain can be clearly seen after 1100 UTC, whereas prior to 1030 UTC the rain type could be considered convective. The $N_w$ versus $D_0$ plots shown in Fig. 7a correspond to these two time periods (open gray circles for time $>1100$ UTC and solid black circles for time $<1030$ UTC). Also shown in Fig. 7a are points that correspond to the transition period between 1030 and 1100 UTC (denoted with ‘‘+’’). To reaffirm the three rain types, the vertical wind velocity data from the 50-MHz profiler were also used. The vertical wind velocity data are given in Fig. 8c. Briefly, in the convective periods, the buildup case (5 January 2006) had a symmetric (nearly Gaussian-shaped) updraft profile in the vertical with peak values of $\sim$15 m s$^{-1}$ centered at 8-km altitude (and extending mainly from 7 to 9 km). The downdraft peaks were $<5$ m s$^{-1}$ between 3–4-km altitude. In contrast the monsoon example (19–20 January 2006) had a uniform updraft profile with peak values of 10–12 m s$^{-1}$, mainly in the altitude interval 5.5–10 km. The peak downdrafts were $<3$ m s$^{-1}$ at 2-km altitude.

Figures 7a,b show a very clear separation of convective and stratiform rain types in the $N_w$–$D_0$ domain. The straight lines (drawn by visual inspection) in both figures represent the separator between the two rain types, which is given by

$$\log_{10}(N_{w,\text{sep}}) = -1.6D_0 + 6.3,$$

where $D_0$ is in units of mm and $N_w$ is in units of mm$^{-1}$ m$^{-3}$. Note that (6) is consistent with the Bringi et al. (2003) “global” separation of stratiform rain versus tropical and midlatitude “clusters” that they identify in the $N_w$–$D_0$ plane.

The $N_w$ and $D_0$ estimates derived from the C-POL data can now be tested against the criteria given by Eq. (6), which is solely based on profiler data. For this, we consider the C-POL data corresponding to the buildup event in Fig. 4. From RHI scans taken every 10 min along the profiler azimuth during this event, the attenuation-corrected height profiles of $Z$ at the profiler location were extracted. Figure 8a shows these profiles as a color-intensity plot, using the same $Z$ (dB) scale as Fig. 4. Although the C-POL-based plot is of a much lower resolution (both in time and in height), it very closely resembles the profiler plot in Fig. 4.

The C-POL data ($Z_h$, $Z_{dr}$, and $K_{dp}$) below 4-km height were used to retrieve the $N_w$ and $D_0$ values [see Eqs. (1a), (1b)], which in turn were used to determine an index (which could be interpreted as the separation index) $i$ given by C-POL

$$i = \log_{10}(N_w^{\text{C-POL}}) - \log_{10}(N_{w,\text{sep}}),$$

where $N_w^{\text{C-POL}}$ represents the estimated $N_w$ from C-POL data [see Eq. (2)] and $N_{w,\text{sep}}$ represents the output of (6), when $D_0$ is set to the estimated $D_0$ value from the C-POL data. This was done so that positive values of $i$ represent convective rain and negative values represent stratiform rain. Figure 8b shows the index values resulting from the C-POL retrievals. High negative values of $i$ (shown in blue) represent stratiform rain type, high positive values of $i$ (shown in red) represent convective type, and low-magnitude $i$ values, both positive and negative, indicating transition regions. Note that the blue regions in Fig. 8b correspond to the regions below the bright band in Fig. 8a, as well as in Fig. 4, whereas the red regions in Fig. 8b correspond to regions of strong convection in Fig. 8a, as well as in Fig. 4. The transition regions are also clearly indicated by the yellow regions.
FIG. 8. (a) C-POL reflectivity height profiles as time series, extracted from the RHI scans over the profiler site taken every 10 min, corresponding to the 5 Jan 2006 buildup event shown in Fig. 4; (b) the stratiform/convective separator index determined on the basis of the retrieved DSD parameters using the C-POL polarimetric data; (c) the mean Doppler wind velocity from the 50-MHz profiler, where positive (negative) values indicate updraft (downdraft).
corresponding to areas of low-magnitude \( i \) values. Further confirmation of the rain-type indexing can be seen from Fig. 8c, which shows the vertical wind velocity determined from the 50-MHz profiler data. Updraft and downdraft regions around 1000 UTC correlate well with the regions identified as being convective in Fig. 8b, and low vertical wind velocities in Fig. 8c after 1100 UTC correspond to the regions identified as being stratiform in Fig. 8b. The moderate vertical wind velocities between \( \sim 1030 \) and 1100 UTC can be associated with regions identified as being transitional.

The technique of rain-type indexing in Fig. 8 could also be extended to PPI scans. Figure 9a shows the C-POL reflectivity values (after correcting for attenuation) taken of a squall line during the buildup example on 5 January 2006. The line of convection oriented northeast–south of the radar is embedded within larger regions of less intense rain. Figure 9b shows the rain-type index determined using the retrieved \( N_w \) and \( D_0 \) values from the C-POL data.

