A Robust Error-Based Rain Estimation Method for Polarimetric Radar. Part II: Case Study

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ABSTRACT

Rainfall estimation using polarimetric radar involves the combination of a number of estimators with differing error characteristics to optimize rainfall estimates at all rain rates. In Part I of this paper, a new technique for such combinations was proposed that weights algorithms by the inverse of their theoretical errors. In this paper, the derived algorithms are validated using the “CP2” polarimetric radar in Queensland, Australia, and a collocated rain gauge network for two heavy-rain events during November 2008 and a larger statistical analysis that is based on data from between 2007 and 2009. Use of a weighted combination of polarimetric algorithms offers some improvement over composite methods that are based on decision-tree logic, particularly at moderate to high rain rates and during severe-thunderstorm events.

1. Introduction

The advantages of dual-polarimetric radars over the use of reflectivity alone for precipitation estimation have been documented in numerous papers over the last two decades (e.g., Zrnić and Ryzhkov 1999; Bringi et al. 2004; Ryzhkov et al. 2005; Lee 2006). By measuring signals from both the horizontal and vertical polarizations several additional variables can be calculated, including the differential reflectivity $Z_{DR}$ and specific phase difference $K_{DP}$. These variables add to the information available about the drop size distribution (DSD) and type of precipitation observed (e.g., Seliga and Bringi 1976, 1978; Chandrasekar et al. 1990), allowing the calculation of a variety of rainfall estimators.

Error characteristics as a function of rain rate vary substantially among polarimetric variables. Therefore, no single estimator is best for the full range of rain rates observed. Rain-rate estimates can thus be optimized by combining a number of rainfall estimators to take advantage of these varying error characteristics. This is most commonly achieved through composite algorithms, with various polarimetric estimators applied depending on some explicit criteria. The criteria used can be thresholds of reflectivity alone (e.g., Ryzhkov et al. 2005) or multi-leveled criteria that are based on both reflectivity thresholds and the values of the polarimetric variables (e.g., Bringi et al. 2004; Silvestro et al. 2009). More-complex criteria can also include the initial separation of convective from stratiform rain (e.g., Le Bouar et al. 2001) or the inclusion of hydrometeor classification regimes (e.g., Giangrande and Ryzhkov 2008; Cifelli et al. 2011). Polarimetric variables can also be used for rain estimation from derived DSDs, which can employ some combinatorial framework (e.g., Bringi et al. 2004) or the derivation of factors such as the $\beta$ parameter (Gorgucci et al. 2001).

In Part I of this paper (Pepler et al. 2011, hereinafter Part I) we identified that polarimetric rainfall estimation algorithms are often combined using decision-tree logic. The paper proposed to instead apply weighted combinations of estimators on the basis of their error characteristics at various rain rates, expanding on previous work by Chandrasekar et al. (1993). This was expected to improve robustness of estimates and to represent better the true variation of error characteristics with rain rate while avoiding discontinuities at
threshold values. For this paper, two methods, described in section 3, were used to derive appropriate weighting factors on the basis of 1-min rainfall and simulated radar variables from a 2D video disdrometer located 17 km from the “CP2” radar in southeast Queensland, Australia. Both methods resulted in significant reduction of errors when compared with composite (decision tree) methods using the simulated radar dataset, particularly at moderate to high rain rates above 10 mm h$^{-1}$. This was consistent when simulated measurement errors were applied to the disdrometer dataset, with weighted methods continuing to outperform both locally derived composite estimators and comparable algorithms from Ryzhkov et al. (2005) and Bringi et al. (2004).

The simulated error relationships are simplistic, however, and did not account for factors such as smoothing of radar variables. Furthermore, because the polarimetric algorithms and weighting factors were both derived from the same disdrometer dataset used for validation, the results are not independent. In Part II of this study the polarimetric algorithms derived for the CP2 radar in Part I (referred to as “locally derived”) and combinations thereof are validated using an independent dataset for several significant rainfall events in southeast Queensland during 2008 and 2009. Rainfall estimations are validated using the CP2 10-cm dual-polarization radar, in comparison with a colocated network of 288 rain gauges. This radar is not used operationally and currently acts as a test bed for polarimetric radar in Australia. The goal of this paper is thus to investigate the performance of such weighted algorithms during the study period, with results from this study feeding into the development of rainfall estimation schemes for any future operational deployment of dual-polarimetric radars in Australia.

