

## ESTIMATION OF RAINFALL BASED ON THE RESULTS OF POLARIMETRIC ECHO CLASSIFICATION

S. E. Giangrande and A.V. Ryzhkov

Cooperative Institute for Mesoscale Meteorological Studies, University of Oklahoma

### 1. Introduction

Accurate rainfall estimates are vital for most hydrologic applications. The U.S. National Weather Service (NWS) requires estimates of rainfall at ranges up to 230 km from the radar. However, the quality of radar rainfall estimates degrades with distance as a result of beam broadening, the effect of Earth curvature, and overshooting precipitation. At longer distances from the radar, the radar resolution volume is more likely filled with mixed-phase or frozen hydrometeors and the radar measurements aloft are quite loosely related to rainfall near the ground.

Contamination from nonliquid hydrometeors is especially pronounced in colder climates where the melting layer (or bright band) is particularly low. Even in relatively warm climates, this contamination generally occurs over a significant portion of the required NWS radar rainfall coverage area. For a typical melting level height in central Oklahoma (~3 km AGL), contamination of radar rainfall estimates at the 0.5° elevation angle due to the presence of mixed-phase and frozen hydrometeors is usually observed as close as 120 km from the radar. As a result, the accuracy of rain estimation may be compromised in over two-thirds of the radar rainfall coverage area required by the NWS.

Polarimetric radar provides new opportunities to improve the accuracy of rain measurements as numerous theoretical and validation studies show. Polarimetric rainfall estimation techniques are more robust with respect to drop size distribution (DSD) variations and the presence of hail than the conventional  $R(Z)$  relations. The measurements of specific differential phase  $K_{DP}$ , which is immune to radar miscalibration, attenuation, and partial beam blockage, benefit precipitation estimation by providing methods to correct radar reflectivity biases that result from those listed factors or through the direct estimation of rainfall using  $R(K_{DP})$  relations. In addition, polarimetric radar is uniquely suited for discriminating between different classes of meteorological and nonmeteorological echo, which may also benefit estimation of rain. The anticipated improvement in quantitative precipitation estimation is one of the primary motivations for the forthcoming polarimetric upgrade of the Weather Surveillance Radar-1988 Doppler (WSR-88D) network.

This paper assesses the quality of polarimetric rainfall estimation for a broad range of distances from the radar. The data were collected with the KOUN radar in central Oklahoma. Polarimetric echo classification

---

*Corresponding author address:* Scott Giangrande,  
CIMMS/NSSL, 1313 Halley Circle, Norman, OK 73069  
Email: [Scott.Giangrande@noaa.gov](mailto:Scott.Giangrande@noaa.gov)

has been integrated to investigate the performance of radar rainfall estimation contingent on the type of hydrometeors that fill the radar resolution volume. Hourly Agricultural Research Service (ARS) Micronet and Oklahoma Mesonet rain gage accumulations are used to validate conventional and polarimetric radar rainfall measurements. ARS and Mesonet gages are well calibrated and located at distances between 25 km and 250 km from the KOUN radar.

### 2. Radar Dataset and Echo Classification

A total of 46 events observed by the KOUN radar between the years of 2002 and 2005 have been selected for analysis. The dataset includes gage observations from over 100 Oklahoma Mesonet stations and comprises 179 hours of radar data. Concurrent gage observations were available from the densely-spaced ARS network stations located at ranges of 50-88 km from the KOUN radar. The total number of ARS gages with an average spacing of about 5 km is 42 (24 after 2004 when some gages were decommissioned). At such distances, the accuracy of radar rain retrievals is mainly affected by DSD variability and the possible presence of hail rather than ground clutter or contamination from melting layer or frozen hydrometeors.

Radar reflectivity factor  $Z$ , differential reflectivity  $Z_{DR}$ , specific differential phase  $K_{DP}$ , and cross-correlation coefficient  $\rho_{HV}$  were measured at a radial resolution of 0.250 - 0.267 km using a short dwell time (48 radar samples) to satisfy NEXRAD antenna rotation rate (3 rpm) and azimuthal resolution (1°) requirements. Radar rainfall estimates and echo classification results were obtained using data collected at the 0.5° elevation scan with an update time update varying between 2 and 6 minutes. Radar reflectivity measured by KOUN was matched with  $Z$  obtained from the nearby KTLX WSR-88D radar, which was assumed to be well calibrated.  $Z_{DR}$  was calibrated using polarimetric signatures of dry aggregated snow above the melting level following Ryzhkov et al. (2005c). Attenuation correction of  $Z$  and  $Z_{DR}$  was performed using differential phase  $\Phi_{DP}$  and relations:  $\Delta Z(\text{dB}) = 0.04\Phi_{DP}$  (degrees) and  $\Delta Z_{DR}(\text{dB}) = 0.004\Phi_{DP}$  (degrees) (Ryzhkov and Znic 1995). A minimum  $\rho_{HV} = 0.85$  threshold was applied to filter echoes of nonmeteorological origin. Radar reflectivity was capped at 53 dBZ to mitigate hail contamination. Additional details of radar data processing can be found in Ryzhkov et al. (2005a).

