Separating Cloud and Drizzle Signals in Radar Doppler Spectra Using a Parametric Time Domain Method

SHASHANK S. JOSHIL
Colorado State University, Fort Collins, Colorado

CUONG M. NGUYEN
National Research Council Canada, Ottawa, Ontario, Canada

V. CHANDRASEKAR
Colorado State University, Fort Collins, Colorado

J. CHRISTINE CHIU
Department of Atmospheric Science, Colorado State University, Fort Collins, Colorado

YANN BLANCHARD
Department of Earth and Atmospheric Sciences, University of Quebec at Montreal, Montreal, Quebec, Canada

(Manuscript received 23 April 2020, in final form 2 July 2020)

ABSTRACT

The ability to separate cloud and drizzle returns in active remote sensing observations is important for understanding the microphysics of clouds and precipitation. Yet, robust separations remain challenging in radar remote sensing. Prior methods for cloud and drizzle separation for radar observations use the properties of the Doppler spectra such as skewness. However, these methods have challenges when the drizzle becomes dominant in the observation volume. This paper presents a parametric time domain method (PTDM) that separates cloud and drizzle using the Doppler spectra measurements without assuming any prior properties of cloud and drizzle. The advantage of PTDM is that it can estimate the signal properties in the time domain and can obtain the cloud and drizzle estimates simultaneously. Based on our radar signal simulations, the uncertainty in estimated power and velocity from PTDM are within 2 dB and 0.02 m s\(^{-1}\), respectively. We have also evaluated the PTDM algorithm using observations from the Atmospheric Radiation Measurement (ARM) Program W-band cloud radar in the Clouds, Aerosols, and Precipitation in the Marine Boundary Layer (CAP-MBL) campaign at the Azores in 2009–10. Two cases corresponding to light and moderate drizzling conditions are considered for the study. The statistics of the estimates obtained show that the PTDM method performs well in separating the cloud and drizzle returns. Finally, the estimated cloud and drizzle reflectivity from PTDM were used to retrieve their corresponding microphysical properties, showing that the retrieved liquid water path agrees to 25 g m\(^{-2}\) with the benchmark microwave method.

1. Introduction

Boundary layer clouds are fundamental to Earth’s radiation budget due to their vast cloud cover and high albedo (Hartmann et al. 1992; Hahn and Warren 2007). They drizzle frequently (Petty 1995; Rémillard et al. 2012; Wu et al. 2017); the drizzle process not only influences cloud organization and life cycle, but also modulates boundary layer structure and the energy budget (Wood 2012; Ahlgrimm and Forbes 2014; Yamaguchi et al. 2017; Zhou et al. 2017). These complex and intertwined interactions make it difficult to determine how these clouds will respond to a warmer climate. Consequently, boundary layer clouds represent one of the largest contributions to uncertainty in climate change predictions (Boucher et al. 2013).

To reduce the uncertainty, our understanding of drizzle formation needs to advance at process levels. This involves processes of activation, condensation, evaporation,
collision–coalescence, and sedimentation. Among these processes, the collision–coalescence, including autoconversion that produces rainwater by the coalescence between cloud droplets, and accretion that produces rainwater by the coalescence between cloud droplets and raindrops, has received considerable attention. The attention arises because the representation of autoconversion and accretion has significant impacts on the amount and distribution of precipitation (Bennartz et al. 2011; Weber and Quaas 2012; Takahashi et al. 2017), the cloud responses to aerosol perturbation (Gettelman et al. 2013; Tonttila et al. 2015; Michibata and Takemura 2015; Jing et al. 2019), and the evolution of global mean surface air temperature in models (Golaz et al. 2013).

To better understand the collision–coalescence process from observations, concurrent cloud and drizzle properties are required. However, it is challenging to separate these two species in active remote sensing observations, because drizzle drops dominate radar reflectivity and obscure cloud signals. This challenge has recently been tackled by several methods, which can be roughly grouped to two categories. The first category is to assume that the vertical profile of cloud water content follows either a linear relationship (Fielding et al. 2015) or certain shapes (Rusli et al. 2017). The second category, introducing an advanced multiple spectral method for separating cloud and drizzle returns in radar signals. The technique, a parametric time domain method (PTDM), has been used to separate precipitation signals from ground clutter in weather radar observations (Nguyen et al. 2008), but it is the first time for separating cloud and drizzle in cloud radar observations. PTDM can handle situations when the signals from the two species largely overlap. It does not suppress or remove any part of the Doppler spectra, avoiding any alteration that might lead to significant errors in cloud/drizzle attributions. In section 2, we detail the theory and the practical implementation of PTDM and report the associated uncertainty in its estimations. In section 3, we perform a number of intercomparisons to discuss the performance of PTDM, using measurements from the W-band ARM Cloud Radar (WACR) during the Clouds, Aerosols, and Precipitation in the Marine Boundary Layer (CAP-MBL) campaign in 2009–10. Finally, a summary of key findings will be given.

