Polarimetric Variability of Classic Supercell Storms as a Function of Environment

MATTHEW S. VAN DEN BROEKE
Department of Earth and Atmospheric Sciences, University of Nebraska–Lincoln, Lincoln, Nebraska

(Manuscript received 2 December 2015, in final form 2 June 2016)

ABSTRACT

Classic supercell storms occur in a generally well understood environment characterized by instability and vertical wind shear. Within this broadly favorable environment, large day-to-day variability in environmental parameters may lead to widely varying radar presentation of storms. Of interest here is whether specific storm structures exhibit repeatable characteristics in similar environments and whether radar presentation can be predicted with knowledge of environmental characteristics. Specifically, this paper focuses on (i) updraft characteristics inferred using differential reflectivity $Z_{\text{DR}}$ columns, (ii) characteristics of storm-relative inflow inferred using $Z_{\text{DR}}$ arcs, and (iii) areal extent and cyclicality of polarimetrically inferred hailfall at low levels. Variability of these radar features is compared among storms in similar environments and among a larger subset of storms across highly varying environments. The similarity of storms in similar and different environments is quantified, and tornadic and nontornadic storms are compared. Associations between inferred updraft, inflow, and hailfall characteristics and environmental variables are discussed. Storm features generally exhibit greater similarity among storms in similar environments than across environments, although exceptions occur. The results indicate that many radar features of classic supercells may be useful to learn about microphysical variability across environments.

1. Introduction

Polarimetric weather radar observations can be used to infer mean scatterer properties such as shape, phase, size, and orientation. Thus, these observations remain our best source of data for microphysical studies on large spatial and temporal scales. Storm-scale processes and associated microphysics are of great interest in supercell storms, since they produce a large proportion of high-impact severe weather in the United States. In particular, how these processes and their microphysical manifestations vary as a function of environmental characteristics can be studied using polarimetric radar observations. Differing environmental distributions of wind and moisture, and especially the vertical profile of these variables, may lead to dissimilar storm outcomes (e.g., Beatty et al. 2008; Van Den Broeke 2014; Davenport and Parker 2015). These dissimilarities should be reflected in the radar presentation.

Classic supercell storms (e.g., Moller et al. 1994) that generally remained isolated are examined in this study. These storms have well-reported and relatively well-understood polarimetric radar signatures (e.g., Kumjian and Ryzhkov 2008; Romine et al. 2008; Van Den Broeke et al. 2008; Kumjian et al. 2010), facilitating comparison across environments. Polarimetric variables used to assess microphysics in these storms include (e.g., Bringi and Chandrasekar 2001) reflectivity factor at horizontal polarization $Z_{\text{HH}}$, differential reflectivity $Z_{\text{DR}}$, copolar cross-correlation coefficient $\rho_{hv}$, and specific differential phase $K_{\text{DP}}$. Some radar features of supercell storms are especially ubiquitous and useful to infer storm-scale evolution. They will be the focus in this paper, and include the following:

1) Differential reflectivity columns (e.g., Herzegh and Jameson 1992; Brandes et al. 1995; Kumjian et al. 2010) represent a region of liquid drops lofted above the ambient 0°C level within updraft and are apparent as regions with relatively high $Z_{\text{DR}}$ values when compared with their surroundings. Updraft characteristics can be inferred using the $Z_{\text{DR}}$ column—maximum altitude and its variations may indicate changes in updraft strength, and areal extent of the $Z_{\text{DR}}$ column is a measure of updraft broadness. Broader updrafts may be generally stronger (e.g., Kumjian et al. 2010), though this association may be weak (e.g., Anderson et al. 2005). An algorithm is available to detect $Z_{\text{DR}}$
columns in Weather Surveillance Radar-1988 Doppler (WSR-88D) data (Snyder et al. 2015).

2) Differential reflectivity arcs (e.g., Kumjian and Ryzhkov 2008, 2009, 2012; Dawson et al. 2014, 2015) are regions of locally enhanced $Z_{DR}$ values along a supercell’s forward flank where inflow acts to sort raindrops and melting hail. They are related to the mean storm-relative wind over the sorting-layer depth. Changes in their orientation and intensity have been used to indicate tornado potential (Palmer et al. 2011; Crowe et al. 2012).

3) Areas of polarimetrically inferred hailfall at low levels (e.g., Balakrishnan and Zrnić 1990; Zrnić et al. 1993; Kumjian and Ryzhkov 2008; Van Den Broeke et al. 2008) may be prominent in classic supercell storms, but often exhibit substantial cyclical, particularly in tornadic storms (Kumjian and Ryzhkov 2008). Hail fallout regions may be influenced by the vertical wind and moisture profiles (Van Den Broeke 2014), possibly influencing storm-scale evolution.

These polarimetric features of classic supercell storms offer a way to test the hypothesis that storms in similar environments (e.g., characterized by similar instability and/or shear and moisture parameters) should exhibit more similarity than storms across environments with different instability and/or shear and moisture parameters. The degree of similarity or dissimilarity between storms can be quantified given time series of quantified radar metrics. While it is anecdotally known that storms often appear similar in shape and behavior on a given day, quantification of these radar metrics, and assessment of the degree of overlap in characteristics of storms across diverse environments, is necessary to determine the plausibility of using polarimetric radar observations to assess the influence of changing environments on storm characteristics. As a first step in this direction, this study aims to

1) quantify the similarity or dissimilarity in $Z_{DR}$ column, $Z_{DR}$ arc, and hailfall characteristics of classic supercell storms in similar environments;
2) describe the differences in these characteristics across a range of environments characterized by varying shear, instability, and moisture; and
3) relate $Z_{DR}$ column, $Z_{DR}$ arc, and hailfall characteristics to environmental variables.

