Current Status and Future Challenges of Weather Radar Polarimetry: Bridging the Gap between Radar Meteorology/Hydrology/Engineering and Numerical Weather Prediction

By

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Abstract

After decades of research and development, the WSR-88D (NEXRAD) network in the United States had been upgraded with dual-polarization capability, providing polarimetric radar data (PRD) that has the potential to improve weather observations, quantification, forecasting, and warnings. The weather radar networks in China (CINRAD) and other countries are also being upgraded with the dual-polarization capability. Now, with radar polarimetry technology matured and polarimetric radar data (PRD) available both nationally and globally, it is important to understand current status and future challenges and opportunities. The potential impact of PRD has been limited by their oftentimes subjective and empirical use. More importantly, the community has not begun to regularly derive from PRD the state parameters, such as water mixing ratios and number concentrations, used in numerical weather prediction (NWP) models.

In this review, we summarize the current status of weather radar polarimetry, discuss the issues and limitations of PRD usage, and explore potential approaches to more efficiently use PRD for quantitative precipitation estimation (QPE) and forecast (QPF) based on statistical retrieval with physical constraints where prior information is used and observation error is included. This approach aligns the observation-based retrievals favored by the radar meteorology community with the model-based analysis of the NWP community. We will also examine the challenges and opportunities of polarimetric phased array radar research and development for future weather observation.

Key words: Weather radar polarimetry, radar meteorology, numerical weather prediction, data assimilation, microphysics parameterization, forward operator

Article Highlights:

- Review the current status/limitations and future challenges/opportunities of weather radar polarimetry.
- Reveal the gap between radar meteorology/hydrology/engineering and NWP communities and discuss possible approaches to bridge them.
- Explore new methods and technology to advance weather radar polarimetry to meet future needs.

1. Introduction and motivation

Radar is a very important tool in weather observations and forecasts, and there is an increasing need for faster data updates and more informative measurements to advance atmospheric sciences as stated by Bluestein et al. (2014). While the faster data updates can be realized with phased array radar technology, multi-parameter weather measurements can be made by radar polarimetry. Weather radar polarimetry aims to obtain more detailed weather information from radars with polarization diversity (Doviak and Zrnic 1993; Bringi and Chandrasekar 2001; Zhang 2016). Through decades of research and development, radar polarimetry had been matured and implemented on the network of Weather Surveillance Radars – 1988 Doppler in the United States (WSR-88D), also called Next-Generation Radar (NEXRAD; Doviak et al. 2000). Doppler weather radars in China (CINRAD) and other countries have also been or are being upgraded with the dual-polarization capability. Polarimetric radar data (PRD) are now available nationally and globally. The dual-polarization upgrade is an important and imperative milestone in weather radar technology because the additional information it provides about the shape, composition, and phase of hydrometeors is much needed for further understanding, quantifying, and predicting weather.

A single polarization Doppler radar can only measure the reflectivity factor (also called reflectivity: Z or Z_H), radial velocity (v_r), and spectrum width (σ_v or SW). The Doppler measurements v_r and σ_v respectively represent the dynamic motion: the mean and standard deviation (including shear) of the radial velocity of scatterers. Only the reflectivity directly provides microphysics information, but this one measurement is obviously not sufficient to fully characterize the complex cloud and precipitation microphysics. For example, cloud microphysics is normally represented in convective scale numerical weather prediction (NWP) models not by the one observed parameter, *Z*, but by several to over a dozen state variables used in microphysics parameterization schemes. These variables include the water mixing ratios and number concentrations for the five or six hydrometeor species (cloud water, cloud ice, rain, snow, and hail/graupel) used in many double-moment or multi-moment schemes (e.g., Milbrandt and Yau 2005a, b; Morrison et al. 2005, 2009). There can be ten times more unknowns if spectrum bin microphysics is used (Khain et al. 2015).

Because reflectivity only cannot fully characterize cloud microphysics, efforts and attempts have been made to increase the number of independent radar measurements to better understand and characterize weather conditions through frequency/wavelength and/or polarization diversities. For example, the Global Precipitation Measurement (GPM) core observatory carries the space-borne Ku/Ka-band Dual-frequency Precipitation Radar (DPR) (https://pmm.nasa.gov/GPM/flight-project/DPR), which was advanced from the Tropical Rain Measurement Mission (TRMM) single frequency precipitation radar (PR) (Huffman et al. 2007). While a multi-frequency radar can provide more information, it is essentially multiple radars and therefore expensive to build (Eccles and Atlas 1973; Gossett and Sauvageot 1992). The data from a multi-frequency radar are also complicated to analyze. For ground-based remote sensing, radar polarimetry is both cost-effective and efficient in providing more microphysical information (Seliga and Bringi 1976; Seliga et al. 1979; Zrnic and Aydin 1992).

In addition to the single polarization radar measurements of Z, v_r, and σ_v, a polarimetric radar can produce differential reflectivity (Z_{DR}) – the ratio of reflectivity between the horizontally and vertically polarized waves; co-polar correlation coefficient (ρ_{hv}); differential phase (Φ_{DP}) and/or its range derivative – specific differential phase (K_{DP}); linear depolarization ratio (LDR); and correlation coefficients between co-polar and cross-polar signals (ρ_{xh} and ρ_{xv}). Radar polarimetry is normally implemented in one of two modes: i) dual-polarization (simultaneous transmission and simultaneous reception: STSR) mode, and ii) full polarization (alternate transmission and simultaneous reception: ATSR) mode. For practical reasons as stated in Section 4 of Doviak et al. (2000), most operational weather radars, including the WSR-88D, use dual-polarization STSR mode and produce polarimetric radar data (PRD) of Z, v_r, σ_v, Z_{DR}, ρ_{hv}, and Φ_{DP}/K_{DP}. Nevertheless, these PRD contain information about hydrometeor size, shape, orientation, and phase/composition, allowing for better characterization of cloud and precipitation microphysics (e.g., Zrnic and Ryzhkov 1999). PRD have enormous, but as yet not fully tapped, potential to improve severe weather detection and warnings, and quantitative precipitation estimation (QPE) and forecast (QPF).

Currently, we use PRD in severe weather observation and detection, hydrometeor classification, winter precipitation applications, and QPE. In observational studies, certain polarimetric radar signatures such as the Z_{DR} arc, ρ_{hv} ring, and K_{DP} foot are identified and connected to certain microphysical processes (Kumjian and Ryzhkov 2008; Romine et al. 2008). In hydrometeor classification (HC), a set of PRD are used in a fuzzy logic classification algorithm whereby the membership function of a radar variable for a species is established based on experience, and then the membership values are combined to make a decision as to which class the set of PRD represents (Vivekanandan et al. 1999; Park et al. 2009; Straka et al. 2000; Chandrasekar 2013; Dolan et al. 2013). The classification results are used to detect severe weather and to select radar estimators to improve QPE (Giangrande and Ryzhkov 2008). These uses of PRD in severe weather observations and detection have utility in the weather forecasting community. For example, the Warning Decision Training Division (WDTD) of the U.S. National Weather Service (NWS) offers a Radar and Applications Course (RAC) as the initial training on the use of the WSR-88D for severe weather operations (http://training.weather.gov/wdtd/courses/rac/). The application of PRD is a fundamental part of the course due to the recent upgrade of the WSR-88D network to dual-polarization. The course includes training on following topics: base PRD, HC, the melting layer algorithm, QPE rainfall products, severe hail detection, supercell morphology, and the tornado debris signature (TDS) as well as winter weather applications.

The use of PRD can provide vital real-time information to forecasters, which help to improve severe weather detection and warnings, but many of the methods are oftentimes subjective and empirical, and have limitations in realizing the full potential of PRD. In QPE, deterministic power-law relations are used for rain estimation from PRD (Zhang et al. 2016; Chen et al. 2017), which may not be optimal. Also, uncertainties of radar-derived products have not been accurately quantified and provided together with the products. More importantly, the community has not begun to regularly derive from PRD the state parameters used in convective scale high-resolution NWP models, such as water mixing ratios and number concentration. The question is: How should we efficiently utilize PRD to improve severe weather detection, aviation weather services, QPE, and QPF?

