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DEVELOPMENT AND VALIDATION OF DOWNBURST PREDICTION EQUATIONS FOR THE DDPDA

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1. Introduction

The Damaging Downburst Prediction and Detection Algorithm (DDPDA) detects and predicts the onset of damaging outflows from storm cells that form in an environment of high CAPE and weak environmental wind shear. Earlier work (Smith et al 1998) presented an analysis based on a data set that was limited in quantity of events and quality of storm cell identifications that were used as input to the DDPDA. The current work consists of several steps to expand on this previous effort. First, the number of downburst days and non-event days used to develop downburst prediction equations are significantly increased. The data set is filtered to remove erroneous storm cell information. Finally, prediction equations are developed and skill scores calculated.

2. Dataset

The DDPDA's predictive capabilities are based on adequate vertical sampling of the storm by the WSR-88D. The DDPDA uses that information to predict the occurrence of strong outflows at the surface with a 1-15 minute lead-time. The DDPDA development and testing data set consists of 64 days, including 91 severe downburst events and 1247 null events. These cases are broken into two range categories that span 20-45 km and 45-80 km from each radar (Table 1). No events within 20 km of a WSR-88D are included, as the radar did not sample the upper levels of most storm cells at those ranges.

Several parameters are stored for the lifetime of each cell in the database (Table 2). Each parameter measures some aspect of the cell that may be used for predicting downburst events. Each parameter is an integrated quantity based on one 5-6 minute WSR-88D volume scan. Parameters that measure the rate of change of other variables are excluded from this study, as the DDPDA depends the WSR-88D Storm Cell Identification and Tracking algorithm, which is frequently fraught with storm tracking errors. Previous studies have shown that

	Downburst cells	Null cells
20-45 km	50	492
45-80 km	41	755
total	91	1247

Table 1: Breakdown of downburst-producing cells and non-events ("null cells") by range.

strong, deep mid-altitude convergence and a high-reflectivity core that rapidly elongates and descends may be precursors to downburst events (Roberts and Wilson 1989, Eilts et al. 1996). These characteristics are used to create and validate prediction equations using linear discriminant analysis.

3. Analysis

The data set is randomly split into two parts in order to develop and evaluate a method to predict strong downburst events. The first part consists of 65% of the downburst-producing and null storm cells in each range band and is used to train prediction equations using linear discriminant analysis. The second part consists of the remaining 35% of the cells in each range band and is used to evaluate the equations. This process of randomly sampling the training/evaluation data sets is repeated one hundred times in order to find the expected distribution of skill scores for the prediction equations as well as the most important parameters for use in predicting downburst events. A new prediction equation is developed for each of the one hundred training/evaluation set pairs.

Heidke's Skill Statistic (HSS; see Wilks 1995 for a discussion of various skill score calculations), along with Probability of Detection (POD), False Alarm Rate (FAR), and Critical Success Index (CSI) are calculated for all one hundred evaluation data sets in both range bands (figure 1). HSS is the primary tool used to evaluate the skill of the algorithm, as it takes into account correct predictions of non-events (null events) as well as correct forecasts. An HSS of 1.0 is equivalent to perfect forecast skill, while an HSS of 0 equates to the skill of results from purely random forecasts. The DDPDA has much better skill in the 20-45 km range, with a median HSS of 0.4, than in the 45-80 km range, with a median HSS of 0.17. This is likely caused by poor beam resolution at long ranges, and may be an artifact of a smaller