This work may aid operational forecasters as they interpret radar features of classic supercell storms, and establishes preliminary methods and results in the area of using polarimetric radar signatures to assess supercell variability across diverse environments. For future studies of the influence of varying environments on supercell structure and microphysical distributions, it may be beneficial to know which radar metrics display large variation between environments.

2. Data and methods

From a large database of supercell storms for which polarimetric radar data were available spanning 2012–14, any short time periods (<2–3 h) were sought during which multiple classic (Moller et al. 1994), relatively isolated, cyclonically rotating (right moving) supercell storms were present when viewed from the same radar. Supercells were required to exhibit typical supercell structures such as a $Z_{DR}$ arc, $Z_{DR}$ column, and midlevel rotation throughout the analysis period. Analysis periods were then included only if entire storms were <100 km from the radar site, to ensure high-quality data. Preference was given to storms for which base-scan altitude was <1 km over a long time period. Twelve analysis periods were selected using these criteria, each representing a unique environment with two or three representative storms (Table 1). Nine analysis periods contained tornadic supercells, while three contained non-tornadic storms.

Analysis periods had to be characterized by low spatial variability of the environment. Radar, satellite, and surface observations were utilized to increase confidence that no low-level boundaries were present with which storms may have interacted. Mid- and upper-level winds were also examined to ensure no strong shear gradients over the regions of interest. Analysis periods were required to have a representative proximity sounding (model initialization) available from Rapid Update Cycle (RUC) or Rapid Refresh (RAP) output. Soundings were selected to spatially correspond with the undisturbed far-field environment when possible, and were temporally taken from within 30 min of the center of the analysis period. When an analysis period was >1 h in length, values from two model soundings were averaged to obtain an average environment over the analysis period. This method may lead to error if the storm-scale environment changes substantially over the analysis period, because of, for example, outflow from a nearby storm. This was apparently not the case for the vast majority of analysis periods used herein, as the included storms were reasonably isolated.

For each analysis period, level II radar data were obtained from the National Centers for Environmental Information (NCEI) from the WSR-88D spatially nearest the storms of interest. These data were analyzed using NCEI’s Weather and Climate Toolkit and via geographical information system (GIS) and pixel analysis approaches. For instance, after a particular signature such as the $Z_{DR}$ column aloft was demarcated, GIS
was used to measure its areal extent. For other radar metrics, such as mean value of \( Z_{DR} \) within the \( Z_{DR} \) arc, all pixels within the feature of interest were identified and statistics were computed on them. Distributions of many of the features observed (e.g., areal extent of the \( Z_{DR} \) column aloft) were not Gaussian (Fig. 1), so Wilcoxon–Mann–Whitney (WMW) statistics were utilized (e.g., Corder and Foreman 2014). WMW \( p \) values were used to assess whether values of a metric from two storms, treated as two separate populations, could have been drawn from the same population, that is, could have statistically come from the same storm. In this case, a high \( p \) value indicates that populations from two storms are statistically similar. WMW \( p \) values were also calculated between environments to determine the degree of cross-environment similarity or difference (Table 2). In the cross-environment comparisons, all values of a given radar metric from one environment (from two or three storms, at all analysis times) formed one population, and the set of all such values from a different environment formed the second population.

For each radar metric analyzed, a predictive equation was developed using multiple linear regression. Predictors were environmental variables for which strong correlation had been noted. Some of the environmental variables included in a predictive equation were moderately to strongly correlated (\( r \sim 0.70 \) for a few variable pairs), though it is possible that each variable may still bring unique information to the predictive equation; for example, a given environmental variable may be influenced by several factors. To test whether the information being added by the chosen set of variables was sufficiently different, the condition index was used to check for collinearity (e.g., Belsley et al. 2005). Values of the condition index <30 generally indicate nonsevere collinearity and value in retaining all variables in a predictive equation. Maximum condition indices were found to be <15 for all predictive equations (Table 2). One of the equations with a condition index of 14.8, on further examination, was found to contain two variables that each accounted for a large percentage of the predictability, so one was removed. As a result of these procedures, we are confident that the predictive equations presented here are robust and not heavily influenced by codependences between the variables.

