Recent modifications to a new surface-based polarimetric Hydrometeor Classification Algorithm for the WSR-88D network

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1 Introduction

Precipitation types common to transitional winter events, such as freezing rain and sleet, typically result from thermodynamic and microphysical processes that occur in very shallow layers above the surface. Because of this, it is not uncommon for the lowest elevation scan from the radar to overshoot transitional winter weather precipitation types at ranges as close as even a few tens of km from the radar. The problem, therefore, is not always one of correctly identifying the precipitation type in the radar beam, but rather that of being able to *diagnose* what is reaching the surface below it, a problem that is compounded at even more distant ranges where the precipitation type sampled by the radar is even less representative of what is reaching the surface. We have therefore adopted a classification approach where thermodynamic output from numerical models is used to create a “background classification” that is then later modified, when warranted, by radar observations.

In this paper, we describe recent modifications to a new, surface-based polarimetric Hydrometeor Classification Algorithm (HCA) that uses thermodynamic output from the High Resolution Rapid Refresh (HRRR) model. An earlier version of this HCA has been discussed by Schuur et al. (2012) and Schuur et al. (2013). Recent modifications include efforts to take what was initially designed to strictly be a surface-based winter weather HCA and modifying it to be an “all-season” precipitation classification algorithm.

2 Background Classification

As noted, because the dominant precipitation type observed at the surface in winter storms often results from thermodynamic and precipitation processes that occur well below the radar’s beam, an accurate background classification of precipitation type is a fundamental component in the development of our algorithm. Schuur et al. (2012) reported on initial work to develop a background classification for this work. Using T_w profiles from the 13 km Rapid Refresh model, they devised a scheme whereby the number of T_w layers found in the vertical profile above each surface location were used to decide whether the “background” precipitation type in transitional winter weather events was rain, snow, freezing rain, ice pellets, or a freezing rain/ice pellets mix. The scheme did not consider the depth of each layer. Reeves et al. (2014) have since conducted a much more thorough investigation in which the model-based background classification scheme of Schuur et al. (2012) was compared to the results of other model-based classification techniques, including those of Ramer (1993), Baldwin et al. (1994), and Bourgouin (2000). More recently, work at NSSL has also explored the potential of creating a background classification using a simple one-dimensional model with spectral (bin) microphysics that explicitly treats the processes of melting / refreezing by taking the initial size distribution and density of dry snowflakes into account. It describes the evolution of mass water fraction and density of hydrometeors as they fall to the ground separately in 80 size bins. Ultimately, testing and a comparison of all background classification scheme results to surface observations from the Meteorological Phenomena Identification Near the Ground (mPING, Elmore et al. 2014) project will be used to identify the optimal background classification for our new surface-based HCA.

3 Algorithm Description

Figure 1 presents a schematic that summarizes the classification procedures of the new HCA. The first step of the process is to run the fuzzy-logic-based classification that is currently deployed on the WSR-88D network (Park et al. 2009). The algorithm then allows fuzzy-logic-based classifications from the lowest elevation sweep to be projected to the surface as snow or ice crystals for cold season events where the entire atmospheric column above a location has $T < -5$ºC and as rain, big drops, or hail for warm season events where the surface temperature at a location has a $T > 5$ºC. For intermediate conditions typical of transitional winter weather events, the algorithm uses vertical profiles of model wet bulb temperature profiles to provide a background precipitation classification type. Polarimetric radar observations are then used to either confirm or reject the background classification. For example, if a radar bright band (suggesting an elevated warm layer) is observed immediately above a background classification of dry snow (suggesting the absence of an elevated warm layer in the model output), the background classification is found to be inconsistent with observations and is modified according to a set of empirical rules. The polarimetric radar data are also used to provide further refinement of precipitation type categories when the observations are found to be consistent with the background classification.