In this study we compare hourly gage and radar rainfall accumulations over gage locations within 250 km of KOUN. Hourly radar accumulations are defined as an

hourly rainfall estimate averaged over an area centered on an individual gage. Radar rainrates are averaged using 5 gates centered over the gage location and two closest azimuths separated by 1 degree. Such averaging produces a radial resolution of 1.0 km and transverse resolution that varies with range.

To establish the quality of the conventional and polarimetric radar rainfall algorithms, absolute differences between radar and gage estimates (expressed in mm) are examined rather than standard fractional errors, which are heavily weighted towards small accumulations. Rainfall estimates are characterized by the bias  $B = \langle \Delta \rangle$  and the rms error  $RMSE = \langle |\Delta|^2 \rangle^{1/2}$ , where  $\Delta = T_R - T_G$  is the difference between radar and gage hourly totals for any given radar-gage pair and brackets imply averaging over all such pairs.

An objective of this study is to examine the quality of radar rain measurements as a function of radar echo type and to explore the value of polarimetric hydrometeor classification for quantitative precipitation estimation. For this purpose, the type of scatterers in the radar sampling volume corresponding to a particular gage location were identified using a polarimetric classification algorithm based on fuzzy logic principles following Ryzhkov et al. (2007). The classifier distinguishes between 10 classes of radar echo, including AP and Ground Clutter (AP / GC), Biological Scatterers (BS), Light to Moderate Rain (RA), Heavy Rain (HR), Rain/Hail (RH), Big Drops (BD), Graupel (GR), Wet Snow (WS), Dry Snow (DS), and Ice Crystals (CR). The classification algorithm in this study utilizes four radar variables:  $Z$ ,  $Z_{DR}$ ,  $\rho_{HV}$  and a texture parameter  $SD(Z)$ , i.e., the standard deviation of small-scale fluctuations of  $Z$  along a radial. Melting level height, which is required as an input into the classification scheme, is determined from the closest available NWS sounding in Norman, OK.

The classification code distinguishes between 4 types of rain: RA, HR, RH, and BD. The membership functions in the fuzzy logic scheme for 4 classes of rain overlap significantly in terms of all 4 radar variables and are constructed in such a way that distinction between light to moderate rain (RA) and heavy rain (HR) is primarily based on  $Z$  using a 45 dBZ borderline. Rain-hail mixture (RH), on the other hand, is recognized and distinguished from heavy rain (HR) with the same  $Z$  by significantly lower values of  $Z_{DR}$  and  $\rho_{HV}$ . Rain associated with significant presence of big drops and/or a relative deficit of small drops is usually characterized by anomalously high  $Z_{DR}$  (for a given  $Z$ ) and is identified as BD in the echo classifier. Rain belonging to BD category is commonly observed in the updraft areas of the storms where vigorous size sorting of raindrops occurs.

Echo classification is performed over each gage location during every radar scan, whereas radar and gage rainfall accumulations are computed for each hour. Because classification results generally change from scan to scan at the same location, several class designations may be associated with a single hourly rain total. To quantify the accuracy of hourly rainfall

estimation for individual echo classes, we prefer to assign the hourly rain total to a single, dominant echo class for that hour. Such a dominant class should be designated for at least 70% of radar scans that constitute a particular hour of observations at a given gage location.

Since convective echo detections are relatively infrequent, the number of hours and gages over which convective signatures are dominant according to the previous criteria is too small for obtaining reliable statistics. Even after the three convective categories: Big Drops, Heavy Rain, and Rain/Hail are combined into a single convective rain category, the number of "convective" hours remain relatively small. In this study, we consider a particular hour as associated with convective rain if RA, BD, HR, and RH are detected for at least 70% of time and one of the three convective categories (i.e., BD, HR, or RH) is identified for no less than 20% of time.

### 3. Rainfall Associated With Different Echo Types

The performance of different rainfall relations is investigated contingent on the results of polarimetric echo classification. It is known that conventional radar rainfall estimates obtained from  $R(Z)$  relations deteriorate in the presence of mixed-phase and frozen hydrometeors. Previous studies have shown that the  $R(Z, Z_{DR})$  relation is less prone to DSD variability, but it is not immune to hail contamination and is not efficient in situations of melting layer contamination and precipitation overshooting (e.g., Giangrande and Ryzhkov 2003, Ryzhkov et al. 2005b). Rainfall algorithms based on  $K_{DP}$  are more robust in the presence of hail, but are not optimal for light rain. Giangrande and Ryzhkov (2003) demonstrate that  $R(K_{DP})$  outperforms  $R(Z)$  in melting layer regions, but the improvement may be fortuitous and requires further clarification. The results of polarimetric echo classification can be utilized to further investigate the nature of the errors inherent to all three types of rainfall relations depending on the type of radar echo. This section highlights the performance of different rainfall relations separately in rain below the melting layer and within the melting layer where wet snowflakes are the dominant scatterers. Similar analysis has been performed for echo classifications observed above the melting layer (e.g., Graupel, Dry Snow, Crystals, not shown in this manuscript).