Ideally, PRD should be used to determine cloud and precipitation physics state variables and to improve microphysical parameterization in NWP models, which in turn are expected to improve the accuracy of weather quantification and to shorten the spin-up time of the NWP model forecast. Unfortunately, this cannot be done easily for several reasons: i) the number of independent pieces of information from PRD is limited and is usually less than the number of state variables that are used in NWP models in the case of multi-moment and/or multi-species microphysics, resulting in underdetermined problems; ii) relationships between state variables and polarimetric radar variables are not linear, and sometimes they are not entirely known, especially for ice phase and mixed phase species; iii) there are errors in radar measurements of PRD and in the forward operators which connect model state variables to the radar variables; iv) there are large errors and uncertainty in convective scale NWP model physics and parameterization when NWP model constraints are used in retrieval through data assimilation – these prevent the PRD from substantially contributing to the model initialization and prediction; and v) there is a disconnect between the radar meteorology and NWP communities in their use of PRD.

Although it is difficult and challenging, the efficient use of PRD and advancing radar technology for severe weather detection & warnings, QPE, and QPF are still our goals, which motivate us to write this article. We discuss and explore the following issues:

- Limitation of current usage of PRD
- Gap between radar meteorology/hydrology and NWP communities
- Difficulty in assimilating PRD into NWP models
- Development status of new radar technology, phased array radar polarimetry, to meet future needs

Only once these shortcomings are realized and these challenges tackled can the optimal usage of PRD and efficient advancement of radar technology be achieved. The rest of this paper is organized as follows. Section 2 shows examples of PRD and PRD usages/products from WSR-88D. The issues and limitations of current PRD usage and the gap between the radar meteorology and the NWP communities are discussed in Section 3. Section 4 suggests a unified statistical approach of using PRD. An example of an NWP model-based analysis of PRD is shown in Section 5. Section 6 discusses the status and challenges of research and development of polarimetric phased array radar polarimetry. Section 7 ends with a summary.

2. Current Status of Using Polarimetric Radar Data

After the dual-polarization upgrade completed in 2013, archived PRD from WSR-88D became available at NOAA's National Centers for Environmental Information (NCEI) (https://www.ncdc.noaa.gov/nexradinv/index.jsp) in level II and level III format, which is summarized in Fig. 1. Level II data (left column) are base data estimated from pulsed radar signals, from which level III data/products are derived. The dashed boxes are the single polarization radar data and their derived products, and the solid boxes are for dual-polarization data and PRD-derived products. Compared with that over a dozen of single polarization products (middle column), the PRD-derived products (right) are still very limited – only three, indicating future challenges exist and opportunities are to be explored. In this section, we'll discuss the current usage of PRD for weather observation, hydrometeor classification, and QPE.

2.1 Polarimetric radar data (PRD) for weather observation and forecast

As shown in left column of Fig. 1, WSR-88D level II data contain six variables, consisting of three existing single polarization variables (Z, v_r, σ_v) and three added dual-polarization variables (Z_{DR}, ρ_{hv}, and Φ_{DP}), which contain a wealth of information about cloud and precipitation microphysics.

Each dual-polarization variable has specific properties/characteristics with regard to different weather or non-weather radar echoes, and, together with Z, they reveal the microphysical properties of clouds and precipitation. Z_{DR} is a measure of the reflectivity weighted shape of the scatterers and tends to increase for more oblate scatterers (within the Rayleigh regime). ρ_{hv} represents the similarity between the horizontal and vertical polarization signals, and it is reduced when there is increased randomness and diversity between the horizontally and vertically polarized backscattered waves, especially for non-Rayleigh scattering. Finally, Φ_{DP} is the difference in phase shift between horizontally and vertically polarized waves, including both differential scattering phase (δ) and differential propagation phase (ϕ_{DP}). ϕ_{DP} increases rapidly for heavy rain because the horizontally polarized wave propagates more slowly than the vertically polarized wave as its polarization is in the direction of the larger dimension of oblate particles.

When used in conjunction with ground-based observations and storm reports (when available), their understanding of the storm morphology, and the near-storm environment (i.e., mesoanalysis), meteorologists who serve as warning forecasters at the U.S. NWS use radar data to make warning decisions on whether a thunderstorm is capable of producing severe weather ($\geq$26 m/s winds and/or $\geq$2.54 cm hail) and/or a tornado. If a forecaster has enough confidence for severe weather and/or a tornado, the forecaster can issue a severe thunderstorm warning or tornado warning with the potential hazards (i.e., estimated maximum hail size, estimated maximum wind speed, and tornado damage threat). The addition of PRD gives forecasters additional information on the storm morphology, which can assist in warning-decision making.

An example from a warm-season event is used to demonstrate the PRD and its utility in weather observations and warnings. Figure 2 shows the plan position indicator (PPI) images of these data at an elevation of 1.3 degrees for a tornadic supercell event observed by the S-band polarimetric WSR-88D (KFDR) radar in southwest Oklahoma at 22:43 UTC on 16 May 2015. Six PPI images represent the polarimetric Doppler weather radar measurements of reflectivity (Z) (Fig. 2a), radial velocity (v_r) (Fig. 2b), and spectrum width (σ_v) (Fig. 2c), as well as the added dual-polarization measurements of differential reflectivity (Z_{DR}) (Fig. 2d), copolar correlation coefficient (ρ_{hv}) (Fig. 2e), and differential phase (Φ_{DP}) (Fig. 2f). The red polygon is a tornado warning that was issued by NWS Norman, Oklahoma, Weather Forecast Office (WFO).

The storm is a classic supercell with a hook echo. At the tip of the hook (on the southwest flank of the storm), a mesocyclone is sampled by the radar, as indicated by a cyclonic velocity couplet. On the forward flank of the supercell, along with the reflectivity gradient on the southern edge, there is an increase in Z_{DR}. This feature is known as a Z_{DR} arc, which occurs due to size-sorting in a supercell that occurs because of vertical wind shear (Kumjian and Ryzhkov 2008). Northwest of the Z_{DR} arc, Φ_{DP} increases markedly with range. This is due to very heavy rainfall in the forward flank downdraft (FFD) of the supercell. Immediately to the west-northwest of the hook, there is a reduction in Z_{DR} and ρ_{hv} within an area of high reflectivity. These measurements are likely due to the presence of hail mixing with rain. The final signature to note is a local minimum in the ρ_{hv} and Z_{DR} at the center of the velocity couplet, which is coincident with reflectivity >40 dBZ. The low ρ_{hv} and Z_{DR} indicates the presence of non-meteorological targets. This signature, known as a TDS, exists due to debris being lofted by a tornado (Ryzhkov et al. 2005; Kumjian and Ryzhkov 2008; Kumjian 2013; Van Den Broeke and Jauemic 2014). In this event, the presence of a TDS resulted in the NWS Norman WFO issuing a severe weather statement (i.e., updated tornado warning) where the hazard in the warning became "damaging tornado" and the source for the warning became "radar confirmed tornado." In this example, the PRD had an important role in warning decision-making by providing information that heightened the wording of the warning statement.

Though the previous example is a warm-season event, PRD have applications in the cold season too (Zhang et al. 2011; Andrić et al. 2013), including melting-layer detection and precipitation type transition zones (Brandes and Ikeda 2004; Giangrande et al. 2008; Bukovčić et al. 2017), and in the study of ice microphysical processes (Griffin et al. 2018). Polarimetric radars have also been successfully used in the study of tropical meteorology (Rauber et al. 2007; May et al. 2008; Brown et al. 2016; Wang et al. 2016; Didlake et al. 2017).

2.2 PRD products

2.2.1 Hydrometeor Classification (HC)

While it is informative to look at the individual polarimetric variable images, it is more scientific, rigorous, and efficient to systematically and automatically use the PRD for accurate weather measurement and forecast (Straka and Zrnic 1993; Straka 1996). The first such use was in hydrometeor (or echo) classification based on a fuzzy logic algorithm (Vivekanandan et al. 1999; Liu and Chandrasekar 2000). An updated version of the hydrometeor classification algorithm (HCA) described by Park et al. (2009) is implemented on the WSR-88D. Its input parameters are Z, Z_{DR}, $\rho_{hv,}$ logarithm of K_{DP}, standard deviation of reflectivity std(Z), and standard deviation of differential phase std(Φ_{DP}). Its output is ten classes of radar returns: light/moderate rain, heavy rain, rain/hail mix, big drops, dry snow, wet snow, crystals, graupel, biological, ground clutter; the hybrid version of twelve classes (with no echo and unknown added) are available as part of the WSR-88D level III data. Recent modifications to the HCA include a hail size discrimination for the rain/hail mix category (Ryzhkov et al. 2013a,b; Ortega et al. 2016). Using the graupel classification from the HCA as a primary input, the WSR-88D algorithm suite now also includes an icing hazard level (IHL) product that is used by the Federal Aviation Administration to detect regions of icing aloft.