This paper begins with a description of the radar and associated gauge network, followed by a discussion of the various polarimetric and combination rainfall estimators used in this paper, in addition to a brief comparison of the accuracy of the polarimetric estimators with comparable studies. In section 4, the locally derived weighted and decision-tree combinations of polarimetric algorithms are compared for two severe-thunderstorm events in southeast Queensland during November of 2008 to investigate performance under various conditions. Last, 20 days of radar data for available rainfall events in 2008 and 2009 are used as a larger statistical analysis to investigate the overall performance of the weighted rainfall estimation methods in comparison with comparable composite (Ryzhkov et al. 2005) and DSD-based (Bringi et al. 2004; Gorgucci et al. 2001) estimation methods.

2. Data

This study uses data collected by the 10-cm CP2 radar during the Queensland Cloud Seeding Research Project, which ran between 2007 and 2009 in Brisbane (Tessendorf et al. 2012). During the study period, the CP2 radar was primarily used for research operations, with data collected under a variety of scanning strategies during the project. For the purpose of this study only data collected in volumetric scanning mode were analyzed, with a temporal resolution of 6 min, an azimuthal resolution of 1°, and a radial resolution of 150 m, with a maximum range of 142.35 km.

To obtain a useful amount of high-rainfall-intensity information, data were extracted for seven prolonged heavy-rain events during the period. These events covered 20 high-rainfall days, with 665 complete half-hours of data available for comparison with gauge data. A majority of the data were from warm-season thunderstorms, with seven days associated with a major storm period from 16 to 22 November 2009, for which a national disaster was declared in southern Queensland. One significant winter East Coast low event from 30 May to 2 June 2008 was also available—the only winter event in the dataset. Note that because it occurred in a subtropical region there was no snow associated with this winter rain event, with surface temperatures remaining above 12°C at nearby weather stations throughout the event. Drop sizes tended to be smaller during this event, however, with $Z_{DR}$ of less than 1.2 dB in all cases in which rain rate exceeded 30 mm h$^{-1}$, whereas values of greater than 1.2 dB occurred at more than 20% of such instances during warm-season rain events. The heaviest half-hourly rainfall totals were recorded on 19 November 2008, with gauge observations as high as 129.6 mm h$^{-1}$ at 0730 UTC and 134 gauge records exceeding 50 mm h$^{-1}$; this was the wettest November day on record in parts of the CP2 region. This case will be discussed in greater detail in section 4.

For each event, the reflectivity $Z$, differential reflectivity $Z_{DR}$ (the lowercase indicates linear units), differential phase $\varphi_{DP}$ and specific phase difference $K_{DP}$, and cross-polar correlation coefficient $\rho_{HV}$ were extracted. Note that $K_{DP}$ was derived over 14 range gates (2 km). In this study, only the lowest (0.5°) elevation is used, because higher elevations showed no improvements in radar estimation when compared with gauge data near the radar but showed a large increase in error for gauges that were located more than 50 km from the radar.

A basic clutter-removal and quality-control (QC) procedure was initially applied to the radar data to remove anomalous echoes and nonmeteorological
signals. It is based on the best-practice QC for the CP2 radar as determined by V. N. Bringi and M. Thurai (2008, personal communication) and is consistent with QC processes in other recent studies (e.g., Marks et al. 2011). The steps are

1) all data with $\rho_{HV} < 0.8$ or $\sigma(\phi_{DP}) > 10^\circ$ over 10 range gates were removed to exclude nonmeteorological echoes,
2) all negative values of $Z_H$, $Z_{DR}$, or $K_{DP}$ were removed,
3) all values of $Z_H > 53$ dBZ were removed to limit the influence of hail, which is known to have occurred during the period of interest,
4) anomalously high values of $K_{DP} > 3.5^\circ$ km$^{-1}$ or $Z_{DR} > 3.5$ dB were removed [these values are close to those derived for tropical rain (e.g., Marks et al. 2011) and are based on the maximum 1-min values simulated using the collocated disdrometer dataset (3.3 dB and 3.6$^\circ$ km$^{-1}$ respectively)], and
5) $Z_{DR}$ and $K_{DP}$ were first-order smoothed over five range gates and two azimuths to remove noisiness in the raw data, particularly for $Z_{DR}$.

Future improvements of this method could include application of hail-detection algorithms and use of the rain $R$ estimation algorithm $R(K_{DP})$ alone in these cases (e.g., Zrnić and Ryzhkov 1996), in addition to more-complex clutter-removal schemes.

