Shallow Precipitation Detection and Classification Using Multifrequency Radar Observations and Model Simulations

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Supplemental Material

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S1. Review of Rainfall Classification Algorithm

The rainfall regime classification strategy used in the TRMM-PR (13.8 GHz; Ku-Band) retrieval algorithm uses two methods, one focusing on the horizontal structure, and the other on the vertical structure of PR reflectivity and the presence of a bright band (BB), that is the very high reflectivity layer associated with the partial melting of ice hydrometeors in the case of stratiform conditions (Duan et al. 2015; Berg et al. 2006). A final TRMM classification product, TRMM-2A23, was derived by combining the two methods (Awaka et al. 1997). Steiner et al. (1995) suggests that the precipitation classification based on BB detection (vertical method) is not operationally feasible since the presence of BB is not clear during the initial stages of stratiform precipitation or when rainfall intensity is high, thus underestimating rainfall. They developed a classification algorithm to overcome BB ambiguity by focusing instead on identifying the convective center of the radar echo profiles based on the intensity and sharpness of the peak. The premise is to locate the convective center of the radar echoes (and precipitation events) without distinguishing first between convective and stratiform conditions toward reducing the underestimation of stratiform events. Biggerstaff and Listemaa (2000) extended the Steiner et al. (1995) algorithm for heavy stratiform and light convective events with a classification based: vertical lapse rate of reflectivity, BB fraction at every grid point, and the magnitude of the horizontal gradient of the reflectivity factor. The modified method was tested with ground-based Weather Surveillance Radar data in Houston, Texas and showed improvement in classification accuracy compared to Steiner et al. (1995), but further testing for different hydrometeorological conditions and using satellite-based radar products was not attempted.
Schumacher and Houze (2003) developed a new classification algorithm by merging the algorithm developed by Awaka et al. (1997) (Vertical Method) and Steiner et al. (1995) (Horizontal Method) to identify shallow isolated echo rain in TRMM V6 (version 6) that was a major source of error in the earlier TRMM V5 (version-5) products but BB detection errors in the Vertical Method were not eliminated in TRMM-V6, and the BB reflectivity for low freezing heights is often misclassified as maximum reflectivity in the Horizontal Method. Zafar and Chandrasekar (2004) proposed an algorithm to overcome the issues in the Vertical and Horizontal Methods by decomposing and reconstructing the profiles to Approximate, Vertical, Horizontal and Diagonal Coefficients using wavelet transforms. They reported agreement with TRMM 2A23 about 80% of the time in five case-studies with a 15% increase in BB detection, and 11% increase in the classification of stratiform events that were otherwise classified as convective in TRMM 2A23, though with small differences (approximately 5%) in the overall precipitation classification.

Other approaches to developing precipitation classification algorithms have used passive microwave observations from space (e.g., Spatial Sensor Microwave/Imager, SSM/I), and ground-based radars and disdrometers. Hong et al. (1999) classified convective and stratiform precipitation over the tropical ocean using the brightness temperatures at 19, 37 and 85 GHz for simulated profiles of TRMM and SSM/I. Thurai et al. (2016) utilized X-band radar profiles to identify the bright band and drop size distributions measured by 2-D video disdrometers to classify precipitation events. The method developed by Thurai et al. (2016) was tested using data from Ontario, CA and Huntsville, Alabama, USA, and the authors suggest that the method would not work efficiently for frequent shallow rainfall over the tropical oceans. Wang et al. (2008) implemented a back-propagation and artificial neural network algorithm to classify the precipitation events with CAPPI (Constant Altitude Plan Position Indicator) reflectivity profiles from ground-based S-band radar. The algorithm was trained with reflectivity profiles between 5 km and 10 km altitudes only and tested at one location in China, and thus further validation is needed for generalized application.