2. Methodology

a. The basis of the method

Consider \( \mathbf{V} \) to be the vector of received voltage samples in radar measurements. Then, \( \mathbf{R}_y = \mathbf{VV}^H \) gives us the sample covariance matrix and \( \mathbf{R} = E(\mathbf{VV}^H) \) gives us the covariance matrix, where the superscript \( H \) denotes transpose conjugate. Because the individual signals coming from scatters in the radar resolution volume have similar statistical properties, the joint probability density function (pdf) of the received signal can be considered to be a normal distribution with a zero mean (Bringi and Chandrasekar 2001). In other words, the pdf of the complex voltage can be expressed by

\[
    f(V) = \frac{1}{\pi^{N/2}|\mathbf{R}|} \exp\left[-\text{Tr}(\mathbf{V}^H\mathbf{R}^{-1}\mathbf{V})\right] = \frac{1}{\pi^{N/2}|\mathbf{R}|} \exp\left[-\text{Tr}(\mathbf{R}^{-1}\mathbf{R}_y)\right],
\]

where \( \text{Tr} \) is the trace of the matrix.

Suppose that the Doppler spectra of cloud and drizzle follow a Gaussian distribution, which can be characterized by its moments: signal power \( (\bar{P}) \), mean velocity \( (\bar{v}) \) and spectrum width \( (\sigma) \). When the radar resolution volume contains either cloud droplets or drizzle, the Doppler spectrum can be well approximated by a single Gaussian distribution. When the radar resolution volume contains both cloud and drizzle, the Doppler
The observed spectra $S$, as a function of velocity $v$, can be approximated by

$$S(v) = \frac{P_C}{\sqrt{2\pi \sigma_C^2}} \exp \left[-\frac{1}{2} \left( \frac{v - \bar{v}_C}{\sigma_C} \right)^2 \right] + \frac{P_D}{\sqrt{2\pi \sigma_D^2}} \exp \left[-\frac{1}{2} \left( \frac{v - \bar{v}_D}{\sigma_D} \right)^2 \right] + \frac{2T_s}{\lambda} \sigma_N^2,$$

where the subscript $C$ and $D$ denotes cloud and drizzle, respectively; $T_s$, $\lambda$, and $\sigma_N^2$ are the radar operating interpulse period, wavelength, and the noise power, respectively. From Eq. (2), the covariance matrix of the measured radar signal can be given as (Nguyen et al. 2008):

$$R_{kl} = P_C \exp \left[-\frac{8\sigma_C^2(k-l)^2T_s^2}{\lambda^2} \right] \exp \left[-\frac{j4\pi\sigma_C^2(k-l)T_s}{\lambda} \right] + P_D \exp \left[-\frac{8\sigma_D^2(k-l)^2T_s^2}{\lambda^2} \right] \times \exp \left[-\frac{j4\pi\sigma_D^2(k-l)T_s}{\lambda} \right] + \sigma_N^2 \delta(k-l),$$

$k, l = 1, 2, \ldots, N$, (3)

where $k$ and $l$ denote the index of matrix elements, $\delta$ is the delta function, and $N$ is the sample size. Note that we have assumed a mixture of two Gaussian distributions in the above derivations. We refer to it as a two-echo PTDM model. The derivations can be modified and adapted for the case that only cloud or drizzle exists. For such a case, we refer to the method as a one-echo PTDM model.

