A REVIEW OF RESEARCH ACTIVITY RELATED TO WSR-88D ALGORITHMS

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1 INTRODUCTION

This report presents results of a literature search for articles that relate to existing and potential WSR-88D algorithms. Brief summaries of papers that address technical needs (as identified by the NEXRAD Technical Advisory Committee), evaluate current algorithms, and describe possible extensions to the current algorithm suite are collected in a topical activities summary (Section 2). Section 3 gives an overview of "data mining", an entire industry that has sprung up to extract information from databases. The topic is quite broad and the discussion is necessarily limited by the constraints of time and available technical resources. Consequently, the intent is to describe some of the analysis tools, summarize applications that potentially relate to WSR-88D activities, and direct interested readers toward sources of information. As in previous years, the report concludes with a bibliography containing short abstracts of all reviewed papers (Section 4).

Maturation of the NEXRAD program has led to a noticeable shift in published research. There is less activity recently regarding the verification of existing tornado, mesocyclone, and hail detection algorithms. Rather, greater access to radar datasets has led to increasing numbers of papers that describe possible embellishments to existing algorithms or new applications. Innovative tools have been developed for the analysis of tropical cyclones, predicting the onset of lightning, and assessing icing hazards.

Clutter mitigation is addressed in several studies. Post data collection schemes based on neural networks and fuzzy logic are under development. An alternate approach with regressive filters, implemented at the radar processing stage, is also summarized. Two studies focus on wind field retrieval with low-cost bistatic radar systems. Two articles describe variational methods for retrieving wind fields from the measurements of single radars.

Active areas of research, as in recent years, continue to be precipitation analysis and radar polarimetry. Several researchers seek to improve rainfall estimates by making adjustments for the vertical gradient of reflectivity and by incorporating rain gauge observations; others evaluate the utility of WSR-88D measurements and PPS products for rainfall estimation. Consensus seems to be that stratiform and warm cloud precipitation is underestimated (often by a factor of 2 or more). Convective precipitation estimates exhibit less bias or even small overestimates. Problems in rainfall estimation, other than those arising from hardware calibration, appear to be dominated by issues concerning vertical precipitation gradients and the lack of a procedure for specifying Z–R relations by precipitation type.

A broad spectrum of papers in radar polarimetry is reviewed given the likelihood of this capability being added to the WSR-88D in the future. Benefits for the general estimation of rainfall and the estimation of rain in complex terrain are demonstrated. Several papers are concerned with hail detection and hydrometeor discrimination. Other papers discuss techniques for improving radar hardware calibration and for reducing the bias with specific differential-phase rainfall estimators that arises from filtering and measurement error.

No papers were found that specifically address prioritized technical needs regarding the archiving of storm events, data compaction and transmission techniques, and turbulence studies.

2 TOPICAL ACTIVITIES SUMMARY

2.1 Velocity Dealiasing and Range Unfolding

Doppler velocity fields are contaminated by folding whenever the true radial wind speed exceeds the unambiguous velocity (v_a) of the radar as given by v_a=PRFλ/4 where PRF is the pulse repetition frequency and λ is the radar wavelength. The true radial velocity is the radar measured value plus $2nv_a$ where n is the Nyquist interval number. Commonly used unfolding schemes may become confused if the initial velocity value along a radial is folded. Yamada and Chong (1999) propose to determine the proper Nyquist interval from the Fourier expansion used in velocity azimuth display (VAD) analyses. The method requires no prior information regarding the wind profile. The paper begins with a summary of previously proposed methods that rely on continuity in range and azimuth, estimated terminal velocities, a procedure using a Fourier analysis dependent on azimuth, and dual-PRF methods. With the proposed method the wind field is assumed to be linear in the horizontal and uniform in the vertical and, consequently, described by a second-order (harmonic) Fourier series of the form

$$v_r=a_0+a_1\cos\phi+b_1\sin\phi+a_2\cos2\phi+b_2\sin2\phi \quad .$$

v_r is the true radial velocity, ϕ is the azimuthal angle, and the a's and b's are Fourier coefficients relating to components of the mean wind. A global shift in the velocity field only affects a_0. The desired n causes a_0+2nv_a to fall within the interval $\pm v_a$. Key steps in the procedure are to 1) determine the radar range with the largest number of valid velocity data, 2) make a first guess of the unfolded velocities by applying a simple continuity test, 3) apply a least-squares fit to find the Fourier coefficients, 4) modify a_0 to get a fold-free Fourier curve, and 5) unfold the remaining data with the computed n. Application to three events with widespread precipitation reveals that the correct Nyquist interval is assigned for azimuthal data sectors bigger than 130 to 160^o provided non-linear effects are not present. The technique would seem to work best for folding related to strong ambient winds rather than folding associated with strong mesocyclones or tornadoes.

A known problem with pulsed radars is the range limitation imposed by the pulse length whereby radar echoes from precipitation at intervals of the unambiguous range arrive at the radar simultaneously. Historically, range-folded echoes have been detected by varying the radar frequency (pulse repetition time) and by using phase-coded signals and random-phase coding. Phase coding alters the spectra of the overlaid echoes in a recognizable way. Sachidananda and Zrnić (1999) propose a variation of the method using systematic coding and a modified decoding procedure. Transmitted pulses are phase shifted with a systematic code sequence. Returned signals are multiplied by a known factor to make the first trip echoes coherent. Echoes from other multiples of the unambiguous range are phase modulated so that their autocorrelation functions are zero (noise). This is accomplished by making second and higher trip signals periodic over the sampling interval and effectively removing the bias of overlaid signals from the desired coherent signal. The second trip signal is made coherent by application of proper multipliers which render other trips phase modulated. A series of experiments is performed to test the scheme. The standard error for recovered velocities using the proposed systematic coding was reduced compared to random-phase coding. The scheme requires a powerful processor.

An alternate method for ameliorating range and velocity ambiguities involves staggered-pulse repetition times. Implementation of staggered-pulse methods has been hampered by clutter echoes which must be removed before ambiguities can be resolved. [Nonuniform sampling aliases the power from some Doppler frequencies to values near zero.] Previously suggested clutter removal methods often yield velocity estimates with large errors. Sachidananda and Zrnić (2000) describe a scheme which employs improved clutter filtering and then reconstructs the signal spectrum from staggered time series measurements with a Fourier transform and deconvolution procedure. The technique requires considerably more processing power than pulse-pair methods.

2.2 Severe Weather Detection

2.2.1 MESOCYCLONES

Apparent fluctuations in the intensity of radar-detected mesocyclones that arise simply because of discrete azimuthal sampling and radar range were examined by Wood and Brown (2000). For continuous sampling of mesocyclones whose centers correspond with a radar beam volume there is a gradual decrease in mesocyclone width, the distance between outbound and inbound wind maxima, and mean rotational velocity as the distance from the radar increases. Discrete 1^{o} azimuthal sampling results in wide fluctuations in mesocyclone width and strength simply because of the measurement locations relative to the mesocyclone. Intensity changes are oscillatory in nature (± 3 m s^{-1}). Core diameter fluctuations are discontinuous and can be as large as 3 km for mesocyclones at 100 km. Simulations of the case in which the closest data point is 0.5^{o} from the circulation center indicate that error fluctuations have a different phase and that the fluctuations in mesocyclone diameter are much larger than those with continuous sampling (no azimuthal blocking). A final simulation presents average results for azimuthal samples that are randomly spaced within a $\pm 0.5^{o}$ interval.

Observational studies suggest that 30% to 50% of storms with mesocyclones ultimately produce tornadoes. Hence, an important problem for those issuing weather warnings is predicting whether or not a detected mesocyclone will produce a tornado. Trapp (1999) performed a detailed analysis of the kinematic properties of three thunderstorms, observed with an airborne Doppler radar, that produced moderate-to-strong mesocyclones but did not spawn tornadoes. Tornado "failure" was defined as the absence of a tornado in a mesocyclone that produced a low-level vertical vorticity ≥ 0.01 s^{-1} and persisted for 15 min or more. All three events exhibited low-level mesocyclones, rainy downdraft, hook echoes, and bounded-weak-echo regions (BWERs) and produced severe hail. Although rear-flank gust fronts were evident, they did not advance to what is commonly referred to as the "occlusion stage". A TVS was detected in one storm (~2 km above ground) by a local WSR-88D. Tornadic mesocyclones (also a three-storm sample) had higher vertical vorticity, smaller radii of maximum wind, and greater stretching generation of vertical vorticity. Interestingly, swirl ratios, determined from the ratio of tangential and inflow wind components and geometric factors related to inflow depth and updraft radius, were larger in non-tornadic mesocyclones than in tornadic mesocyclones. Tornado failure was attributed to an intermediate range of swirl ratios for flows with Reynolds numbers that inhibit inflow and consequently suppress vorticity amplification via stretching. The dataset is rather small; hence, the explanation should be regarded as tentative. Also, dual-Doppler analyses presented are highly smoothed. Potential distinguishing characteristics, e.g., outflow boundaries and surface-layer flows, may not be well represented.

Mesocyclone detection with wavelets is examined in the study of Desrochers and Lee (1999). The procedure effectively filters small scales (noise) and is relatively insensitive to data voids. A nice review notes that previous detection schemes often find other shear features (e.g., gust fronts), are susceptible to noise and data gaps, and do not identify the mesocyclone vortex couplet directly but infer its existence with shear segments. Limitations of these methods are illustrated with a severe thunderstorm viewed by two radars. A description of wavelets and their application follows. Wavelets are basis functions used for decomposing signals, much like Fourier sines and cosines; but their impact is more local rather than global. Signal reconstruction is confined to scales of interest. A B-spline wavelet was used for analysis in this case because its shape is similar to the velocity profile in a Rankine-combined vortex. With radar data, processing is in the radial and azimuthal directions with special allowances for the polar coordinates and array sizes. A search area for final mesocyclone designation is determined by constructing azimuthal shear segments from the filtered data, identifying velocity extrema computed from the original data in the search region, and fitting the ensemble of points with an ellipse. The derived major and minor axes and mesocyclone orientation were similar for the two radars.

2.2.2 TORNADOES

Trapp et al. (1999) test the hypothesis that tornadoes form aloft and then descend to ground. "Tornadoes aloft" were defined as elevated vortex signature maxima (above 3 km) with gate-to-gate differential velocities $\geq$ 15 m s^{-1}. A parameter S, defined as

$$S = \frac{\Delta V_{peak} - \Delta V_{low}}{z_{peak} - z_{low}} ,$$

was computed, where ΔV_{peak} is the maximum velocity differential within a volume scan, ΔV_{low} is the velocity differential at the base 0.5^{o} elevation and the z's are the corresponding heights. To qualify as "descending tornadoes", S was required to be $\geq$ 2.25 m s^{-1} km^{-1} for at least one observation time prior to tornadogenesis. Signatures from 52 tornadic storms detected by WSR-88Ds revealed that only 52% had descending tornado signatures. Initial detections were typically two volume scans (~ 10 min) prior to tornado touch down. Because non-descending tornadic vortex signatures are quite common, forecasters should be alert to the fact that tornadogenesis may be in progress when the maximum velocity difference is at the base elevation. Low-level tornado formation was thought to be more common with squall lines than with supercells.