3. Environments of storms analyzed

Representative values of many variables characterizing each storm-scale environment were collected; these variables were obtained or calculated from archived RAP/RUC soundings as in, for example, Thompson et al. (2003). They included several measures of instability: mixed-layer convective available potential energy (MLCAPE; Thompson et al. 2003), most unstable convective available potential energy (MUCAPE; Evans and Doswell 2001), and convective inhibition (CIN; Colby 1984). Several measures of shear were also obtained, including shear in the 0–1-, 0–3-, and 0–6-km layers (e.g., Thompson et al. 2003), and effective bulk shear (ESHEAR; Thompson et al. 2007). Measures of helicity included storm-relative helicity (SRH; Rasmussen and Blanchard 1998) in the 0–1- and 0–3-km layers (Rasmussen 2003), and effective SRH (ESRH; Thompson et al. 2007). Altitude of the level of free convection (LFC) and altitude/temperature of the lifting
FIG. 1. Histograms of all measurements of (a) maximum altitude of the 1-dB $Z_{DR}$ column (km), (b) areal extent of the 0.5-dB $Z_{DR}$ column at −1 km above the ambient 0°C level (km²), (c) width of the 2-dB $Z_{DR}$ arc (km), (d) areal extent of the 3.5-dB $Z_{DR}$ arc (km²), and (e) areal extent of the polarimetrically inferred hailfall region (km²).
condensation level (LCL) were collected. Altitude of the ambient 0°C level was included, since it may influence the amount of hail reaching the surface. Several variables related to the vertical moisture profile were collected or calculated, including relative humidity (RH) at 3-, 6-, and 9-km altitude, and mean RH values in the 3–6-, 6–9-, and 3–9-km layers. Finally, several composite parameters commonly used in severe weather forecasting were included (Thompson et al. 2003): supercell composite parameter (SCP), significant tornado parameter (STP), and the 0–1-km energy–helicity index (EHI; Rasmussen 2003). One limitation of this approach is that the vertical profiles of wind and moisture may vary substantially in close proximity to supercell storms (e.g., Parker 2014). Each environmental variable was assessed for an association with each radar metric, though the only variables shown in the figures are those that either were relatively strongly correlated to the radar metric being examined, and/or those that appeared in the predictive equation for that radar variable.

The 12 environments in which analyzed storms occurred were diverse, encompassing a large portion of the typical supercell parameter space. Representative plots are shown in Fig. 2 to illustrate the cross-environment differences for some variables that have either been used to differentiate supercell environments (e.g., instability and shear parameters), or because these variables are predictive of the character of particular supercell polarimetric features. Instability varied widely, represented by MLCAPE (Fig. 2a). The median value was ~1203 J Kg⁻¹, with a few cases characterized by values <700 or >2500 J Kg⁻¹. Very high-instability supercell environments (e.g., Seimon 1993; Bluestein 2009) are not represented in this sample. Vertical wind shear, represented by ESHEAR (Fig. 2b), spanned the range of values typical of supercell environments (from <10 to >25 m s⁻¹; Thompson et al. 2007). Another measure of the wind profile, ESRH (Fig. 2c), spanned the parameter space from 19 to 542 m²s⁻², representative of the range typically seen across supercell environments (Thompson et al. 2007). Another set of variables showed relationships with polarimetric observables, so are also shown in Fig. 2. LFC height (Fig. 2d) ranged from <1 to >3 km above the surface. Given the spread of sampled environments across all seasons, altitude of the ambient 0°C level varied widely, from ~2800 to >3800 m above the surface (Fig. 2e). Average midlevel (3–6 km) RH varied from <30% to >90% (Fig. 2f).

Differences between MLCAPE and 0–6-km shear for the individual environments were examined in more detail, since instability and shear are often used to characterize convective environments. Figure 2g shows that environments were characterized by a wide variety of MLCAPE values, with overlap among several environments with MLCAPE <250 J Kg⁻¹; 0–6-km shear was less variable, with many environments characterized by values ~20–25 m s⁻¹ (Fig. 2g). Figure 2g is comparable to the results of Rasmussen and Blanchard (1998), and shows that much of their parameter space for supercell storms is included in this sample as well.

### 4. Differential reflectivity column characteristics

Convective updrafts, characterized by a positive temperature perturbation above the ambient 0°C level, can be inferred by the presence of a ZDR column (e.g., Figs. 3a,b). In numerical simulations, environmental factors influence updraft characteristics. Gilmore et al. (2004) found that updrafts in simulated supercells tend to become more intense and larger in areal extent as vertical wind shear increases. In simulated supercells storms, updraft intensity is also influenced by hodograph shape and magnitude of vertical wind shear (e.g., Weisman and Klemp 1982, 1984; McCaul and Weisman 2001; Van Den Broeke et al. 2010), and by changes to the vertical moisture profile (e.g., Weisman and Klemp...
Fig. 2. Illustrations of environmental variability among storms analyzed. (a) MUCAPE (J kg$^{-1}$), (b) ESHEAR (m s$^{-1}$), (c) ESRH (m$^2$ s$^{-2}$), (d) LFC height (m), (e) the ambient 0°C level (m), and (f) the average RH value in the 3–6-km layer (%). The bottom of the box in each panel is the first quartile, and the top of the box is the third quartile. The orange bar indicates the median value, and the red plus sign marks the mean value. Bars are at the 9th and 91st percentiles, with outliers indicated as circles even farther removed from the median value. (g) Scatterplot of MLCAPE (J kg$^{-1}$) vs 0–6-km shear (m s$^{-1}$), as in Rasmussen and Blanchard (1998).
Here, $Z_{DR}$-inferred updraft areal extent at a fixed altitude above the ambient 0°C level (Fig. 3c) and maximum vertical extent of the $Z_{DR}$ column above the ambient 0°C level are used as measures of updraft intensity (e.g., Kumjian et al. 2010). Maximum altitude of the 1-dB $Z_{DR}$ column above the ambient 0°C level was a metric used to characterize the updraft. This $Z_{DR}$ threshold was chosen to reduce the effects of noisy data (e.g., Fig. 3b), and is consistent with the $Z_{DR}$ column detection algorithm of Snyder et al. (2015). This metric was assessed for each time step in the analysis period regardless of storm–radar distance, though values are more accurate for storms closer to the radar since beam centerlines of successively higher elevation angles spread out vertically with distance. Once values were estimated for each sample volume in each storm, a mean value was calculated for each individual storm by taking a simple average of all estimates. Individual values for each storm also formed a population that was compared with other storms’ populations of metric values via the WMW $p$ value.