#### a. Rainfall Relation Comparisons in Rain

Rain is most often classified at relatively close distances from the radar. Both Oklahoma Mesonet and ARS Micronet gage network accumulations are available to validate radar rainfall algorithms in rain. In this paper, we highlight ARS gage comparisons in rain due to the improved spatial resolution of KOUN radar measurements over these gages. The following  $R(Z)$ ,  $R(K_{DP})$  and  $R(Z, Z_{DR})$  relations have been selected for analysis:

$$R(Z) = 1.7 \times 10^{-2} Z^{0.714}, \quad (1)$$

$$R(K_{DP}) = 44.0 |K_{DP}|^{0.822} \text{sign}(K_{DP}), \quad (2)$$

$$\text{and} \\ R(Z, Z_{DR}) = 1.42 \times 10^{-2} Z^{0.770} Z_{DR}^{-1.67}. \quad (3)$$

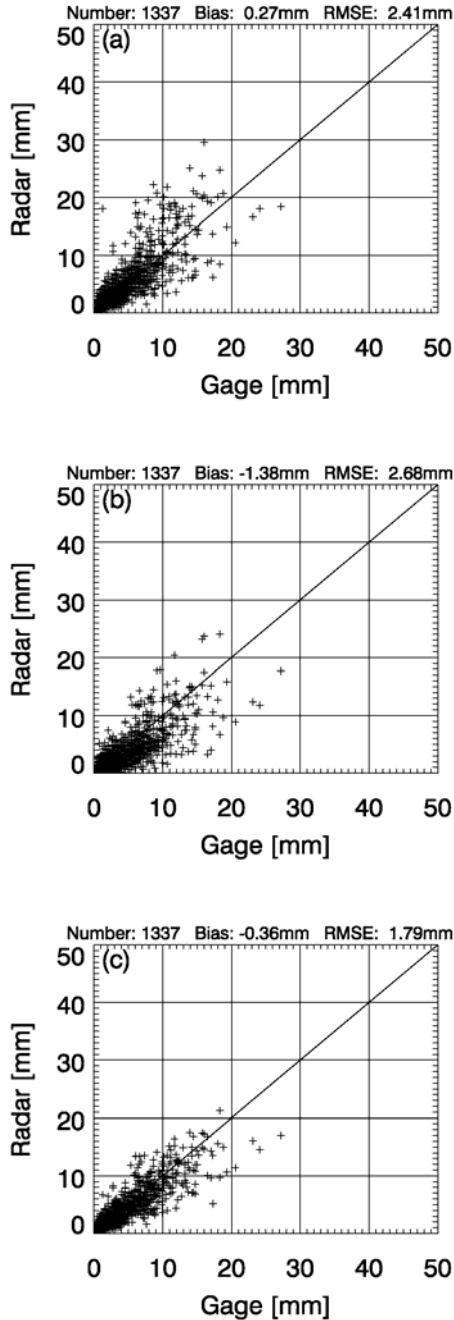


Figure 1: Hourly radar-gage rainfall accumulation scatterplots for Light/Moderate Rain echo over ARS network gage locations: (a)  $R(Z)$ , (b)  $R(K_{DP})$ , (c)  $R(Z, Z_{DR})$ .

The conventional  $R(Z)$  relation in (1) is the inversion of the standard NEXRAD formula  $Z = 300 R^{1.4}$ , where  $Z$  is

expressed in  $\text{mm}^6 \text{m}^{-3}$  and  $R$  in  $\text{mm hr}^{-1}$ .  $K_{DP}$  in (2) is expressed in  $^{\circ} \text{km}^{-1}$  and the  $\text{sign}(K_{DP})$  term allows negative values of  $R$ . Lowercase subscript in  $Z_{dr}$  in (3) indicates linear units as opposed to uppercase subscript which denotes logarithmic scale. Polarimetric relations (2) and (3) are selected because of their optimum performance in rain for central Oklahoma during the JPOLE field campaign (e.g., Ryzhkov et al. 2005a).

Scatterplots of hourly rainfall totals obtained from the radar relations (1) - (3) versus hourly gage accumulations are displayed in Figs. 1 and 2. Fig. 1 illustrates radar – gage comparisons using ARS gages if rain is classified as Light/Moderate Rain as specified in section 2. A plot showing the performance of the three rainfall relations in convective rain (as determined in the previous section) is provided in Fig. 2.

In Light/Moderate Rain, the tested relations show similar performance. The  $R(Z, Z_{DR})$  relation is relatively unbiased and has the lowest rms errors for both gage networks. The improvement in  $R(Z, Z_{DR})$  rainfall estimation is more pronounced over the ARS network than over the Oklahoma Mesonet (not shown).