Marzban et al. (1999) use the tornado detection algorithm as an example in a general discussion of how to select "best predictors" when developing algorithms. The study indicates that certain inputs in the current algorithm, namely the parameter pairs of height of the maximum gate-to-gate velocity difference/height of the maximum shear and the low-level shear/maximum shear, provide redundant information. Also, the radar distance has no predictive value. Good predictors include the low-level gate-to-gate velocity difference, the height of the TVS above the radar, and a tornado strength index.

2.2.3 TROPICAL CYCLONES

To better deduce the flow structure of tropical cyclones observed with a single Doppler radar Lee et al. (1999) and Lee and Marks (2000) are developing the Ground-Based Velocity Track Display (GBVTD) technique. Part I of the study (Lee et al.) evaluates the retrieval technique with analytical wind fields that simulate tangential and radial wind components, cyclone motion, and imposed disturbances (wavenumbers 1–3). The procedure consists of 1) data interpolation from polar coordinates to a constant-altitude PPI (CAPPI), 2) establishing the tropical cyclone center, 3) interpolating the CAPPI data to a cyclone-based cylindrical coordinate system, and 4) wind field construction. The model and the Doppler observations are matched with a least-squares fit. Mean tangential and radial flows were well resolved, but retrievals for cyclones with a cross-beam translation component and imposed disturbances became somewhat distorted. The precise cause of the distortion can be determined by examining the characteristics of the zero Doppler velocity contour.

In Part II, Lee and Marks acknowledge that the GBVTD wind retrieval method is sensitive to the assumed location of the circulation center. For example, missing the actual circulation center by 5 km can cause a severe (~20%) underestimate of the maximum tangential wind and create a significantly aliased wavenumber 1 wind component. They propose an iterative procedure for determining the cyclone center (the relative vorticity maximum) which involves the construction of search triangles that are modified in a systematic manner to find the radius of maximum wind.

Convergence to a solution is sped by the presence of strong velocity gradients. Designated circulation centers for analytical cyclones were within 0.34 km. Application to observed tropical storms is influenced by data voids and weak velocity gradients. Accuracies of 1–2 km are expected.

2.2.4 Icing

A capability for remotely detecting icing conditions would be of tremendous benefit to the aviation community. Supercooled water occurs in the updraft regions of subfreezing clouds when the generation of vapor exceeds the depletion by depositional growth on frozen particles. Unfortunately, other than freezing rain, icing situations are typically characterized by drops with diameters < 200 μm and concentrations that are not detectable with the WSR-88D. Zawadzki et al. (2000) have developed a diagnostic tool, initialized by single-Doppler radar measurements, that could alert forecasters to potential icing conditions. It's assumed that supercooled water coexists with detectable frozen precipitation. A variational analysis is performed with radar reflectivity and radial velocity measurements to derive the three-dimensional flow in areas of precipitation. The wind field (assumed steady) and a local sounding are then used to initialize a cloud model. The model finds an equilibrium liquid water content that is consistent with the retrieved updraft and the observed distribution of snow. A detailed description of the model and enabling assumptions is given. In the diagnostic model the excess of water vapor above saturation, minus the deposition on snow, yields the condensation on supercooled cloud drops. Using the retrieved updraft speed to find the supercooled water presents some difficulties that are discussed in the paper. The feasibility of diagnosing supercooled liquid was demonstrated with simulations using a kinematic model and radar measurements from two stratiform events. A limitation of the technique may be the presence of undetected ice crystals which would deplete the supercooled water and result in an overestimation of the icing threat.

2.2.5 Lightning

An ability to predict the onset of lightning in thunderstorms would have utility for those engaged in outside activities as well as the aviation and recreation industries. Lightning activity typically begins when convective updrafts reach the −10 to −15°C level and charge separation processes are initiated. Gremillion and Orville (1999) investigate the potential for predicting the lightning onset in air mass thunderstorms from radar measurements and a temperature sounding. Data from the WSR-88D at Melbourne, Florida were first interpolated to a Cartesian grid. The reflectivity values at temperature levels of −10, −15, and −20°C were determined and overlaid on cloud-to-ground lightning locations. Results were quantized at 5 dB intervals. An event was not defined until two consecutive radar measurements surpassed a reflectivity threshold. Detailed case studies of a storm with lightning and one without are presented. The latter was characterized by a reduced storm top (9 km versus 13.5 km). Although the top was well above the −20°C level, the reflectivity values were much less than with lightning producing storms. A statistical analysis was performed of 31 storms with lightning and 8 without. At the −10°C level and a reflectivity threshold of 35 dBZ, the POD for lightning detection was 0.88, the FAR was 0.20, and a CSI of 0.72 was determined. The median time lag to the first lightning strike was 7.5 min. For a reflectivity threshold of 40 dBZ the POD, FAR, and CSI were 0.84, 0.07, and 0.79, respectively. Testing on an independent dataset and perhaps on other thunderstorm types (e.g., mesoscale convective systems and squall lines) seems in order.

2.3 Precipitation Analysis

2.3.1 ACCUMULATION TECHNIQUES

Anagnostou and Krajewski (1999a) describe an algorithm designed for real-time precipitation estimation that combines weather radar data and rain gauge observations. The algorithm makes range–height corrections using the radar reflectivity profile, constructs a hybrid reflectivity map from the lowest two elevation angles, classifies precipitation as stratiform or convective, makes corrections for mean-field and range-dependent bias, and incorporates an advection scheme to mitigate the effects of discrete radar temporal sampling. Adjustments are made on a global basis. The algorithm generates output precipitation fields for 1 h, 3 h, and storm accumulations on 2 and 4 km grids. Range–height corrections account for bright-band effects, changes in the dielectric constant, and incomplete beam filling when the radar beam overshoots the precipitation. The adjustments are based on either mean vertical profiles (assuming spatial uniformity) or climatological information. Precipitation type classification is made with an adaptation of the method developed by Steiner et al. (1995)[1]. Storm advection corrections are based on cross-correlation coefficient analyses between consecutive rain maps. A final step consists of the application of a mean-field bias adjustment derived from gauge–radar comparisons.

An evaluation of their rainfall estimation technique and comparison with the WSR-88D Precipitation Processing Subsystem (PPS) is described by Anagnostou and Krajewski (1999b). For ranges out to 50–70 km, integration of radar reflectivity from the lowest two elevation angles was beneficial. Beyond 70 km only data from the lowest elevation angle are used. Their results suggest the algorithm can be improved by setting the exponent of the Z–R relation to a value between 1.6 and 1.7. [By itself, such a change would cause a sizeable reduction in rain rates.] Other analyses suggest that root-mean-square errors (RMSEs) are sensitive to an apparent agreement between the Z–R relation exponent and the hail threshold. A physical explanation for the agreement was not given. Application to a two-month dataset from the Melbourne, Florida WSR-88D disclosed an overall correlation between gauge amounts and radar estimates of 0.81 and a bias of 1.03. Improvements over the PPS were estimated at 20%. The advection scheme resulted in only modest improvements in rainfall estimates. Supposedly, storm velocities were often contaminated by new growth.

Young et al. (2000) examine bias in NEXRAD precipitation estimates and evaluate procedures that combine rain gauge observations and radar measurements. Of concern are the benefits and the quality of the combined dataset compared to rainfall estimates derived from gauge or radar data alone. The dataset included hourly precipitation estimates made by the Arkansas-Red River Basin River Forecast Center. The Center produced two sets of gauge-adjusted precipitation estimates. One method (Stage III) computed a mean bias adjustment factor, based on gauge–radar comparisons, which was then applied to the radar data. This analysis was then combined with a gauge-only analysis. With the second adjustment method (P1) gauge–radar comparisons were made at gauge sites and adjustments applied to the radar precipitation field by a distance-weighing scheme. Pronounced range-dependent biases, rings, and spokes persisted in the Stage III analyses but were largely absent in the P1 analysis. The authors were unwilling to declare one method superior to the other. They argue that an in-depth error analysis is required and that the necessary data do not exist.

A procedure used by Swedish and Finnish researchers for combining radar and gauge observations is described by Michelson and Koistinen (2000). The procedure is applied to a network of radars surrounding the Baltic Sea. As a first step, rainfall estimates from individual radars are adjusted for known system (calibration) biases to reduce mean differences between the radar estimates and gauges. To ensure a stable database, radar–gauge pairs with radar sums

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[1] Steiner, M., R.A. Houze Jr. and S.E. Yuter, 1995: Climatological characterization of three-dimensional storm structure from operationa and raingauge data. *J. Appl. Meteor.*, **34**, 1978-2007.

under 0.1 mm and gauge values < 0.5 mm are removed. Data pairs may be collected over several days to obtain ratios over the operational range of the radars. A range adjustment, based on a second-order fit applied to logarithms of gauge-to-radar ratios, is then made to account for the mean vertical reflectivity profile (on the intermediate time scale). [Short-term variations caused by different precipitation regimes, which could be important, are smoothed in this approach.] Recent gauge–radar comparisons are then given weights according to their perceived quality, i.e., their deviation from the distribution mean. Data pairs with quality weights are combined with an inverse distance-weighing scheme to make local adjustments to the radar rainfall field. Although the explained variance in the adjusted precipitation field is low (0.30), it is significantly higher than that of the unadjusted field (0.18). Curiously, the adjustment procedure leads to higher accumulations for small amounts and lower accumulations for large amounts.

Quality control and radar corrections applied by the United Kingdom Meteorological Office in generating their precipitation products are described by Harrison et al. (2000). The paper begins with an overview of the various problems that affect radar rainfall estimates in the United Kingdom. The British Isles are covered by a network of 15 C-band radars which transmit radar images to a central site for composition under their Nimrod system. Preliminary precipitation estimates are made with the Marshall and Palmer Z–R relation. Images are examined for completeness and compared to infrared and visual satellite images to identify and remove anomalous propagation. The surface precipitation rate is found by applying an idealized vertical reflectivity profile, which is weighted by the radar beam characteristics, and the radar measured reflectivity at the base of the bright band. Rainfall estimates are compared to rainfall at select gauges and an adjustment factor is applied to remove any calibration bias. Spatial adjustments are not attempted–other than the range adjustment inferred from the vertical profile. As part of verification procedures, the quality controlled (raw) and adjusted rainfall estimates are compared to hourly rainfall observations from gauges. Residual bias and random errors among point comparisons are determined. Typically, a RMSE reduction of ~30% is achieved. Similar comparisons are also made for monthly periods. The comparisons confirm the utility of the vertical profile adjustment for reducing range bias. When examined as a function of azimuth, the data disclose the validity of occultation and clutter mitigation procedures.