Let us define $\mu$, the vector to be estimated, as

$$\mu = [\bar{v}_C, \sigma_C, \bar{v}_D, \sigma_D, \sigma_N^2].$$

containing the spectral moments of cloud and drizzle along with the noise. The best estimate of $\mu$ is obtained from the standard maximum-likelihood technique. Considering the pdf shown in Eq. (1) and rewriting $R$ as $R(\mu)$, we then basically minimize the negative log-likelihood function $L(\mu)$ given as

$$L(\mu) = \ln(|R(\mu)|) + \text{Tr}(R^{-1}(\mu)R_V).$$

The minimization of Eq. (5) follows the procedure described in Nguyen et al. (2008). The solution space used for the proposed research is listed in Table 1.

### Table 1. Lower and upper bounds of the solution space for the parameters estimated by the PTDM method with $v_o$, the unambiguous mean velocity, determined by the radar operating parameters; $S_{tot}$ the total signal power; and $\sigma_{N,sys}^2$ is the system noise floor.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Lower bound</th>
<th>Upper bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>Signal power $P_{C,D}$ (dB)</td>
<td>0</td>
<td>$S_{tot}$ + 5</td>
</tr>
<tr>
<td>Mean velocity $\bar{v}_{C,D}$ (m s$^{-1}$)</td>
<td>$-v_o$</td>
<td>$+v_o$</td>
</tr>
<tr>
<td>Spectral width $\sigma_{C,D}$ (m s$^{-1}$)</td>
<td>0.1</td>
<td>4</td>
</tr>
<tr>
<td>Noise power $\sigma_N^2$ (dB)</td>
<td>$\sigma_{N,sys}^2$</td>
<td>$\sigma_{N,sys}^2$ + 5</td>
</tr>
</tbody>
</table>

b. Practical implementation

The spectral separation between cloud and drizzle include the following practical steps (see Fig. 1 for the flow-chart). For all signals, we first apply the one-echo PTDM model and determine whether the radar resolution volume contains more than cloud or drizzle. The determination of the scene is relied on the goodness of the fit for a Gaussian distribution, but also constrained by cloud base height provided by ceilometers. If a unimodal distribution is found, the signal is classified as a cloud signal for radar gates above cloud-base height and classified as drizzle for gates below cloud base. Only when a non-Gaussian spectrum is detected above cloud base, we pursue further separations between cloud and drizzle and apply the two-echo PTDM model. The final output is the estimated spectral moments for clouds and/or drizzle at each radar gate.

Two metrics are used to determine the goodness of fit. The first metric is the trace of variance, $\text{Tr}_{var}$, defined as

$$\text{Tr}_{var} = \text{std}\{\text{diag}[R^{-1}(\hat{\mu})R_V]\},$$

where $\hat{\mu}$ is the estimated parameter, and the second metric is the fraction of the total signal variance explained by the PTDM model $R_{sq}$ given as

$$R_{sq} = 1 - \frac{\sum_{k=1}^{m} |R_{k,1}(\hat{\mu}) - R_{V,k,1}|^2}{\sum_{k=1}^{m} |R_{V,k,1} - \langle R_{V,k,1} \rangle|^2},$$

where the angle brackets $\langle \cdot \rangle$ denote the mean value. The value of $R_{sq}$ ranges from 0 to 1; a value of $R_{sq}$ of unity indicates a perfect fit, capturing all the variance in signals. We use a high threshold of 0.95 to ensure the dual-signal model fits well.

c. Performance and uncertainty estimate

For the performance and uncertainty evaluations, we run a series of radar signal simulations, as illustrated by a
These simulations are based on the setting of ARM W-band cloud radar (see Table 2), e.g., with a pulse repetition frequency of 10 KHz, a 95.05-GHz radar frequency, and the 256-point Fourier transform. As shown in Table 3, the power level from drizzle was kept constant and the power from cloud was varied through a range of values from 5 to 30 dB, mimicking situations from drizzle dominant to cloud dominant. The other parameters such as velocity and spectral width were kept constant to typical observational conditions.