There is a clear benefit in polarimetric rainfall estimation within convective echo. Accumulation comparisons in Fig. 2 indicate that polarimetric relations are less susceptible to hail contamination and DSD variability and exhibit a sizable reduction in rms errors. The conventional  $R(Z)$  relation overestimates convective rainfall even after  $Z$  is capped at the 53 dBZ level to mitigate hail contamination. This overestimation is attributed to large raindrops and/or melting hailstones, typical for convective storms during warm season in Oklahoma.

The performance of the  $R(K_{DP})$  and  $R(Z, Z_{DR})$  relations in convective rain is comparable. At closer distances from the radar, where the radar estimates are validated against ARS rain gages, the relations yield slightly smaller bias and rms errors than over Oklahoma Mesonet gages (not shown). In Fig. 2, the  $R(Z, Z_{DR})$  rainfall estimates outperform  $R(K_{DP})$  estimates. The opposite is true for the Oklahoma Mesonet dataset. We also note that the  $R(Z, Z_{DR})$  relation cannot be applied in rain / hail mixture (RH) once the increase in  $Z$  is not compensated by the proportional increase of  $Z_{DR}$  in Eq (3).

The choice between  $R(K_{DP})$  and  $R(Z, Z_{DR})$  in heavy rain and “big drops” is affected by the quality of absolute calibration of  $Z$  and  $Z_{DR}$ , severity of the nonuniform beam filling (NBF) effects, and required spatial resolution of rain estimates. Specific differential phase is immune to radar miscalibration and attenuation. Because estimates of  $K_{DP}$  are noisier and more prone to NBF, the fields of  $R(K_{DP})$  and even corresponding hourly totals may contain spurious perturbations and “holes” associated with unphysical negative rain rates or accumulations. The  $R(Z, Z_{DR})$  relation generally produces less noisy, “hole-free” fields of rain totals and may be favorable for operational forecast/warning applications, which require high spatial and temporal resolution. The  $R(K_{DP})$  relation may be preferred in hydrological applications, which need unbiased

estimates of rain integrated over large spatial / temporal domains.

*b. Rainfall Relation Comparisons in Wet Snow*

Wet Snow echoes are associated with (but not limited to) locations of pronounced bright band signatures in Z. Wet snow is identified with greater confidence if Z is supplemented with polarimetric variables  $Z_{DR}$  and  $\rho_{hv}$ . For the KOUN radar, Wet Snow echoes are best characterized by values of  $\rho_{hv}$  between 0.90 and 0.97 and  $Z_{DR}$  values exceeding 0.7 dB.

The comparison between hourly rain totals obtained from Eq (1) – (3) and Oklahoma Mesonet gages in the cases when the radar samples Wet Snow above the gages is illustrated in Fig. 3. At elevation 0.5°, Wet Snow is usually classified at distances beyond 80 km from the radar and beyond the ARS Micronet gage network.

As expected, the conventional R(Z) relation overestimates rain within the melting layer (Fig. 3a). A modest improvement in terms of the bias and rms error is observed if polarimetric relations are used. Because  $Z_{DR}$  is high in wet snow, the combined use of Z and  $Z_{DR}$  helps to partially mitigate the overestimation inherent to R(Z). However, the peaks in the vertical profiles of Z and  $Z_{DR}$  through the bright band generally do not coincide in height and Z and  $Z_{DR}$  do not correlate to the extent typical for ordinary rain. In addition,  $Z_{DR}$  is quite prone to the NBF effects in the presence of very strong vertical gradients in the melting layer (Ryzhkov 2007) and is rather noisy due to low  $\rho_{hv}$ . Thus, the use of Eq (3) in Wet Snow is not as beneficial as in rain.

The R( $K_{DP}$ ) relation yields slightly better statistical results than the other two algorithms in Wet Snow, which is consistent with earlier findings by Giangrande and Ryzhkov (2003). The reason for this is not well understood. Although the  $K_{DP}$ -based algorithm might work well in Wet Snow after extensive averaging in spatial / temporal domain, the corresponding fields of rain rates and accumulations look much noisier than the ones retrieved from Z. The reasons for this are the same as in rain: inherent noisiness of  $K_{DP}$  measurements and the impact of the NBF effects. In Wet Snow, both factors are further exacerbated by lower  $\rho_{hv}$  and stronger vertical gradients.

In view of these considerations, we recommend using a modified R(Z) relation if the radar echo is classified as Wet Snow. Such a modification implies multiplying the right side of Eq (1) by a factor that can be determined empirically by minimizing the bias and rms error in the rain estimate. In the case of Wet Snow, this factor was determined to be 0.6, i.e., the relation  $R = 0.6 R(Z)$  works the best (Fig. 3d).