The TRMM follow-on Global Precipitation Mission (GPM) core satellite (Hou et al. 2014) is equipped with a dual-frequency Ku-Ka Precipitation Radar (DPR). Le and Chandrasekar (2013) proposed a classification algorithm for the GPM-DPR based on the ratio of the normalized difference Dual Frequency Ratio (DFR) index calculated from the maximum and minimum of the measured DFR profiles and the mean slope of the DFR profile well above the ground-surface. The DFR is a measure of the spectral width of the drop size distributions detected using two distinct radar frequencies, and it is expected to increase as the particle size increases (Matrosov et al. 2005). The algorithm was demonstrated for oceanic precipitation using aircraft-based Dual Frequency Ratio (DFR) profiles over the Atlantic Ocean and over Wakasa Bay, Japan. Threshold values of the classification index for convective and stratiform precipitation cases were defined for the 90% of the empirical cumulative density function, thus implying a minimum acceptable 10% misclassification error.
Early assessments of TRMM-PR rainfall products in complex terrain reported large estimation errors. (e.g. Prat and Barros 2010). Duan et al. (2015) specifically highlighted uncertainty associated with “stratiform” and “probably stratiform” classes in TRMM-V6 and V7 products that correspond to shallow rainfall systems and reverse orographic enhancement effects (Wilson and Barros 2014, 2015, 2017). Despite significant improvements in radar rainfall retrievals in the TRMM era (Iguchi et al. 2000), ongoing studies (not shown) similar to Duan et al. (2015) suggest that error statistics have not changed significantly between TRMM-PR to GPM-DPR over complex terrain in the Andes and in the Southern Appalachians.

S2. Application of SRDC algorithm in the Southern Great Plains (SGP)

a. Data Description

The ARM Program has been operating a long-term observational network in the Southern Great Plains (SGP) for the past few decades. This site is characterized by homogeneous topography, and large intra- and inter-seasonal variability of radiative energy fluxes. The central facility of ARM-SGP site is located at Lamont in north Central Oklahoma (Fig. 1a), and it consists of various collocated ground-based instrumentation supporting research related to surface meteorology, aerosols, cloud properties, and atmospheric profilers. In this study, observations from the collocated Ka-band Zenith Radar (Ka-ZR), W-band Scanning ARM Cloud Radar (W-SACR), and optical rain gauge are used.

The ARM-SGP Ka-ZR is placed at 316 m AMSL and it operates at 35 GHz with range resolution of 30 m approximately, with a dual polarization transmitter and an antenna with 3-dB beam width of 0.2° Widener et al. (2012a). It operates in two modes, general and moderate sensitivity mode. The general sensitivity mode is used here considered for analysis due to the long-term availability of data. The W-SACR radar operates at 94 GHz and is placed at 318 m AMSL. It is equipped with a horizontal linear transmitter operating in vertically pointing mode, and the antenna beam width is around 0.33° (Widener et al. 2012b).

Various collocated instruments are available at the ARM-SGP site including a tipping bucket rain gauge, a disdrometer, and an optical rain gauge to measure surface precipitation. Due to the lack of continuity of the quality-controlled radar records, various periods April 20, 2011 and June 2014 were selected for analysis depending on data availability, and for these periods, the optical rain gauge provided the most consistent and continuous records of precipitation rate measurement at the same elevation as the radars.

b. Results

Observations from the ARM-SGP Central facility in Lamont, Oklahoma were used to test the SRCD algorithm under a broader range of storm regimes. The W-band Scanning ARM Cloud Radar (W-SACR) placed at SGP has been operating intermittently for the past 5 years. A total of
thirty days of collocated W-SACR and Ka-ZR data (8 days between April 20, 2011 and June 12, 2011 and 22 days from June 4, 2012 to June 26, 2012) are considered for this analysis corresponding to 149 minutes of precipitation events. Most of the precipitation events considered during this period of analysis were short-lived (duration less than 2 hours). Three cases of isolated deep structure events showed strong reflectivity values extending up to 10 km. The shallow events were generally restricted to \( z_c = 5 \) km. The SGP observations exhibit entirely different hydrometeorological properties and precipitation structure compared to ARM-TMP and MV. For this case, the vertical range for the Ka-Band profile was \( z_1 = 10 \) km and \( z_2 = 2 \) km for the W-band profile in the column VCS calculations. These vertical ranges are consistent with Clothiaux et al. (2000) who developed climatology of cloud heights and radar reflectivities at the ARM SGP site and found that most of the hydrometeors are observed between 1 and 10 km.