A hydrometeorologic forecast system that combines radar and gauge information has been developed by Pereira Fo and Crawford (1999). The radar field is treated as background and adjusted by the gauge observations. The two precipitation fields are weighted according to their two-dimensional covariance structure. Adjustments to the radar analyses effectively correct for hail contamination, attenuation, range effects, and calibration bias. The authors note that rainfall estimates with the Twin Lakes WSR-88D (KTLX) are 28% low on average. Hydrologic verification of the analyses was hampered by data gaps in the radar record. Results show that runoff is highly sensitive to the rainfall estimate. The radar underestimate in rain accumulations resulted in a three-to-five-fold runoff underestimate.

2.3.2 Vertical reflectivity profiles

It's known that the increase in beam height and beam broadening with range can cause significant bias in radar rainfall estimates. The deterioration is sensitive to vertical gradients of precipitation, melting layer (bright-band) effects, and changes in precipitation phase. Underestimates can arise from attenuation and whenever the radar overshoots the precipitation. Overestimates result from the smoothing of precipitation gradients. There have been numerous attempts to improve rainfall estimates by making adjustments for observed vertical reflectivity gradients. Retrieval of the profile beyond a few tens of kilometers is difficult because of poor vertical sampling resolution and the fact that the melting layer (usually a 0.5–1 km layer) generally is not well resolved by the radar. Consequently, procedures have been adopted to compute profiles at short radar ranges and then apply them at distant ranges. This procedure usually assumes homogeneity. To lessen range effects Seo et al. (2000) propose a real-time adjustment procedure to account for nonuniform vertical reflectivity profiles (VRPs). The authors give a nice mathematical treatment to the procedure and present applications in situations with strong beam blockage. The procedure causes rainfall estimates from the lower elevation angles to converge to a similar value, reduces bright-band contamination, and reduces spoke-like features in accumulated rain fields. However, RMSEs after removing residual biases are reduced by only 10%, and considerable scatter remains in gauge–radar comparisons. The residual problems may be tied to spatial variations in DSDs (and consequently Z–R relations) and uncompensated bright band effects.

Issues regarding vertical reflectivity profiles, which are amplified with stratiform rains, have been studied extensively in Europe, particularly by the French and Swiss. These studies show benefits are gained when VRPs at distant locations are modified by mean conditions deduced at short ranges. The studies also suggest that further improvement is possible by accounting for spatial variations. Vignal et al. (1999) have a procedure for computing local VRPs on roughly a 20 km scale from volumetric radar observations. The problem is cast in terms of radar reflectivity ratios (using the lowest radar elevation as a base). Normalized profiles are computed for subdomains of the radar umbrella and matched with an idealized profile. The procedure includes a de-convolution of the "apparent VRP" to recover the details of the "true" profile lost by beam broadening with range. Sensitivity tests indicate that the range of maximum profile identification is 70–120 km, depending on the number of vertical samples and bright-band characteristics. An efficiency parameter is calculated to determine the goodness of fit. Efficiencies at more distant ranges can be improved somewhat by increasing the computational domain. The procedure is applied to a case study and evaluated in terms of surface rainfall estimates. Detailed reflectivity profiles with strong vertical reflectivity features, not apparent in the discrete radar measurements at 60–90 km, are retrieved. Small improvements in the RMSE (11 versus 13%) were determined over rainfall estimates made with measurements from a low elevation angle. Greater improvement (11 versus 43%) occurred when higher elevation data were used as a base.

Vignal et al. (2000) compare VRP adjustment schemes based on a climatological profile (averaged over time and space), an hourly mean vertical reflectivity profile determined in real time by averaging measurements within 70 km of the radar (the current Swiss method), and a procedure that computes VRPs on an ~20 km grid (described above). With the latter scheme the profiles were de-convoluted to account for beam smoothing. Reflectivity estimates were extrapolated to ground with the three techniques. Calculated rainfalls were then compared to gauge observations at ranges of 20 to 130 km. Results revealed significant improvement in the rainfall estimates for all three methods. Fractional standard errors (FSEs) for the climatological adjustment procedure were 31% compared to 44% for no adjustment. The FSEs for mean and variable adjustments were 25 and 23%, respectively. Thus, ~90% of the total possible benefit occurred with the single mean-profile method. The mean profile was believed to be suitable for locations with beam blockage and severe clutter. The computation of more frequent profiles (30 and 5 min) did not lead to marked improvement with a convective event and only small improvement with a stratiform event.

2.3.3 WSR-88D PRODUCT EVALUATION

The utility of the WSR-88D for estimating rainfall was examined in several recent studies. Brandes et al. (1999) compared rainfall estimates from WSR-88Ds in Colorado (Denver, KFTG) and Kansas (Wichita, KICT) with dense rain gauge observations and found correlation coefficients of 0.78 to 0.95. Bias factors were 1.07 and 1.05 (small underestimates). The rain estimates were highly correlated with those from a collocated research radar suggesting that storm-to-storm bias fluctuations were due in large part to variations in drop-size distributions. Klazura et al. (1999) stratified rainfall estimates from WSR-88Ds according to subjectively-determined horizontal reflectivity gradients. A bias factor of 0.88 (a small radar overestimate) was determined for the high gradient (generally strong convective) events. Stratiform events had a bias factor of 2.23. Both precipitation types had significant range biases. Underestimates occurred for both precipitation types at ranges less than 50 km.

The impact of distance on precipitation processing subsystem (PPS) products for a flash flood probed by WSR-

88Ds at Dover Air force Base, Delaware (KDOX) and Wakefield, Virginia (KAKQ) are examined in a study by Stuart (1999). The radars were located 90–120 nm from the event. [Rainfall estimates from the WSR-88D at Sterling, Virginia (~40 nm distance) were not used.] No hail reports were received. At the time of the event, the PPS was using the default hybrid scan. Adaptable parameters for the two radars were identical except for the maximum reflectivity outlier value and the reflectivity threshold maximum for computing rain rates. The latter values were 53 dBZ (KAKQ) and 70 dBZ (KDOX). Maximum rain accumulations were 3–4 in for the Wakefield radar and 5–6.2 in for the Dover Air Force Base radar. The latter estimates agreed more closely with surface reports. Because maximum radar reflectivities were as high as 60 dBZ, the lower threshold was thought to have contributed to the underestimate with the Wakefield WSR-88D. Another source of bias with the KAKQ radar was believed to be the ground clutter suppression procedure. Medium suppression was employed for all ranges. Smoothing is also mentioned as a possible contributor to the rainfall underestimates; but the argument is not compelling because the smoothing of gradients generally associates with an overestimate of precipitation.

Nicosia et al. (1999) evaluate WSR-88D precipitation products for a flash flood produced by a lake-enhanced rainband that occurred near Erie, Pennsylvania. With the Z–R default relation, the Cleveland, Ohio radar (KCLE) underestimated the maximum rainfall from the rainband by ~40%. Convective rainfall in neighboring areas was overestimated. The underestimate was attributed to warm-rain processes occurring below the radar beam. It's postulated that the radar beam overshot higher reflectivity values at low levels. Application of the "tropical" Z–R relation of Rosenfield et al. (1993)[2] improved the estimates in the flood region but overestimated the rainfall in the area of convection by 200–400%. Alternately, adjusting rainfalls in the flood region based on radar–gauge comparisons from the convective rainfall would have further degraded the estimates of the flooding.

A study of the Fort Collins, Colorado flash flood of 28 July 1997 was reported by Petersen et al. (1999). Rainfall estimates from the WSR-88D at Cheyenne, Wyoming (KCYS) were compared to gauge-observed rainfalls and to estimates made with a research radar. A maximum rainfall of 10.2 in was recorded at one gauge in a 6-h period. KCYS maximum rainfall estimates with the NEXRAD default relation were 5.0 in (more than a factor of 2 low). Bias with the tropical Z–R relation was much less; the maximum estimated rainfall was 10.8 in. The KCYS estimates were ~75% those of the research radar, signifying a calibration difference. Precipitation production was thought to have been dominated by warm rain processes. That the drops may have been uncharacteristically small is supported by improved rainfall estimates with the reflectivity–differential reflectivity measurement pair.

The performance of the WSR-88D PPS bias adjustment procedure for a heavy rain event in Colorado was examined by Fulton (1999). The PPS determines the radar bias by comparing hourly gauge reports and corresponding radar estimates at selected sites. The calculated bias, a multiplicative factor intended to bring the radar estimates in line with the gauge amounts, is assumed to be valid for the hour following receipt of the gauge reports. [This procedure can introduce bias if the adjusting gauges are at one range interval and the adjustment made at another range interval. Bias can also be introduced if the character of the precipitation changes, e.g., from convective to stratiform over the hour interval.] The tested version of the algorithm estimated the bias from the nine data bins that surrounded each gauge location. In one experiment, it was assumed that there was no bias if the gauge observation was within the numerical range of the surrounding radar bins. If the gauge observation fell outside the range of radar data bins, the numerically closest radar value was paired with the gauge observation. This procedure minimizes the bias adjustment and yielded hourly bias values of 0.96–1.00. In a second experiment, the algorithm was modified to pair the radar data bin in which the gauge resided with the gauge report. A bias of 0.61 was determined. Application of this factor greatly reduced the

[2]Rosenfeld, D., D. B. Wolff, and D. Atlas, 1993: General probability-matched relations between radar reflectivity and rain rate. *J. Appl Meteor.,* **32,** 50-72.

estimated rainfalls at test gauges (errors decreased from 63 to 25%). However, the adjustment caused a significant underestimate of the flash flood.

An evaluation of WSR-88D quantitative precipitation estimates over coastal regions in the western U.S. is given by Westrick et al. (1999). Problems endemic to the region arise from beam blockage by mountains, shallow orographic precipitation (often confined to a surface layer below 2 km), and low freezing levels. The problem is compounded by the considerable elevation of several radar sites. Under typical conditions quantitative precipitation estimates can be made over only one third of the region (assuming beam blockages less than 50%). Moreover, estimation is poorest in flood prone areas. Specific recommendations call for implementation of 0^{o} or negative scan angles, additional scans at low elevation, more radars placed in coastal regions, and research aimed at integrating radar and gauge observations.

2.3.4 Z–R RELATION AND GAUGE/RADAR COMPARISON ISSUES

The variability in Z–R relations reported in the literature is generally attributed to fluctuations in DSDs. Ciach and Krajewski (1999) investigate possible contributions to the observed variance from the application of different computational methods for estimating relations and from measurement error. The experimental model consists of a fixed relation between radar reflectivity and rain rate. Parameterizations are made for radar measurement errors due to differences between the true surface reflectivity and radar-measured values and for differences between radar estimated rainfall intensity and point gauge observations. It is assumed that the errors for the gauges and radar are not related and that they have lognormal distributions. Methods for deriving Z–R relations examined are the direct nonlinear regression from R to Z, reverse regression (Z to R), and the probability-matching method. The estimated exponent for R using direct regression always exceeds that of the assumed model due to errors in reflectivity measurements. Reverse regression underestimates the exponent due to variability in the rainfall intensity and related point–area differences. Interestingly, the probability matching method, which is dependent on both the radar and gauge errors, is found to be the geometric mean of the two nonlinear regressions. The authors conclude that measurement errors contribute significantly to the variation in Z–R relations reported in the literature.