Figure 3a shows the HCA output from the KFDR radar for the event depicted in Fig. 2. Although it is not easy to verify the HCA output by comparisons with in-situ measurements, the results of the classification in Fig. 3a fit the accepted microphysical understanding of a severe super-cell storm. As expected, the area of high reflectivity with reduced Z_{DR} and ρ_{hv} is classified as rain and hail (HA: red). Heavy rain (HR: dark green) is identified in the FFD region, consistent with the rapid increase in Φ_{DP} noted in the previous subsection. Light and moderate rain (RA: light green) are identified at the south-west edge of the storm. The leading side of the storm is classified as big drops (BD: brown), which is reasonable due to size sorting. It is also reasonable to see biological scatterers (BI: light gray) identified ahead of the storm near the radar where insects normally appear.

However, a couple of issues presently exist and are being addressed: the tornado debris signature is not detected as a class of the HCA output, and the melting layer with high reflectivity has been misclassified as graupel and big drops. Efforts are underway to accurately classify hydrometeors in the melting layer as wet snow. Also, notice that the transition between liquid and frozen hydrometeors is flat. This is an outcome of the assumption that the 0^{o}-isotherm is assumed to be at a constant altitude. While this approximation may be safe for warm-season precipitation, it is known to cause some issues for the cold season (Reeves et al. 2014). An improved melting layer detection algorithm that allows for variations in the height of the melting layer is under development (Reeves 2016). A recent advancement in HCA with PRD is to use an objective approach to derive statistical relations based on cluster analysis (Wen et al. 2015, 2016).

2.2.2 Quantitative Precipitation Estimation (QPE)

Whereas HCA is very successful in systematically utilizing PRD for revealing cloud and precipitation microphysics, it is qualitative and empirical rather than quantitative. One of the main motivations to develop weather radar polarimetry was to improve QPE with polarimetric measurements, such as Z_{DR} (Seliga and Bringi 1976; Seliga et al. 1979; Ulbrich and Atlas 1984) and K_{DP} (Sachidananda and Zrnic 1987; Ryzhkov and Zrnic 1996), because polarimetric measurements depend on the shape of hydrometeors, and rain drop shape is monotonically related to the drop size. Hence, radar rain estimators with different combinations of Z, Z_{DR}, and K_{DP} were developed using simulated or measured rain DSDs and electromagnetic scattering models (Jameson 1991; Vivekanandan et al. 1991; Ryzhkov and Zrnic 1995). The improvement of QPE with PRD has been demonstrated with real data in a subtropical environment (Brandes et al. 2002), in the Southern Great Plains region (Giangrande and Ryzhkov 2008), and in a tropical region (May et al. 1999; Chang et al. 2009) as well as in Europe (Figueras i Ventura and Tabary 2013). It is generally accepted that the estimation error decreases from 30-40% uncertainty for a single polarization reflectivity to about 15% error for polarimetric measurements (Brandes et al. 2002).

A synthetic polarimetric radar rain estimator that combines different estimators based on HCA results was initially adapted by dual-pol WSR-88D to produce level III QPE products (Giangrande and Ryzhkov 2008). The dual-polarization QPE products are currently generated based on the three primary rain estimators:

$$R(Z) = 0.017Z^{0.714} \leftrightarrow Z = 300R^{1.4} \tag{1}$$
$$R(K_{DP}) = 44|K_{DP}|^{0.822} sign(K_{DP}) \tag{2}$$
$$R(Z, Z_{dr}) = 0.0142Z^{0.77} {Z_{dr}}^{-1.67} \tag{3}$$

where $sign(K_{DP})$ allows for negative K_{DP} values and both "Z" and "Z_{dr}" are in linear units instead of logarithmic values for Z/Z_H and Z_{DR}. The three rain estimators are used/chosen based on HCA results. For example, if the echo is classified as light to moderate rain, Eq. (3) of $R(Z, Z_{dr})$ is used to estimate rain rate; if the echo is classified as hail rain mixture, Eq. (2) of $R(K_{DP})$ is used to mitigate hail contamination. Figure 3b shows the dual-polarization radar-based QPE result that has much less contamination from anomalous propagation clutter and biological scatterers. The dual-polarization QPE, based on Z, Z_{dr}, and K_{DP}, provided improved precipitation estimates over the previous single polarization QPE in warm season events where the freezing level was high. However, it has relatively large random errors due to its sensitivity to errors in Z_{dr}, which are significant at times. The dual-polarization QPE also suffers from discontinuities and some biases near the melting layer. The $R(K_{DP})$ estimator can produce a negative rain rate, which is physically impossible, if K_{DP} is estimated from Φ_{DP} using a least-squares fit as is currently used for WSR-88D. A recent advancement is to improve K_{DP} estimation for better QPE by using a hybrid method of combining linear programming (also called linear optimization) and physical constraints (Giangrande et al. 2013, Huang et al. 2017), which yields the best match with observed Φ_{DP} while ensuring positive K_{DP} estimates. The latest developments also include the use of specific attenuation (A) for rainfall estimation (Ryzhkov et al. 2014; Zhang et al. 2017). There is also interest in using X-band polarimetric radar networks to improve QPE and low-level coverage (Chen and Chandrasekar 2015).

3. Issues with Current PRD Usage

As discussed in last section, it is informative and intuitive to observe polarimetric radar signatures for detection and warning of severe storms and aviation hazards, exciting to see PRD HC results reveal cloud and precipitation microphysics, and satisfactory to improve QPE with PRD. PRD can serve the community better and its potential can be better realized if the issues and limitations of the current usage of PRD are acknowledged and resolved. These issues are described as follows:

As noted in the introduction, the independent information of PRD is still limited, and the relative errors of polarimetric measurements can be large. The number of independent pieces of information varies depending on the hydrometeor species: ~1 for drizzle or dry snow, 3~4 for melting snow or hail. The relative error of Z_{DR} and K_{DP} can be 100% for light rain due to the small intrinsic values. Furthermore, system uncertainty and bias affect the accuracy of polarimetric measurements (Zrnic et al. 2006). Even with a well-calibrated radar system, the overall uncertainty of the bias/error has historically been greater than the required tolerance (e.g., 0.1 dB bias for Z_{DR}), limiting the quantitative usage of PRD (Ice et al. 2014).

Severe weather (such as hail and tornado) related observation studies with PRD have been highly subjective and empirical. It is difficult to automatically use and expand the subjectively decided polarimetric signatures/knowledge for operational usage in severe weather detection, prediction, and warning. It would be beneficial to warning forecasters if there are products that utilize PRD to better quantify potential hazards, such as maximum hail size or tornado damage threat. As shown in Fig. 1, there is no severe weather detection product that has been generated in WSR-88D level-III PRD products (with the exception of hail size discriminator in the latest HCA), compared with many reflectivity-derived velocity-derived products. This is because not all the weather science has been fully understood, and rigorous relations between weather states and PRD have not been fully established. Therefore, further research and development need to be done.

Hydrometeor classifications have been successful, but are still qualitative, and some severe weather conditions (e.g., TDS) are not in the HCA output. Also, a dominant contributor to PRD may not necessarily be the main contributor to microphysics states/processes. For example, a hydrometeor class determined from PRD may not necessarily have the highest water mixing ratio or evaporation rate if other classes exist in the radar resolution volume. This is because radar measurements are mainly determined by higher DSD moments (e.g., approximately 6^{th} moment for reflectivity) dominated by a few large particles rather than the large number of small drops which have important effects on microphysical processes, thermodynamics, and storm development.

Power-law type polarimetric radar rain estimators (e.g., Eqs. (1-3)) may not be optimal, because it is difficult to use prior information and measurement errors in rain estimation once a power-law estimator is chosen. True relations (if they exist at all) between rain rate and radar variables may not necessarily be in power-law form. For example, if rain DSDs are exponentially or gamma distributed, the analytically derived $R(Z, Z_{dr})$ is not in power-law form (See Eq. (6.26) of Zhang 2016). The power-law form was used for simplicity because it becomes a linear function after taking the logarithm of both sides; this makes for an easy fit to data. Even if the functional form is acceptable, the least square fitting with a constant weight for all data points is optimal only if the errors are Gaussian distributed in the logarithm domain. Otherwise, least square fitting does not yield the minimal error. Furthermore, a minimal error in the logarithm domain does not necessarily yield a minimal error in the linear domain for rain estimation. Also, the HC-based QPE can cause discontinuity in rain estimation because the chosen estimator switches relations discretely according to subjectively determined conditions, even though the underlying microphysical condition has evolved only continuously. Furthermore, model errors, measurement errors of the involved radar variables and rain rate, and data sampling/collection issues are not considered in the formulating and fitting procedure, yielding uncertainty in QPE results.