The radar data were compared with 30-min rainfall totals from the Bureau of Meteorology tipping-bucket rain gauge network, with gauge resolution varying between 0.2 and 1 mm. Approximately 290 such stations exist in the range covered by the radar (Fig. 1), with an average gauge spacing of 15 km, although gauges were particularly concentrated in Brisbane city and on the coastline to the east. An initial QC was performed through a spaghetti analysis of gauge accumulations, with two gauges excluded at which accumulated rainfall was significantly lower than at surrounding sites. These gauges are maintained and calibrated at least annually, with the majority of failures related to anomalously high totals (over 250 mm in 1 h), which are screened for and removed. It is important to note that these gauges are maintained by a variety of agencies for flood warning purposes, with variable rain-rate resolution (up to 1-mm tips) and no significant postevent processing of data, and therefore some inaccurate gauge readings may persist.

Comparisons between radar estimates of rainfall and gauge records were achieved by applying the radar estimation algorithms derived in Part I and described in section 3 to the quality-controlled radar data at 6-min intervals. This result was then averaged across the 1° × 1 km scan area surrounding each gauge (three range gates to either side and the two adjacent azimuths) to determine the corresponding 6-min rainfall intensity. This smoothing region was selected using the 2D video disdrometer to supply 6-min simulated radar variables (as described in Part I) for events with both disdrometer and radar data available. A variety of smoothing regions were then applied to the actual CP2 6-min radar data over the disdrometer location, with fractional root-mean-square (FRMS) errors derived for each smoothing region in relation to the simulated variables. The optimum region identified was consistent with those used in previous studies such as Ryzhkov et al. (2005). Five consecutive 6-min scans were then averaged to derive the half-hourly rain rate corresponding to the gauge total. A total of 665 complete half-hours of radar data were available for each of 290 rain gauges, with 33 000 radar–gauge comparison points exceeded the tipping-bucket threshold of 1 mm h$^{-1}$. The maximum half-hourly rain rate observed was 129.6 mm h$^{-1}$.

The radar–gauge network comparison will be used as an independent dataset to validate the polarimetric estimators derived in Part I of this paper. Accuracy is compared using the mean fractional bias, in addition to the median and 90th percentile of the absolute fractional error.
where subscripts $R$ and $G$ indicate rain rates for radar and gauge, respectively, and $i$ indicates a given data pair. In all cases, only data with gauge rain rates of at least $2 \text{ mm h}^{-1}$, corresponding to the 1-mm tip threshold of the tipping-bucket gauges, will be used for comparisons so as to reduce gauge-related error.

### 3. Rainfall estimation methods

Locally valid polarimetric estimators $R_D$ were derived for the CP2 region using 1-min rainfall data and simulated radar variables from a 2D video disdrometer that was situated 17 km from the CP2 radar, with a detailed description of the simulation process and derivation of algorithms discussed in Part I. Disdrometer data were available for 18 rain days between November of 2008 and February of 2009 and do not include data for any hail events during the period. The algorithms were defined as

\begin{equation}
Z_h = 200R_D^{1.36},
\end{equation}

\begin{equation}
R_D(K_{DP}) = 44K_{DP}^{0.8},
\end{equation}

\begin{equation}
R_D(Z_h, Z_{dr}) = 0.017Z_h^{0.84}Z_{dr}^{-4.47}.
\end{equation}

\begin{equation}
R_D(K_{DP}, Z_{dr}) = 88.9K_{DP}^{0.88}Z_{dr}^{-2.51}.
\end{equation}

In Part I of this paper, these algorithms were found to show significant improvement over comparable methods from other studies using the simulated rainfall data from the 2D video disdrometer. For the current paper we initially confirmed these results using the CP2 radar–rain gauge dataset described in section 2, prior to investigation of combination methods. As expected, the $Z$–$R$ and $R(Z_h, Z_{dr})$ derived for the CP2 location had small fractional biases, on the order of $\pm 10\%$. In comparison, biases were larger than $-35\%$ for the Next Generation Weather Radar (NEXRAD) and Marshall–Palmer $Z$–$R$ relations, with similar biases for the most accurate of six $R(Z_h, Z_{dr})$ estimators collated by Ryzhkov et al. (2005). This smaller bias is reflected in smaller median fractional errors for the locally derived estimators, particularly at high rain rates (Fig. 2).