Related problems were investigated by Campos and Zawadzki (2000). They compared the contribution of drop-size distribution measurement uncertainty on derived Z–R relations. DSD measurements were available from a Joss–Waldvogel impact disdrometer, an optical spectro-pluviometer, and spectra obtained with a specialized Doppler radar. Differences in Z–R relations derived from linear regression of 10logZ versus logR for the three instruments show wide fluctuations similar to that seen in the literature and widely ascribed to meteorological factors. Campos and Zawadzki also derive relations with nonlinear regression between Z and R. The relationships determined with the latter method have significantly smaller coefficients and larger exponents. The authors argue that the former regression (10logZ versus logR) minimizes absolute errors and gives better rain rate estimates while the second method (Z versus R) yields more precise accumulations. They then derived relations with R as the dependent variable (similar to an experiment conducted by Ciach and Krajewski), performing a linear regression of logR as a function of 10logZ, and then inverting the relations. Yet another distinctive set of estimators was obtained.

Rainfall estimate errors due to variations in Z–R relations and the radar constant were investigated by Ulbrich and Lee (1999). They compared radar reflectivity estimates from the Greer, South Carolina WSR-88D (KGSP) and a raindrop disdrometer. The radar underestimated the reflectivity by 3.5 dB. By varying the coefficient of the Z–R relation to conform with relations for stratiform and convective rainfalls (200 and 450, respectively), they determine the WSR-88D relation should underestimate stratiform rain by 25% and overestimate convective rain by 33%. Other experiments were conducted in which the exponent was also allowed to vary. Computations with a hypothesized −4 dB radar calibration error predicted bias factors of 2.55 for stratiform rain and 1.35 for convective rainfalls. Because these biases exceed that for precipitation type, the authors conclude that the large bias with the KGSP WSR-88D lies with a calibration error.

An algorithm for classifying precipitation echoes as either convective or stratiform would improve estimates of heating rates in the atmosphere and improve rainfall estimates. Successful partitioning of precipitation types and subsequent improvement in rainfall estimates has proven elusive. Biggerstaff and Listemaa (2000) modify the technique of Steiner et al. (1995)[1], which tended to misclassify heavy stratiform rain as convective and light rains at the edges of convective cells as stratiform. The authors propose a three-dimensional approach with new diagnostic parameters for the vertical gradient of reflectivity, bright-band fraction, and reflectivity gradients. A global consistency check was also added. A consequence of this last step was that small convective elements were occasionally classified as stratiform. The new algorithm was tested on three events and results compared to that of Steiner et al. Performance was judged on the percentage of echoes reclassified with the proposed algorithm. Largest changes occurred with unorganized convection. The new algorithm overcomes some problems with the method of Steiner et al. Whether heating or rainfall estimates were improved is not demonstrated.

Sampling differences between point and area gauge measurements of rainfall and their role in gauge–radar comparisons were investigated by Anagnostou et al. (1999). Radar and gauge errors were expressed as ratios of their true values and assumed to represent a stochastic process in which the ratios are distributed lognormally (with a mean linear value of 1) and with zero covariance. Other important assumptions are that radar and rain gauge data are unbiased, statistics are homogeneous within the domain, and that radar errors are uncorrelated at distances larger than the grid interval (4 km). Results show that as much as 60% of the variance between gauge and radar rainfalls arises from area–point differences. Extension to other geographical regions, seasons, and precipitation types is not straightforward because rainfall statistics must first be developed.

2.4 Wind Analysis Techniques

2.4.1 BISTATIC NETWORKS

An inexpensive multiple Doppler radar network can be assembled using a primary radar for transmitting radar signals and recording scattered returns at remote locations with passive non-scanning receivers. Each remote (bistatic) site measures the Doppler shift of the transmitted energy as obliquely scattered by precipitation. The wind field is reconstructed by combining Doppler measurements from one or more passive sites with those from the primary radar. Low-cost, broad-beam antennas and low-gain receivers are used. An advantage with a bistatic network is that measurements at a particular point in space are made simultaneously with all receivers. Volumetric sampling is dictated by the scanning strategy of the primary radar (typically 5 min or so). Potential problems arising from the use of broad-beam, low-gain antennas are thought surmountable by employing multiple receivers. Protat and Zawadzki (1999) describe the operational bistatic network at McGill University. Three-dimensional wind fields are retrieved with a method used previously with multiple Doppler radars. The technique applies a semi-adjoint constraining (variational) model (Laroche and Zawadzki 1995)[3] under the assumption that the reflectivity and radial velocity fields have conservative properties. The paper begins with a concise explanation of how a bistatic network operates. The radial velocities are used as weak constraints and the continuity equation is a strong constraint. The problem is overdetermined with more than one bistatic receiver. Steps in the procedure are: 1) make an initial guess of the horizontal wind components, 2) calculate the vertical velocity, 3) calculate the gradient of a cost function, 4) evaluate convergence

[3]Laroche, S., and I. Zawadzki, 1995: Retrievals of horizontal winds from single-Doppler radar clear-air data by methods of cross correla variational analysis. *J. Atmos. Oceanic Technol.*, **12,** 721-738.

criteria, 5) calculate new components of the horizontal wind with a conjugate–gradient method, and 6) iterate until the desired solution is achieved. Several examples are presented.

An evaluation of sidelobe contamination with the McGill University bistatic network is presented by de Elía and Zawadzki (2000). The passive sites are equipped with low-gain receivers which have lower sensitivity than traditional high-gain radars. Also, the broad beams cause the bistatic receivers to be more sensitive to multiple scattering effects and side lobe contamination. Because contamination is proportional to the one-way antenna gain, sidelobes are twice as intense as those with traditional antennas. The particular sidelobe pattern depends on the characteristics of both the transmitting radar and the receiver and can be contaminated by ground clutter. A simulation model and contamination index were developed to quantify sidelobe influences on reflectivity and Doppler fields and to aid in the design of bistatic networks. Contamination of the bistatic Doppler and reflectivity measurements generally concentrates in the direction of an ellipsoid with its foci at the radar sites. Impacts are most pronounced in regions of weak echo with nearby strong convection. Several examples are shown. The authors note that, if the beam patterns are known, a correction scheme can be built into the wind retrieval algorithm. Additional receivers may be part of a solution.

2.4.2 SINGLE-DOPPLER WIND-FIELD RETRIEVAL

Studies of wind-field retrieval from single-Doppler measurements are presented by Lazarus et al. (1999) and Liou (1999). Both studies evaluate a variational technique originally proposed by Zhang and Gal-Chen (1996)[4] whereby the three-dimensional wind field is retrieved from multiple time levels of radar data. The primary assumptions are that the reflectivity pattern is conserved and that the velocity field is steady in a reference frame given by the mean translation velocity. Mean and perturbation components of the wind field are retrieved as a least-squares minimization problem with constraints for reflectivity conservation and for geometric terms that relate the radial velocity and Cartesian wind components. The process involves the minimization of a cost function. The weights of each constraint are inversely proportionate to their variances. Lazarus et al. give an excellent summary of the method. They then conduct a series of sensitivity experiments utilizing simple simulated radar reflectivity and wind patterns. They note that the mean flow cannot be determined in regions without a reflectivity gradient. Also, the retrieved mean flow is sensitive to small-scale reflectivity errors. The error decreases as the domain increases. Analyses are also presented for various signal-to-noise ratios and for the retrieval of a simple divergent wind pattern for various analysis domains.

Liou suggests a modification of the Zhang–Gal-Chen variational method for minimizing time derivatives of a scalar field in a moving reference frame. New terms representing mass conservation and vertical vorticity are added to the cost function to reduce noise. Cost function minimization involves making an initial guess, determining the gradients of the cost function, using a conjugate-gradient algorithm to find a new estimate of the wind field, and repeating the process until a minimum cost function is achieved. Tests showed higher correlations between the retrieved and model wind field and reduced RMSEs. The improvement comes largely from the mass conservation term. Other experiments are conducted with multiple time levels to represent different scanning strategies. Retrievals improve with the number of input time levels and for longer intervals between data insertions (270 s versus 180 s). Other experiments are conducted assuming various error levels in the data and using reflectivity measurements alone for the retrieval. For the latter experiment the radial velocity information is not used but a degraded wind field can be estimated from the time series of reflectivity using the reflectivity conservation equation, the continuity equation, and the vorticity term (three equations and three unknowns).

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[4] Zhang, J. and T. Gal-Chen, 1996: Single-Doppler wind retrieval in the moving frame of reference. *J. Atmos. Sci.*, **53,** 2609-2623.

2.5 Radar Analysis Techniques

2.5.1 GROUND CLUTTER MITIGATION

The removal of ground echoes from radar signals is highly desired because of their potential impact on algorithm performance. Ground clutter is of two types, permanent echoes associated with nearby structures, trees, and terrain and transient clutter that occurs whenever atmospheric conditions cause the radar beam to be ducted along the ground. Radar reflectivity returns from clutter typically have high intensities and high spatial variance; Doppler returns are characterized by mean radial velocities near zero and small spectrum widths. Velocity contamination is often removed with notch filters. A potential new method for removing ground clutter echoes from Doppler signals with a regressive filter is proposed by Torres and Zrnić (1999). Classical digital filters are either finite impulse or infinite response filters where filtering is achieved by superposition of signal samples. Regressive filters approximate radar signals with polynomial functions in the time domain. The technique assumes that clutter echoes vary slowly in time compared to meteorological echoes. The utility of regressive filters is demonstrated by imposing a narrow-band Gaussian process having zero mean velocity on a weather signal. The composite signal is filtered to obtain the Doppler moments. The clutter suppression ratio for the regressive filter with a narrow clutter spectrum was 10 dB better than the high-suppression elliptical filter used on the WSR-88D. There was also less suppression of weather signals. Superiority of the regressive filter was also shown for a dataset collected with a WSR-88D.

A neural network (NN) method for detecting anomalous propagation and ground clutter echoes in radar reflectivity fields is proposed by Grecu and Krajewski (2000). [For a discussion of neural networks and data mining see Section 3.] Key steps in the process are the selection of predictors and network calibration. The Doppler information was not used. System predictors include the translational velocity of reflectivity features, the local velocity variance of these features, echo heights, height of the maximum reflectivity, the reflectivity magnitude, the range of the echo, the local reflectivity variance, a fluctuation parameter, and the local maximum reflectivity gradient. Datasets consisting entirely of anomalous propagation (AP) and precipitation were selected for calibration (training). Continuity checks are made to ensure that the same designation is made throughout a vertical column. The procedure was applied to datasets obtained from two WSR-88Ds. Of the predictors evaluated, echo height provided the best separation of AP and precipitation. Classifications were compared to those determined with a "quadratic discrimination function". The error reduction with the NN was about a factor of two. Performance varied according to the training dataset. An obvious improvement to the scheme would be to add the Doppler information.