Another issue – likely the most important – is the difficulty involved in using the current PRD or PRD products to improve NWP. The difficulty comes from i) large variety/uncertainty in storm-scale NWP models and model parameterization (will be discussed further is section 5) and

ii) a disconnect between model basic state variables (e.g., water mixing ratio and number concentration) and polarimetric variables. Efforts have been made to develop PRD simulators (i.e., forward operators) to connect model variables with PRD variables through cloud/precipitation microphysics (MP) rooted in drop/particle size distribution (DSD/PSD), N(D), and other physical and statistical properties such as shape, orientation, and composition reflected in scattering matrix elements (s_{hh}, s_{vv}), as in section 8.5.2.2 of Doviak and Zrnic (1993), section 3.10.1 of Bringi and Chandrasekar (2001) and section 4.2.6 of Zhang (2016). Based on scattering calculations with the T-matrix method (Waterman 1965; Vivekanandan et al. 1991), Jung et al. (2008a, 2010), Pfeifer et al. (2008), Ryzhkov et al. (2011) all developed different forward operators, and were able to simulate realistic PRD signatures from NWP model output. The computer code in Fortran language for PRD operators is posted on the University of Oklahoma website (http://arps.ou.edu/downloadpyDualPol.html). There is also a freely available Cloud Resolving Model Radar Simulator (CR-SIM) (http://radarscience.weebly.com/radar-simulators.html) developed by a group of scientists from Stony Brook University and Brookhaven National Laboratory. Colorado State University (CSU) and NASA Gaddard Space Flight Center also developed the POLArimetric Radar Retrieval and Instrument Simulator (POLARRIS) (https://cloud.gsfc.nasa.gov/POLARRIS/). Still, efficient and accurate PRD operators, like the one in Mahale et al. (2019) for rain, are still lacking and in need for ice and mixed phase species to make PRD assimilation more feasible and efficient.

The current status of using polarimetric radar data is due to the fact the PRD and products thereof are generated from radar engineering and meteorology point of view, with little influence from the NWP community thus far. Rigorous retrieval methods developed from the information theory and NWP communities have not been successfully adapted. Radar meteorology and NWP fields developed and evolved from their communities independently from each other. Radar meteorology was developed based on the theory/model of electromagnetic (EM) wave scattering by hydrometeors, and by observing and relating radar measurements for understanding and estimating weather with empirical relations. NWP, on the other hand, is formulated from a set of physical, dynamic and thermodynamic conservation equations. There has not been enough connection between the two research areas. This disconnect is reflected in the different variables commonly used to represent the weather state (e.g., water mixing ratio (q) in NWP models; rain rate (R) in radar meteorology), the difference of unit usage between NWP state and radar variables, and the different values used to characterize PRD errors for two different realities in the two communities. For example, it is generally accepted by the radar meteorology community that the measurement error for Z is about 1.0 dB, which is usually ignored in direct observation retrieval; however, 2.0 to 5.0 dB error is usually used in NWP community. The gap between radar meteorology and NWP needs to be bridged, and the approaches adapted to use PRD need to be aligned for optimal results.

4. A Unified Statistical Approach

Since the purpose of both radar meteorology and NWP is to understand and predict weather, one way to advance the usage of PRD is to improve model parameterizations and initialization for more accurate weather forecasts and warnings. Considering that radar measurements contain errors, weather states vary, observational information are not enough and not uniformly available across the atmosphere, and physical constraints and prior information are needed to facilitate retrieval, a statistical approach is warranted. In this framework, both state variables and radar measurements are treated as random variables, and both the prior background and observations are used.

As shown in Fig. 4, let **x** be the state vector; **y** the measureable vector; and they are related by the forward operator as: **y**=H(**x**). An optimal retrieval is to find the state vector **x** that has the best match with a given prior background, $\mathbf{x}_b$, and a set of observation, $\mathbf{y}_o$, while accounting for their given uncertainties. This is equivalent to minimizing the cost function J

$$J = [\mathbf{x} - \mathbf{x}_\mathrm{b}]^t \mathbf{B}^{-1} [\mathbf{x} - \mathbf{x}_\mathrm{b}] + [\mathbf{y}_\mathrm{o} - H(\mathbf{x})]^t \mathbf{R}^{-1} [\mathbf{y}_\mathrm{o} - H(\mathbf{x})] \quad (4)$$

where **B** and **R** represent the background error covariance and observation error covariance, respectively, and $H(\ldots)$ is a forward observation operator. This serves as the basis for variational (VAR) analysis and the ensemble Kalman filter (EnKF) analysis (Lorenc 1986). The VAR approach has been used in improving QPE and microphysics retrieval with PRD in Hogan (2007), Cao et al. (2010,2013), Yoshikawa et al. (2014) and Chang et al. (2016), in which the background information is obtained from previous measurements/knowledge. In EnKF analysis, the forward operator is assumed to be linear, the flow-dependent covariance **B** is estimated from a limited number of ensemble forecasts, and the analyzed state vector is solved from (4) iteratively, whose application in data assimilation (DA) with PRD is presented in Section 5.

The procedure to derive Z-R relations is a special case of the variational approach, in which background information is lacking (the first term in (4) is ignored), only the Z observations are used, and each data point is normally equally weighted to fit with a power-law relation ($\mathrm{Z} = a\mathrm{R}^b$) in the logarithm domain to determine the coefficients a and b. Hence the Z-R relation highly depends on data collection/selection, filtering, and the weighting and fitting procedure used, which is obviously not optimal because the data quality and weighting issues cannot be taken into account in rain estimation once a Z-R relation is chosen. Therefore, the statistical approach represented by Eq. (4) is more fundamental and complete in formulating PRD-based retrieval, and has the potential to achieve optimal usage because the prior background information can be used and measurement error effects are included. Since it is already in use in the NWP community for radar data assimilation, the statistical approach is one way to align the radar meteorology/hydrology with the NWP community, and applicable to both observation-based and DA-based retrievals.

While the statistical retrieval approach has been formulated and successfully used in the data assimilation community (Rodgers 2000; Kalnay 2003), it has seen little success in the optimal usage of PRD due to its complexity. The reason for this is that there are many issues in optimally utilizing PRD for improving QPE and QPF, as discussed in last section (Section 3). Importantly, there are large uncertainties in storm scale NWP models and model microphysics parameterization (will be further discussed in section 5). These large errors in NWP that DA depends on as background information (first term of Eq. (4)), and large uncertainty and non-linearity in PRD operators prevent the substantial positive impact of limited information from PRD (2$^{\mathrm{nd}}$ term of Eq. (4)).

Considering all aforementioned issues, the vision for optimal utilization of PRD with different components is modified from Fig. 7.14 of Zhang (2016) and shown in Fig. 5. As sketched in the top row (red) of the figure, observation-based studies and retrievals are normally conducted in radar meteorology, which deals with in-situ measurements and processing, PRD observation, hydrometeor classification and precipitation estimation through empirical relations, and PRD quality control (QC) and error characterization to determine observation error covariance (**R**). The direct and empirical methods have been used in observation-based studies, but the error covariance and prior information are usually ignored in the retrieval. As shown in the bottom row (blue) of

Fig. 5, DA-based retrieval/analysis is used by the NWP community. It involves selection and improvement of microphysical parameterization schemes and NWP models, as well as estimation of background error covariance (**B**). The stochastic nature of microphysics variety contributes significantly, which is ignored in most current model parameterizations, and should be included in future improvement (Finlon et al. 2016). As sketched in the middle row (brown), the forward operators, which result from MP modeling and EM modeling, and statistical retrieval algorithms are required for both observation-based and DA-based retrievals. Each of the retrievals needs to have compatible microphysics models such as DSD/PSD models and shape/density relations, electromagnetic modeling and calculations, etc., as well as statistical retrieval algorithms that can handle measurement error and background information and covariance, such as the one presented earlier in this section. To achieve best possible results, all the components need to be accurately determined and selected, and used in conjunction and cross-verified with each other in the statistical retrieval algorithms as depicted in the figure.