In comparison, the Gorgucci et al. (2001) DSD-based $R_b(Z_h, Z_{dr})$ estimator slightly overestimates rainfall, with a fractional bias of $+18\%$, but has a significantly lower median fractional error ($0.40$) than does the locally derived estimate ($0.49$), particularly at small to moderate rain rates (Fig. 2b). Furthermore, this method also outperforms the local $Z$–$R$ relationship, even at small rain rates for which $Z_{dr}$ typically adds little value. Less variation in error was observed between $K_{DP}$-based estimators, with the median fractional error at rain rates above $10 \text{ mm h}^{-1}$ varying between 0.25 for the local $R(K_{DP}, Z_{dr})$ algorithm to 0.32 for the Gorgucci et al. (2001) $R_b(K_{DP})$ algorithm (not shown). Because locally derived estimators consistently have lower biases and errors than those defined for other locations, these can be effectively applied for development of composite polarimetric estimators; the strong performance of the Gorgucci et al. (2001) $R_b(Z_h, Z_{dr})$ estimator, however, suggests that DSD-based methods may improve on
individual polarimetric estimators and are a useful point of comparison with the combination methods derived for this study, described below.

On the basis of the locally derived polarimetric algorithms [(2)–(5)], three combination methods were defined, as summarized in Table 1. The initial synthetic or “composite” estimator was developed for this location using simple decision-tree logic, similar to those in previous studies such as Ryzhkov et al. (2005). The reflectivity thresholds chosen were based on the FRMS errors of each algorithm as a function of rain rate using the disdrometer data and are similar to those in studies such as Ryzhkov et al. (2005), with multivariable thresholds [as in Bringi et al. (2004)] offering no improvement in accuracy. It is expected that $R_D(K_{DP})$ would be applied where hail is observed, although no hail-detection algorithm was included in this study. The thresholds are given by

\[ R_C = R_D(Z_h) \quad \text{where} \quad Z < 25 \text{ dB}, \quad (6) \]
\[ R_C = R_D(Z_h; Z_{dr}) \quad \text{where} \quad 25 \leq Z < 40 \text{ dB}, \quad (7) \]
\[ R_C = R_D(K_{DP}; Z_{dr}) \quad \text{where} \quad Z \geq 40 \text{ dB}. \quad (8) \]

Two methods of combining polarimetric estimators in terms of their theoretical error characteristics were also developed, with substantial improvements in accuracy observed using simulated radar data in Part I. Both of these methods weighted polarimetric algorithms by the inverse of their theoretical error as a function of polarimetric variables. Both the estimation of the error and the method by which weighting is applied vary, however, with each method showing different advantages.

The first method, referred to as “theoretically weighted,” was a weighted sum of algorithms $R_i$ by their errors as a function of the derived rain rate by

\[ R_T = \sum_{i=1}^{4} \frac{a}{\sigma_i} R_{Di}, \quad \text{where} \quad \frac{1}{a} = \sum_{i=1}^{4} \frac{1}{\sigma_i}. \quad (9) \]

In this case, the total error $\sigma$ was defined as the sum of the theoretical measurement $[\sigma(e_M)]$ and parameterization $[\sigma(e_P)]$ errors, with the total error equations used given in Table 2; $a$ was a normalization factor derived so that the weighting factors sum to 1. Measurement errors were derived from the theoretical error characteristics of the polarimetric radar variables, as described in Part I and best represented as $\sigma(R)/R$. Parameterization errors were calculated using the observed error characteristics of each rainfall algorithm when applied to the disdrometer data in the CP2 region. A number of error approximations were compared, with the most accurate rainfall estimation using a linear regression of the FRMS error as a function of the derived rain rate.

This method has generally low errors when compared with gauge data at moderate to high rain rates, above 10 mm h$^{-1}$, as discussed in section 5. The simple method of error calculation also makes weighting factors easy to derive for different polarimetric algorithms and locations as necessary. The weighting method does not, however, account for variation as a function of the individual radar variables, which can significantly influence error characteristics. In addition, the weighting factors underestimate the large errors in $K_{DP}$-based algorithms at low rain rates below 10 mm h$^{-1}$, with such algorithms having too large of an influence on derived

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Measurement error</th>
<th>Parameterization error</th>
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<tbody>
<tr>
<td>$R_D(Z_h)$</td>
<td>0.3525</td>
<td>0.1551 + 0.0068$R_D(Z_h)$</td>
</tr>
<tr>
<td>$R_D(K_{DP})$</td>
<td>0.596/$K_{DP}$</td>
<td>0.2133 - 0.012$R_D(K_{DP})$</td>
</tr>
<tr>
<td>$R_D(Z_{DR}; Z_{dr})$</td>
<td>0.729</td>
<td>0.1638</td>
</tr>
<tr>
<td>$R_D(K_{DP}; Z_{dr})$</td>
<td>$[(0.43/K_{DP})^2 + 0.1165]^{1/2}$</td>
<td>0.1714 + 0.0009$R_D(K_{DP}; Z_{dr})$</td>
</tr>
</tbody>
</table>
rain rate, resulting in large errors in these conditions. This can potentially be compensated for by using a hybrid theoretically weighted method, in which the $Z$--$R$ relationship was applied for reflectivities below 25 dBZ.