Kessinger et al. (1999) have been developing an AP detection algorithm that utilizes fuzzy logic. Input parameters are the magnitude of the radial velocity, the spectrum width, the texture of the velocity and reflectivity fields, and the vertical gradient of reflectivity.

2.5.2 TERRAIN INFLUENCE

To aid in the interpretation of radar data in mountainous terrain James et al. (2000) superimpose radar observations (reflectivity and radial velocity) on 30-s digital elevation information available from the Defense Mapping Agency and the National Aeronautics and Space Administration. The terrain information is believed important for explaining enhanced precipitation in upslope regions and suppressed precipitation in downslope areas. The plots are thought useful for data quality assurance in regions where clutter suppression has been implemented and where the beam may be blocked.

2.5.3 ECHO EVOLUTION/MOVEMENT

In support of aviation activities, MacKeen et al. (1999) attempted to predict the remaining lifetime of single and multicell thunderstorms from their radar reflectivity characteristics at a specific development stage. Previous studies have shown storm intensity, size, and height to be of some value. Sixteen parameters generated by the WSR-88D storm cell identification and tracking (SCIT) algorithm and hail detection algorithm (HDA) were selected for study. Variables where determined for each 6 min data collection (VCP21) and correlated with the remaining lifetime. Variables weakly correlated with storm lifetime (linear correlation coefficients > 0.3) were the maximum reflectivity, height of the reflectivity maximum, height of the center of mass, height of the 40-dBZ reflectivity core, cell-based VIL, and storm-top height. [Note that these parameters are not all independent.] A multiple regression with all variables gave a correlation coefficient of 0.43. Tests with trends determined from every other or every third volume scan did not improve the results. Probability density functions of the remaining lifetimes were computed for various reflectivity thresholds. Expectedly, thunderstorms with lower maximum reflectivities were more likely to dissipate. Because the explained variance was so low ($\leq$ 18%), the authors conclude that longevity forecasts made with reflectivity parameters have no utility. Failure is attributed in part to non-linear relationships between radar characteristics and storm lifetime, sampling limitations presented by the scanning mode and deterioration with range, and the fact that reflectivity patterns are only by-products of meteorological processes. Although some improvement is expected if velocity and environmental data are added, the authors seem to favor making lifetime predictions with cloud models.

An interesting new approach to forecasting precipitation is described by Otsuka et al. (1999). The method, based on the assumption that pattern A will be followed by pattern B, is offered as an alternative to extrapolation. Forecasts are made by examining the historical record for similar events and retrieving previous outcomes. The challenge is to format the historical record into a manageable form for real-time application. The present application decomposes precipitation patterns into local and global textural features. Extracted local information consists of features that describe element motion, the degree of element formation and dissipation, and cell arrangement. Global features describe the shape of the overall echo pattern and its motion. Descriptors are represented by eigenvectors and eigenvalues. Their motion is used for comparison with the historical record. Matches are judged by computing a "dissimilarity" index. The historical record consisted of 1000 h of winter precipitation data (12000 images). Some examples of large-scale pattern designations and forecasts are shown. All considered features contributed to pattern designations (echo band, oriented stratiform rain, and scattered echoes). Overall, 87% of the patterns were correctly detected.

2.6 Data Acquisition Strategies

It's clear that radar scanning strategies influence algorithm performance. For example, designated echo tops with volume coverage pattern VCP-21 with 9 elevation scans and coarse elevation angles above 4.3^{o} would be expected to be less accurate than echo tops determined with the 14 elevation scans of VCP-11. Brown et al. (2000a) quantify the difference. The study incorporated VCP-11 scans and deleted scan elevations at 5.25, 7.5, 8.7, 12.0, and 16.7^{o} to construct a simulated VCP-21. The dataset consisted of several hours of measurements from the Melbourne, Florida and Frederick, Oklahoma WSR-88Ds. The storm cell identification and tracking (SCIT) algorithm, hail detection algorithm (HDA), mesocyclone algorithm (MESO), and velocity azimuth display (VAD) were selected for comparison. Potential upgrades to current WSR-88D mesocyclone and tornado detection algorithms were also studied. Components from the SCIT algorithm examined were the maximum height of the 30-dBZ echo and the vertically integrated liquid (VIL). There was a marked tendency for the 30-dBZ echo heights with the simulated VCP-21 scans to be lower than the VCP-11 tops. The differences occur out to a range of ~125 km. Beyond that distance storm heights generally are below 5^{o} and results for the two VCPs converge. Comparison of VILs reveals that those computed from VCP-21 were somewhat higher because the smaller number of measurements at middle storm levels, where the reflectivity is often a maximum, had greater relative weight. The spacing of vertical samples had less impact on the predicted size of hailstones. Diameter differences were typically < 0.6 cm. The probabilities of hail and probability of severe hail differed by ± 10%.

Mesocyclone depths with VCP-21 were smaller than that with VCP-11 ~10% of the time. Results for the proposed mesocyclone algorithm upgrade were similar. A considerable scanning strategy impact occurred with the tornado algorithm where tornado depths are less with VCP-21 approximately 25% of the time. When the analysis was restricted to locations where elevation angles > 5° were involved (i.e., for relatively short radar ranges) , the percentage of algorithm values that differed for VCP-11 and the simulated VCP-21 exceed 40% for all tested parameters except those for the HDA. Depending on the algorithm, significant over or underwarnings could result, suggesting that different warning criteria are required for the two VCPs.

In a companion paper Brown et al. (2000b) propose a methodology for optimizing scanning strategies. The technique seeks to minimize the uncertainty in storm height with range. A maximum storm height for surveillance purposes and the maximum height underestimate to be tolerated are specified. A minimum elevation angle is selected. This elevation sets the maximum range for data collection. The range is reduced until the height falls below the threshold for maximum height underestimate. [The maximum height underestimate with the current VCP-11, assuming a storm top of 16 km and a range of 230 km, is ~4 km at 2.4° antenna elevation.] At that point the second elevation angle is determined provided the angular difference is more than a half beam width. The process is repeated and constructs a VCP that is consistent with the selected maximum height underestimate. The latter parameter sets the number of scans that must be made. The duration of the scan is also determined by the desired accuracy of the measurements and the antenna rotation rate. The maximum feasible rate is selected. If the potential scan duration is too long, the maximum acceptable height underestimate can be increased. Considering all factors, such as the double passes currently made at the lowest two elevation angles and allowing for antenna motion between scans, Brown et al. show that a VCP with 19 elevation angles to a maximum elevation angle of 49° (having a maximum height underestimate of 18% or 2.9 km for a 16 km maximum storm height) could be made in 6 min 5 s. VCPs with 13 elevation angles and a maximum height underestimate of 28% would have durations of 4 min 58 s. The procedure could allow increased elevation samples, give better low-level coverage, and reduce the unsampled cone above the radar. The advantage of optimized scans is demonstrated with simulated VIL calculations and for microburst precursor detection.

2.7 Polarimetric Radar[5]

Polarimetric radar measurements are sensitive to scatterer size, shape, orientation, and composition. They can be used to identify ground echoes and biological scatterers and to discriminate among hydrometeor types. Radar polarimetry should lead to improved understanding of microphysical processes in storms, new algorithms for detecting weather hazards, and improved methods for estimating rainfall. Prospects for making polarimetric measurements with the WSR-88D are investigated by Doviak et al. (2000). They propose to simultaneously transmit horizontally and vertically polarized pulses. To ensure the purity of returned signals a possible modification of the current three-spar antenna feed horn support was considered. [The current design has a spar in the vertical plane.] At first it was thought that a switch to a four-spar system creating an X pattern would result in a better match between the radiation patterns of the two radar beams. However, measurements with research radars revealed the four-spar feed system had higher sidelobes. Consequently, the decision was made to retain the current configuration. Antenna pattern measurements were then made with the NSSL WSR-88D before and after a modification of the antenna feed from a single port (designed to

[5]A tutorial of dual-polarization radar fundamentals and description of potential algorithms can be found in last year’s report (http: www.osf.noaa.gov/app/sta/algorithm.htm).

transmit horizontally-polarized waves) to a dual-port system. Sidelobe patterns met original specifications for the WSR-88D, and the horizontal and vertical beam patterns agreed to within a fraction of a decibel down to a −20-dB signal level. While a weak cross-polarization signal was found, the authors conclude that the leakage should not compromise the polarimetric measurements. Another key consideration is the selection of a polarimetric basis that strikes a balance among desires to obtain the maximum precipitation information, to hold down radar modification costs, and to meet operational needs. A detailed theoretical comparison is made of linear and circular polarimetric bases. It's concluded that specific differential phase and differential reflectivity cannot be reliably determined with a circular basis, especially for light rainfalls. Also, circularly polarized waves can be significantly attenuated in an anisotropic medium. Thus, a linear horizontal–vertical basis is preferred.

For implementation on the WSR-88D Doviak et al. recommend two operational modes: 1) a dual-polarization mode with simultaneous transmission/reception and 2) a single-polarization mode. Some advantages with this system are the direct measurement of the correlation coefficient at zero lag, direct measurement of the differential phase shift, and faster scanning rates (or increased numbers of samples). A disadvantage with this scheme is that the linear depolarization ratio cannot be routinely measured and simple automatic detection of range-folded echoes is not possible. Potentially, a coupling of horizontally and vertically polarized waves could create significant bias in the polarimetric parameters. A related bias could be introduced by hydrometeor canting. Examples of polarimetric parameters determined from measurements in a data collection mode that alternated between horizontal and vertical polarization and a simultaneous transmission and alternate reception (STAR) mode designed to replicate simultaneous transmission and reception are presented. Unexplained differences in specific differential phase up to 0.5^o km^{-1} were found. Also, the correlation coefficient (ρ_{HV}) was lower for the STAR mode, possibly due to depolarization. The authors argue that simultaneous transmission and reception should give better results than either of the tested methods.

A description of the polarimetric radar operated by Colorado State University is given by Brunkow et al. (2000). Topics covered are system characteristics, processing capabilities, and calibration procedures. Polarimetric measurements are shown for a vertical cross-section through a thunderstorm.

