4B.1 RAINFALL ESTIMATION WITH A POLARIMETRIC PROTOTYPE OF THE OPERATIONAL WSR-88D RADAR

Alexander V. Ryzhkov, Scott Giangrande, and Terry J. Schuur
Cooperative Institute for Mesoscale Meteorological Studies, University of Oklahoma, Norman, OK, USA

1. INTRODUCTION

Improvement of Quantitative Precipitation Estimation (QPE) is one of the primary benefits of a dual-polarization radar. Several different polarimetric relations for rain rate estimation have been suggested during the last two decades. These relations utilize differential reflectivity Z_{DR}, specific differential phase K_{DP}, and conventional radar reflectivity factor Z in different combinations. The relations were obtained for different radar wavelengths using either simulated or measured drop size distributions (DSDs) with various assumptions about the size and shape dependence of raindrops.

The performance of many suggested polarimetric rainfall estimation techniques has been tested on several extended data sets from Oklahoma (Ryzhkov and Zrnic 1996, Ryzhkov et al 2000, Ryzhkov et al 2001), Colorado and Kansas (Brandes et al 2001), Florida (Brandes et al 2002) for S-band radars, Australia (May et al 1999) for C-band radar, and Virginia (Matrosov et al 2002) for X-band radar.

All of the above validation studies have shown that (a) there is an improvement in rainfall estimation if a dual-polarization radar is used and (b) polarimetric rainfall estimation techniques are more robust with respect to DSD variations than are the conventional R(Z) relations. At the moment, however, there is no consensus on the degree of improvement and the choice of an optimal polarization relation. The most significant improvement was reported in the latest study in Oklahoma (Ryzhkov et al 2002a) using the $R(K_{DP}, Z_{DR})$ relation. Relatively modest improvement was observed in Florida (Brandes et al 2002) with the best results obtained from the $R(Z, Z_{DR})$ relation.

As part of the evolution and future enhancement of the WSR-88D, the National Severe Storms Laboratory recently upgraded the KOUN WSR-88D radar to include polarimetric capability. In this paper, we assess the quality of rainfall estimation with the new radar using a dense micronetwork of 42 gages in the area approximately 40 x 30 km in central Oklahoma. Various polarimetric rainfall algorithms have been tested for large data set.

2. RADAR DATA SET

Data collection with the WSR-88D KOUN prototype dual-polarized radar started on 19 March 2002. Since then, the polarimetric data have been collected and archived for about 80 days of observation. Ancillary data from the operational KTLX WSR-88D radar have been collected for the majority of precipitation events. We have selected for in-depth analysis a subset of 20 rain events with 40 hours of observations for which the ARS gages recorded sizeable amount of precipitation. This subset consists of 14 convective and 6 stratiform rain cases observed from June 2002 to May 2003.

Radar variables Z, Z_{DR}, K_{DP}, and the cross-correlation coefficient ρ_{hv} were estimated using quite short dwell time (48 radar samples) in order to satisfy the NEXRAD requirement for rapid antenna rotation rate (3 rpm) and the 1° azimuthal resolution. Update times for rain rate estimates, however, were different for the cases observed in 2002 and 2003. In 2002, volume coverage pattern (VCP) included only two lowest elevation tilts: 0.5° and 1.5°, whereas in 2003 the VCP consisting of 14 – 15 elevation angles was implemented. Thus, the update times for rain rate estimates were about 2 and 6 minutes in 2002 and 2003 respectively. Range resolution of the raw radar polarimetric data is 267 m and total number of range gates is 1125.

The ρ_{hv} threshold of 0.85 is used to filter out the echoes of non-meteorological origin (ground clutter, AP, biological scatterers, chaff, etc). Radar reflectivity calibration for the KOUN radar was performed either by matching one-hour areal rainfall estimate using the standard R(Z) algorithm with the one obtained from the operational KTLX radar, or by applying a polarimetric consistency technique (Gorgucci et al 1999). The latter capitalizes on interdependence of Z, Z_{DR}, and K_{DP} in rain medium. Radar reflectivity biases retrieved with these two methods usually did not differ by more than 1 dB.