The second method, referred to as “discretely weighted,” was designed to reduce these sources of unreliability by calculating errors as a function of one or more radar variables, with lowest errors when the FRMS error as a function of three variables $Z$, $Z_{DR}$, and $K_{DP}$ was used to derive weighting factors (Part I). This method creates a three-dimensional weighting matrix for each of the four polarimetric algorithms through the following process:

1) Theoretical measurement errors for each radar variable were applied to the original disdrometer datasets, creating a new dataset with simulated measurement error.

2) The FRMS errors for each polarimetric algorithm were calculated using this simulated error dataset for discrete domains as a function of all three radar variables.

3) The FRMS errors for each algorithm were used to calculate normalized weighting factors as for the theoretically weighted method above.

4) For each radar grid point, a weighted sum of the four polarimetric estimators was obtained on the basis of the values of $Z$, $Z_{DR}$, and $K_{DP}$.

A number of error-calculation methods and resolutions for the discrete intervals were investigated, with the lowest overall errors for the weighted combination observed for FRMS error at a resolution of $0.5^\circ$ km$^{-1} \times 0.5$ dB $\times 5$ dBZ. This resolution is intended to optimize the range of data covered while remaining robust to variations in error. The advantage of this method over the theoretically weighted approach is an increased robustness to variations as a function of the radar variables, in addition to a very low weighting factor for $K_{DP}$-based algorithms at low rain rates. No weighting factors are available for variable combinations not sampled in the disdrometer database, however, and the algorithm may perform poorly in infrequently sampled conditions, particularly at high rain rates. The use of a longer disdrometer dataset may enable more robust estimation of errors, particularly under infrequently sampled conditions and at extremely high rain rates, through improved sampling and potentially finer resolution.

The weighted rainfall estimators are validated in this paper using the CP2 radar–rain gauge database, in comparison with some alternative combination methods derived in previous studies. The first is the synthetic rainfall estimator derived by Ryzhkov et al. (2005) using a research S-band radar in Norman, Oklahoma, that is similar to that applied in the upcoming NEXRAD operational polarimetric radar in the United States (Giangrande and Ryzhkov 2008) without the hail-identification component. This method determines which algorithm to apply on the basis of the rain rate derived by the NEXRAD $Z$--$R$ relation equivalent to reflectivity values, with thresholds similar to those applied in this study. The Bringi et al. (2004) DSD-based estimation method is also considered, in which the constants of a $Z$--$R$ relationship are derived on the basis of the properties of the DSD—expected to be better applicable to a wide range of rain types. Last, the Gorgucci et al. (2001) $R_s(Z, Z_{DR})$ algorithm is also investigated to compare the robustness of such DSD-based algorithms in different locations and rain regimes.

4. Case studies: Heavy-rain events

It is useful to look at the performance of the two weighted algorithms as well as the composite method for individual storm events before expanding to the entire case-study period. We have selected two cases from November of 2008 during which particularly heavy rainfall occurred in Queensland, including record-breaking daily rainfall at some gauges, in addition to a winter severe-rain event (East Coast low) during June of 2008. All times are given in UTC, which is local time $-10$ h.

Southeast Queensland experienced a number of severe-rain events in November of 2008, with monthly totals close to a record over much of the Greater Brisbane area. This month was typified by northeasterly wind patterns that drove moist tropical air over southeast Queensland, which combined with a series of surface low pressure troughs to cause unstable conditions and several severe-thunderstorm events associated with strong winds, hail, flash flooding, and high instantaneous rain rates. The wettest period during the month occurred between 16 and 19 November (Fig. 3). Particularly heavy events were sampled on 16 and 19 November and will be used for detailed analysis.