The statistical retrieval allows observation errors and prior information to be characterized and included, and it reduces to the direct retrieval when the observation errors are zero and the prior information is absent. The optimal usage of PRD is to find the balance between the measurements used and the prior information obtained for a specific application as well as errors in the measurements and information used and characterized. Since observation errors are included, the contribution from each measurement is automatically weighted differently based on its relative information compared with the error to produce optimal estimates as done in Mahale et al. (2019) for rain microphysics retrieval, without having to empirically changing one estimator to another as in Eqs. (1-3). To include flow-dependent background information in the retrieval, assimilating PRD into a NWP model is needed, which is discussed next.

5. An Example of DA Analysis with PRD

It is accepted that one of the main uses of radar observations, including PRD, is the assimilation of these observations into a convective scale NWP model. It was realized that the assimilation of reflectivity data helps reduce the spin-up problem (Sun and Crook 1997, 1998; Hu et al. 2006, b; Gao and Stensrud 2012), and a variety of real case studies have shown these data help improve QPF (Jung et al. 2012; Ge et al. 2013; Yussouf et al. 2013; Putnam et al. 2014; Wheatley et al. 2014; Yussouf et al. 2015; Snook et al. 2016; Putnam et al. 2017a). However, many issues still exist because although reflectivity has proven to be useful, reflectivity alone is not sufficient to analyze all the state variables included in advanced multi-moment microphysics schemes (e.g., hydrometeor mixing ratios and number concentrations). PRD may help resolve these issues with additional information about cloud microphysics and physics processes (Vivekanandan et al. 1999; Zhang et al. 2006; Ryzhkov et al. 2013a, b; Kumjian et al. 2014, Carlin et al. 2016).

Several studies have been conducted to initialize a NWP model with PRD (Wu et al. 2000; Jung et al. 2008b, Li et al. 2010; Posselt et al. 2015, Li et al. 2017). However, in those studies, polarimetric data were assimilated indirectly (e.g. Wu et al. 2000; Li et al. 2010), assimilated directly but in the observing system simulation experiment framework (Jung et al. 2008b), or using a single-moment microphysics scheme, which is unable to simulate size sorting (e.g., Posselt et al. 2015; Li et al. 2017). Recently, there was a more advanced PRD assimilation of Z_{DR} in addition to Z and $\mathrm{v_r}$ using an EnKF and a multi-moment microphysics scheme for the 20 May 2013 Newcastle – Moore tornadic supercell case, as shown in Fig. 6 (adapted from Putnam et al. 2019). The analysis with differential reflectivity increased the low-level Z_{DR} values with fewer, larger raindrops along the right forward flank of the supercell adjacent to the updraft in the vicinity of the observed Z_{DR} arc polarimetric signatures (Kumjian and Ryzhkov. 2008). The Z_{DR} values are lower downshear in the forward flank in the storm in the transition region between and the supercell immediately to its north. Additionally, the gradient of hail mean mass diameter was larger aloft and similar to hail patterns studied in Dawson et al. (2014, see their Fig. 17), which demonstrated the importance of size sorting of rimed-ice in producing a low-level Z_{DR} arc, further indicating the positive impact of PRD assimilation.

There is some evidence that PRD also contains information about storm dynamic and moisture information, which can also be used to initialize NWP models (Snyder et al. 2015; Carlin et al. 2017). Their studies indicate that Z_{DR} columns can be used to identify regions of positive temperature perturbations from latent heat release due to condensation and/or freezing. Realizing this, Carlin et al. (2017) explored the impact of assimilating real PRD through a modified cloud analysis (Hu et al. 2006). Preliminary findings suggested a marked improvement in analyzed updraft location. Quantitative analysis of Equitable Threat Score for Z also revealed improved performance when using the modified cloud analysis routine in several experiments with Z_{DR} column than that of the control experiment without using Z_{DR} column. The study is also very preliminary.

Many challenges still remain for PRD assimilation. The May 20 study demonstrated how the number of predicted moments in model microphysics schemes affect microphysical processes, where excessive size sorting known to occur with double moment microphysics schemes (Dawson et al. 2010; Morrison and Milbrandt 2011; Dawson et al. 2015) had a significant impact on the effectiveness of PRD data assimilation. Also, the forward operators and microphysics schemes must be improved, specifically in regard to the treatment of frozen hydrometeors as well as mixed-phase hydrometeors, which most microphysics schemes do not predict. Additionally, the choice of model resolution has a significant impact on the detailed polarimetric patterns and signatures that can be resolved. The 20 May study used a 500m grid spacing, and continuing advances in computer power can allow for even higher resolution experiments. PRD assimilation is still in its infancy, but the additional microphysical information provided can help to improve our understanding of current model deficiencies, both through assimilation experiments like those referenced here and direct simulation comparisons similar to Johnson et al. (2016) and Putnam et al. (2017b).

6. Polarimetric phased array radar technology

While radar polarimetry allows for more microphysical information measured, there is increasing need for faster data updates. To timely detect and predict fast evolving weather phenomena such as tornadoes and downbursts, it is desirable to rapidly acquire volumetric radar data at intervals of one or less minute, as opposed to the current five minutes with WSR-88D. For this reason, rapid scan phased array radar (PAR) with agile beam scanning capability was recently introduced to the weather community (Weber et al. 2007; Zrnic et al. 2007; Heinselman and Torres 2011). Simulation experiments demonstrate assimilation of PAR observations at 1-min intervals over a short 15-min period yields significantly better analyses and ensemble forecasts than those produced using WSR-88D observations (Yussouf and Stensrud 2010). Thus, there is the potential to increase the tornado warning lead time beyond the present 10 to 15 minutes.

Another motivation to introduce PAR technology is the MPAR (multifunction PAR) and SENSR (Spectrum Efficient National Surveillance Radar) initiatives to use one radar network to replace the four radar networks in the United States of (1) National Weather Surveillance Radar (WSR-88D), (2) Terminal Doppler Weather Radar (TDWR) for detecting low altitude wind shear; (3) Airport Surveillance Radar (ASR) for air traffic control; and (4) Air Route Surveillance Radar (ARSR) for the long range air surveillance (Stailey and Hondl 2016) Since all the radars share the same principle in detecting EM wave scattering from targeted media, it is efficient to use a single radar network to service all the missions. To do so, PAR fast scanning capability is needed. Because WSR-88D has the dual-polarization capability, future PAR for weather observation needs to have the polarimetry capability as well, i.e., polarimetric PAR (PPAR).

PPARs have been developed for satellite and military applications, but with limited scanning angles (Jordan et al. 1995). For ground-based weather measurements, it is challenging to develop the PPAR technology because of the requirements of wide angle scan and high accuracy for polarimetric measurements (Z_{DR} error <0.2 dB, ρ_{hv} error < 0.01, ϕ_{DP} error < 3 degrees). Nevertheless, the challenges and difficulty have not stopped the enthusiasm and efforts of the community to formulate PPAR theory and design and develop PPAR systems for future weather observation and multi-missions (Zhang et al. 2009).

Several PPAR configurations and systems have been attempted, including 1) A planar PPAR (PPPAR) with one-dimension (1D) electronic scan capability antenna mounted on a mechanically steerable platform, e.g., the CASA phase tilted radar (Hopf et al. 2009); 2) a two-dimension (2D) electronic scan PPPAR, like the NSSL ten-panel demonstrator (Shown in Fig. 7a); and 3) a cylindrical PPAR (CPPAR) demonstrator (Fig. 7b) being developed jointly between OU and NSSL (Zhang et al. 2011, Karimkashi and Zhang 2015, Fulton et al. 2017). Each of these PPARs can cover the volume more quickly than a mechanically steered beam due to beam agility, versatility in beam shape, speed of changing pointing direction, and/or four radars operating simultaneously. Although a considerable amount of effort has been put into developing PPPAR, no satisfactory polarimetric weather measurements have appeared in the literature. Initial testing results of CPPAR are promising, but still preliminary, as documented in a technical report by Byrd et al. (2017). A set of CPPAR measurements compared to the WSR-88D KTLX measurements are duplicated in Fig. 8. Since the CPPAR has a lower power (<2kW) and smaller aperture (<2 m in diameter), the lower sensitivity is expected, yielding less data coverage than KTLX. It is promising to see the similar features in Z_{DR}, and Z_H appear in both with the CPPAR and the KTLX measurements. However, ρ_{hv} is low and not up to expectations due to the antenna beam mismatch and other system instability issues. The beam mismatch is being addressed by a redesign of the frequency-scan dual-polarization column antennas (Saeidi-Manesh et al. 2017). The CPPAR electronics is also being redesigned and rebuilt to have a stable system so that many CPPAR related issues such as commutating scan, sector-to-sector isolation, surface wave effects, and accurate weather measurements can be addressed/demonstrated.