We compare one-hour rain totals obtained from the radar and gages that are located at the distances 50 to 88 km from the KOUN radar. Both point and areal estimates of the one-hour rain accumulation are examined. By point estimate we mean an hourly total averaged over small-size area (1 – 1.5 km) centered on individual gage. Areal mean hourly total or areal mean rain rate is determined as a sum of hourly accumulations from all gages that recorded rain divided by the number of such gages.

To assess the quality of different polarimetric rain algorithms, we prefer to examine absolute differences between radar and gage estimates (expressed in mm) rather than standard fractional errors which are heavily weighted with small accumulations. Rainfall estimates are characterized by the bias $B = \langle\Delta\rangle$, standard deviation $SD = \langle|\Delta-B|^2\rangle^{1/2}$, and the rms error $RMSE=\langle|\Delta|^2\rangle^{1/2}$, where $\Delta = T_R - T_G$ is a difference between radar and gage hourly totals for any given radar – gage pair and brackets mean averaging over all such pairs.

Corresponding author address: Alexander Ryzhkov, CIMMS/NSSL, 1313 Halley Circle, Norman, OK, 73069, e-mail: Alexander.Ryzhkov@noaa.gov

3. RAINFALL ALGORITHMS AND THEIR PERFORMANCE.

Two groups of polarimetric rainfall algorithms have been tested. One group includes almost all power law $R(K_{DP})$, $R(Z,Z_{DR})$, and $R(K_{DP},Z_{DR})$ relations that we found in literature for S band. Another group consists of similar algorithms that we derived using multi-year statistics of DSD measurements in central Oklahoma.

Four different assumptions about raindrop shape – size dependencies were made: (1) equilibrium shapes defined by Beard and Chuang (1987), (2) "oscillating raindrop" shapes from Bringi et al (2003), (3) the shapes specified by Brandes et al (2002), and (4) linear dependence of the drop axis ratio on equivolume diameter. An average slope $\beta = 0.052$ mm^{-1} of a linear dependence was found in (Ryzhkov and Schuur 2003) from polarimetric radar observations using the approach described by Gorgucci et al (2000). In all simulations, we assumed that the drops are canted with the mean canting angle equal to zero and the width of the canting angle distribution of 10°.

We started our testing from the simplest one-parameter algorithms $R(Z)$ and $R(K_{DP})$. A standard NEXRAD relation is used as the $R(Z)$ algorithm

$$R(Z) = 1.70\ 10^{-2}\ Z^{0.714} \qquad (1)$$

where Z is expressed in mm^6m^{-3}, R – in mm h^{-1}. Values of Z were threshoded at the level of 53 dBZ in order to mitigate hail contamination. Among numerous $R(K_{DP})$ relations, we selected the one that performed best in terms of overall RMS errors.

$$R(K_{DP}) = 45.3\ |K_{DP}|^{0.786}\ \mathrm{sign}(K_{DP}), \qquad (2)$$

where K_{DP} is expressed in deg km^{-1}. This relation was obtained using 17470 1-minute DSD measured with a 2D-video disdrometer under assumption of raindrop shape defined by Brandes et al (2002). There is an obvious overall improvement in rainfall estimation when we switch from $R(Z)$ to $R(K_{DP})$ (see Table 1). This

Table 1. Mean biases, standard deviations, and RMS errors of the radar estimates of one-hour rain totals (in mm) and areal mean rain rates (in mm h^{-1}) for different radar rainfall algorithms.

Algorithm	Bias	Point SD	Point RMSE	Areal SD	Areal RMSE
$R(Z)$	0.32	4.18	4.20	2.76	2.81
$R(K_{DP})$	-0.55	3.63	3.68	2.20	2.23
$R(Z,Z_{DR})$	-0.81	2.86	2.98	1.54	1.72
$R(K_{DP},Z_{DR})$	-0.86	2.94	3.06	1.33	1.57
$R(Z,K_{DP},Z_{DR})$	-0.10	2.80	2.80	1.11	1.11