Qualitatively, storms in similar environments tended to have similar mean values of this metric, indicated by the similar height of contiguous same-colored bars in Fig. 4a. The $Z_{DR}$ column vertical extent above the 0°C level exhibited moderate overlap between environments (Fig. 4a). WMW two-tailed $p$ values were calculated for the two storms in each environment. In the environment with three storms (Table 1; three sky-blue bars in Fig. 4a), a WMW two-tailed $p$ value was calculated for the two storms with the most dissimilar mean values. Over the 12 environments, $p$ values ranged from 0.04 to 0.94 (Fig. 4a), with only one environment exhibiting a $p$ value <0.12 and a mean $p$ value across all environments of 0.409 (Table 2). In contrast, when
WMW $p$ values were calculated between environments (66 comparisons), $p > 0.05$ for 11 comparisons (17%) and $p < 0.001$ for 40 comparisons (61%). These results indicate that maximum altitude of the 1-dB $Z_{DR}$ column above the ambient $0^\circ$C level is, overall, statistically similar between storms in similar environments and statistically different between storms in different environments. Nontornadic storms were indistinguishable from tornadic storms using this metric (Fig. 4a), as nontornadic storms did not have repeatably high or low mean metric values relative to the tornadic storms.

A simple model developed using multiple linear regression explains 75.0% of the variance of mean 1-dB $Z_{DR}$ column maximum extent above the ambient $0^\circ$C level (km):

$$Z_{DR\text{-}\text{column\ altitude\ above\ }0^\circ\text{C\ (km)}} = 0.96 + 3.85 \times 10^{-4}(a) + 2.49 \times 10^{-3}(b) + 1.2 \times 10^{-2}(c),$$

where $a$ is MUCAPE (J kg$^{-1}$), $b$ is ESRH (m$^2$ s$^{-2}$), and $c$ is LCL temperature ($^\circ$C). MUCAPE was strongly

![Graph 1](image1)

![Graph 2](image2)

![Graph 3](image3)

![Graph 4](image4)

**Fig. 4.** (a) Mean values of maximum 1-dB $Z_{DR}$ column altitude above the ambient $0^\circ$C level (km) for all analysis periods for each storm; each bar represents one storm, and each contiguous group of same-colored bars represents storms in the same analysis period. NT indicates a nontornadic environment; values above groups of bars indicate WMW $p$ value between storms in that environment. Environments ordered by increasing MUCAPE from left to right. Mean values of maximum 1-dB $Z_{DR}$ column altitude above the ambient $0^\circ$C level (km) for each environment vs (b) MUCAPE (J kg$^{-1}$), (c) ESRH (m$^2$ s$^{-2}$), (d) temperature at the LCL ($^\circ$C), and (e) RH at 3 km (%).
positively correlated to this metric (Fig. 4b), likely because a higher-MUCAPE value should result in stronger vertical accelerations and therefore a larger quantity of warm air lofted above the ambient 0°C level. ESRH was moderately correlated to this metric (Fig. 4c), consistent with stronger updrafts in high-helicity environments (e.g., Brooks and Wilhelmson 1993). Warm LCL temperatures tended to be associated with high-altitude $Z_{DR}$ columns (Fig. 4d), likely since if warmer air near cloud base is lofted in the updraft, it is likely to remain warmer than 0°C for a longer time. Finally, relatively dry air at midlevels led to high-altitude $Z_{DR}$ columns (Fig. 4e), likely reflecting the higher altitude of precipitation formation in those environments.

Potentially of some operational value is maximum altitude of the $Z_{DR}$ column (magnitude), not corrected for the environmental 0°C level. A model developed using multiple linear regression explains 83.0% of the variance of this metric (km):

$$Z_{DR} \text{ column maximum altitude (km)} = 1.24 + 4.29 \times 10^{-4}(a) + 2.54 \times 10^{-3}(b)$$

$$+ 9.54 \times 10^{-4}(c),$$

where $a$ is MUCAPE (J kg$^{-1}$), $b$ is ESRH (m$^2$ s$^{-2}$), and $c$ is the ambient 0°C level (m). MUCAPE and ESRH are thought to be significant for the same reasons as discussed above. Higher ambient 0°C levels may indicate more cloud at warm temperatures and/or warmer temperatures in lower portions of the cloud, which might be expected to lead to relatively tall $Z_{DR}$ columns.

Updraft intensity was also assessed using areal extent of the 0.5-dB $Z_{DR}$ column at an altitude ~1 km above the ambient 0°C level (Fig. 3c). So a larger number of data points could be included, the acceptable vertical range was extended to 0.7–1.3 km. The ambient 0°C altitude was estimated using the representative archived RUC or RAP sounding(s). A 0.5-dB threshold seemed to effectively reduce the influence of noise in the $Z_{DR}$ field (Fig. 3c). This metric was assessed for each time step in the analysis period that had an elevation angle with data in the required altitude range.

Quantitatively, as with maximum $Z_{DR}$ column altitude above the ambient 0°C level, storms in similar environments tended to have similar mean values of this metric, with substantial overlap between environments (Fig. 5a). WMW $p$ values comparing two storms in similar environments were $>0.05$ for all 12 environments (Fig. 5a), with an average $p$ value of 0.474 (Table 2). Between environments (66 comparisons), $p > 0.05$ for 11 comparisons (17%) and $p < 0.001$ for 48 comparisons (73%). Thus, $Z_{DR}$ column areal extent defined at this altitude and with this $Z_{DR}$ threshold appears to be statistically similar in similar environments and statistically different across environments. Again, non-tornadic storms had similar characteristics when compared with tornadic storms (Fig. 5a).