**Table 2. Operating parameters of the ARM W-band cloud Doppler radar.**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency</td>
<td>95.04 GHz</td>
</tr>
<tr>
<td>Pulse repetition frequency</td>
<td>10 kHz</td>
</tr>
<tr>
<td>Gate spacing</td>
<td>42.857 m</td>
</tr>
<tr>
<td>Unambiguous velocity</td>
<td>7.885 m s⁻¹</td>
</tr>
<tr>
<td>Velocity resolution</td>
<td>0.0616 m s⁻¹</td>
</tr>
<tr>
<td>Integration time</td>
<td>2.048 s</td>
</tr>
<tr>
<td>FFT length</td>
<td>256</td>
</tr>
<tr>
<td>No. of spectral averages</td>
<td>160</td>
</tr>
<tr>
<td>Peak transmit power</td>
<td>1500 W</td>
</tr>
<tr>
<td>Antenna beamwidth</td>
<td>0.32°</td>
</tr>
</tbody>
</table>
values. Radar signal simulations were carried out to generate the required input signal, then this signal was sent through the PTDM model to obtain cloud and drizzle reflectivity estimates. 250 iterations at each power level were performed to find the mean and standard deviation of the output estimates to evaluate the uncertainty.

The results in Table 3 indicate that the uncertainties in estimated power of cloud and drizzle are both less than 2 dB. The difference between the mean and the true power for clouds ranges between 0.12 and 0.59 dB, demonstrating that the PTDM estimates agree to better than 3% with the truth. The errors in drizzle estimates are also within 3%. Similar simulations were also performed for velocity. As shown in Table 4, the uncertainty in estimated velocity is on the order of 0.02 m s\(^{-1}\). The errors in the mean velocity for cloud and drizzle are within 5% and 1%, respectively.

3. Results

In this section, we apply PTDM to observations from the ARM W-band cloud radar in the CAP-MBL deployment at the Azores in 2009–10. The radar is a zenith pointing Doppler radar operated with both cross-polarization and copolarization mode. For the following case studies, we have considered only data from copolarization mode.

a. Statistics in comparisons near cloud base

Similar to Luke and Kollias (2013), we check the consistency in drizzle spectral moments in gates near the cloud base for the ARM campaign cases. For convenience, the gate at the cloud base is denoted as CB, while gates just below and above the cloud base is denoted as CB\(-1\) and CB\(+1\), respectively. Recall that radar reflectivity and velocity at CB\(-1\) are purely due to drizzle particles; these values are obtained directly from radar measurements and provide unambiguous drizzle moments. At CB and CB\(+1\), the radar moments begin to be influenced by both cloud and drizzle. With a radar range resolution of \(~50\) m in ARM measurements, the drizzle moments at CB and CB\(+1\) should be almost identical to that at CB\(-1\) in moderate and heavy drizzle cases, based on typical observed radar reflectivity profiles (Comstock et al. 2004). For light drizzle cases, the difference between these gates can be relatively larger depending on how fast drizzle evaporates below clouds. Based on our simulations in Tables 3 and 4, the error in each gate is within 1 dB and thus the reflectivity values between gates should match within 2 dB. Similarly, the velocity values should match within a few tenths of m s\(^{-1}\). While such a comparison provides an opportunity for evaluating PTDM-estimated moments, we note that this comparison does not intend to represent the performance for all cloud layers, but it is informative as the first step of the evaluation processes.

The performance of PTDM is evaluated using two cases. The first case on 29 November 2009 was used in Mann et al. (2014) for studying aerosol impacts on precipitation. It is a typical marine precipitating stratocumulus case in which cloud decks were persistent for

### Table 3. Uncertainty estimates in output power (dB) of cloud and drizzle using radar signal simulations. The mean velocity of cloud and drizzle is respectively kept as 0.2 and 1.5 m s\(^{-1}\), while the spectrum widths for cloud and drizzle are both kept as 0.1 m s\(^{-1}\).

<table>
<thead>
<tr>
<th>Input power for cloud</th>
<th>Input power for drizzle</th>
<th>Output power from cloud (mean ± 1 standard deviation)</th>
<th>Output power from drizzle (mean ± 1 standard deviation)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>20</td>
<td>4.88 ± 1.65</td>
<td>19.80 ± 1.86</td>
</tr>
<tr>
<td>10</td>
<td>20</td>
<td>9.78 ± 1.61</td>
<td>19.49 ± 1.78</td>
</tr>
<tr>
<td>15</td>
<td>20</td>
<td>14.72 ± 1.84</td>
<td>19.78 ± 1.88</td>
</tr>
<tr>
<td>20</td>
<td>20</td>
<td>19.44 ± 1.84</td>
<td>19.60 ± 1.92</td>
</tr>
<tr>
<td>25</td>
<td>20</td>
<td>24.41 ± 1.88</td>
<td>19.50 ± 1.67</td>
</tr>
<tr>
<td>30</td>
<td>20</td>
<td>29.67 ± 1.67</td>
<td>19.72 ± 1.80</td>
</tr>
</tbody>
</table>

### Table 4. As in Table 3, but for velocity estimates (m s\(^{-1}\)). The signal powers of cloud and drizzle are kept as 25 and 30 dB, respectively.