improvement is especially well pronounced for heavy rain events for which rain is often mixed with hail. The $R(K_{DP})$ estimates are noisier than the $R(Z)$ estimates for light rain with R < 5 – 6 mm h^{-1}. Both $R(Z)$ and $R(K_{DP})$ relations usually underestimate light stratiform rain. Notable is high correlation between these two rainfall estimates and their strong dependence on the net value of differential reflectivity $<Z_{DR}>$ that is defined as a weighted average Z_{DR} for a particular hour over a whole gage network. Each Z_{DR} measurement is weighted proportionally to rain rate computed from the $R(Z)$ relation. Thus, the net Z_{DR} characterizes most intense part of rain for a given hour in the gage area. Fig. 1 shows the net Z_{DR}, as well as the ratios of hourly areal totals obtained from the radar and gages as functions of hour of observations ranked in a chronological order. First 32 hours of observations conducted in 2002 are represented in Fig. 1.

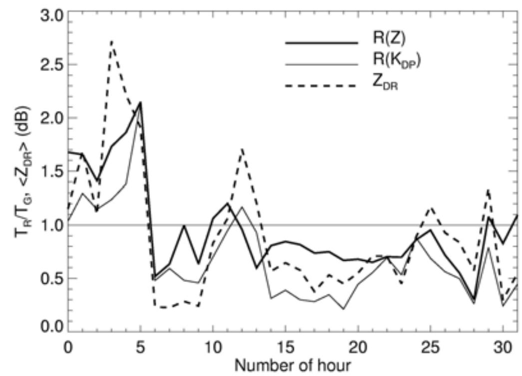

Fig. 1 Net Z_{DR} and ratios of mean areal rain rates from radar and gages versus hour of observations.

It is quite clear from Fig. 1 that both $R(Z)$ and $R(K_{DP})$ tend to underestimate rain with DSD dominated by smaller drops (low Z_{DR}) and overestimate it if rain is characterized with large raindrop median diameter (high Z_{DR}). This means that Z_{DR} should be involved in rain measurements together with Z or K_{DP}.

As a second step, we tested various two-parameter algorithms $R(Z,Z_{DR})$ and $R(K_{DP},Z_{DR})$. After examining the performance of about dozen different two-parameter algorithms, we selected the best ones for each category:

$$R(Z,Z_{DR}) = 1.42\ 10^{-2}\ Z^{0.770}\ Z_{dr}^{-1.67} \qquad (3)$$

and

$$R(K_{DP},Z_{DR}) = 136\ |K_{DP}|^{0.968} Z_{dr}^{-2.86}\ \mathrm{sign}(K_{DP}), \qquad (4)$$

where Z_{dr} is differential reflectivity expressed in linear units. Eq (3) was derived using a local DSD statistics with the assumption of equilibrium drop shapes, whereas Eq (4) was taken from Brandes et al (2002).

Although both algorithms (3) and (4) produce larger overall biases in rain measurements, they apparently outperform the one-parameter algorithms in terms of standard deviation and RMS errors (Table 1). The $R(K_{DP},Z_{DR})$ algorithms perform better than the $R(Z,Z_{DR})$ relations for areal rain estimation and higher rain rates, whereas the $R(Z,Z_{DR})$ algorithm is a leading contender at low rain rates where the K_{DP} estimates are quite noisy. Since both Z and Z_{DR} are strongly affected by the presence of hail, one has to be very cautious using these variables for estimation of heavy rain which is likely contaminated with hail.

Combining the merits of different algorithms, we eventually come up with the "synthetic" one that suggests the use of different combinations of radar variables depending on rain rate estimated with the conventional R(Z) relation. We denote the synthetic algorithm as a $R(Z,K_{DP},Z_{DR})$ relation. The following is a description of the proposed algorithm.