Environmental variables were not as strongly predictive of $Z_{DR}$ column areal extent. A model explaining 65.3% of the variance of this metric is

$$Z_{DR} \text{ column areal extent (km$^2$)} = 2.12 \times 10^{-3}(a) - 5.85 \times 10^{-1}(b)$$

$$+ 2.75 \times 10^{-2}(c) - 14.53,$$ (3)

where $a$ is MUCAPE (J kg$^{-1}$), $b$ is 3-km RH (%), and $c$ is altitude of the 0°C level (m). MUCAPE (Fig. 5b), 3-km relative humidity (Fig. 5c), and 0°C-level altitude (Fig. 5d) again showed moderate associations, likely for the same reasons as discussed above for $Z_{DR}$ column altitude. ESHEAR was also moderately correlated (Fig. 5e), consistent with stronger updrafts in strongly sheared environments.

5. Differential reflectivity arc characteristics

Mean storm-relative winds in a shallow inflow layer along a supercell’s forward flank often sorts raindrops and melting hail there, resulting in a band of high $Z_{DR}$ values (Kumjian and Ryzhkov 2008; Dawson et al. 2015). These often-striking features of classic supercell storms warrant further investigation since they appear to convey valuable information about, for example, tornadogenesis potential (Palmer et al. 2011; Crowe et al. 2012). Three metrics related to the $Z_{DR}$ arc were investigated among this sample of storms: mean $Z_{DR}$ arc width (Figs. 6a,b), areal extent of high $Z_{DR}$ values within the arc (Fig. 6c), and mean $Z_{DR}$ values within the arc. Since $Z_{DR}$ arc characteristics should be determined largely by sorting in a layer above the $Z_{DR}$ arc (e.g., Dawson et al. 2015), the 1–3-km shear was also calculated for each environment. Shear in this layer was more strongly correlated with $Z_{DR}$ arc characteristics of the storms examined here than shear in other layers (0–1, 0–2, 0–3, and 0–6 km, and effective inflow layer).

The $Z_{DR}$ arc width was defined as the width of the 2-dB $Z_{DR}$ arc measured perpendicular to the $Z_{HH}$ gradient along the supercell forward flank. Thus, $Z_{DR}$ arc width is measured roughly perpendicular to the direction of storm motion. Figure 6b shows the demarcation of the $Z_{DR}$ arc, along with several transects across the arc that would be averaged to estimate a mean width. One mean width value was recorded for each sample volume at the lowest elevation angle,
provided that the altitude of the $Z_{DR}$ arc was fully <1 km. This altitude requirement was established so comparisons between storms are more representative. This metric is of interest since $Z_{DR}$ arc width and separation from the storm core may yield information about the low-level wind shear; for instance, $Z_{DR}$ arc–storm core distance should be directly related to vertical wind shear magnitude in the inflow layer (Ganson and Kumjian 2015).

Storms in similar environments generally had similar $Z_{DR}$ arc width (Fig. 7a). An exception was one storm in the group of three occurring in the domain of the Frederick, Oklahoma, WSR-88D (three contiguous sky blue bars; Fig. 7a)—though two storms in this environment were characterized by large $Z_{DR}$ arc width, the third had a much smaller mean value. Over nine environments for which two-tailed WMW $p$ values could be calculated, $p < 0.05$ for two and $p \geq 0.19$ for the remaining seven, with an average $p$ value of 0.453 (Table 2). Between environments (55 comparisons), $p > 0.05$ for 12 comparisons (22%) and $p < 0.001$ for 36 comparisons (65%). As with metrics discussed prior, these results support overall statistical $Z_{DR}$ arc width similarities for storms in similar environments and statistical differences for storms across environments.

Individual environmental variables were generally less correlated to $Z_{DR}$ arc width than for $Z_{DR}$ column metrics, though a combination of variables produced a predictive equation explaining 95.9% of the variance in mean 2-dB $Z_{DR}$ arc width (km):
据图6所示，KFDR雷达在UTC2352时04年4月17日的回波情况。图(a)为基波扫描的ZH (dBZ) (中心为白色区域，0.518;约0.88-km高度)，图(b)为ZDR (dB)的基波扫描，图(c)为ZDR (dB)的基波扫描，与3.5-dB阈值应用（中心为白色区域，0.79-km高度），图(d)为ZHH (dB)的基波扫描，图(e)为ZDR (dB)的基波扫描。标注区域在(a)和(b)中，ZDR弧，交叉斜线在(b)中，ZDR弧宽度被平均来估计平均宽度。白色标注在(c)中，表示3.5-dB ZDR弧的分界线。白色标注在(d)和(e)中，对应于极化推断的冰雹区域。

\[
2\text{-dBZ}_{DR} \text{ arc width (km)} = -0.309 + 1.45 \times 10^{-3}(a) + 3.80 \\
\times 10^{-3}(b) - 1.96 \times 10^{-2}(c),
\]

其中，a是MUCAPE (J kg\(^{-1}\)), b是1-3-km风切变 (m s\(^{-1}\)), c是3-6-km RH的平均值（%）。1-3-km的风切变与平均ZDR弧宽度（图7b）有强烈相关性。
stronger shear in this layer, which extends above the ZDR arc, was associated with wider ZDR arcs, possibly indicating more vigorous sorting in accord with prior work (e.g., Dawson et al. 2015). Other shear and helicity variables were not as strongly correlated with ZDR arc width. Relative humidity at midlevels was predictive of ZDR arc width (e.g., Fig. 7c), with drier air corresponding to wider ZDR arcs. This may reflect the higher formation altitude of precipitation when the ambient air is dry, leading to a larger fall distance before reaching base-scan level and thus a longer period of time for size sorting to act.