As a general observation, high positive values of the rain-type index (regions of red, indicating strongly convective regions) can be seen to correspond to high reflectivity values in Fig. 9a, whereas high negative values of the rain-type index (regions of blue, indicating stratiform regions) can be seen to correspond to low reflectivity values. It should be noted, however, that the value of \( i \) does not have a linear (or even near-linear) variation with \( Z \) (in dB). Instead, for a given \( Z \) (dBZ), \( i \) can have multiple values (and vice versa), depending on \( D_0 \), which is given by

\[
i = c_1 + c_2 Z_{\text{dBZ}} + f(D_0),
\]

where \( c_1 \) and \( c_2 \) are constants and \( f(D_0) \) is a function of \( D_0 \). Equation (8) arises because of the dependence of \( N_w \) on \( Z \) as well as \( D_0 \), which is given in section 2a. It follows that the convective/stratiform separation cannot be based on \( Z \) (or \( R \)) alone.

Some caveats are in order here. The separation technique works well in majority of the cases in the rain regions (as seen from Figs. 8, 9), with the magnitude of \( i \) indicating the general likelihood of the classification, as mentioned earlier. However, in the rare cases of updraft regions where it may be possible to have low \( Z \) and high \( Z_{\text{dr}} \) (i.e., positive \( Z_{\text{dr}} \) columns), the method is likely to give incorrect classifications. Such regions can be easily identified by applying a suitable hydrometeor classification scheme (e.g., the big drop zones in Ryzhkov et al. 2005); however, in the case of Figs. 8 and 9 and other events analyzed in this study, there were no such regions.

The second point to note is that, when RHI scans are considered, the indexing scheme should be limited to heights well below the 0°C isotherm. The high values of \( i \) at the very top of Fig. 8b from 1200 to 1300 UTC are due to the presence of not fully melted hydrometeors; for such cases, the retrieved \( N_w-D_0 \) estimates would—in any case—be incorrect and inapplicable (see May et al. 2001 for polarimetric signatures in the mixed phase region).

Finally, the applicability of the method is yet to be tested for rainfall regions with tropical DSD characteristics, other than those during the buildup and monsoon events.
As described in section 2a, a number of steps are involved prior to obtaining reliable $Z_{\text{dr}}$ data, after which the $D_0$ is estimated from (1). The fractional standard error in the estimate of $D_0$ was estimated there to be around 9%, which is subject to the caveat that system offsets are accurately determined and accurately corrected for differential attenuation. In the following, we show histograms of $D_0$ as well as some key parameters, such as mean, standard deviation, and skewness. Small differences in the mean values (about a few tenths of a millimeter) are also interpreted to be statistically different. Given that the $1\sigma$ error from section 2a was estimated to be around 0.116 mm for $Z_{\text{dr}}$ in the most frequently occurring range of 0.5–2.5 dB, the confidence interval in estimation of the mean $D_0$ would be much smaller considering the large number (several thousands) of samples in the histogram. Hence, we are justified in interpreting small differences in mean $D_0$ (of a few tenths of a millimeter) as being statistically significant.

**b. $D_0$ histograms**

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**Figure 10** shows two sets of histograms of $D_0$ derived from low-elevation-angle ($-1^\circ$) PPI scans after rain classification by using this indexing technique. Note that the only threshold used is that the radar resolution volume be classified as being from precipitation echoes. As mentioned earlier, this was based on the standard deviation of differential propagation phase over a 10-gate moving window be $<15^\circ$. Thus, the histograms shown here are unconditioned and only dependent on the sensitivity of the radar. Figures 10a,b correspond to the monsoon and buildup regimes, respectively, with their corresponding differences in boundary layer structure, midlevel moisture, and aerosol loadings. In both cases, the retrieved $D_0$ values of pixels (from PPI scans) identified as being stratiform or convective were used to derive the histograms. The mean, standard deviation, and skewness of the histograms are shown in Table 1.

The first noteworthy aspect is that the widths of the $D_0$ distributions $\sigma$ are significantly larger (0.38 mm) for the buildup example than for the monsoon (0.20 mm) independent of rain type. Further, the mean $D_0$ for convective rain in the buildup example (1.6 mm) is significantly larger than in the convective monsoon (1.44 mm). The mean $D_0$ in stratiform rain is also significantly larger in the buildup (1.34 mm) than in the monsoon (1.22 mm); however, the modes for buildup versus monsoon are 1.1 and 1.3 mm, respectively. Finally, the skewness factor is significantly negative ($-0.54$ to $-0.33$) for the monsoon example, whereas it is positively skewed (0.50) for both the buildup stratiform and the buildup convective examples. The monsoon histograms are characterized by rapid fall off in the frequency of occurrence of $D_0$ of approximately $>1.5$ mm which, as expected, is very different from the buildup example, where a significant fraction of $D_0$ values that are $>1.5$ mm are found.