Severe-thunderstorm activity affected southeast Queensland on 16 November 2008, with 15-min rainfall accumulation reports of as high as 52 mm and a maximum half-hourly rain rate of 129.6 mm h$^{-1}$ at 0730 UTC, in addition to hail and damaging wind. This storm was typified by an intense, fast-moving core of severe rain amid a band of moderate rainfall, with the area of maximum reflectivity moving approximately 10 km between 0706 and 0730 UTC and areas experiencing changes in reflectivity of up to 40 dBZ in less than 30 min, which is typical for thunderstorms. As a consequence, maximum
rain rates remained above 50 mm h\(^{-1}\) between 0400 and 0930 UTC, with average rain rates across all gauges of as high as 9.6 mm h\(^{-1}\) at 0700 UTC, but in any half hour less than one-third of the domain experienced rain above 5 mm h\(^{-1}\).

During this rain event, between 0400 and 1000 UTC, all methods tended to overestimate rainfall, with the lowest fractional biases being observed for the composite method and relatively higher errors being observed for the weighted estimation methods (Table 3), particularly at low rain rates. Above 10 mm h\(^{-1}\), the median fractional errors are relatively similar for the discretely weighted and composite methods, although biases are significantly different. These metrics conceal significantly different overall performance, however, with the composite method consistently overestimating low rain but underestimating at high rain rates (Fig. 4, left panel), resulting in limited use for nowcasting of heavy rain when compared with the discretely weighted method (Fig. 4, right panel).

The second major event occurred on 19 November 2008. This event developed as a series of thunderstorm cells to the west of the CP2 radar that merged into a continuous rain sheet in the evening, causing widespread moderate to heavy falls until the early hours of the morning. Between 1330 and 1530 UTC, more than 50% of gauges experienced rain rates above 5 mm h\(^{-1}\), of which at least 30 gauges exceeded 25 mm h\(^{-1}\). This event consequently had higher average rain rates across the domain, reaching 13.5 mm h\(^{-1}\) at 1500 UTC, although the peak rainfall was slightly lower than the 16 November event at 123.4 mm h\(^{-1}\) at 1200 UTC, with few areas exceeding reflectivities of 50 dBZ and no hail reported.

During the heaviest period of the event, between 1100 and 1700 UTC, errors were consistently lower than for the 16 November event (Table 4), reflecting both the more uniform nature of the rainfall as well as 3 times the number of gauge records exceeding 2 mm h\(^{-1}\). In this case, the choice of estimation method had little influence on errors, with median fractional errors being approximately +0.15 above 10 mm h\(^{-1}\) for all methods. There is significant scatter in estimates using the composite method at high rain rates (Fig. 5, left panel), however, despite the slope of the regression being close to 1. The theoretically weighted method (not shown) is also more sensitive to the errors at low rain rates visible in Fig. 5, resulting in larger overall bias. Such anomalies are likely due to gauge underestimation of heavy rain or the effect of rapidly moving storm systems, because all points with derived rain of greater than 30 mm h\(^{-1}\) but gauge observations of less than 10 mm h\(^{-1}\) had reflectivity of at least 28 dBZ, averaging 37 dBZ.

Because of the widespread sustained nature of the event, it was also possible to investigate the accumulated rainfall at individual gauges. For the 183 gauges with at

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**Table 3. Various error characteristics for rainfall estimation methods between 0400 and 1000 UTC 16 Nov 2008.**

<table>
<thead>
<tr>
<th>Method</th>
<th>Fractional bias</th>
<th>Median fractional error</th>
<th>Slope (rain vs gauge)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rain ≥ 2 mm h(^{-1})</td>
<td>Rain ≥ 10 mm h(^{-1})</td>
<td>Rain ≥ 2 mm h(^{-1})</td>
</tr>
<tr>
<td>Composite</td>
<td>+31%</td>
<td>−9%</td>
<td>0.35</td>
</tr>
<tr>
<td>Discretely weighted</td>
<td>+52%</td>
<td>+12%</td>
<td>0.46</td>
</tr>
<tr>
<td>Theoretically weighted</td>
<td>+80%</td>
<td>+35%</td>
<td>0.65</td>
</tr>
</tbody>
</table>

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**Fig. 3.** Average rain rates across all gauges in the CP2 region for each half-hourly interval with available data between 0000 UTC 16 Nov and 2330 UTC 19 Nov 2008.
least five half-hour periods with radar estimations unaffected by QC and hail-removal procedures, the average accumulated rainfall between 0800 and 1800 UTC was 53 mm, as compared with 55 mm for the discretely weighted method, 58 mm for the composite method, and 66 mm for the theoretically weighted method. The discretely weighted method was also prone to underestimating heavy gauge accumulations, however, with radar totals an average of 12 mm lower than gauge accumulations above 50 mm, as compared with overestimation by 5 mm for the composite method and 10 mm for the theoretically weighted method.