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Since the radar-based modification of the underlying background classification is strongly dependent on detection of the presence/absence of an elevated warm layer, a new hybrid technique to detect the melting layer (discussed in detail in a separate paper) is also introduced. With this new melting layer (ML) detection technique, Gaussian weighting functions that depend on range from the radar, horizontal gradients in model wet-bulb temperatures, and time from the most recent model analyses are used to create a "blended" map of ML detections by combining contributions from high elevation radar scans (accurate ML detection, but limited to short ranges from the radar), low elevation radar scans (ML detection available to more distant ranges, but often contaminated by effects of beam broadening), and model suggested ML locations. This "hybrid" ML detection algorithm is described in detail by Schuur et al. (2014, this conference). The final stage of the classification process is to run the hail-sizing algorithm of Ortega et al. (2013) and applying it to all locations where the fuzzy-logic HCA identified hail.

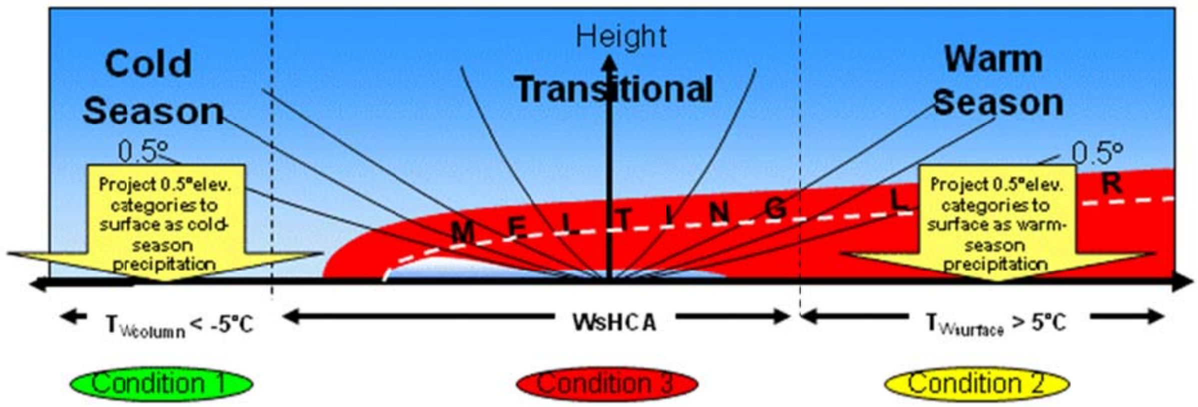

Figure 1: Schematic showing the classification process of the new surface-based HCA. For cold-season conditions where T_w through the entire atmospheric column is < -5ºC, the fuzzy-logic-based precipitation type categories from the 0.5º elevation scan are projected to the ground as either ice crystals or snow (condition 1). For warm-season conditions where T_w at the surface is > 5ºC, the fuzzy-logic-based precipitation type categories from the 0.5º elevation scan are projected to the ground as either rain, big drops, or hail (condition 2). For intermediate conditions typical of transitional winter weather events, the full model-based background classification is determined and later modified, when warranted, by the polarimetric radar observations (condition 3).

4 Example

We now present examples of the algorithm output from several different events. As noted earlier, we are still conducting comprehensive testing to determine the optimal background classification. For that reason, the "NSSL" background classification of Schuur et al. (2012) is used for the examples provided. Since the "hybrid" ML detection algorithm (Schuur et al. (2014) is similarly in a stage of development and testing, the algorithm results shown here rely upon ML detection using the procedures described by Schuur et al. (2012). That is, the radar-based modification is conducted when the vertical column above any surface location contains a radar gate with a thresholds of $Z \geq 25$ dBZ, $Z_{DR} \geq 0.8$, $\rho_{HV} \leq 0.97$, and SNR > 5 dB.

The first example we present is an event from the Pittsburgh, PA (KPBZ) on 21 January 2012. This event is discussed in more detail by Schuur et al. (2013). On this day, and extensive region of warm air advanced towards KPBZ from the south, eventually extending northward to a point ~10 km to the south of the radar. Surface air underneath the air was predominantly subfreezing with a small region on the far southern edge of the radar domain with a surface T_w of >0C. This event provides an excellent dataset to illustrate two features: 1) the limitations of the current fuzzy-logic based HCA (and benefits provided by the new surface-based algorithm) for conditions where an elevated layer of warm air covers only a portion of the radar domain, and 2) an example of an event where the surface-based algorithm that is proposed in this paper meets all 3 conditions (cold-season, warm-season, and transitional winter weather) illustrated in Figure 1.