Figure S1 shows the W- and Ka-band radar reflectivity profiles for a shallow precipitation event observed at the SGP on July 8, 2012. Detailed analysis similar to that presented for MV and ARM-TMP was repeated for this case. The optimal time-window computation showed similar results with 15-minute duration providing the best trade-off between missed detection and false alarms (Fig. S2a). The PDFs of precipitation detection for the 15-minute moving window are shown in Fig. S2(b). The threshold value for the precipitation detection from modified entropies calculated following Method-1 and -2 is \( H^*_{\text{det}}=1.3 \). Precipitation detection fails for 7 minutes only out of the 149 mins tested here, corresponding to 4.7% error; the false alarms amount to 4.54% error. Fig. S3 shows the VCS time-series for the July 8, 2012 event. VCS computed according to Method-1 fails to detect rainfall, while the opposite is true for Method-2. The precipitation detection algorithm accurately detects 42 deep-structured and 100 shallow events (events with vertical extent below \( z_c = 5 \) km). The column VCS (Method-1) is used for the classification of precipitation events, and Fig. S4(a) shows the PDF of the precipitation classification. The precipitation classification algorithm misses 7 deep-structured precipitation events and no shallow event using \( H^*_{\text{cla}} = 1.5 \) as the threshold value. Table S1 shows the contingency matrix derived using the detection and classification thresholds. The precipitation rate distributions of shallow and deep-structure events are shown in Fig. S4(b). Around 75% of the shallow and deep events considered for this study are light rainfall with precipitation rate less than 2 mm/h, while 15% of the light, deep-structured precipitation events were missed by the algorithm. The classification skill at ARM-SGP for the deep structured events was better than for shallow events for MV and ARM-TMP. We attribute the contrasting behavior at ARM-SGP to the small sample size of quality controlled data available at the time this study was conducted and the specific period of study.
## Table S1: Contingency table for precipitation detection and classification by SRDC Method 1 and 2 for profiles observed at ARM-SGP

<table>
<thead>
<tr>
<th></th>
<th>Classified as</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Deep</td>
<td>Shallow</td>
<td>No Precipitation</td>
<td></td>
</tr>
<tr>
<td>Actual</td>
<td>Deep</td>
<td>79.6 %</td>
<td>13.6 %</td>
<td>6.8 %</td>
</tr>
<tr>
<td></td>
<td>Shallow</td>
<td>0 %</td>
<td>95.2 %</td>
<td>4.8 %</td>
</tr>
<tr>
<td>No Precipitation</td>
<td></td>
<td>7.2 %</td>
<td>0.2 %</td>
<td>92.6%</td>
</tr>
</tbody>
</table>
Figure S1: Equivalent Radar Reflectivity factor

(a) Ka-Band Reflectivity
July 08, 2012

(b) W-Band Reflectivity
July 08, 2012

Figure S1: Equivalent Reflectivity factor of (a) Ka-Band Zenith Radar and (b) W-Band Scanning ARM Cloud Radar observed at ARM-SGP in Oklahoma, USA, on July 08, 2012.
Figure S2: SRDC Precipitation Detection

(a) Performance of the SRDC precipitation detection algorithm with varying window-size. (b) PDF of precipitation detection (optimal time-window 15-min) for the ARM-SGP in Oklahoma, USA.
Figure S3: Rain-rate observed by optical rain gauge compared with VCS computed by SRDC Method-1 (column VCS calculated up to 10 km for Ka-Band) and Method 2 of the algorithm at the ARM-SGP in Oklahoma, USA, on July 8, 2012. The red and black dotted lines denote the threshold for precipitation detection and classification, respectively. The orange and purple lines mark false alarm (FA) and missed detection (MD) occurrences.
Figure S4: SRDC Precipitation Classification

Figure S4: (a) PDF of 15-min Method-1 VCS values for classification of precipitation events at 1-min time-scale; (b) Histogram of detection skill for different deep and shallow precipitation classes as a function of precipitation intensity at the ARM-SGP site in Oklahoma, US.

Supplemental Material References