Achieving comparable or better accuracy in the polarimetric measurements than on the WSR-88D is challenging. It is most difficult for the 2D PPPAR with multiple faces because the polarization basis for a planar array changes and becomes coupled for a pair of radiators and can cause bias/error that are much larger than the maximum allowed error. The 1D PPPAR with a mechanical scan in azimuth is feasible because of its relative simplicity in maintaining polarization purity and azimuthal scan invariant beam characteristics, but needs to be demonstrated. CPPAR is an alternate solution for accurate polarimetric PAR measurements, which scans in the azimuth by commutating its beam position to achieve the high performance beam characteristics like the 1D PPPAR. Further research and development are needed to realize this potential.

7. Conclusions and discussions

We have reviewed the status of weather radar polarimetry, identified the limitations and challenges of using polarimetric radar data, and proposed possible solutions and unification of approaches. We have also discussed challenges and explored the research and development for future weather observation using phased array radar polarimetry technology. The main objective of this paper is to bring up these issues and generate consensus for finding a path forward.

Collaborative efforts between the radar engineering/meteorology/hydrology and NWP communities are necessary to develop feasible new technology and to more efficiently utilize the existing PRD to better monitor, quantify, and forecast weather. Although radar data are becoming a dominant factor and PRD are useful in short-term forecasting and warning, PRD alone do not guarantee accurate short-term forecasts. Other measurements such as satellite remote sensing data and cellular communication signals (Overeem et al. 2013) can be included to enhance the information content. On the other hand, NWP model microphysics parameterizations need to be improved so that the utilization of PRD can make substantial contributions to improving the accuracy of weather forecasts. Direct comparisons between NWP simulated PRD and polarimetric radar measurements open a feasible way to reveal model deficiencies and to improve model physics and microphysics parameterizations. Assimilation of PRD and data from other in situ and remote sensors such as satellites into high-resolution convective scale NWP models, together with judicious interpretation by meteorologists, is required to produce further improvements of QPE, QPF, and severe weather warning lead time.

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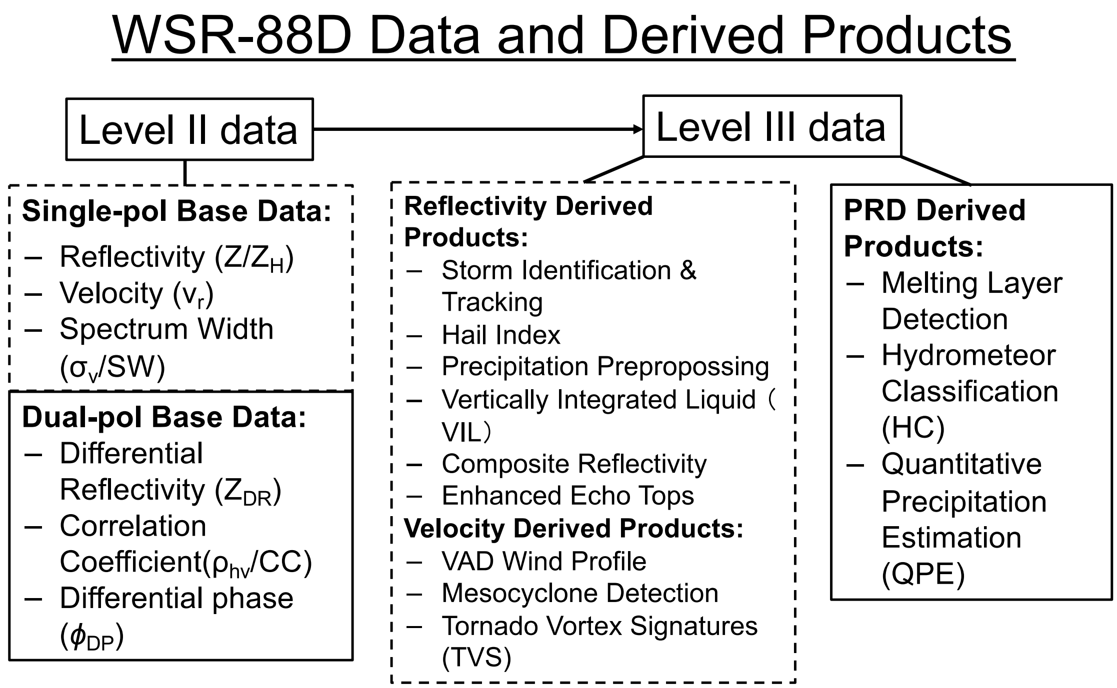

Figure 1. WSR-88D data and their derived products after the dual-polarization upgrade. The data and products in the dashed boxes are for single polarization.

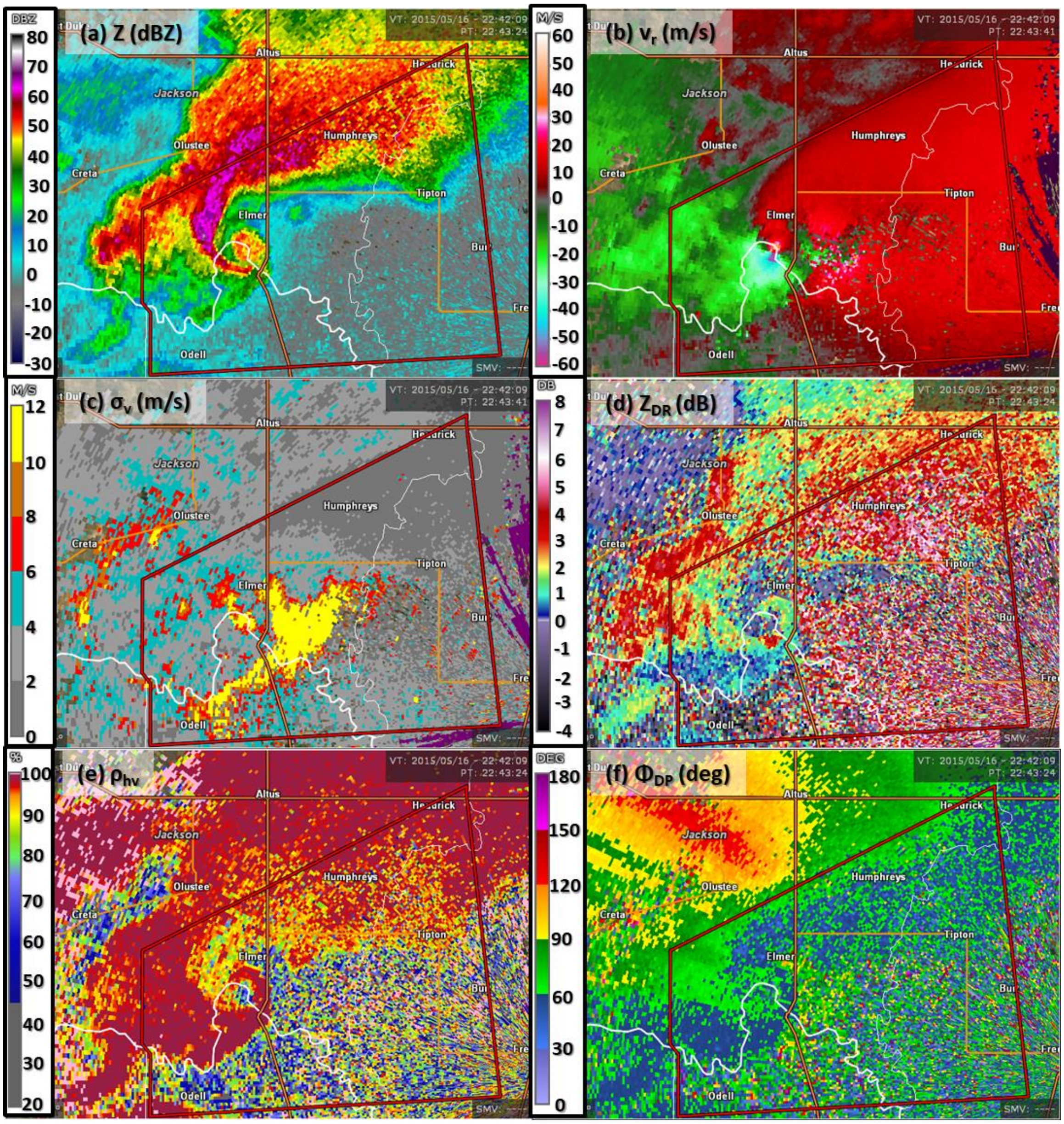

Figure 2. Polarimetric variables at S-band radar KFDR for a supercell observed in southwest Oklahoma, US at 22:43 UTC on 16 May 2015. a) Reflectivity (Z); b) Radial velocity (v_r); c) Spectrum width (σ_v); d) Differential reflectivity (Z_{DR}); (e) Copolar correlation coefficient (ρ_{hv}); and f) Differential phase (Φ_{DP}). The radar (not shown) is located southeast of the supercell. The white lines are county or state borders, and the orange and brown lines are roadways. Plotted using GR2Analyst software.