Figure 2 presents the KPBZ results of the fuzzy-logic-based classification for this event and the results from the new surface-based algorithm at 0802 UTC on 21 January 2012. The differences between the 2 classification schemes is dramatic, with the new surface-based HCA providing a much more realistic transitional winter weather classification over the southern part of the radar domain where both the HRRR model and KPBZ Z_{DR} and ρ_{HV} fields indicated the presence of an extensive region of elevated ML. The reason the fuzzy-logic-based scheme performed so poorly for this event (and the new surface-based algorithm performed better) is that the elevated ML always remained to the south of KPBZ. As a result, the fuzzy-logic-based ML detection algorithm (which relies on ML detections at elevation angles between 4 and 10º) never identified a

ML layer in the near vicinity to the radar and thereby erroneously assumed that the entire radar domain was located within a deep column of cold air. As a result, precipitation classified over the entire domain was classified as snow and ice crystals (with small pockets of graupel in region of high Z). On the other hand, the surface-based algorithm provided classifications to the south of the radar that consisted of extensive regions rain, freezing rain, ice pellets, and a freezing rain / ice pellet mix. This classification is far more consistent with both the HRRR model output and radar observations to the south of the radar.

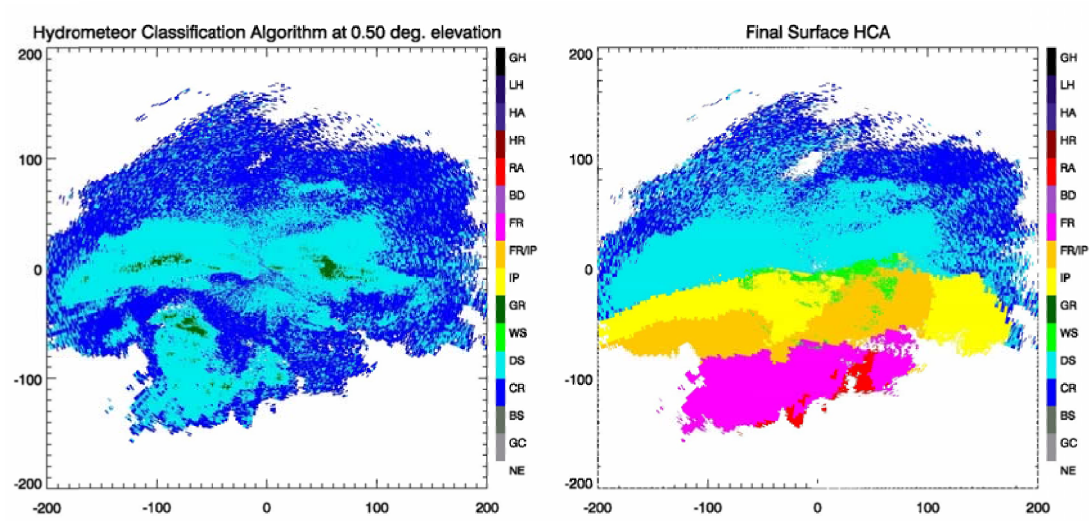

Figure 2: Precipitation type classification centered on the KPBZ radar from the (left panel) fuzzy-logic-based HCA at 0.5º elevation, and (right panel) WsHCA at 08 UTC on 21 January 2012. Precipitation type categories are no echo (NE), ground clutter (GC), biological scatterers (BS), crystals (CR), dry snow (DS), wet snow (WS), graupel (GR), ice pellets (IP), freezing rain/ice pellets (FR/IP), freezing rain (FR), big drops (BD), rain (RA), heavy rain (HR), hail (HA), large hail (LH), and giant hail (GH).