If $R(Z) < 6$ mm h^{-1}, then

$$R = R(Z)/(0.4+5.05\,(Z_{dr}-1)^{1.17}) \;; \qquad (5)$$

if $6 < R(Z) < 50$ mm h^{-1}, then

$$R = R(K_{DP})/(0.4+3.48\,(Z_{dr}-1)^{1.72}) \;; \qquad (6)$$

If $R(Z) > 50$ mm h^{-1}, then $R = R(K_{DP})$,

where R(Z) and $R(K_{DP})$ are determined by Eq (1) and (2). The expressions (5) and (6) were obtained empirically by finding best fit to the dependences $T_R(Z)/T_G = f(<Z_{dr}>)$ and $T_R(K_{DP})/T_G = f(<Z_{dr}>)$ i.e., using the approach described by Fulton et al (1999). Only a portion of a whole data set was used for such matching. This subset consists of rain events observed in 2002 and accounts for about 70% of total rain in a whole data set.

The $R(Z,K_{DP},Z_{DR})$ algorithm is structured in such a way that the combination of K_{DP} and Z_{DR} is used for estimation of about half of all rainfall in Oklahoma according to the DSD statistics. It is known from simulations that the $R(K_{DP},Z_{DR})$ algorithm is least affected by DSD variations and uncertainties in raindrop shapes and canting compared to the R(Z), $R(K_{DP})$, and $R(Z,Z_{DR})$ relations. At lower rain rates (< 6 mm h^{-1}), the combination of K_{DP} and Z_{DR} is less efficient because K_{DP} becomes too noisy. Therefore, Z (instead of K_{DP}) should be used jointly with Z_{DR}. For very high rain rates (> 50 mm h^{-1}), both Z_{DR} and Z are very likely contaminated with hail, and the synthetic algorithm relies exclusively on K_{DP}. Another advantage of such approach is that reflectivity calibration is required only for light rain that accounts for about 32% of annual rain in Oklahoma.

It is not surprising that the $R(Z,K_{DP},Z_{DR})$ algorithm outperforms all others according to all 5 statistical criteria: it has lowest bias, standard deviations, and RMS errors for point and areal rainfall estimates (Table 1). Fig. 2 – 4 show scatterplots of hourly totals obtained from the R(Z) and $R(Z,K_{DP},Z_{DR})$ relations versus one-hour gage accumulations for individual radar-gage comparisons, areal estimations, and flash flood event on 14 May 2003 that produced highest hourly amount of precipitation over the test area. The synthetic polarimetric algorithm demonstrates particularly significant improvement for areal rain estimation (2.5 times in terms of RMSE) and for flash flood event.

The scattergram in Fig. 2b shows about dozen of apparent outliers (out of total 963 points) even for the best polarimetric algorithm. Notably, practically all outliers belong to only one rain event on 20 May 2003 which was characterized by extremely localized strong convection. Detailed analysis of rain accumulation fields

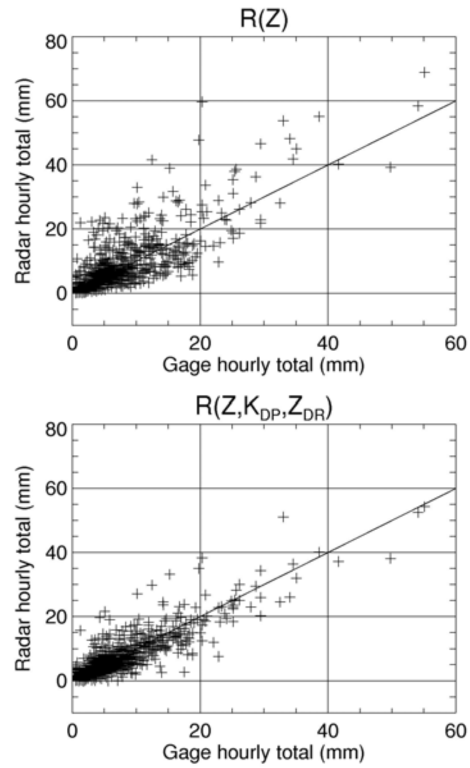

Fig. 2 One-hour individual gage rain accumulations versus their estimates from the R(Z) and $R(Z,K_{DP}, Z_{DR})$ algorithms (20 rain events, 40 hours of observations)