Given the fundamental importance for ZDR arc characteristics of the magnitude of storm-relative mean wind in the inflow layer (e.g., Dawson et al. 2015), this variable was also estimated. A mean pressure-weighted environmental wind was estimated from RAP or RUC soundings in the 0–2-km layer (representative of the effective inflow layer in which the ZDR arc forms; e.g., Thompson et al. 2007), and a mean storm motion vector was estimated for each storm analyzed over the analysis period. Then, the resulting storm-relative mean inflow-layer wind was compared with mean ZDR arc width for each storm (Fig. 7d). The ZDR arc width generally increased with...
mean inflow-layer storm-relative wind \( (r = 0.42) \), with many exceptions to the general upward trend. The exceptions may be partially due to rapidly changing environments near supercells (e.g., Parker 2014) and may partially reflect the use of model data to represent the near-storm environments. Additionally, it may reflect the choice of 0–2 km as the representative inflow layer, which in reality varies between storms.

A related metric was areal extent (km²) of the 3.5-dB \( Z_{DR} \) arc. This threshold well captured the region of the \( Z_{DR} \) arc dominated by very high values (Fig. 6c) and reflected temporal changes in \( Z_{DR} \) arc areal extent. The \( Z_{DR} \) arc was again required to be fully located at an altitude <1 km for this metric to be calculated. Mean \( Z_{DR} \) arc areal extent appeared qualitatively less similar for storms in similar environments (Fig. 8a), often with substantial variability between the two or three storms in a similar environment. Over nine environments for which two-tailed WMW \( p \) values could be calculated, \( p < 0.05 \) in four and \( p > 0.12 \) for the remaining five, with an average \( p \) value of 0.303 (Table 2). In this small sample, storms appeared relatively similar in lower-MUCAPE environments and dissimilar in higher-MUCAPE environments (Fig. 8a). Between environments (66 comparisons), \( p > 0.05 \) for 16 comparisons (24%) and \( p < 0.001 \) for 46 comparisons (70%). These results suggest that, while \( Z_{DR} \) arc areal extent is relatively similar in similar environments and relatively different between environments, this contrast may not be as strong as for other polarimetric metrics examined.

Despite generally smaller correlation with individual environmental variables, \( Z_{DR} \) arc areal extent was strongly predictable when using several environmental variables together. A model developed using multiple linear regression explains 85.5% of the variability in 3.5-dB \( Z_{DR} \) arc areal extent (km²):

\[
3.5\text{-dB } Z_{DR} \text{ arc areal extent (km}^2) = 3.29 \times 10^{-2}(a) + 5 \times 10^{-2}(b) - 7.37 \times 10^{-1}(c) - 44.86, \tag{5}
\]

where \( a \) is MUCAPE (J kg\(^{-1}\)), \( b \) is LFC height (m), and \( c \) is mean 3–6-km RH (%). The positive association with MUCAPE may reflect the stronger updraft and higher supersaturation values therein with high MUCAPE, which results in broader drop size distributions (e.g., Politovich and Cooper 1988). Large shields of high \( Z_{DR} \) within the arc were associated with high levels of free convection (Fig. 8b) and low mean relative humidity in the 3–6-km layer (Fig. 8c). A high LFC and dry midlevel air would be associated with precipitation formation at

![Graph showing mean inflow-layer storm-relative wind](image)
higher altitude, meaning that falling droplets may have longer for sorting to act and thus a band of higher $Z_{DR}$ values may be able to form along the inflow edge of the storm. Predictive equations developed using 1–3-km shear did not explain as much of the variability, even though 1–3-km shear was the environmental variable best correlated with $Z_{DR}$ arc areal extent among all environmental variables examined ($r = 0.634$; not shown).

Finally, mean value of $Z_{DR}$ within the $Z_{DR}$ arc was calculated for each storm over all pixels with $Z_{DR} \geq 0$ dB (e.g., as denoted in Fig. 6b). Given the areal dependence of the calculation, times with larger $Z_{DR}$ arcs would contribute slightly more to the average $Z_{DR}$ value than times with small $Z_{DR}$ arcs; this variability was generally small. Again, the $Z_{DR}$ arc was required to be fully <1 km above radar level (ARL) for a value to be calculated. Mean $Z_{DR}$ arc values were qualitatively similar for storms in similar environments, with degree of dissimilarity again possibly increasing with MUCAPE (Fig. 9a). Given the number of $Z_{DR}$ pixel values for each storm, WMW statistics were not practical to calculate. A multiple regression model explains 80.5% of the variability in $Z_{DR}$ arc values:

$$\text{mean } Z_{DR} \text{ arc value (dB)}$$
$$= 8.12 \times 10^{-7}(a) - 5.79 \times 10^{-3}(b)$$
$$+ 6.74 \times 10^{-2}(c) + 1.995,$$  

(6)

where $a$ is LFC height (m), $b$ is 6-km RH (%), and $c$ is 1–3-km shear (m s$^{-1}$). The $Z_{DR}$ values in the arc increased with LFC height (Fig. 9b), likely because of a longer residence time in the sorting layer before radar sampling, and with decreasing 6-km relative humidity values (Fig. 9c), again indicating greater time for size sorting to act in environments where precipitation forms at relatively high altitude. The inclusion of 1–3-km shear in the model (Fig. 9d) is consistent with prior findings that the inflow-layer shear magnitude is important to $Z_{DR}$ arc characteristics.