Thus, although the discretely weighted method is most consistently accurate for both of the events examined, some underestimation is apparent at higher rain rates during the more widespread event (Fig. 5, right panel), but not during the heavy-rain event on 16 November. This is likely related to substantial difference in the DSDs of the two events. During the event on 16 November, the $Z_{DR}$ where rain exceeded 50 mm h$^{-1}$ was 1.6 dB, representing very large droplets, resulting in the $R–Z$ algorithm significantly overestimating rainfall (Fig. 6). Weighted approaches thus seem to be less sensitive to DSD-related variability than is the composite method. In comparison, the average $Z_{DR}$ where rain exceeded 50 mm h$^{-1}$ on 19 November was just 0.8 dB. In this case, both the $Z–R$ and $R(Z_h, Z_{dr})$ algorithms slightly underestimated rainfall, with weaker impacts on both the discretely weighted and composite methods. These results further confirm that weighted methods are more robust to a range of conditions, with composite methods being of little use in extremely severe events, for which accurate rainfall estimation is critical.

5. Error characteristics for rainfall estimation methods

The analysis was then extended to examine the error characteristics for all combination rainfall estimators using the 665 available hours of radar–rain gauge comparison data for the CP2 case study. This included several summer events during January–February 2008 and November 2008–February 2009, as well as one winter event during May–June 2008. These represent a variety of rain systems, expected to improve the robustness of results. The relative accuracy of the various combination methods is discussed in addition to comparison with alternative synthetic (Ryzhkov et al. 2005) and DSD-based (Bringi et al. 2004; Gorgucci et al. 2001)

<table>
<thead>
<tr>
<th>Fractional bias</th>
<th>Median fractional error</th>
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<tbody>
<tr>
<td></td>
<td>Rain $\geq$ 2 mm h$^{-1}$</td>
</tr>
<tr>
<td>Composite</td>
<td>+22%</td>
</tr>
<tr>
<td>Discretely weighted</td>
<td>+24%</td>
</tr>
<tr>
<td>Theoretically weighted</td>
<td>+56%</td>
</tr>
</tbody>
</table>
combination estimators. This study minimizes the impact of hail by not using data with reflectivity greater than 53 dBZ. In future developments a particle identification method will be incorporated (e.g., Straka et al. 2000), with $K_{DP}$-based methods applied in hail situations (e.g., Zrnić and Ryzhkov 1999).

With use of all data with rain rates exceeding 2 mm h$^{-1}$ (Table 5), the fractional biases estimated using the entire radar–rain gauge dataset were generally smaller than were observed for the extreme events, including just $-3\%$ for the composite method and $+5\%$ for the discretely weighted method. The discretely weighted method and composite method also have very similar error characteristics at low to moderate rain rates; both weighted methods have errors 30% lower than the composite method at heavy rainfall rates above 30 mm h$^{-1}$, however (Fig. 7).

The theoretically weighted method is the most accurate at rain rates above 10 mm h$^{-1}$, with no substantial bias, in comparison with systemic underestimation of rain by $\sim 20\%$ at moderate to high rain rates by both the discretely weighted and composite methods and large errors for the composite method (Fig. 8). This method is very sensitive to outliers at low rain rates, however, resulting in overestimation of light rain. A hybrid version that is based on $Z_{H} > 25$ dBZ also offers little improvement in errors at low rain rates despite decreased fractional biases, as most outliers were associated with $Z_{H}$ greater than 30 dBZ rather than errors from $K_{DP}$ alone.

As expected, both median errors and fractional biases are typically larger for both comparable estimators on the basis of different regions (Ryzhkov et al. 2005; Bringi et al. 2004) at all rain rates (Fig. 9), despite the attempt to employ DSD-based corrections for the latter method. This is in part due to the importance of using algorithms derived for the study location and factors such as the $K_{DP}$ estimation method. Applying the theoretically weighted method using only the most accurate algorithms from Ryzhkov et al. (2005), as discussed in section 3, however, offers significant improvement on the original synthetic algorithm, particularly at low to moderate rain rates (Fig. 9). This suggests that the use of weighted algorithm combinations that are based on theoretical error may have potential for improving errors even in the absence of locally derived data.