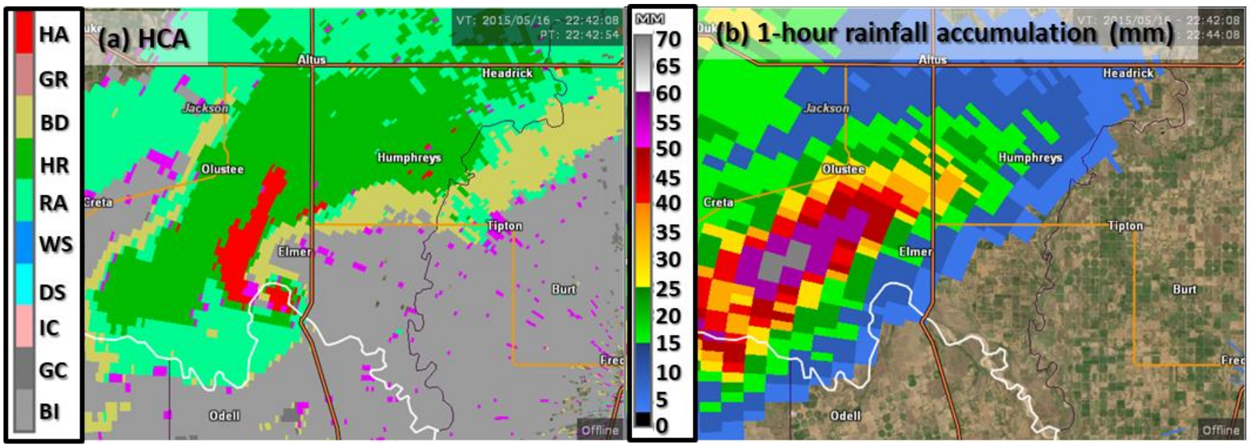

Figure 3. a) Hydrometeor Classification product generated from National Severe Storm Laboratory (NSSL) hydrometeor classification algorithm (HCA) at 22:43 UTC at 16 May 2015, and b) Dual-polarization radar estimated 1-hour rainfall accumulation. The radar is located southeast of the supercell (not shown). The white lines are county or state borders, and the orange and brown lines are roadways. Plotted using GR3Analyst software.

*Echo class notations are: Biological scatterers (BI); Ground clutter (GC); Ice crystals (IC); Dry snow (DS); Wet snow (WS); Light/Moderate rain (RA); Heavy rain (HR); Big drops (BD); Graupel (GR); and Rain and hail (HA). Purple areas represent unknown classification

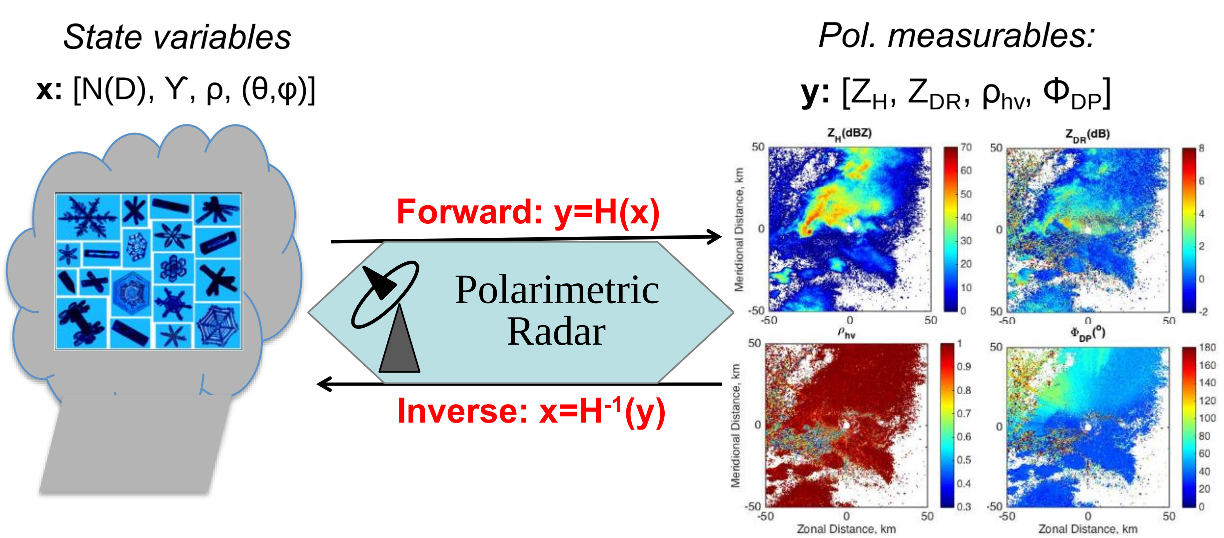

Figure 4. Sketch of the weather physics state variables of DSD (N(D)), axis ratio (γ), density (ρ), and orientation angles (θ,φ) versus polarimetric radar measurables.

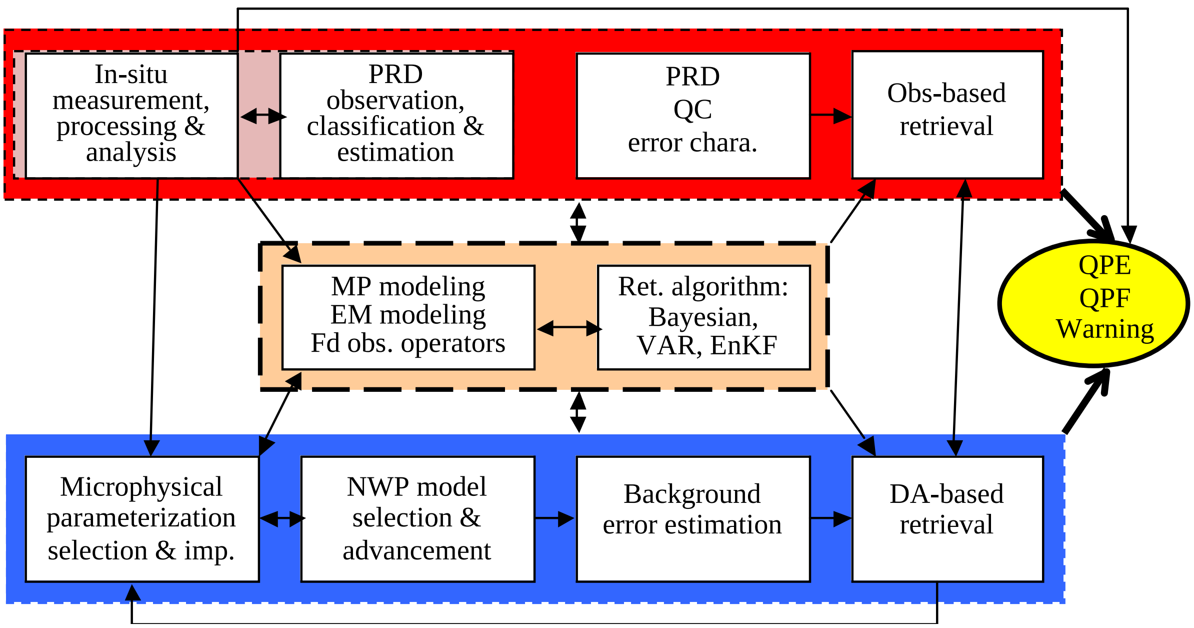

Figure 5: Sketch of different components for optimal utilization of PRD and connections between observation-based retrieval that can be used in radar meteorology and DA based retrieval used in NWP.

*Acronyms are: Polarimetric radar data (PRD); Quality control (QC); Microphysics (MP); Electromagnetic (EM); Forward observation operators (Fd obs. operators); Variational (VAR); Ensemble Kalman filter (EnKF); Quantitative precipitation estimation (QPE); Quantitative precipitation forecast (QPF), Numerical weather prediction (NWP); Data assimilation (DA).