6. Hailfall characteristics

Supercell storms often contain regions of hailfall, inferable by collocated high $Z_{HH}$ and near-zero $Z_{DR}$ values (e.g., Balakrishnan and Zrnić 1990; Kumjian and Ryzhkov 2008; Figs. 6d,e). Areas of hail are typically most pronounced downshear from the mesocyclone, though hail may also wrap around the west side of the mesocyclone in the echo appendage. Some volume scans may appear nearly devoid of hail at low levels, while other scans from the same storm may contain large regions of hail. This cyclicity may be associated with the tornado life cycle (Van Den Broeke et al. 2008), and may be less prominent in nontornadic storms (Kumjian and Ryzhkov 2008). Areal extent and cyclicity of the low-level hail signature were investigated relative to environmental variability.

Regions of hail were polarimetrically inferred by collocated high $Z_{HH}$ and lowered $Z_{DR}$ values (generally <1 dB) within the storm core (Figs. 6d,e), as in prior studies (e.g., Kumjian and Ryzhkov 2008; Park et al. 2009). Only data at an altitude <1 km were used to avoid sampling midlevel hail cores, and so observations between storms are more comparable. Extent of inferred hail was determined by calculating the area of the storm-core region characterized by lowered $Z_{DR}$ values (generally <1 dB), and a storm mean value was calculated by averaging the values from each analysis time across the same storm. Storms in similar environments generally had quantitatively similar mean values of hail areal extent (Fig. 10a), supported by WMW $p$ values >0.09 for six of eight comparisons for which $p$ values could be calculated (75%) and an average $p$ value of 0.410 (Table 2); $p$ values were not calculated if only one storm was available for a given environment. Between environments (55 comparisons), $p > 0.05$ for 13 comparisons (24%) and $p < 0.001$ for 34 comparisons (62%). While these results suggest that storms are more similar in similar environments than in different environments, the cross-environment comparisons indicate greater similarity than for other metrics examined. This appeared to be true since hail distributions were often quite cyclic (e.g., Fig. 10b)—variance of hail areal extent was high for many storms, increasing the probability of overlap with values from other storms. Mean hail areal extent was larger in some nontornadic storms (Fig. 10a).

Environmental predictability of hail areal extent was weaker than for other metrics examined. A model developed using multiple linear regression explained only 51.2% of the variability in hail areal extent:

$$\text{mean base-scan hail areal extent (km}^2)$$
$$= 7.527 + 1.31 \times 10^{-2}(a) - 2.41 \times 10^{-1}(b)$$
$$- 6.36 \times 10^{-2}(c),$$  

(7)

where $a$ is LFC height (m), $b$ is 6-km RH (%), and $c$ is CIN (J kg$^{-1}$). The two variables most strongly associated with hail areal extent were LFC height (Fig. 10c) and 6-km relative humidity (Fig. 10d). It is speculated that high LFCs may be associated with greater hail areal extent because, on a day with a high LFC, the updraft is at a higher altitude and therefore colder. This may be supported by greater hail areal extent when $Z_{DR}$ columns extended farther above the ambient 0°C level, though correlation between the two metrics was not high ($r = 0.38$; not shown). The moisture variable best
correlated with hail areal extent was 6-km RH, though RH at most levels and in most layers was negatively correlated. For instance, $r = -0.45$ between RH in the 3–6-km layer, which is more relevant to what happens to hail during descent, and hail areal extent. Lower RH values in the layer through which hailstones descend lead to greater evaporative cooling once hailstones begin melting and therefore to survival of greater hailstone mass to the surface, all else being equal. In this study, RH below 3 km was not examined. Another variable that was hypothesized to be important for hail areal extent was altitude of the 0°C level, since an onset of melting closer to the surface should mean that more hailstone mass survives to base-scan level. In our sample, correlation was weak ($r = -0.24$) between 0°C altitude and hail areal extent. This may be partially a result of the small sample size, and likely indicates that other factors are more important in controlling hail production among this sample of storms.

Storm-relative mean wind magnitude in the 0–2-km (inflow) layer, which was not one of the environmental variables used in development of the predictive equation, explained 56.7% of the variability of hail areal extent when all storms were included (Fig. 10e). This is stronger predictability than when other environmental variables are used (e.g., as in the equation above), and agrees with prior work that hail production should increase in supercells as the storm-relative mean wind increases (e.g., Van Den Broeke et al. 2010; Dennis and Kumjian 2014).

An important finding is that hail cyclicity was strongly predicted by environment. This result is anticipated since hail production should be tied to updraft pulses and mesocyclone cycling (e.g., Dowell and Bluestein 2002; Adlerman and Droegemeier 2005; Van Den Broeke et al. 2010; Dennis and Kumjian 2014).
2010). “Cyclicality” is defined here as the coefficient of variation, and is calculated for each storm as the standard deviation of all hail areal extent values divided by the mean value across all times for the same storm. Normalization by mean hail areal extent allows values to be compared between storms. Values ranged from 0.21 (hail areal extent was generally similar through time) to 1.40 (variations in hail areal extent exceeded the mean value). Since one value is calculated for each storm, WMW $p$ values are not applicable.