One unexpected result was the performance of the Gorgucci et al. (2001) DSD-based $R_{b}(Z, Z_{dr})$, which had fractional biases and median errors that were...
comparable to the weighted combination methods across most rain rates (Fig. 9). This algorithm constantly offers significant potential for improved estimation of rainfall in the absence of locally valid algorithms. Both the theoretically and discretely weighted methods have smaller errors for high rain rates above 40 mm h$^{-1}$, however, where the Gorgucci et al. (2001) method performs poorly. Of interest is that the Gorgucci et al. method particularly overestimates heavy rain where $Z_{DR}$ is low, including the 19 November event, showing a very different influence of DSD variation than for weighted methods. Future work will incorporate the Gorgucci algorithm into the weighted ensemble of estimates.

6. Conclusions

In this paper we used the CP2 research radar and an associated gauge network to investigate a number of methods of estimating rainfall using polarimetric radar, on the basis of research described in Part I. During two severe-storm events in November of 2008, the average rain rates achieved using a discretely weighted algorithm best approximated those observed at rain gauges, particularly at high rain rates and in severe storms where $Z_{DR}$ was large. In comparison, the theoretically weighted combination had lowest mean errors at rain rates above 10 mm h$^{-1}$ and had closer accumulated rainfall to gauge totals during events with heavy sustained rain but was more affected by outliers at low rain rates. Further investigation suggests that these readings may be related to gauge rather than algorithm errors; if so, the theoretically weighted method proves the most useful of all methods for nowcasting of rain, particularly for the heaviest-rain regions.

Using data from 20 rain days between 2008 and 2009, the variation between methods using radar data was smaller than was observed when using simulated data.

<table>
<thead>
<tr>
<th>Method</th>
<th>Fractional bias</th>
<th>Median fractional error</th>
<th>90th-percentile fractional error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rain ≥ 2 mm h$^{-1}$</td>
<td>Rain ≥ 10 mm h$^{-1}$</td>
<td>Rain ≥ 2 mm h$^{-1}$</td>
</tr>
<tr>
<td>Composite</td>
<td>-3%</td>
<td>-18%</td>
<td>0.38</td>
</tr>
<tr>
<td>Discretely weighted</td>
<td>+5%</td>
<td>-15%</td>
<td>0.37</td>
</tr>
<tr>
<td>Theory-weighted</td>
<td>+31%</td>
<td>+1%</td>
<td>0.35</td>
</tr>
<tr>
<td>Ryzhkov et al. (2005) synthetic</td>
<td>-21%</td>
<td>-27%</td>
<td>0.62</td>
</tr>
<tr>
<td>Theory weighted (Ryzhkov algorithms)</td>
<td>-10%</td>
<td>-30%</td>
<td>0.38</td>
</tr>
<tr>
<td>Bringi et al. (2004) DSD $Z-R$</td>
<td>+33%</td>
<td>+30%</td>
<td>0.52</td>
</tr>
<tr>
<td>Gorgucci et al. (2001) $R(Z_h, Z_{dr})$</td>
<td>+25%</td>
<td>+1%</td>
<td>0.36</td>
</tr>
</tbody>
</table>

Fig. 7. (left) Median and (right) 90th percentile of absolute fractional errors using CP2 radar measurements in comparison with gauge data for locally derived multiple-algorithm polarimetric estimators.
in Part I, with decreased sensitivity to errors at very low rain rates. This is likely related to spatial smoothing of the radar data, reducing the impact of expected measurement errors. In general, weighted methods showed their greatest benefit at high rain rates above 30 mm h\(^{-1}\), where both discrete and theoretical methods improve rain estimation accuracy by over 20% when compared with locally derived composite methods. The Gorgucci et al. (2001) DSD-based \(R_b(Z, Z_{dr})\) estimation method was also found to well represent the rainfall in this region, with this method recommended in cases in which local disdrometer data are not available for determining weighted methods, although it may be sensitive to overestimation during heavy-rain events for which \(Z_{DR}\) is small. Future developments will investigate the use of the Gorgucci method in a weighted scheme, in addition to the incorporation of some explicit hail-identification scheme.

This method has been tuned to the subtropics, but the approach described can be applied more generally, with the underlying polarimetric algorithms demonstrated to be robust to variations in underlying DSDs in this study and elsewhere (e.g., Ryzhkov et al. 2005; Zrnić and Ryzhkov 1999; Gorgucci et al. 2001).
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