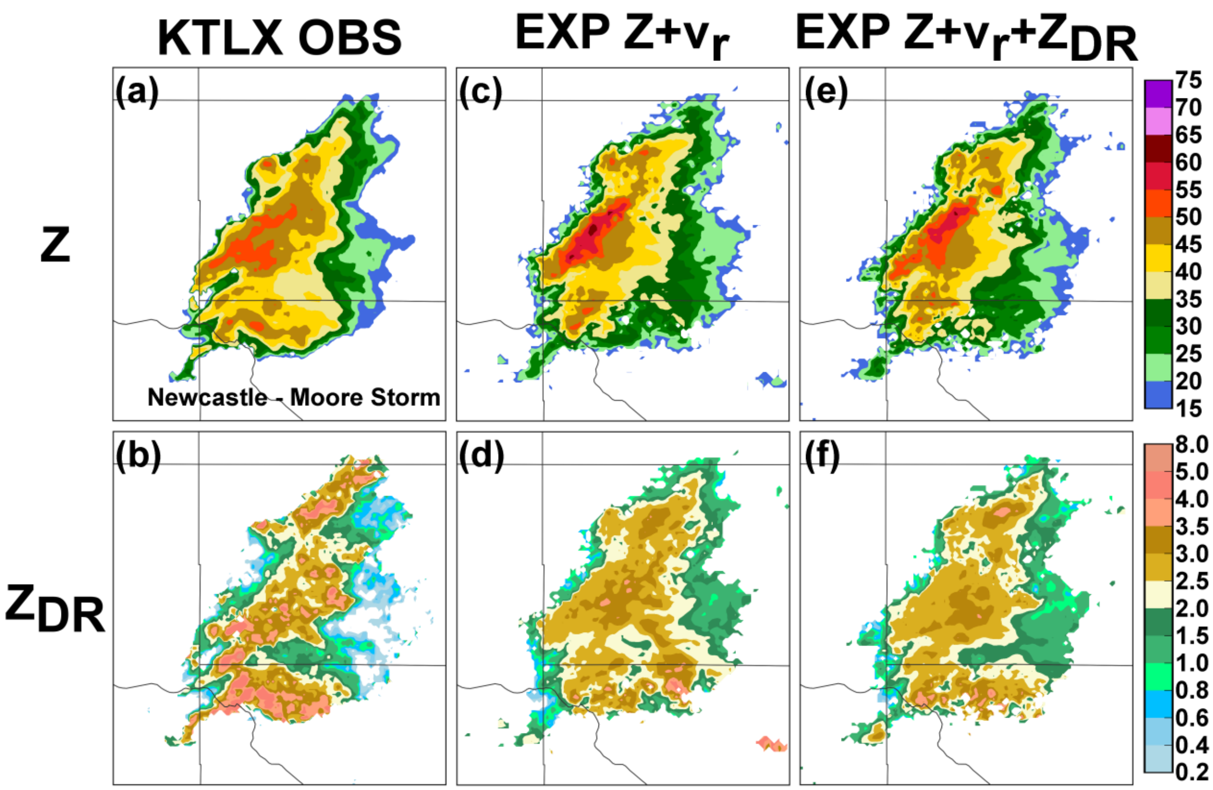

Figure 6: Comparison between polarimetric radar observation and DA analysis: (a) Observed reflectivity and (b) differential reflectivity from KTLX of the Newcastle-Moore tornadic supercell at 1938 UTC on 20 May 2013, with storm location noted in (a); (c) analyzed reflectivity and (d) differential reflectivity at 1940 UTC from an EnKF experiment that assimilated only reflectivity and radial velocity (EXP $Z + v_r$) as well as (e) analyzed reflectivity and (f) differential reflectivity from an EnKF experiment that assimilated differential reflectivity in addition to reflectivity and radial velocity (EXP Z + v_r + Z_{DR}).

(a) NSSL TPD

(b) OU-NSSL CPPAR

Figure 7: Pictures of polarimetric phased array radars that are under development. (a) NSSL 2D ten-panel planar PPAR (PPPAR) demonstrator (TPD), and (b) OU-NSSL cylindrical PPAR (CPPAR).

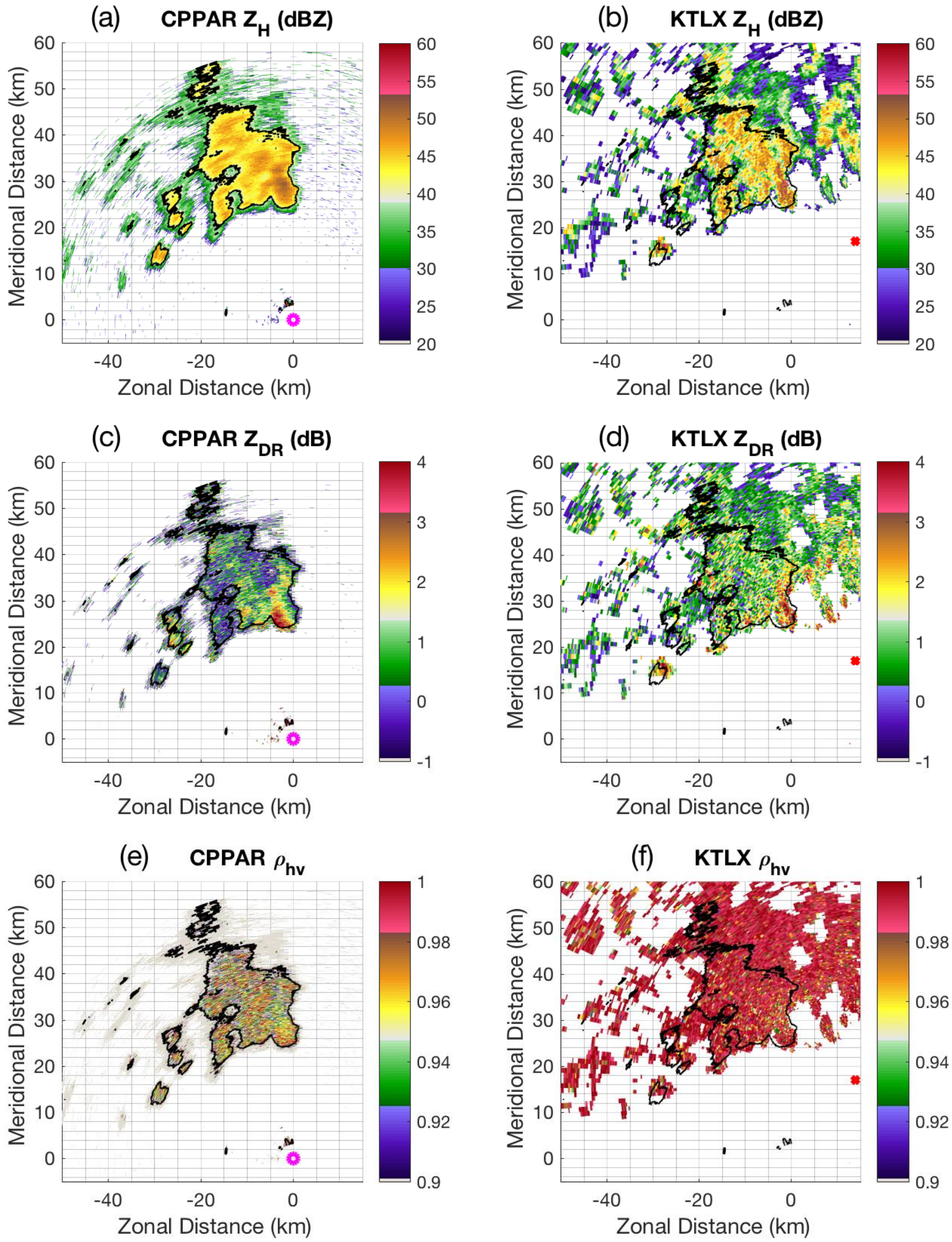

Figure 8: Comparison of polarimetric weather measurements between the CPPAR demonstrator located at the pink circle "o" and WSR-88D KTLX radar at the red asterisk "*". The data were collected on September 10, 2016 at 04:13:47 UTC for CPPAR and 04:13:50 UTC for KTLX. (Data points with Z < 20dBZ were excluded. There are echoes in KTLX data, but not in CPPAR data because CPPAR has a much lower sensitivity due to its smaller antenna and lower transmitted power).