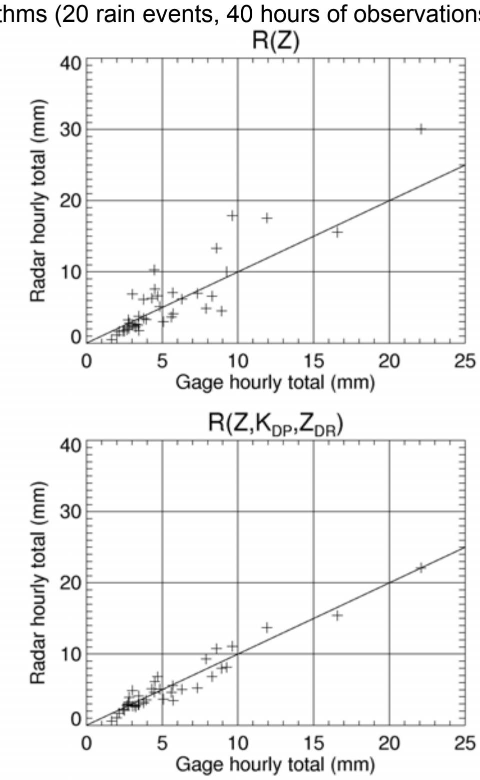

Fig.3 Mean areal rain rates from gages versus their estimates from the R(Z) and $R(Z,K_{DP},Z_{DR})$ algorithms (20 rain events, 40 hours of observations).

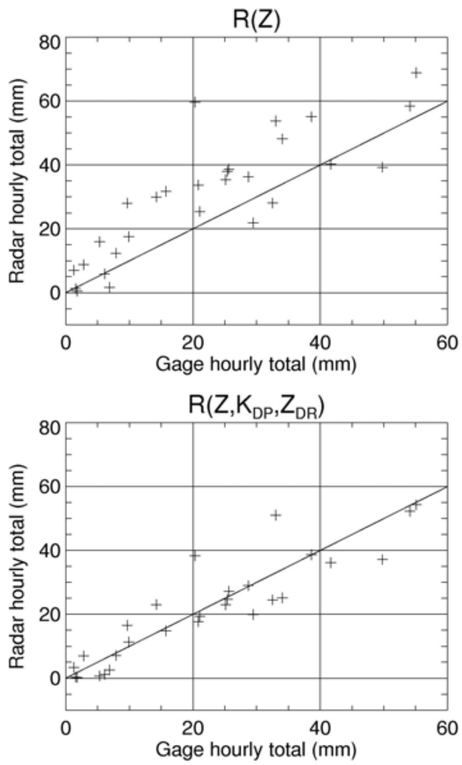

Fig. 4 Same as in Fig. 2 but for flash flood event on 14 May 2003.

indicates that radar – gage mismatches occur in the areas of strong gradients of rain. Bearing in mind that all hourly rain totals in 2003 were calculated from only 9 – 10 successive scans, we attribute such a discrepancy to a sampling problem rather than to deficiency of the algorithm. The influence of radar sampling is substantially alleviated in areal rain estimates (Fig. 3b).

Although relations (5) and (6) were derived empirically to optimize the performance of the synthetic algorithm for the 2002 rain events, the $R(Z,K_{DP},Z_{DR})$ algorithm proves to be the best for the 2003 observations and in comparisons with the Oklahoma Mesonet gages that are located at the distances closer than 100 – 120 km form the radar (Giangrande and Ryzhkov 2003).

4. CONCLUSIONS

Testing different polarimetirc methods for rainfall estimation using a dual-polarization prototype of the WSR-88D operational radar shows that the best polarimeitric rainfall algorithm $R(Z,K_{DP},Z_{DR})$ demonstrates superior performance compared to the conventional R(Z) relation. At the distances less than 100 km from the radar, the RMS error of the one-hour total estimate is reduced by factor of 1.5 for point estimates and by factor 2.5 for areal rainfall estimates.

Most significant improvement is achieved in areal rainfall estimation and in measurements of heavy precipitation. These results have important practical implications for (a) river flash flooding forecast and management that require reliable measurements of areal rain accumulations regardless of rain intensity and (b) urban flash flooding forecast that requires accurate estimation of heavy rain with high spatial resolution.

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