Figure 3 shows the same grid as in Figure 2, but illustrating the regions over the radar domain at which each of the 3 conditions depicted in Figure 1 were met. As can be seen, all 3 conditions (cold-season with Tw < -5ºC over the entire column, warm-season with Tw at the surface > 5ºC, and transitional winter weather) were met at this time over some portion of the radar domain, with the transition between the conditions providing a seamless transition.

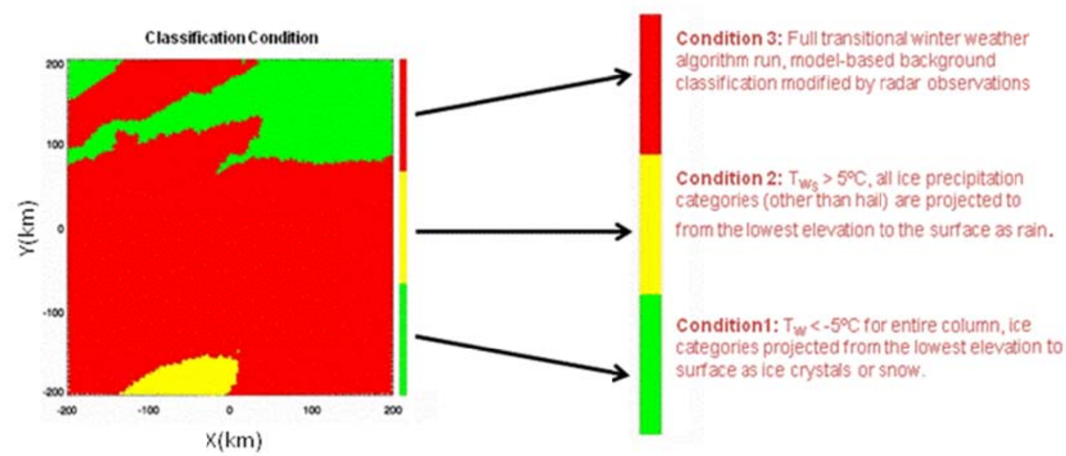

Figure 3: Classification condition followed in the decision tree in Fig. 2 centered on the KPBZ radar at 08 UTC on 21 January 2012. Condition 1 (green) shows locations where snow and ice crystals are projected to the surface for "cold season" conditions when the entire atmospheric column above that location has T < -5ºC, condition 2 (yellow) shows locations where all ice categories are projected to the surface as either rain, big drops, or hail for "warm season" conditions when the surface temperature at a location is > 5ºC, and condition 3 (red) shows locations where intermediate conditions typical of transitional winter weather are met and the full WsHCA is run to determine surface precipitation type.

Shortly after the above event, our group developed and released an iPhone and Adroid app (referred to as mPING, Elmore et al. 2014) that provides the general public an opportunity to participate in our research by providing time-stamped, geo-tagged observations of precipitation type. In the 2 winter seasons since the apps release, we have collected over 600,000 precipitation type observations that have greatly aided our research. We now present results from 2 events with mPING surface observations overlaid.

On 8 February 2013, the Northeastern U.S. experienced a historic winter storm that resulted in snow accumulations up to 100 cm in depth. Figure 4, at 1504 UTC on 8 February 2013, shows Z, Z_{DR}, and ρ_{HV} from the KOKX (New York City National Weather Service Office, located on Long Island at Upton, NY) WSR-88D radar. From an examination of the Z_{DR} and ρ_{HV} fields, it is clear that a widespread region layer of warm air to the north shore of Long Island (with a few pockets of radar-indicated ML extending over Long Island Sound) at this time. Precipitation type reports overlaid on top of the Z, Z_{DR}, ρ_{HV} and surface-based HCA fields at this time show good overall agreement, with rain over much of long island and snow to the north. An analysis of this same event at a later time by Schuur et al. (2014, this conference) demonstrated that the transition region slowly progressed to the south over the next several hours, eventually resulting in snow and ice pellet observations over much of Long Island.