<table>
<thead>
<tr>
<th>Input velocity for cloud</th>
<th>Input velocity for drizzle</th>
<th>Output velocity of cloud (mean ± 1 standard deviation)</th>
<th>Output velocity of drizzle (mean ± 1 standard deviation)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0</td>
<td>2</td>
<td>0.000 ± 0.016</td>
<td>1.999 ± 0.015</td>
</tr>
<tr>
<td>0.2</td>
<td>2</td>
<td>0.190 ± 0.017</td>
<td>1.999 ± 0.017</td>
</tr>
<tr>
<td>0.4</td>
<td>2</td>
<td>0.400 ± 0.019</td>
<td>1.998 ± 0.016</td>
</tr>
<tr>
<td>0.6</td>
<td>2</td>
<td>0.590 ± 0.019</td>
<td>1.995 ± 0.017</td>
</tr>
<tr>
<td>0.8</td>
<td>2</td>
<td>0.790 ± 0.023</td>
<td>1.998 ± 0.016</td>
</tr>
<tr>
<td>1.0</td>
<td>2</td>
<td>1.000 ± 0.025</td>
<td>2.001 ± 0.019</td>
</tr>
</tbody>
</table>
several hours and cloud geometric thickness deepened over time. Zooming in the time period of 1430–1600 UTC as shown in Fig. 3, we see a moderately drizzling case with the maximum radar reflectivity up to $2 \times 10^3$ dBZ and with virga depths of about 500 m. In contrast, the second case on 27 July 2010 represents a lightly drizzling case with the maximum radar reflectivity up to $2 \times 10^2$ dBZ (Fig. 4), used in Luke and Kollias (2013) for evaluating their separation technique. In this case, the increase in radar reflectivity with height is evident, indicating the dominant particle growth due to condensation, a signature often found in nonprecipitating clouds as well.

![Time–height plots](image)

The density scatterplots for both cases are shown in Figs. 5 and 6. For the first case, the majority of the data points fall into the 1:1 line, leading to respective correlation coefficients of 0.9 and 0.78 for drizzle reflectivity and velocity in the comparisons.
between CB and CB − 1 (see Table 5). Based on the error histograms, the mean reflectivity difference is 0.0 dBZ with a root-mean-square difference (RMSD) of 4.9 dBZ; the velocity difference is 0.0 m s⁻¹ with a RMSD of 0.3 m s⁻¹. The performance is degraded in the comparisons between CB + 1 and CB − 1, evident in the derived error statistics and by the departure from the 1:1 line in the reflectivity region between −50 and −30 dBZ. This is likely due to rapid evaporation of drizzle when the reflectivity is small, causing that the reflectivity at CB + 1 is much larger than CB − 1.

For the second case (Fig. 6), the retrieved drizzle reflectivity and velocity are similar to those in Luke and Kollias (2013) by comparing their Fig. 7 with our Fig. 4. As mentioned above, the second case has reflectivity generally 15 to 20 dB lower than the first case and therefore noisier. In the comparisons between CB and CB − 1, the corresponding correlations in both drizzle reflectivity and velocity are slightly worse than the first case, but the mean difference is still within 1 dB for retrieved drizzle reflectivity and well within 0.2 m s⁻¹ for retrieved drizzle velocity (see Table 6). The RMSD is more sensitive to the mean reflectivity level of the cases,
and thus the RMSD in the light drizzle case is about half of that in the moderate drizzle case even the latter has a better correlation. The plot in the comparisons between CB\textsubscript{1} and CB\textsubscript{2} show a significant level of scatter. Similar to the first case, the drizzle reflectivity at CB\textsubscript{1} tends to be larger than that at CB\textsubscript{2}. However, in this case, we see values of velocities above the cloud base are lower than the velocities below the cloud base. As explained by Luke and Kollias (2013), this may be partly due to the enhanced downdraft air motion induced by evaporation cooling of drizzle particles below cloud base.