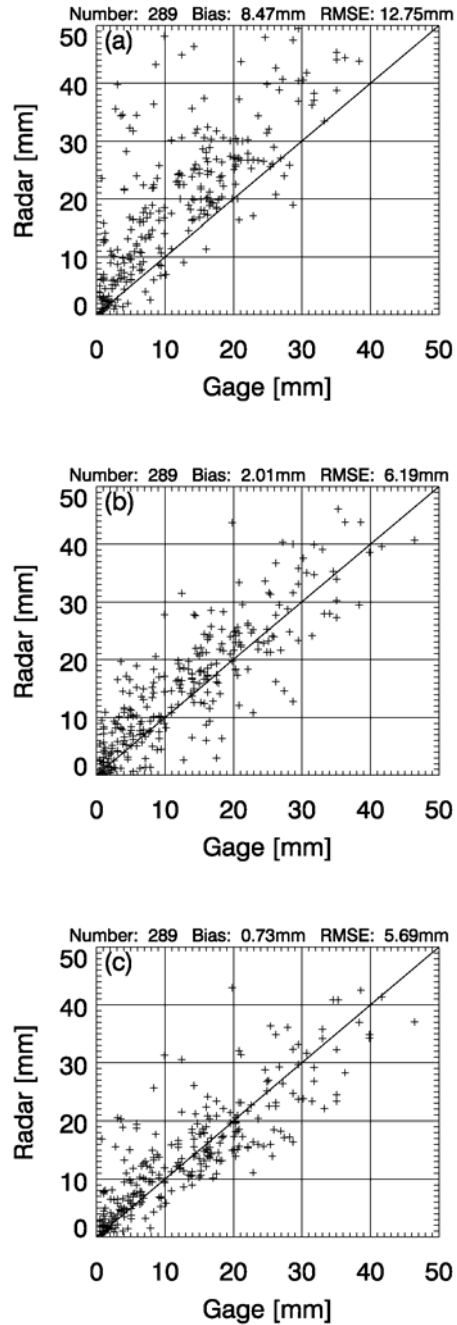


Figure 2: As in Fig. 1, for convective echo gages.