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Variable name	*Type*	*Description*
VIL	R	Cell-based Vertically Integrated Liquid
MASSHT	R	Height of the center of mass
VOL	R	Cell volume
ASP	R	Core aspect ratio (ratio of cell depth to cell width)
SHI	R	Severe Hail Index (Witt et al 1998)
MAXDBZ	R	Maximum reflectivity
DBZHT	R	Height of the maximum reflectivity
DBZ_7KM	R	Maximum reflectivity above 7 km mean sea level (MSL)
ZTHTE	R/E	Maximum reflectivity near the height of the minimum environmental θ_e
ZATHTE	R/E	Maximum reflectivity above the height of the min. env. θ_e
CNVMELT	V/E	Maximum LS convergence near the height of the env. 0 C isotherm
CTHTE	V/E	Maximum LS conv. near the height of the minimum env. θ_e
C16	V	Maximum LS conv. in the 1-6 km MSL layer
DVMELT	V/E	Maximum convergent ΔV near the height of the env. 0 C isotherm
DVTHTE	V/E	Maximum convergent ΔV near the height of the min. env. θ_e
DV16	V	Maximum convergent ΔV in the 1-6 km MSL layer
DPTHC	V	Depth of LS convergence exceeding 0.004 s^{-1}
DPTHDV	V	Depth of convergent ΔV exceeding 10 ms^{-1}
MAXR17	V	Maximum positive rotation in the 1-7 km MSL layer
MINR17	V	Minimum negative rotation in the 1-7 km MSL layer
CMEAN16	V	Mean LS conv. in the 1-6 km MSL layer
DV3	V	Maximum conv. ΔV in the 1-6 km MSL layer, min/max can be separated by up to 3 radials
CONV006	V	Maximum cross-sectional area of cell in the 1-6km MSL layer that exceeds 0.06 s^{-1}
CONV004	V	Same as CONV006, for 0.04 s^{-1}
CONV002	V	Same as CONV006, for 0.02 s^{-1}
CONV001	V	Same as CONV006, for 0.01 s^{-1}

Table 2: The integrated parameters imported or calculated by the DDPDA. The variable name is listed, followed by the type of data the parameter is derived from (R is reflectivity, V is radial velocity, and E is environmental) and a description of how it is calculated.

sample size in the developmental data set in the 45-80 km range band. Although the HSS at 45-80 km is about half that of the 20-45 km range band, the 95% confidence internal for the median is greater than zero, indicating that the prediction equations have skill. Additionally, the median lead time (figure 2) for the 20-45 km range is 5.5 minutes from the downburst prediction to the initial onset of outflow at the surface, while the median lead time for the 45-80 km range band is 0 minutes.

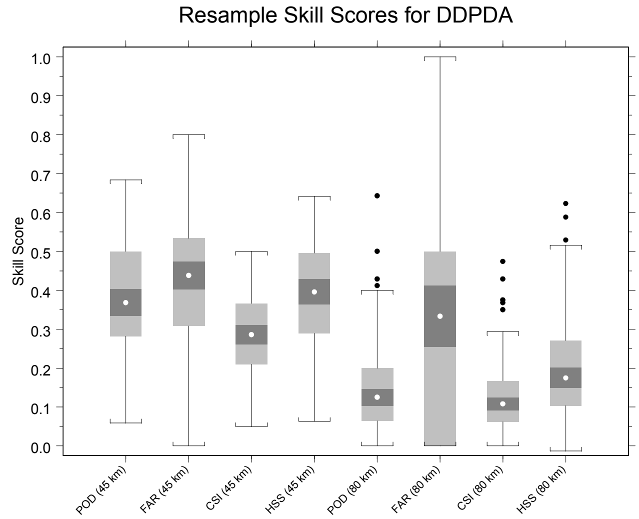

Figure 1: Distribution of validation data set skill scores for the 20-45 km range band ("45 km") and the 45-80 km ("80 km") range band. Each box-and-whisker chart shows the median value (white dot), 95% confidence interval of the median (dark gray box), inter-quartile range (IQR; light gray box), 1.5 x IQR (whiskers), and individual outliers (black dots) for one hundred downburst prediction equations.

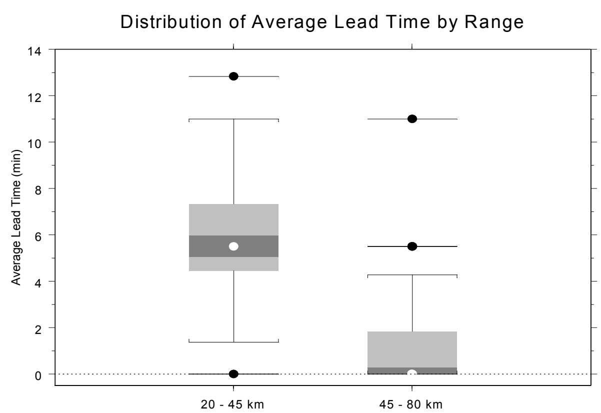

Figure 2: The distribution of the average lead times (minutes) from the issuance of a DDPDA downburst prediction to the initial onset of damaging outflow.