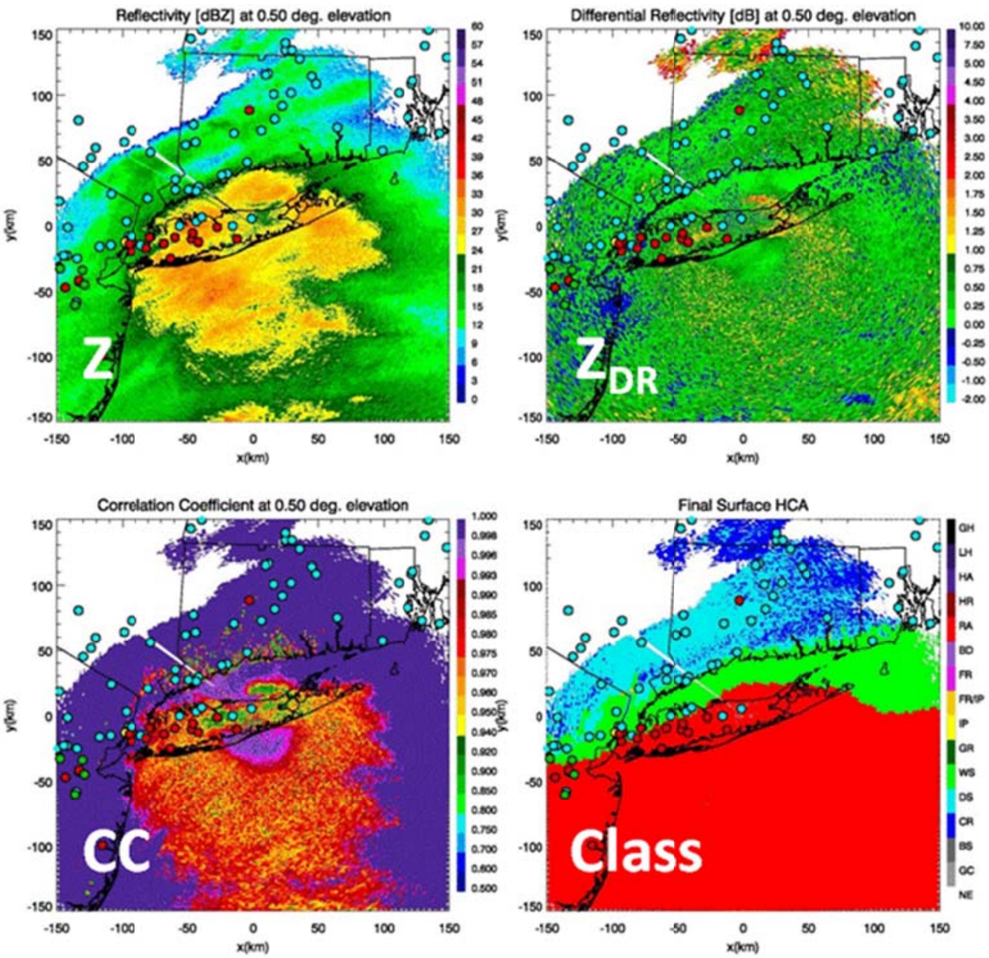

Figure 4: Radar reflectivity (Z), Differential reflectivity (ZDR), Correlation coefficient, and surface HCA for the KOKX (Upton, NY) radar at 1504 UTC on 8 February 2013. Overlaid mPING surface observations follow the same color scheme as that of the surface HCA.

The fuzzy-logic-based HCA results at this time are shown, and compared with the surface based HCA results, in Figure 5. Unlike for the KPBZ event where no ML was observed above the radar site, the fuzzy-logic-based algorithm identified a ML for this event. However, since the algorithm then assumes that the ML detected in regions close to the radar can then be geometrically projected outward along each azimuth, the resultant fuzzy-logic HCA (mapped to the conical surface) showed a broad "bull's eye" of rain that was centered on the radar site and extended well into Connecticut to the north. It is clear that the surface HCA provides much better agreement with both the radar and mPING observations.