2.7.1 RAINFALL ESTIMATION

The estimation of rainfall with the specific differential phase parameter (K_{DP}) has been an active research area in recent years. The signal arises from hydrometeors whose major axes are aligned with the polarization of transmitted radar signals. The parameter (a phase or time measurement) has several advantages over radar reflectivity (a power measurement) for estimating rainfall. For example, the differential phase is insensitive to radar calibration error and relatively insensitive to beam blockage and anomalous propagation. K_{DP} is related to the 4.24th power of the drop-size distribution for light rainfall rates and to the 5.6th power of the DSD for heavy rainfalls. Hence, K_{DP} is more closely related to rainfall rate (3.67th moment of the DSD) than is radar reflectivity (a 6th moment of the DSD). The specific differential phase is defined as one half the range derivative of the differential propagation phase (Φ_{DP}). The computation of K_{DP} entails filtering to reduce error in the Φ_{DP} measurements and assumes that the distribution of Φ_{DP} and consequently the precipitation is linear over the range interval of the calculation. The procedure causes a bias whenever the distribution is not linear. The bias can be either positive or negative and can be as large as 30%. A bias correction scheme has been proposed by Gorgucci et al. (1999). The procedure attempts to recover some of the lost signal by making use of the consistency between polarimetric parameters. That is, the specific differential phase can be computed from the radar reflectivity and differential reflectivity measurements; and the computed value can be compared to that obtained from the measured Φ_{DP}. Gorgucci et al. propose to adjust the radar estimates of K_{DP} with

$$K_{DP} = K_{DP}{}^{*} \frac{\langle K_{DP}{}^{r} \rangle}{(K_{DP}{}^{r})^{*}}$$

where $K_{DP}{}^{*}$ is the slope of the radar observed Φ_{DP} profile, $\langle K_{DP}{}^{r}\rangle$ is the average value of $K_{DP}{}^{r}$ constructed from the self-consistency principle, and $(K_{DP}^{r})^{*}$ is the estimate of $\langle K_{DP}^{r} \rangle$ obtained from the ϕ_{DP}^{r} profile. Application should restore some detail to the radar-estimated K_{DP} profile. While the authors demonstrate that fairly accurate adjustments can be made, the impact on accumulated rainfall estimates was not examined.

Gorgucci et al. (2000a) study the effect of the path length over which K_{DP} is computed on rainfall estimates. They note that K_{DP} estimates are subject to bias related to inhomogeneous rainfall distributions, nonlinearity in the rainfall estimators, and parameterization in algorithm development. In quantifying the errors they find that non-uniform precipitation path lengths cause underestimates of rainfall rate that range from 5% for a 10 dB gradient over the distance K_{DP} is computed to 25% for a 30 dB gradient. Bias due to algorithm nonlinearity causes an overestimate of 5% for a 10 dB gradient and an overestimate of 10-12% for a 30 dB gradient. Parameterization errors associate with underestimates of ~10% for nonlinear estimators regardless of the reflectivity variation. The accumulated effect is expected to be an underestimate of between 10 and 25%. The authors conclude that successful implementation of K_{DP} estimators will require techniques to reduce the bias.

Because K_{DP} is computed as a radial derivative and the exponent of the estimator is close to unity, the mean rainfall rate over a radial interval is largely determined by the change in Φ_{DP} over the end points of the range interval. Ryzhkov et al. (2000) note that this property gives improved rain rate accuracy for watersheds having radial dimensions of 10 km or more and for integration times $\geq$ 1 h. They compared watershed rainfalls estimated from radial distributions of K_{DP} with estimates determined from Φ_{DP} values at the leading and trailing boundaries. Results showed a reduction in bias with the Φ_{DP} method, an 8% underestimate compared to a 13% underestimate based on the spatial distribution of K_{DP}; fractional standard errors fell from 25 to 18%. Computation of watershed rainfall drastically reduces the computation required. The impact of statistical errors and bias introduced by reflectivity gradients is also reduced by the proposed method. The disadvantage is that information regarding the distribution of rainfall within the watershed is lost.

The utility of K_{DP} (at K_u band) for estimating rainfall was examined by Timothy et al. (1999). Application to K_u band introduces backscattering issues that have little impact on rain estimation at S band. Nevertheless, the study finds that the specific differential propagation phase shift is a better estimator of rainfall than radar reflectivity. Calculations are presented that show the dependence of polarimetric variables and rain rate estimators on temperature, assumed drop shapes, and the shape factor (μ) of the gamma DSD. A differential reflectivity rainfall estimator in the form $R=\alpha Z_{DR}^{\beta}$ is derived rather than the usual two-parameter estimator which includes Z_H and Z_{DR}. A comparison of rain rate estimators indicates that for rain rates > 70 mm h^{-1} K_{DP} outperforms Z_H. The Z_{DR} estimator has the largest error for R > 20 mm h^{-1}.

The relative insensitivity of rain accumulations derived from the specific differential phase parameter to beam blockage was examined by Vivekanandan et al. (1999). Rainfall estimates derived from radar reflectivity and specific differential phase were compared for a flash flood event in complex, mountainous terrain. The distribution of the differences in the rain estimates for a relatively unblocked region (< 22% blockage) were Gaussian distributed with a relatively small standard deviation compared to a region of up to 70% blockage where the distribution of differences were skewed and the standard deviation of differences was somewhat broader. The reflectivity rainfall estimates were lower than those from specific differential phase because of the loss of power due to blockage. Percent differences between specific differential phase and reflectivity estimators were nearly linearly related to the percentage of beam blockage. [Blockage in the lower portion of a radar beam restricts the Φ_{DP} measurement to the upper portion of the beam. If there is a significant vertical profile of precipitation or the melting layer is encountered, the specific phase estimates of precipitation could differ significantly from that observed at ground.]

Rainfall estimates with the radar reflectivity–differential reflectivity measurement pair and the specific differential phase are sensitive to the axis ratios of the drops. Recent radar research suggests that oscillating drops in the free atmosphere may be more spherical in the mean than suggested by studies of equilibrium drop shapes and early wind tunnel experiments. A technique for estimating axis ratios (r) from radar measurements would be useful. Gorgucci et al. (2000b) propose to derive an estimate of the axis ratio that is consistent with the radar reflectivity factor, the differential reflectivity, and the specific differential phase measurements. The drop shape versus size relation is expressed as $r=1.03-\beta D$ where β is the magnitude of the DSD slope and D is the drop equivalent diameter. The authors show how β can be calculated from Z_H, Z_{DR}, and K_{DP} and derive the necessary relation from simulations where the parameters of a gamma DSD are allowed to vary randomly. An error analysis suggests that β can be estimated within 10%. Gorgucci et al. compute K_{DP} values over 50 range samples and restrict their analysis to $K_{DP} > 0.4^o\ km^{-1}$ (a rain rate of roughly 18 mm h^{-1}). Data analysis revealed that β decreased as reflectivity increased from 45 to > 53 dBZ. The utility of the relation needs to be proved. Note that other studies, including those of the authors, use inconsistencies among the same three parameters, to calibrate radars. Also, drop canting affects the three radar measurements in ways similar to changes in drop shapes.

2.7.2 HYDROMETEOR CLASSIFICATION AND DETECTION

Because polarimetric radar measurements are sensitive to particle size, shape, orientation, phase (liquid or solid), and density (wet, dry, aggregates, or rimed), they can be used to discriminate between various particle types. For example, hail stones usually tumble as they fall, and the orientation of their major axes tends to be random. As a consequence, the differential reflectivity parameter, the difference in reflectivity at horizontal and vertical polarization (when expressed in dB), is close to zero. Hail signatures are generally quite distinct from those for heavy rain. The ensemble of polarimetric measurements and other parameters, such as the standard deviations of velocity, differential reflectivity, and differential phase, can be used to designate the type of dominant scatterer at each measurement location. Several recent papers focus on issues related to hydrometeor classification. A comprehensive review of related observational studies and simulations has been prepared by Straka et al. (2000). Topics discussed include definitions and descriptions of the polarimetric radar variables, hydrometeor characteristics, and relations between polarimetric variables and bulk properties of hydrometeor types. Polarimetric signatures for hydrometeor distributions consisting of hail, graupel and/or small hail, rain, rain–wet hail mixtures, mixed-phase hydrometeors, snow crystals, and aggregates are presented. The studies summarized provide a foundation for “rule-based” or “fuzzy-logic” classification schemes under development. [An overview of fuzzy logic methods for diagnosis is given in Section 3.3.4.]

Vivekanandan et al. (1999) outline a potential algorithm for particle discrimination. Because signatures for various particles may overlap, they propose a fuzzy logic approach to discriminate between scatterers. The methodology employs “membership functions” to determine the degree to which a particular radar parameter measurement (radar reflectivity, differential reflectivity, ... etc.) belongs to a particular precipitation classification (rain, hail, wet snow, ... etc.). The value of the membership function varies from 0 (no membership) to 1 (complete membership). The shape of the membership functions is based on experience and simulations. The radar reflectivity membership function for hail has a value of 0 for reflectivities < 45 dBZ and a value of 1 for reflectivities > 50 dBZ. The membership function increases linearly for intermediate reflectivities. The fuzzy logic approach ensures that particular classifications are insensitive to the details of the membership functions. Final scatterer designations, based on a weighted summation of the membership functions, had 15 categories. The technique was applied to an observed severe thunderstorm.

A competing hydrometeor classification algorithm is described by Liu and Chandrasekar (2000). Input observations include radar reflectivity, differential reflectivity, differential propagation phase, the correlation coefficient between reflectivities at horizontal and vertical polarization, the linear depolarization ratio, and measurement height. A rule-based, fuzzy-logic system is used to infer particle types; and a neural network is used to adjust the parameter weights. Output consists of 10 hydrometeor classes. An advantage with this particular scheme, derived from the neural network component, is the capacity to learn from earlier data collections and thereby refine the fuzzy membership functions. The paper gives a brief history of early efforts in particle classification, provides an overview of fuzzy-logic systems, and details membership functions for particle discrimination in summer and winter storms. Three convective examples with in situ observations obtained by aircraft and an example of rain–snow discrimination are presented. A possible improvement to the system may be to add a temperature sounding.

The utility of polarimetric measurements for hail detection is examined by Smyth et al. (1999). They begin with a summary of previous studies and the theoretical basis for hail detection. The focus is on the utility of the specific differential phase parameter (K_{DP}). An important issue is a significant backscatter component that arises for hydrometeors in the Mie scattering range. Calculations show that polarimetric signatures are sensitive to the hail consistency (whether spongy, wet, or dry) and can become quite large for aligned oblate hailstones. [There is no signal for tumbling hail with a random distribution of axis orientations.] The authors present measurements from an unusual severe hailstorm. In a portion of the storm with reported oblate hail, Z_{DR} was 3–5 dB suggesting that the hail fell with its principal axis roughly aligned in the horizontal. In another region of the storm the differential propagation phase decreased with range in a region of high radar reflectivity and large differential reflectivity. The implication is that large drops in the Mie scattering range (> 7 mm), perhaps supported by ice cores, were present. The authors conclude that there are potentially two problems in using the K_{DP}–Z_H measurement pair for hail detection: 1) the backscatter differential phase shift can mask the propagative component and 2) recent studies suggestive of more spherical drop shapes dictate that the rain contribution to radar reflectivity in a rain–hail mixture can not be uniquely determined from K_{DP}. Smyth et al. propose a new hail detection algorithm that relies on the consistency among polarimetric variables for a rain medium in which the path-integrated phase shift computed from Z_{DR} and Z_H is made to agree with the measured change in Φ_{DP} along the radial. Discrepancies between the calculated phase shifts (assuming rain) and observed phase shifts that exceed expected measurement errors (2–5^o) are interpreted as indicating the presence of hail. The excursions can be positive or negative. Positive values arise when Z_{DR} is reduced by hail; negative values can arise when there is a significant backscatter phase due to aligned hail. In this instance Z_{DR} may be large if the major axes are close to horizontal. When applied to the hail storm, the hail region was characterized by absolute differences exceeding 5^o. Because the sign of the differences can be positive or negative, there is some uncertainty in the region of small differences between extremes. It is possible that hail designations with the proposed algorithm could be triggered by the presence of very large drops (> 7 mm diameter). Nevertheless, difference parameters might be part of an ensemble algorithm that makes use of all the polarimetric measurements.