Mean hail cyclicality varied substantially between tornadic storms (mean coefficient of variation = 0.62) and nontornadic storms (mean coefficient of variation = 0.37). Cyclicality also increased with MLCAPE (Fig. 11a), likely indicating a relationship between ambient instability and updraft characteristics (e.g., Weisman and Klemp 1982; James and Markowski 2010; Naylor and Gilmore 2014), a result that should be further investigated numerically and utilizing observations. Hail cyclicality also decreased with increasing LFC height (Fig. 11b) and increasing mean relatively humidity in the 3–9-km layer (Fig. 11c).

FIG. 10. (a) As in Fig. 4a, but for mean value of base-scan hail areal extent (km$^2$). (b) A typical example of how hail areal extent varies cyclically through time, from a supercell in the domain of KFDR from 2226 to 2357 UTC 17 Apr 2013. Mean hail areal extent for a given environment vs (c) LFC height (m), (d) mean RH at 6-km altitude (%), and (e) mean magnitude of the storm-relative wind in the 0–2-km layer (m s$^{-1}$).
At this time speculation is not presented as to why these variables exhibit this relationship with hail cyclicality; their associations with mesocyclone behavior and hail production likely need to be explored in more depth. Finally, hail cyclicality decreased sharply as ESRH increased (Fig. 11d), opposite the hypothesis that tornadic supercells, associated with high hail cyclicality, are favored in high-SRH environments. One outlier each was removed from the MLCAPE and ESRH distributions to develop a multiple linear regression model for this metric (Figs. 11a,d). It explains 99.3% of the variability of hail cyclicality:

\[
\text{hail cyclicality} = 0.7522 + 2.4 \times 10^{-4}(a) \\
- 6.22 \times 10^{-4}(b) + 3.73 \times 10^{-3}(c) \\
- 3.11 \times 10^{-2}(d),
\]

where \( a \) is MLCAPE (J kg\(^{-1}\)), \( b \) is ESRH (m\(^2\) s\(^{-2}\)), \( c \) is mean 3–9-km RH (%), and \( d \) is LCL temperature (°C). LCL temperature may be important to hail production since a colder LCL is likely to translate to a colder mean updraft, but it is unclear how this would be related to hail cyclicality. Note that ~97% of the variability in hail cyclicality can be explained using the same variables minus LCL temperature. The high degree of predictability of hail cyclicality among this sample of environments calls for further investigation into the relationships between storm-scale environments, microphysics, and mesocyclone cycling. It is also worth examining whether this predictive model works as well when extended to a larger dataset.

7. Summary and discussion

In this study, quantitative metrics that describe common polarimetric radar features of classic supercells have been compared for storms in similar and different environments. This analysis adds new observational evidence for how the storm-scale environment may affect supercell storms, and provides guidance on which features of classic supercell storms may be most useful in studies of how these storms vary microphysically and dynamically between environments. From this sample of storms, metrics describing \( Z_{\text{DR}} \) column altitude and areal extent were generally similar for storms in similar environments \((p \text{ values typically } >0.10)\). The same was true for \( Z_{\text{DR}} \) arc and hailfall metrics, but not to the same extent. The \( Z_{\text{DR}} \) arc width was somewhat more similar between storms in similar environments than areal extent of high values.
within the $Z_{DR}$ arc, although areal extent of high $Z_{DR}$ arc values was generally similar in lower-MUCAPE environments and typically dissimilar in higher-MUCAPE environments. When comparing metrics across variable environments, a large percentage of cross-environment comparisons ($\geq 61\%$ for all metrics examined; $\geq 65\%$ for three of five) had $p < 0.001$, indicating strong differences between environments. Halffall areal extent and $Z_{DR}$ column maximum altitude above the ambient 0°C level were the most similar between different environments. When all measures of variability between environments were considered, areal extent of the 0.5-dB $Z_{DR}$ column at 0.7–1.3 km above the ambient 0°C level emerged as the most similar for storms in similar environments and also most likely to be different for storms in different environments. Therefore, it is most likely to be useful in future studies of supercell variability between environments. Mean value of $Z_{DR}$ within $Z_{DR}$ arcs and hail cyclacity warrant further investigation. Also, features related to the distribution of $K_{DP}$, such as the $K_{DP}$ column (Kumjian and Ryzhkov 2008), $K_{DP}$–$Z_{DR}$ column separation (e.g., Kumjian et al. 2010), and $K_{DP}$ foot (e.g., Jung et al. 2010), were not investigated in this study and may yield useful results.

The results presented here are influenced by cyclacity of the metrics measured, which was often pronounced. Most cyclic, and best predicted by environmental variables, was areal extent of the inferred region of halffall at base-scan level (mean coefficient of variation = 0.52). Cyclacity of halffall areal extent was, however, strongly dependent on whether storms were tornadic or non-tornadic, as noted above. Tornadic storms showed a 68% increase in hail cyclacity relative to nontornadic storms, consistent with the preliminary results of Kumjian and Ryzhkov (2008). The difference between tornadic and nontornadic populations was statistically significant (WMW $p$ value $= 0.044$), warranting continued work in the direction of understanding these observations in the context of storm-scale evolution and microphysics. These results indicate that polarimetric metrics may be used, with care, to back out information about storm-scale behavior and impacts and about the storm-scale environment.

Acknowledgments. Lena Heuscher, Sabrina Januerci, and Nicholas Humrich helped gather the environmental data. This work is supported by NSF Grant IIA-1539070. The author is also supported by an academic appointment at the University of Nebraska–Lincoln. Radar data were obtained from the National Centers for Environmental Information (NCEI), and RAP/RUC output was obtained from Iowa State University.

References