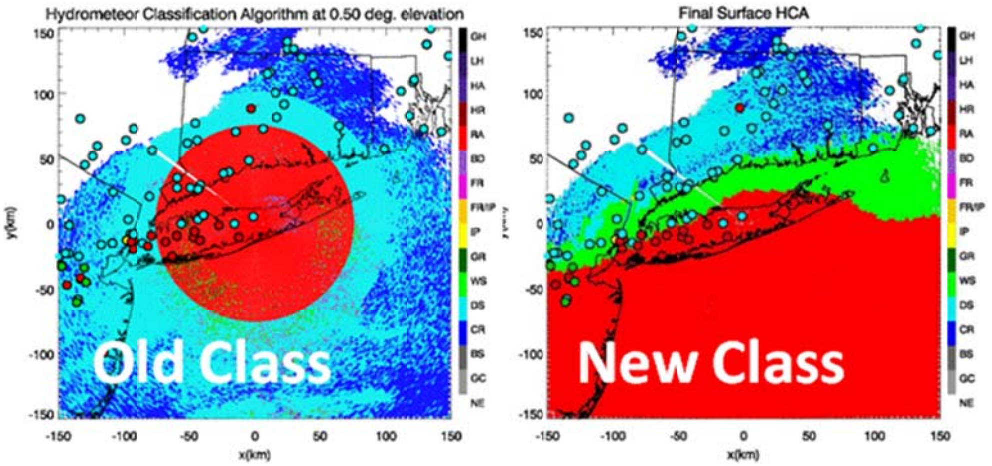

Figure 5: Fuzzy-logic-based HCA and surface HCA for the KOKX (Upton, NY) radar at 1504 UTC on 8 February 2013. Overlaid mPING surface observations follow the same color scheme as that of the surface HCA.

Finally, we present Figure 6, which shows Z, Z_{DR}, and ρ_{HV} from the KLWX (Washington, DC National Weather Service Office, located in Sterling, VA) WSR-88D radar at 1205 UTC on 13 February 2014. As with the above example, this shows a transitional wither weather event over a major metropolitan area, with the surface HCA showing broad regions of freezing rain / ice pellet mix and wet snow over the DC area. According to Reeves et al. (2014), the NSSL background classification appears to over predict the freezing rain / ice pellet category. This appears to be apparent when compared to the mPING observations as very little freezing rain or ice pellets were reported. There was, however, very good consistency with the wet snow category with numerous mPING reports agreeing with the radar-based modification to the background classification, indicating wet snow. As noted earlier, we expect improvement in the background classification after we complete our comparison and testing of various schemes. Ultimately, the “NSSL” classification of Schuur et al. (2012) that was presented with these results will be replaced with the “optimal” background classification as determined from our testing.