b. Comparison with microwave observations via ENCORE

The retrieved cloud and drizzle reflectivity from PTDM are further evaluated, by testing whether they lead to reasonable cloud and drizzle properties compared to independent collocated observations. This test is carried out through an Ensemble Cloud Retrieval method (ENCORE) described in Fielding et al. (2015). Using PTDM-estimated reflectivity along with lidar backscatter and shortwave zenith radiance as input, ENCORE can retrieve height-invariant cloud droplet number concentration, and height-resolving cloud/dizzle water content, effective radius, and drizzle number concentration. The best estimates of these properties are obtained through an iterative ensemble Kalman filter approach; typically, the retrieval solution can converge and match to observations within their uncertainty in a few iterations.

The uncertainty in PTDM-estimated cloud and drizzle reflectivity used in the test is assumed to be 2 dB, as suggested in Table 2. The uncertainty in shortwave radiance is assumed 15%, based on the calibration reported in Chiu et al. (2006). As pointed out by Fielding et al. (2014), radar reflectivity is an important constraint for cloud droplet size, while the shortwave radiance is an important constraint for cloud droplet number concentration. If observations from these two instruments were inconsistent with each other, then the cloud water content and thus the total liquid water path (LWP) would be inaccurate. Therefore, to evaluate whether PTDM has separated cloud from drizzle properly, we compute LWPs from the retrieved cloud and
drizzle water content and compare them with those from microwave radiometer observations that have been considered as a benchmark for remote sensing applications. The ARM microwave radiometer (MWR) has a 5.9° field of view and measures brightness temperatures at 23.8 and 31.4 GHz every 20 s; its LWP retrievals have a nominal uncertainty of 20–30 g m\(^{-2}\) (Marchand et al. 2003; Crewell and Löhnert 2003).

Figure 7 shows the time series of liquid water path retrieved from MWR and from ENCORE along with PTDM-estimated cloud and drizzle reflectivity. The retrieval appears to correlate MWR retrievals well, suggesting that the PTDM-estimated cloud and drizzle reflectivity are appropriate. Additionally, the scatterplot shows that the majority of our retrieved LWP falls within the uncertainty 30 g m\(^{-2}\) of MWR retrievals, although they tend to be smaller than the MWR retrievals. The means from MWR and ENCORE retrievals are 57 and 46 g m\(^{-2}\), respectively, and the corresponding RMSD is 25 g m\(^{-2}\). Note that the MWR retrievals reported here were based on nonscattering microwave radiative transfer. In reality, large drizzle drops in precipitating clouds scatter microwave radiation. If the scattering effects are not accounted for in the retrieval process, it results in a lower brightness temperature and leads to an overestimation in the retrieved LWP. According to the case studies in Cadeddu et al. (2017), the MWR-retrieved LWP without considering

![Figure 7](image.png)

FIG. 6. As in Fig. 5, but for 1000–1100 UTC 27 Jul 2010.

TABLE 5. A summary of Pearson correlation coefficient, mean difference, and root-mean-square difference (RMSD), derived from comparisons between gates at the cloud base (CB), just above cloud base (CB + 1), and just below cloud base (CB − 1). The difference is calculated by subtracting results at CB − 1 from those either at CB or at CB + 1. The statistics were based on 10920 points in the full day on 29 Nov 2009, except nondrizzling time periods.

<table>
<thead>
<tr>
<th></th>
<th>CB vs CB − 1</th>
<th></th>
<th>CB + 1 vs CB − 1</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Correlation</td>
<td>Difference</td>
<td>RMSD</td>
<td>Correlation</td>
</tr>
<tr>
<td>Reflectivity (dBZ)</td>
<td>0.90</td>
<td>0.00</td>
<td>4.90</td>
<td>0.79</td>
</tr>
<tr>
<td>Velocity (m s(^{-1}))</td>
<td>0.78</td>
<td>0.00</td>
<td>0.26</td>
<td>0.50</td>
</tr>
</tbody>
</table>
scattering can be larger by \(\sim 10 \text{ g m}^{-2}\) compared to that with scattering for a cloud with LWP of 200 g m\(^{-2}\). This potential bias due to scattering may partly explain why the mean MWR retrieval is larger than the mean ENCORE retrieval in our case.