Nanni et al. (2000) evaluate the polarimetric hail detection algorithm proposed by Aydin et al. (1986)[6]. The technique is based on the H_{DR} parameter as calculated from reflectivity and differential reflectivity measurements. Hail is indicated by positive values signifying departures from the "rain-only" case. To preclude problems related to attenuation at C-band, detections were restricted to measurements made at 1.4^o antenna elevation. Radar measurement frequency was 15 min. Observations from a network of 330 hail pads within 75 km of the radar provided verification. Several analysis constraints were applied to eliminate issues related to sampling and hail detections arising from attenuation. Hail was found to be associated with H_{DR} > 13 dB rather than all positive values. A probability of detection of 0.9 was determined for radar signatures within 2 km of the hail pads. The critical success index was 0.6, and the false alarm rate was 0.3. Performance may be influenced by imposed constraints which eliminated about one half of the hail events. The authors note that many of the false alarms were close to pads that recorded hail.

El-Magd et al. (2000) show how polarimetric measurements (reflectivity, the copolar correlation coefficient, and linear depolarization ratio) could be used to compute the density of graupel and hail. Ground truth is provided by a storm penetrating aircraft. A simulation reveals that radar reflectivity is more sensitive to hail density than it is to hail

[6] Aydin, K., T. A. Seliga, and V. Balaji, 1986: Remote sensing of hail with a dual-linear polarization radar. *J. Climate Appl. Meteor.*, **25** 1475-1484.

axis ratio and orientation. The authors then argue that, to a first-order approximation, differences between measured radar reflectivity and that calculated from in situ hail observations are due largely to density fluctuations. Assuming that the aircraft-detected hail is spherical and adding the distribution of rain, they compare reflectivity computed from particle observations to that measured by radar. The calculated values are slightly less than that measured by radar. The differences are interpreted as caused by wet-hail density variations between 0.915 and 0.945 g cm^{-3}. The calculations are repeated for a storm containing conical graupel. Densities of 0.48 to 0.62 g cm^{-3} were determined, suggesting that the graupel is dry. The results, which rely on small differences between measured and calculated reflectivity, seem too good. In summary, the authors note that the hail region was characterized by an LDR of −22 dB and a ρ_{HV} of 0.92. The graupel region had an LDR of −26 dB and a ρ_{HV} of 0.97.

2.7.3 C-BAND CAPABILITIES

The lower cost and practical benefits of C-band radars has led to their wide-spread installation as network radars, particularly in Europe and Asia. With heightened interest in polarimetric measurements there is concern about the suitability of short radar wavelengths whenever hail, aggregates, or large rain drops are present. Hydrometeors with diameters larger than about 5 mm are well within the Mie scattering range and cause a resonance in the power measurements. Also, power-based measurements can be significantly attenuated in heavy rain. Because the differential propagation phase signal is inversely related to the radar wavelength, statistical errors in K_{DP} should be less at C band than at S band for a given rain rate. Zrnić et al. (2000) conduct a sensitivity study of the polarimetric variables to simulated drop-size distributions. For monodispersed drops they find marked resonance effects for drop diameters greater than 5 mm. For example, they compute a Z_{DR} of 10 dB for a drop diameter of 6 mm and a Z_{DR} of 4.5 dB for a diameter of 8 mm. The authors then investigate the influence of Marshall–Palmer (exponential) and gamma drop-size distributions on the polarimetric measurements. Because the Marshall–Palmer (MP) distribution has greater numbers of large drops, reflectivities at intense rain rates are higher than those with a gamma DSD at the same rain rate. The differential reflectivity is found to be highly sensitive to the shape of the distribution and the maximum drop size. Interestingly, Z_{DR} increases with rain rate for the MP distribution but decreases with rain rate for the gamma distribution. Attenuation and differential attenuation increase more rapidly with rain rate for a MP DSD than a gamma DSD. This is because the number of large drops increases with rain rate for the Marshall–Palmer DSD but decreases with rain rate for the gamma DSD. The specific differential phase parameter exhibits the least sensitivity to the DSD shape and maximum drop size. DSD affects on rain rate are also examined. The maximum drop diameter (D_{max}) with the MP DSD strongly influences radar reflectivity estimates. When D_{max} exceeds 5 mm, rain rates can be overestimated by a factor of 3. The problem is complicated by attenuation. In contrast, the K_{DP} estimator is far less sensitive to DSD variations. Estimators that combine radar reflectivity and differential reflectivity are also insensitive to DSD variations, but the estimates are subject to attenuation. The latter problem can be corrected with the differential propagation phase measurement.

May et al. (1999) evaluate the utility of C-band differential propagation phase measurements for estimating rainfall. The paper gives a nice historical review of polarimetry for rainfall estimation. Computational procedures for determining K_{DP} and for applying attenuation corrections to Z_H and Z_{DR} are described in detail. Radar–gauge rain rate comparisons were made for Z_H and K_{DP} estimators. Z_H rain rate estimates were made for raw radar reflectivity and for reflectivity corrected for attenuation and beam blockage. Highest correlations and smallest bias between 5 min gauge-observed rain rates and radar were with the K_{DP} estimator. For an event with small drops the rain was underestimated with K_{DP}–suggesting some dependence on the DSD exists. For rainfall estimates at unblocked elevation angles, the results for K_{DP} and Z_H (when corrected for attenuation) converged.

3. DATA MINING

3.1 Overview

"Data mining" refers to an emerging technology that is a response to the information age in which we live. The availability of low cost computers and data storage devices has enabled routine processing of large databases where previously the computation required was either too expensive or time consuming. Databases, consisting of measurements, text, or images, are mined to disclose patterns, trends, and outliers. Enthusiasm for data mining is particularly strong in the retail business sector where potential profits are the primary motivation and in the financial sector for predicting future movements in interest rates or stock prices.

There is undoubtedly great potential for the mining of remotely sensed data from earth satellites and radars. Each WSR-88D tilt sequence produces millions of data points (measurements) consisting of three variables distributed over a large volume. Data refreshment intervals are 5 to 6 min. Typically, a high percentage of the data points are noise, containing no meteorological signal. A radar operator can readily distill vast amounts of data and quickly determine, for example, which thunderstorms are likely to produce severe weather and to require warnings. However, not all radar operators are equally skillful; and the issuance of warnings is just one of the services operational meteorologists perform. Hence, some automation in the form of algorithms is desirable to assist the operator and to free him for other tasks. A number of data mining applications that could have impact on WSR-88D algorithms have appeared in the meteorological literature (see also previous literature reviews of research related to algorithms).

Beginning a program in data mining can be daunting. The diversity of applications has produced a variety of sophisticated tools, such as, "neuro-fuzzy" systems which have a certain "black box" aura; and there is a jargon to be learned. Much of the notation is borrowed from statistics. But some tools do not have rigorous mathematical definitions and may be described with symbols that have precise definitions in other fields.

Data mining begins with databases. The construction of a working dataset may require preprocessing, e.g., quality control measures, making allowances for missing data, and removing irrelevant or redundant data. To be successful it is necessary to have a goal in mind and that a model can be formulated. For most tools it is imperative that the algorithm developer understands the relevant issues concerning the problem being addressed. Above all, the database must contain the necessary information to solve the problem; and the data must be exploitable. Model building is most efficient when basic issues are known and experts guide the process. Uncorrelated inputs are removed, perhaps with simple bivariate analyses (Marzban et al. 1999) or a genetic algorithm (Lakshmanan 2000). Sample size (too few data points) may be an issue. On the other hand, it is usually not necessary to analyze an entire dataset. In fact, an accepted practice is to withhold some data for independent testing. The cleaned data are then mined with appropriate tools. These may be rule-based systems, statistics, statistically-based regression analyses, decision trees, neural networks, and fuzzy logic systems. Restructuring of the data through clustering may be required. Results are validated, evaluated, displayed, and interpreted. The whole process may then be refined by iteration. Generalized approaches to data mining with meteorological databases are presented by Howard and Rayward-Smith (1999) and Büchner et al. (1999).

To summarize data mining activities represents a challenge. The topic is quite broad and applications cover diverse disciplines. Hence, the purpose of this section is simply to present a brief introduction to data mining and point readers toward various sources of information and some recent applications.

3.2 Sources of information

A search of the World Wide Web reveals how fashionable data mining has become. Literally hundreds of thousands of web sites (many ephemeral) are found by using search engines such as AltaVista and Lycos. Smaller numbers (hundreds) are found with Netscape and GoTo. [Similar results are obtained for topical searches with terms such as "vector machines" or "knowledge discovery".] Many organizations are multi-listed. In some cases organizations pay a listing fee that is charged when a user enters the site. Fee payers tend to be larger organizations.

A perusal of selected web sites reveals that the majority are geared toward business activities and represent entrepreneurs with products (software, books, or consulting services) for sale. Successful applications are mentioned but details are not generally provided. A few sites attempt to educate visitors by giving overviews of data mining, presenting white papers, giving a bibliography of introductory references, and listing tool vendors. Some of the more informative web sites, found by searching with GoTo and using the linkages provided, are[7]

Bibliography of Internet Resources about Data Mining: fiat.gslis.utexas.edu. A nice site with lots of information on tools, publications, and vendors.

Data Mining, Data Warehousing, Neural Networks: KnowThis.com: www.knowthis.com. Gives general information on data mining, neural networks, and links with other sites.

Data mining as seen by a professional: home.planet.nl. Presents an overview of data mining from the business perspective.

KDnuggets: Data Mining, Web Mining, and Knowledge Discovery Guide: channel1.com. Lists commercial products, tools, applications, and references.

URL's for data mining: www.galaxy.gmu.edu. Gives general information.

Knowledge discovery in databases and data mining: db.cs.sfu.ca. Gives references.

Data mining: What is data mining?: www.anderson.ucla.edu. Presents an overview.

Data miners home page: www.data-miners.com. Data mining references for business applications.