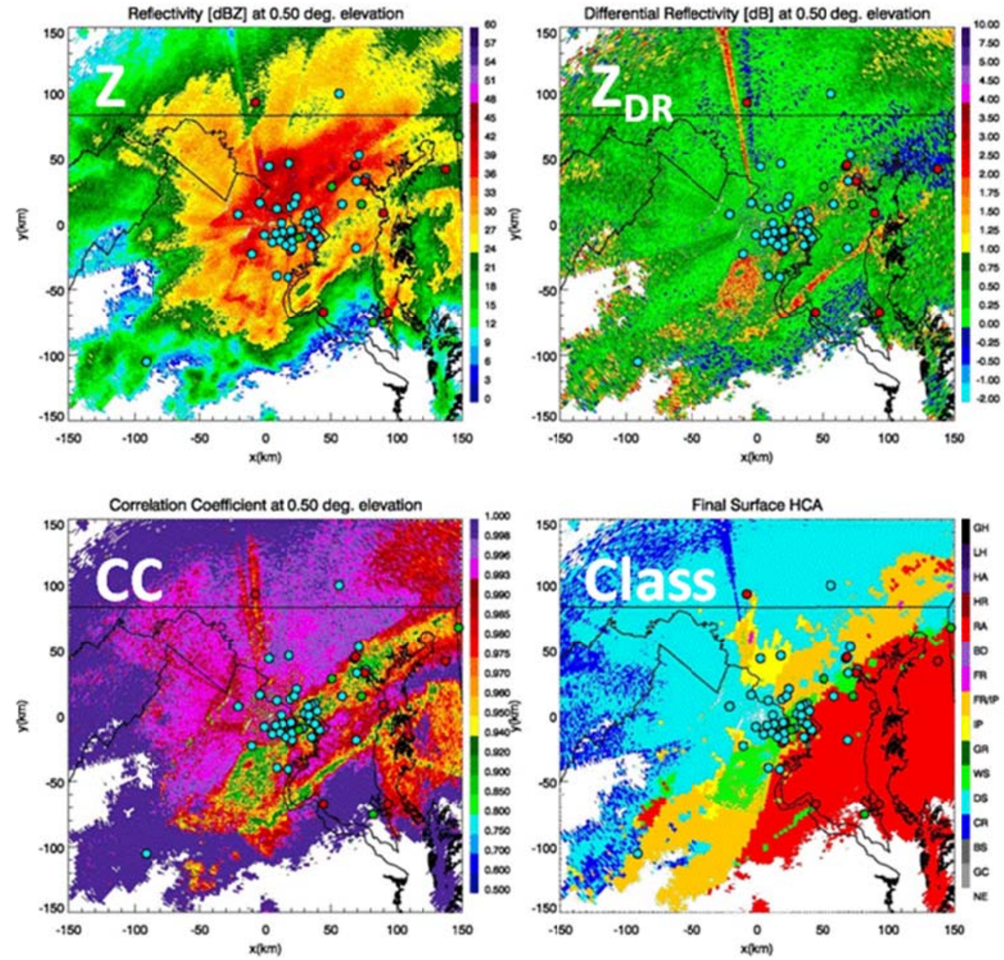

Figure 6: Radar reflectivity (Z), Differential reflectivity (ZDR), Correlation coefficient, and surface HCA for the KLWX (Sterling, VA) radar at 1205 UTC on 13 February 2014. Overlaid mPING surface observations follow the same color scheme as that of the surface HCA.

Summary and Future Work

In this paper, we describe recent modifications to a new, surface-based polarimetric HCA that uses thermodynamic output from the High Resolution Rapid Refresh model. The algorithm allows fuzzy-logic-based classifications from the lowest elevation sweep to be projected to the surface as snow or ice crystals for cold season events where the entire atmospheric column above a location has T < -5ºC and as rain, big drops, or hail for warm season events where the surface temperature at a location has a T > 5ºC. For intermediate conditions typical of transitional winter weather events, the algorithm uses vertical profiles of model wet bulb temperature profiles to provide a background precipitation classification type. Polarimetric radar observations are then used to either confirm or reject the background classification. Since the radar-based modification of the underlying background classification is strongly dependent on detection of the presence/absence of an elevated warm layer, a new hybrid technique to detect the melting layer (discussed in detail in a separate paper) is also introduced. With this new melting layer (ML) detection technique, Gaussian weighting functions that depend on range from the radar, horizontal gradients in model wet-bulb temperatures, and time from the most recent model analyses are used to create a “blended” map of ML detections by combining contributions from high elevation radar scans (accurate ML detection, but limited to short ranges from the radar), low elevation radar scans (ML detection available to more distant ranges, but often contaminated by effects of beam broadening), and model suggested ML locations.

While new elements have been introduced to the algorithm, such as the projection of fuzzy-logic algorithm results to the surface for true cold- and warm-season conditions, the results presented in this paper still rely upon the “NSSL” background classification and threshold based ML detection detailed by Schuur et al. (2012). As outlined by Reeves et al. (2014) and Schuur et al. (2014), the background classification and ML detection algorithm are still being developed and tested. When these “new and improved” components of the algorithm are introduced into the algorithm in the coming year, we will enter a period of extensive testing that will fully utilize both polarimetric WSR-88D radar data and mPING observations across the entire continental U.S.

Acknowledgement

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