4. Summary

We introduce an advanced method for separating cloud signals from drizzle using radar Doppler spectra. This separation is particularly important for studying drizzle formation in marine boundary layer clouds, because concurrent bulk cloud and drizzle properties are necessary to provide observational constraints for the associated collision–coalescence process. The method, dubbed PTDM, is based on a rigorous mathematical framework, and only involves the assumption that the Doppler spectra of cloud and drizzle follow a Gaussian distribution. Using the operational setting of the ARM W-band cloud radar at the Azores, the uncertainty in retrieved reflectivity and velocity from PTDM for cloud and drizzle is about 2 dB and 0.02 m s\(^{-1}\), respectively, based on a series of radar signal simulations.

We apply the PTDM to cloud radar observations from the ARM CAP-MBL campaign for performance evaluations, including light and moderate drizzle cases. Since no coincident in situ cloud probe measurements are available, the PTDM output is evaluated through the following tests. The first test is to check whether drizzle properties between gates near cloud base are consistent. This test is useful because drizzle reflectivity and velocity below cloud base can be directly obtained from radar measurements, and thus provide an unambiguous reference. Results from this test show that the reflectivity values near cloud base tend to agree to each other within 1 dB and that the velocities agree within 0.2 m s\(^{-1}\).

The second test is to use PTDM-retrieved cloud and drizzle reflectivity as an input for an ensemble retrieval method, and then evaluate whether the corresponding cloud and drizzle properties agree with other independent observations. We compared the retrieved total water path against the benchmark retrievals from microwave observations. We found that these two sets of retrievals agree with each other within the uncertainty; the root-mean-square difference is about 25 g m\(^{-2}\). Since drizzle water path is typically one order smaller than cloud water path in marine boundary layer clouds (Wood 2005; Fielding et al. 2015), the agreement in the total water path suggests that the cloud reflectivity must have been incorporated properly for the retrieval method, providing our confidence in cloud and drizzle separations made by PTDM. Even though the PTDM method for separating cloud and drizzle parameters looks complex computationally, it is simple enough to perform in real-time.

### Table 6.

<table>
<thead>
<tr>
<th></th>
<th>CB vs CB − 1</th>
<th></th>
<th>CB + 1 vs CB − 1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Correlation</td>
<td>Difference</td>
<td>RMSD</td>
</tr>
<tr>
<td>Reflectivity (dBZ)</td>
<td>0.80</td>
<td>0.55</td>
<td>2.90</td>
</tr>
<tr>
<td>Velocity (m s(^{-1}))</td>
<td>0.78</td>
<td>−0.01</td>
<td>0.26</td>
</tr>
</tbody>
</table>

**Fig. 7.** (a) Time series of total water path from microwave radiometer observations, along with the combined ENCORE–PTDM method for the first case on 29 Nov 2009. The error bars represent the retrieval uncertainty, 30 g m\(^{-2}\) for microwave-based retrievals and one standard deviation uncertainty for the ENCORE–PTDM-based retrieval. Note that the current PTDM uses cloud-base height from the ARM Archive, which misses some clouds in 1512–1518 UTC. (b) A scatterplot of ENCORE–PTDM-based retrieval vs microwave-based retrievals. The dashed gray line represents the 1:1 line, while the dotted gray lines depart 30 g m\(^{-2}\) from the dashed line.
In addition, the method works well even if the drizzle power is higher than the cloud power which was a limitation in some of the previous work.

Clearly, it would be ideal to evaluate the PTDM retrieved reflectivity and velocity against in situ cloud probe measurements. The recent ARM Aerosol and Cloud Experiments in the Eastern North Atlantic (ACE-ENA) field campaign has carried out a number of flights for drizzling clouds over the Azores. During the ACE-ENA campaign, the W-band cloud radar was operated in a scan mode, and thus will not be suitable for our PTDM method. The method, however, can be applied to the vertically pointing Ka-band radar. This requires further extensive spectral analyses and will be the focus of our future work.

Acknowledgments. This research was supported by the Office of Science (BER), Department of Energy (DOE) under Grant DE SC0018930.

Data availability statement. ARM data are made available online through the U.S. DOE as part of the Atmospheric Radiation Measurement Program at http://www.archive.arm.gov. Retrieved products presented in this paper will be shared and freely available through the Colorado State University Data Sharing Archive.

REFERENCES