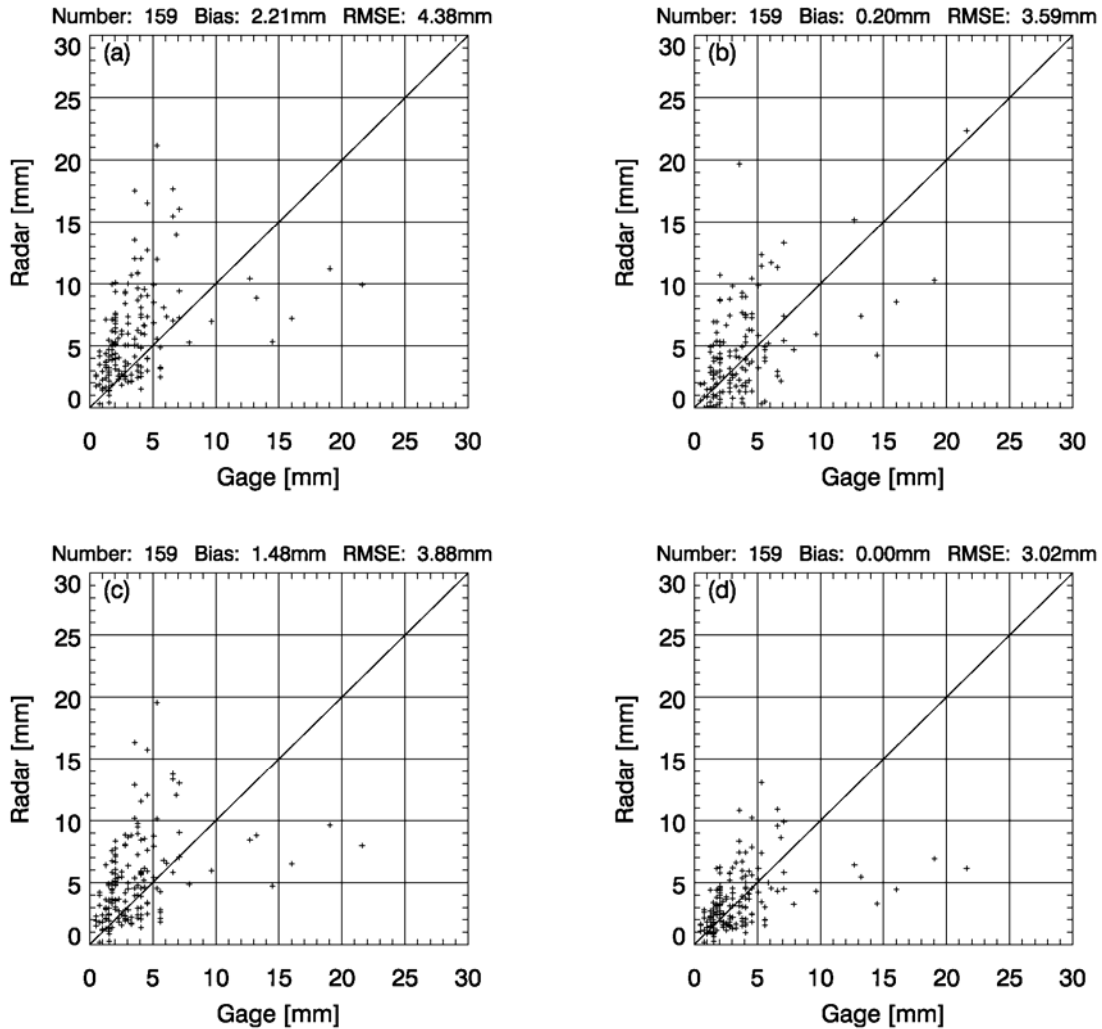


Figure 3: As in Fig. 1, but for Wet Snow: (a)  $R(Z)$ , (b)  $R(K_{DP})$ , (c)  $R(Z, Z_{DR})$ , and (d)  $0.6 \cdot R(Z)$  that minimizes bias.

#### 4. Rainfall Algorithms and Their Performance as a Function of Range

As highlighted in the previous section, different rainfall relations should be utilized for different classes of radar echo. The idea of using multiple relations to optimize rainfall estimation was explored by Ryzhkov et al (2005a). According to the “synthetic algorithm” developed in that study, the choice between various polarimetric rainfall relations is determined solely by the radar reflectivity  $Z$  or  $R(Z)$ , i.e., rain rate computed from  $Z$  using Eq (1). Ryzhkov et al. (2005a) recommend using a  $R(Z, Z_{DR})$  relation in light rain ( $R(Z) < 6$  mm/h),  $R(K_{DP}, Z_{DR})$  relation in moderate-to-heavy rain ( $6 < R(Z) < 50$  mm/h), and  $R(K_{DP})$  relation in heavy rain ( $R(Z) > 50$  mm/h). The three relations were optimized based on the comparison with the ARS gages for rain events during JPOLE in 2002 – 2003. In Ryzhkov et al. (2005a), the “synthetic algorithm” was validated only at distances less than 90 km from the radar, where the contamination from mixed-phase and frozen

hydrometeors is minimal. Note that the  $R(Z, Z_{DR})$  relation in the “synthetic algorithm” is different from the one given by Eq (3).

We suggest another version of the “synthetic algorithm” which is based on the results of polarimetric classification rather than on  $Z$  and is applicable for a wide range of distances from the radar. This algorithm is constructed as follows:

$$\begin{aligned}
 R &= 0 && \text{-- if nonmeteorological echo is classified.} \\
 R &= R(Z, Z_{DR}) && \text{-- if Light/Moderate Rain is classified} \\
 R &= R(Z, Z_{DR}) && \text{-- if Heavy Rain or Big Drops are classified} \\
 R &= R(K_{DP}) && \text{-- if Rain/Hail is classified} \\
 R &= 0.6 \cdot R(Z) && \text{-- if Wet Snow is classified} \\
 R &= 0.8 \cdot R(Z) && \text{-- if Graupel or Rain/Hail classified above the freezing level} \\
 R &= R(Z) && \text{-- if Dry Snow is classified.} \\
 R &= 2.8 \cdot R(Z) && \text{-- if Crystals or distant Dry Snow}
 \end{aligned} \tag{4}$$

where the  $R(Z)$ ,  $R(Z, Z_{DR})$ , and  $R(K_{DP})$  relations are specified by (1) – (3),  $Z$  values are capped at 53 dBZ and rain rate is set to zero if  $\rho_{hv} < 0.85$  to ensure minimal contamination from nonmeteorological echoes. To select an appropriate relation for Dry Snow, the algorithm compares echo height to the geometrical projection of the freezing level onto the base tilt. The algorithm (4) based on echo classification (EC – algorithm herein) as well as the old “synthetic algorithm” by Ryzhkov et al. (2005a), and relations (1) – (3) were tested on the entire dataset containing all 179 hours of data.

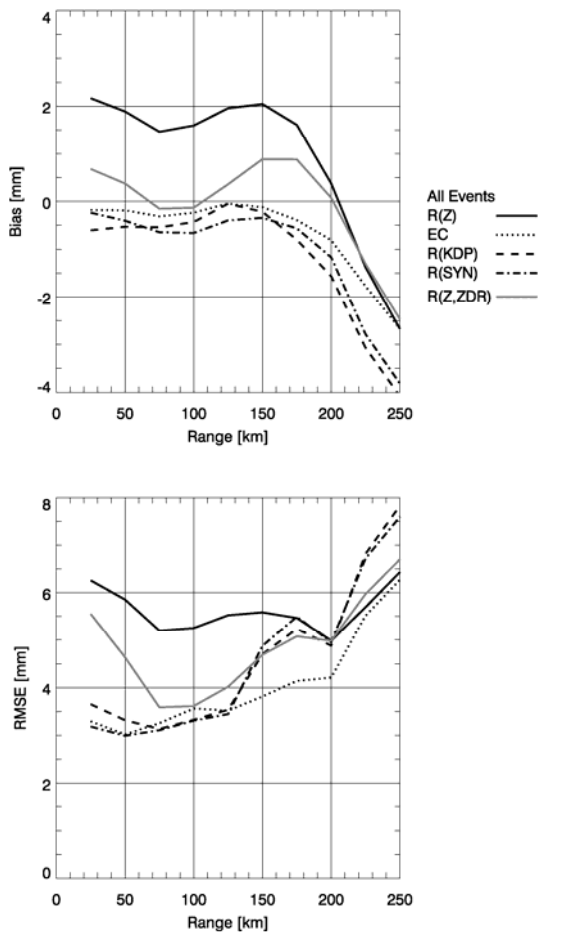


Figure 4: Mean bias (top) and RMS error (bottom) of different radar estimates as a function of range (44 rain events, 174 hours of observation).