Figures 3 and 4 show the distributions of discriminant weights for all the variables, based on one hundred prediction equations, as well as the frequency with which each parameter appears in the equations. Discriminant analysis results exclude the variables that do not contribute to the discrimination between cells that produce downbursts and cells that do not (Statsoft 1995). Therefore, when the dataset is re-sampled many times into new training and validation data sets, the most important parameters should appear in most of the corresponding prediction

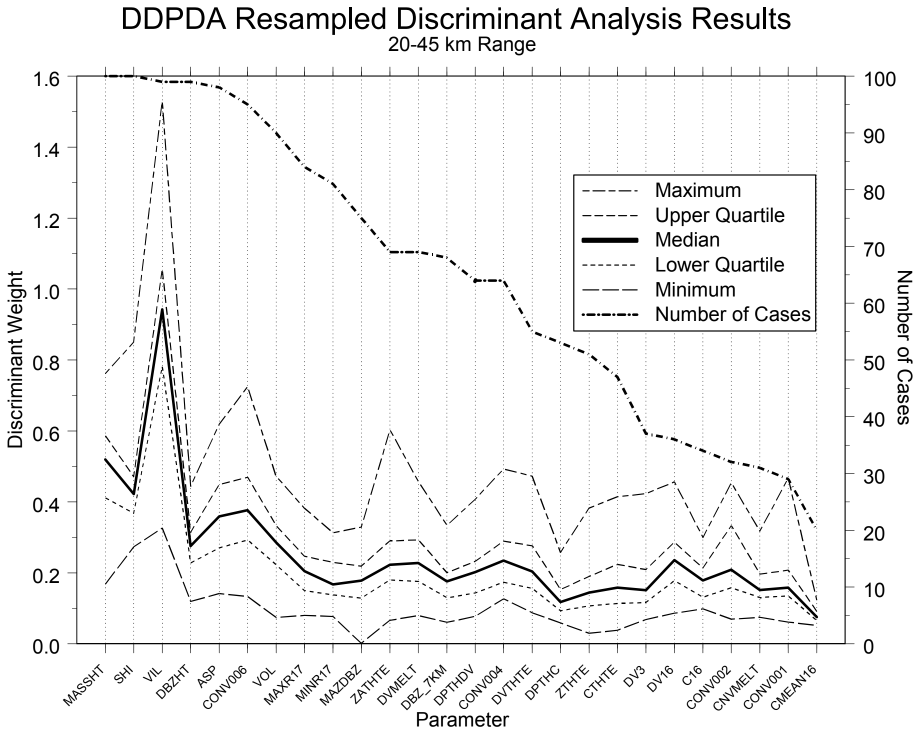

Figure 3: The distribution of discriminant weights of each parameter for the 20-45 km range band and the number of DDPDA prediction equations (out of one hundred) in which they appeared. The parameters are described in table 2.

equations. Additionally, the mean discriminant weight (or *standardized canonical coefficient*) for each variable is given. This coefficient describes the relative contribution of each variable to the ability to discriminate between groups. The larger the standardized coefficient, the greater the contribution of that variable is to the discrimination between downburst-producing storms and non-downburst storms (Statsoft 1995).

4. Discussion

Based on these weightings, the variables that appear to be most important to the timely prediction of downbursts in the 20 to 45 km range band include mostly reflectivity-based parameters: VIL, Severe Hail Index (SHI), height of the center of mass (MASSHT), and core aspect ratio (ASP). The most important velocity-based variable is the cross-sectional area coverage of radial convergence exceeding 0.006 s^{-1} (CONV006). Several environmental parameters were also included in at least 50% of the equations, but do not have a substantial impact in short-term predictions. This suggests that parameters that detect large, elongating reflectivity cores aloft are the most useful in downburst prediction at this range. It also suggests that the contribution of CONV006 as a convergence detection parameter strongly outweighs the contributions of most of the other radial velocity-based parameters, which are clustered with the other seldom-used variables near the far right of the graph.