As a comparison, previous results of Testud et al. (2001) based on airborne imaging probes in oceanic rain during the Tropical Ocean Global Atmosphere Coupled Ocean—Atmosphere Response Experiment (TOGA COARE) found the mean and $\sigma$ in stratiform rain (1.21 mm and 0.26, respectively), which are in good agreement.

**Table 1. Mean, standard deviation, and skewness of the $D_0$ histograms.**

<table>
<thead>
<tr>
<th>Rain Type</th>
<th>Mean (mm)</th>
<th>Std dev (mm)</th>
<th>Skewness</th>
<th>No. of points</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Convective</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monsoon</td>
<td>1.44</td>
<td>0.20</td>
<td>$-0.54$</td>
<td>2531</td>
</tr>
<tr>
<td>Buildup</td>
<td>1.6</td>
<td>0.38</td>
<td>0.50</td>
<td>2855</td>
</tr>
<tr>
<td><strong>Stratiform</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monsoon</td>
<td>1.22</td>
<td>0.21</td>
<td>$-0.33$</td>
<td>5102</td>
</tr>
<tr>
<td>Buildup</td>
<td>1.34</td>
<td>0.38</td>
<td>0.54</td>
<td>3552</td>
</tr>
</tbody>
</table>

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agreement with our monsoon stratiform rain values of 1.22 mm and 0.21, respectively. For convective rain (10 < R < 30 mm h⁻¹), they found corresponding values of 1.32 mm and 0.34, respectively, versus our monsoon convective (1.44 mm and 0.20, respectively), which are relatively similar, given the rain-rate threshold used by Testud et al. (2001). Such agreement between the monsoon case analyzed herein (19–20 January 2006) and the TOGA COARE data may be expected because the monsoon cloud systems experienced near the Darwin area are usually oceanic.

5. Conclusions

A comparison of Z, D₀, and R from C-POL and the dual-frequency profiler located in Darwin showed very good agreement for the two example events selected herein to represent the “buildup” and monsoon regimes. The D₀ values retrieved from C-POL measurements of Zₜ₀ (using an algorithm based on Joss disdrometer DSDs and scattering simulations) were found, on average, to be in excellent agreement with the prior work of Williams and May (2008), who obtained a mean fit to D₀ from the dual-profiler method with C-POL-measured Zₜ₀. The scatter in the D₀ versus Zₜ₀ data was found to be largely within the error bounds (1σ of ~0.17 mm) predicted by Williams and May (2008); however, the scatter was noticeably larger (1σ of ~0.3–0.5 mm) for convective rain, mainly because of the difficulty in deconvolving the 920-MHz Doppler spectra of rain in the presence of turbulence and wind shear, but it was within the predicted error bounds of Schafer et al. (2002; 1σ of ~0.5 mm for clear-air spectral width of 3 m s⁻¹).

The profiler-retrieved N₀ and D₀ data in the rain region showed a clear separation of convective and stratiform rain types. This enabled the derivation of a separator line, which in turn was applied to C-POL-retrieved DSD parameters (N₀ and D₀). The deviation from the separator line for a given D₀ was used to define a smoothly varying index value representing the likelihood of stratiform or convective rain type, including a continuous “transition” region between the two. Using this indexing technique on a number of low-elevation-angle PPI sweeps from the two regime examples, it was possible to construct “unconditioned” histograms of D₀ in stratiform and convective rain (to within the sensitivity of the radar). From the D₀ histograms, three main conclusions can be drawn:

1) The histogram mean is significantly larger in the buildup regime than in the monsoon regime, irrespective of rain type (1.6 versus 1.44 mm for convective and 1.34 versus 1.22 mm for stratiform). However, the stratiform case shows lower mode (1.1 mm) for the buildup regime relative to the monsoon (1.3 mm).

2) The histogram width (or standard deviation) is much larger (0.38 mm) for the buildup regime than for the monsoon regime (0.20 mm), irrespective of rain type.

3) The histogram skewness is negative for the monsoon regime because of a lack of larger D₀ values, whereas the buildup regime was positively skewed, irrespective of rain type.

Although only two examples of events from the buildup and monsoon regimes in the Darwin area have been analyzed, further statistical analysis from more events are needed to generalize the applicability of our results. Furthermore, our classification method will provide a tool based on the underlying cloud microphysics for future work to examine the impact of different precipitation processes on the final drop size distributions as well as the impact of different thermodynamic and boundary layer environments on storm physics.

Acknowledgments. This work was supported by the NASA Precipitation Measurement Mission (PMM) program via Grants NNX07AD47G and NNX07AN32G. MT was supported by the U.S. National Science Foundation via Grant ATM-0603720. PTM is partially supported by the U.S. DOE Atmospheric Radiation Measurement (ARM) program. The Darwin 50-MHz profiler is owned and operated by the Australian Bureau of Meteorology (BoM). The Darwin 920-MHz profiler is owned by NOAA and is maintained and operated by BoM.

REFERENCES


Application to a squall-line event from the TRMM/Brazil campaign. J. Atmos. Oceanic Technol., 19, 633–645.