The mean biases and RMS errors for 5 algorithms are plotted as functions of range for the entire dataset in Fig. 4. The distances from gauges have been partitioned into 50 km wide range bins to smooth the plotting. Due to significant radar rainfall accumulations associated with intense convective lines and hail-producing storms, convective warm season events dominate the overall performance statistics. Separate statistics were obtained for widespread “stratiform”

events for which the bright band played a significant role (Fig. 5). The stratiform subset includes 26 hours of Oklahoma Mesonet gage observations during 10 widespread cold-season precipitation events. A small number of hours featuring very low freezing level heights were removed from the statistics.

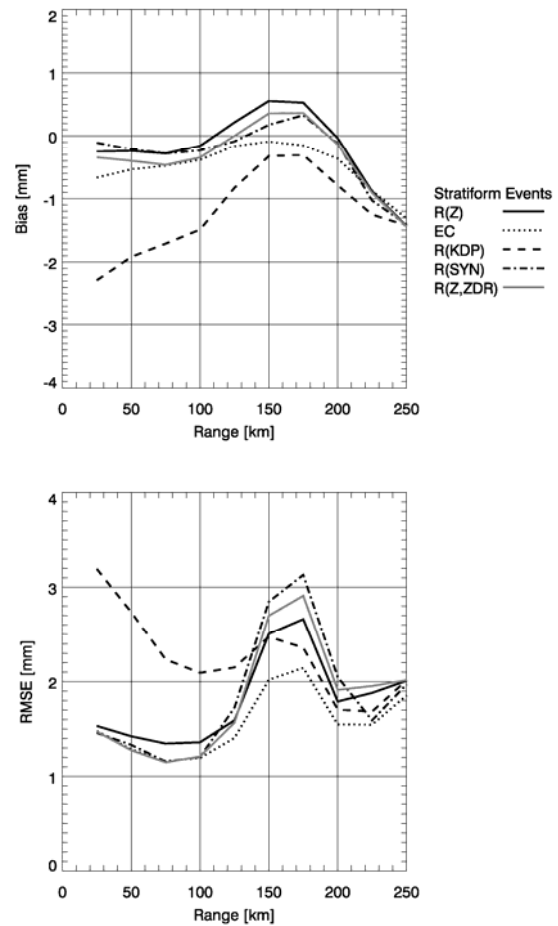


Figure 5: As in Fig. 4, but for pure stratiform events (10 rain events, 26 hours of observation).

As was claimed by Ryzhkov et al. (2005b) and Giangrande and Ryzhkov (2003), the conventional WSR-88D algorithm tends to overestimate rainfall in a wide range of distances up to 200 km from the radar and underestimate it beyond 200 km because of the progressive overshooting of precipitation at longer ranges. The overestimation at ranges below 100 km is primarily due to the impact of large drops and melting hail, which are very common in Oklahoma storms. At ranges between 100 and 200 km, contamination from the bright band is another factor contributing to the positive bias of the conventional rainfall estimate. Depending on the height of the freezing level, the impact of the bright band is strongest in the range interval 130 – 180 km. Conclusions regarding the performance of the conventional WSR-88D  $R(Z)$  relation in this paper are consistent with the results of

independent statistical study by Krajewski and Ciach (2005), who examined a massive amount of radar data collected by the operational KTLX WSR-88D radar in the same region, i.e., central Oklahoma.

The performance of rainfall relations at close distances from the radar (< 100 km) reaffirms initial JPOLE findings, which suggest that polarimetric methods and the “synthetic algorithm” in particular outperform the conventional R(Z) relation for most precipitation regimes. Three polarimetric algorithms: “synthetic”, EC, and R( $K_{DP}$ ) demonstrate similar performance at the ranges up to 130 km with the EC algorithm producing the lowest bias and the “synthetic” one yielding smallest rms errors for all rain events combined (Fig. 4). The EC algorithm significantly outperforms others in the range interval between 130 and 200 km in terms of the rms error.