The variables most important in the 45 to 80 km range band are the reflectivity-based SHI, VIL, and ASP parameters. Other variables that occurred frequently, but were not weighted as heavily, include the cross-sectional area coverage of radial convergence exceeding 0.001 s^{-1} (CONV001), the maximum rotational shear between 1 and 7 km MSL (MAXR17), the depth of convergence exceeding 0.004 s^{-1} (DPTHC), and storm cell volume (VOL). The high weightings of the reflectivity-based parameters suggest that most storms that produced strong outflows likely included ice processes aloft. The next three most-used parameters are all radial velocity-based variables that measure different aspects of the velocity field (convergence strength and depth, and rotation). However, the weightings of these variables in the discriminant equations are relatively low. The poor sampling of the velocity field at long ranges causes the radial convergence field to be weak and noisy; therefore, reflectivity-based indicators have the greatest contribution to discrimination between event types at these ranges.

The median HSS for each range band is a good estimator of the optimal expected long-term performance of each prediction equation. Therefore, the equations that give the median scores at each of

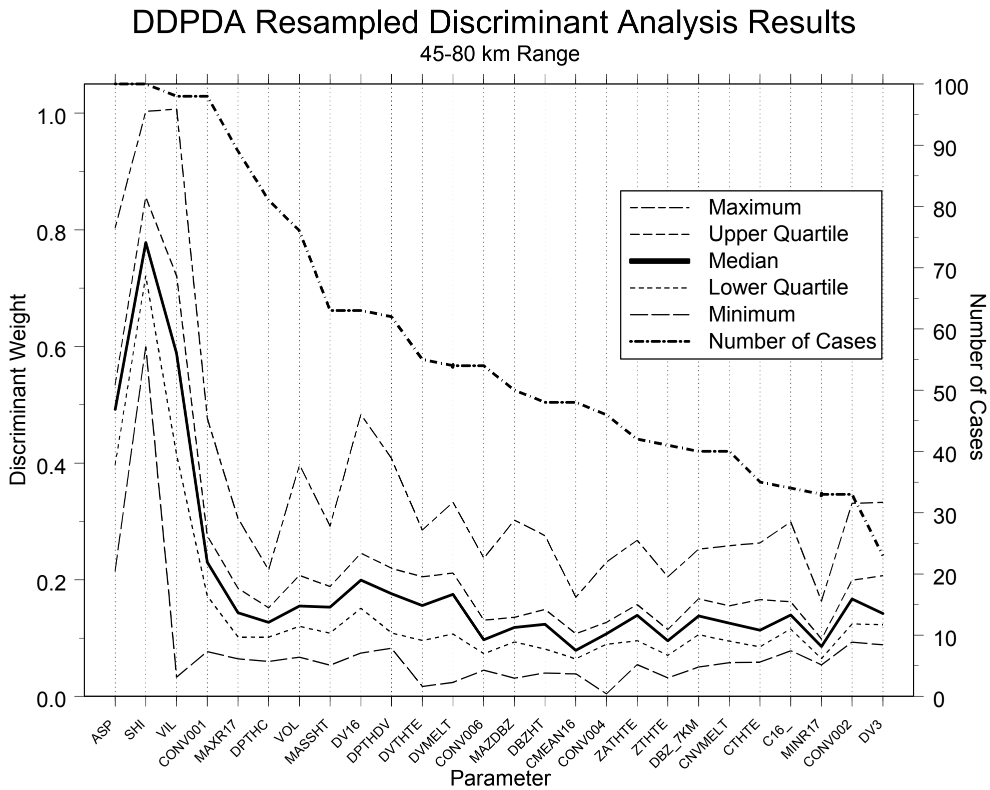

Figure 4: Same as figure 2, except for the 45-80 km range band.

the two range bands were chosen for inclusion in the DDPDA. These median-performance equations are chosen rather than the equations that produced the best skill scores, because the "best" HSS scores are an artifact of the sampling of the training and validation data sets.

5. Acknowledgements

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6. References

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