Utilizing the classification-based polarimetric algorithm (EC) instead of the conventional R(Z) relation results in an impressive reduction of the bias and rms errors of hourly rainfall estimates. At distances within 50 km, the rms error is reduced by roughly a factor of 2 in convective rain. Ryzhkov et al. (2005a) report a 1.7 times reduction for the cases observed during JPOLE. The improvement gradually phases out with increasing distance from the radar. The degree of the rms error reduction exceeds 50% at ranges up to 140 – 150 km and drops to about 20% at 200 km. In stratiform rain typical for colder season, the EC-algorithm also outperforms the conventional one, but to a lesser degree. The most tangible improvement is achieved at longer distances from the radar where the impact of the bright band is maximized (Fig. 5).

It is important that the EC-algorithm is designed to use specific differential phase  $K_{DP}$  more sparingly compared to the “synthetic algorithm” which implies more aggressive use of  $K_{DP}$ . This is dictated by the need to mitigate noisiness in rain fields and the appearance of negative accumulations related to noisy and negative  $K_{DP}$ . However, in some instances the  $K_{DP}$ -based algorithms may produce less bias if substantial averaging over time and space is performed. For example, the “synthetic algorithm” shows slightly smaller bias at shorter distances in stratiform rain than the EC-algorithm. Nevertheless, we believe that the overall performance of the EC-algorithm is better and this algorithm is the better suited for implementation on polarimetric NEXRAD.

## Summary

The performance of the conventional and various polarimetric algorithms for rainfall estimation has been validated at a wide range of distances from the radar. This was accomplished using a large dataset that included radar data collected with polarimetric prototype of the WSR-88D radar and gage data from the ARS Micronet and Oklahoma Mesonet networks in Oklahoma. The type of radar echo in the radar resolution volume over gage locations was identified using the polarimetric classification algorithm. The

accuracy of rainfall estimation was assessed separately for different classes of radar echo including liquid, mixed-phase, and frozen hydrometeors.

A new algorithm that utilizes multiple polarimetric relations and modified R(Z) relations depending on a radar echo class has been developed. According to this strategy, quantitative precipitation estimation should be preceded by and contingent on results of hydrometeor classification. The R(Z,  $Z_{DR}$ ) relation is utilized if the radar echo is classified as rain and R( $K_{DP}$ ) relation is used if large hail is mixed with rain. At longer distances, where the radar resolution volume is filled with mixed-phase and frozen hydrometeors, the polarimetric radar is primarily used as a classifier. R(Z) relations with additional multiplicative factors (or intercept parameters) are applied if the radar scatterers are identified as wet snow, dry snow, crystals, graupel, and hail. The multiplicative factors for each of these classes are determined empirically using rain gage data.

A validation study that incorporates a 4-year polarimetric dataset containing 46 rain events and 179 hours of observations demonstrates that the performance of the suggested algorithm, which is based on echo classification (EC-algorithm), is superior in terms of both bias and rms error. The most impressive improvement, as compared to the conventional WSR-88D algorithm, is found in convective storms where the rms error of hourly rain estimate is reduced by a factor of 2 at distances less than 50 km from the radar. The degree of improvement gradually decreases with range and becomes insignificant at distances beyond 200 km.

## References

Giangrande, S.E, and A.V. Ryzhkov, 2003: The quality of rainfall estimation with the polarimetric WSR-88D radar as a function of range. *Preprints, 31<sup>st</sup> International Conference on Radar Meteorology*, Seattle, Amer. Meteor. Soc., 357-360.

Krajewski, W. F., and G. J. Ciach, 2005: Towards probabilistic quantitative precipitation WSR-88D algorithms: data analysis and development of ensemble model generator: phase 4. Report to Office of Hydrologic Development under NOAA Contract DG133W-02-CN-0089, 69 pp.

Ryzhkov, A.V., and D.S. Znic, 1995: Precipitation and attenuation measurements at a 10-cm wavelength. *J. Appl. Meteorol.*, 34, 2121–2134.

-----, A.V., S.E. Giangrande, and Terry J. Schuur, 2005a: Rainfall estimation with a polarimetric prototype of WSR-88D. *J. Appl. Meteorol.*, 44, 502–515.

-----, A.V., T.J. Schuur, D.W. Burgess, P.L. Heinselman, S.E. Giangrande, and D.S. Znic, 2005b: The joint polarization experiment: polarimetric rainfall measurements and hydrometeor classification. *Bull. Amer. Meteor. Soc.*, 86, 809-824.

-----, S.E. Giangrande, V.M. Melnikov, and T. J. Schuur, 2005c: Calibration issues of dual-polarization radar measurements. *J. Atmos. Oceanic Technol.*, 22, 1138–1155.

-----, 2007: The impact of beam broadening on the quality of radar polarimetric data. *J. Atmos. Oceanic Technol.*, 24, 729 - 744.

-----, D.S. Zrnic, P. Zhang, J. Krause, H. Park, D. Hudak, J. Young, J.L. Alford, M. Knight, and J.W. Conway, 2007: Comparison of polarimetric algorithms for hydrometeor classification at S and C bands. Analysis of the performance in different climate regions. *Preprints, 33<sup>rd</sup> International Conference on Radar Meteorology*, Cairns, Australia, Amer. Meteor. Soc., CD-ROM, 10.3.