Data mining and CRM (Kurt Thearling): www.santafe.edu. Has several white papers and gives references.

The data warehousing information center: www.dwinfocenter.org. Nice site for data warehousing, white papers, and tool vendors.

Other nice web sites are:

University of Birmingham, United Kingdom: References. http://www.cs.bham.ac.uk/~anp/TheDataMine.html.

Exclusive Ore: A detailed description of tools and other information.

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[7] Underlined sites can be reached directly.

http://www.xore.com.

Z Solutions, Inc.: Information on neural networks.
http://www.zsolutions.com.

Major upcoming meetings on data mining are the Seventh ACM SIGKDD International Conference on Knowledge Discovery and Data Mining scheduled to convene 26–29 August, 2001 in San Francisco, California and the 2001 IEEE International Conference on Data Mining to be held in Silicon Valley, California from November 29 to December 2.

Some acronyms used by vendors and advertisers are:

CART	Classification and regression tree
CRM	Customer relationship management
DBMS	Database management system
IT	Information technology
KDD	Knowledge discovery in databases
OLAP	Online analysis processing
SQL	Structured query language.

Another source of information is that available through library search services. A simple search with the words "data mining" produced 270 book titles. Unfortunately, the depth of coverage cannot be determined from the information provided. Some books represent conference proceedings and probably describe specific applications in detail. Other books are designed for businessmen giving an overview of data mining tools and directing readers toward vendors or particular analysis packages. Still others are textbook in nature and intended as reference material for classrooms. An example of the latter is "Data mining: Methods for Knowledge Discovery" (Cios et al., 1998). This technical book (just one of many) describes the mathematical aspects of tools and contains chapters on rough sets, fuzzy sets, Bayesian methods, machine learning, neural networks, clustering, and data preprocessing.

Numerous papers concerned with data mining tools and applications appear in the scientific literature. Many can be found in issues of Signal Processing and IEEE publications. A number of papers have appeared in the journals of the American Meteorological Society. While applications are described in scientific papers, emphasis typically is on technique. Some applied papers can be found in preprint volumes of AMS Conferences on Interactive Information and Processing Systems for Meteorology, Oceanography, and Hydrology.

3.3 Tools

Analysis tools are at the heart of data mining. Those described here represent only a subset of what is available. Tools differ in approach and function. A data mining tool may be an algorithm that simply detects outliers and ascertains whether or not they are legitimate data points or the result of measurement or encoding errors. Outlier detection is often facilitated by plotting the data or searching for data points which lie outside expected domains. Another simple data mining method is that of statistical regression analysis–usually linear regression. While regression analysis can be important for determining relationships, the approach is often limited because system processes are non-linear. Regression analysis is just one example of a statistical or probability (Bayesian) method. Time-series analysis is long used tool for determining trends or making associations with subsequent events. Other tools seek associations by grouping data points according to interrelationships among variables or by classifying data points into particular bins. Membership classification is often binary–the input variable is either in the desired class or it is not. But desired outputs may be a specific value or the degree of membership for a continuous distribution of values. Classification tools frequently used are decision trees, neural networks, and fuzzy logic. More than one tool can be applied to most problems; the search for the particular tool best suited for a particular problem may not be a trivial issue. Further, to solve more complex problems combinations of tools may be required. To make predictions, it is necessary to model the process. This requires a training or learning period and normally involves a database consisting of events with both the desired outcome and non-events. Finally, the model is validated with independent (withheld) data. Importantly, the outcome of a data mining process is dictated largely by the quality of the input observations.

3.3.1 DECISION TREES

A simple data mining model, easily visualized and understood, is the decision tree. Trees constitute a set of decisions or rules (usually binary, yes–no, or if–then) designed to classify a dataset. Decision tree systems have been developed by a number of vendors. An example of a tool which builds trees automatically is the Classification and Regression Tree (CART) system developed by Salford Systems (see www.salford-systems.com for a description). The procedure is concerned with logical sets of statements that determine the effect of a specific event or decision on subsequent events. A related vendor tool is the Chi-squared Automatic Interaction Detection (CHAID) algorithm. A key activity with decision trees is the determination of effective splitting statements to isolate desired outcomes. A tornado detection algorithm might restrict an analysis to storms with maximum reflectivity greater than 40 dBZ. A “yes” might then invoke a second decision concerning the presence of a mesocyclone. A second “yes” could lead to additional decisions regarding the presence of a tornado vortex signature. The process continues until a “no” occurs or all tests are exhausted and a final designation is made. Generally, the decision logic is based on historical data. Algorithms (the tree itself) are refined with repeated passes through the data. The number of passes is dictated by the number of levels in the tree and the number of input variables. It’s possible to map every possible outcome by adding levels, but the data may be overfit and the tree too specific.

Trees begin with a root node containing the input data and are grown by successively splitting the data into subsets. Trees are composed of branches–collections of related nodes. A concluding node at the end of a branch is referred to as a leaf node. Decisions are made at nodes, and each subsequent decision is made at child nodes along the branch. The process continues until it no longer makes sense to subdivide the dataset or a leaf node is reached. The cases at the terminal node are then classified as to the outcome. Recording the number of times a specific node is reached can be helpful for determining the statistical properties of the dataset and for constructing new branches, for pruning trees to cure overfitting, or for removing inappropriate portions of trees generated by automatic algorithms.

Decision trees are popular in computer processing because of their simplicity. They are less applicable for complex problems requiring many decisions thereby reducing the efficiency of the tool. When outputs are not in specific categories, decisions (splits) can be based on expert knowledge or statistics. Tree testing is accomplished with the usual method of withholding a subset of the data.

3.3.2 NAÏVE-BAYESIAN TECHNIQUES

This tool seeks to classify inputs according to statistical relationships between independent (input) and dependent (output) variables. An implicit assumption is that the independent variables are uncorrelated. The method generally requires that inputs be binned, i.e., that they not be continuous. For mesocyclones this could mean classifications such as weak, moderate, and strong rather than using a metric like rotational velocity. The selection of each bounded class is not trivial since it must relate to independent (naïve) variables. The frequency with which each independent variable occurs in combination with each dependent variable is determined. The frequencies are used to find the probability of the dependent variable based on the conditional probabilities for the independent variables. The predicted outcome is found by multiplying the conditional probabilities by the probability of the dependent variable. The conditional probabilities can be helpful for understanding the physical processes involved. A mathematical treatment of Bayesian methods is given by Cios et al. (1998, chapter 4). An illustrative data mining example can be found at the Exclusive Ore web site (http://www.xore.com).

3.3.3 NEAREST NEIGHBOR

This tool, also referred to as k-nearest neighbor, compares an input observation to the historical record, finds a subset of cases (k) that are similar, and then predicts the most likely outcome. Key issues are the definition of "near" and the number of required near cases to ensure system stability. New inputs are expected to have the same outcome as the predominant outcome for similar cases in the past (the training dataset). Predictions are made after passing through the entire dataset. Problems can arise when applying the algorithm to multiple inputs. Presumably different distance measures could be applied for different inputs (e.g., reflectivity and for rotational velocity). The arbitrariness of determining distance measures and the need to peruse the entire dataset to find the nearest neighbors is a drawback to the scheme. For additional information see Cios et al. (1998, chapter 4) and the Exclusive Ore web site (http://www.xore.com).

3.3.4 FUZZY LOGIC

Fuzzy logic tools are considered by developers to be analogous to how the human brain operates in complex situations. Fuzzy logic can be applied in situations where *cause and effect* are not well understood mathematically or understood only in subjective (linguistic) terms. Subjective information might be the realization that, if a tornado was near a specific location at a particular time, it should be relatively near that location a short time later or that turbulence is light, moderate, or severe. Sources of objective information include physical laws, models, and statistics. The technique has been applied for pattern recognition, forecasting trends, quality control, and diagnosis. Early applications required an expert to define the problem. More recent applications with "neuro-fuzzy" schemes are self-training. Applications most likely to benefit from a fuzzy logic approach are processes with variable control parameters, situations where mathematical descriptions do not exist, problems are complex or cannot normally be solved in real time, signal-to-noise ratios are high, and situations where an expert can provide rules related to system behavior (Cox 1992).

Fuzzy numbers have utility for defining classes with continuous rather than abrupt (step) boundaries, that is, they relax dichotomous classifications and permit intermediate values of class membership. Hence, fuzzy numbers may allow for a more realistic interpretation of data when outcomes do not have well-defined boundaries (tornadic mesocyclones versus non-tornadic mesocyclones). Generally, fuzzy logic systems map multiple input data into a single, useable output. Inputs and outputs are generally "crisp" (ordinary) numbers. The degree of membership of each variable to a particular class is expressed in the interval 0 – 1 where 0 represents nonmembership and 1 indicates complete membership. Numbers close to 0 (1) indicate a low (high) degree of membership. For example, it may be desirable to define a number "close to 10", i.e., having a modal value of 10. The membership function may be triangular in shape, increasing linearly from 0 at 8 to a value of 1 at 10 and then decreasing to a value of 0 at 12. Data values $\leq$ 8 or $\geq$ 12 would have a membership value of 0. The assignment of weights is referred to as "fuzzification". The membership function for our example [A(x)] can be expressed as

$$A = \begin{cases} 0 & \text{if } x \leq a \\ (x - a)/(m - a) & \text{if } x \in [a,m] \\ (b - x)/(b - m) & \text{if } x \in [m,b] \\ 0 & \text{if } x \geq b \end{cases}$$

where a = 8, b = 12, m = 10. An equivalent notation is

$$A(x;a,m,b)=\max\{\min[(x-a)/m-a),(b-x)/(b-m)],0\} \quad .$$

The membership functions describe a "fuzzy set". Depending on the application, a variety of membership function shapes, e.g., S, trapezoidal, and Gaussian, can be defined. Membership functions may be further modified through extensions (multiplying by mathematical functions), taking logarithms, squaring, and normalizing. Techniques are being developed to objectively determine membership functions [e.g., Cios et al. (1998, chapter 3)].

The special issue of the IEEE Proceedings (Vol. 83, March 1995) presents several applications. The lead article by Mendel (1995) gives a tutorial on fuzzy systems. Eighty-seven references to other information sources are given. Mendel defines a fuzzy logic system as the path between input and output. Key components of a non-trivial system are a fuzzifier, rules, an inference engine, and a defuzzifier. [A simple example (the operation of a steam turbine) is given by Cox (1992).] The fuzzifier turns input numbers into fuzzy sets. The fuzzy numbers are then subjected to rules provided by experts. The rules typically are in the form of if–then statements. The inference engine maps the fuzzy sets into new sets by combining the individual rules. Defuzzification transforms the output into useful numbers which might be binary (yes–no for tornado designation) or numerical (the probability of a tornado or its estimated location). Another reference with background tutorial material on fuzzy logic is Bowles and Peláez (1995).

As a meteorological example of a fuzzy system, consider the relationship between maximum radar reflectivity within a thunderstorm and the occurrence of hail. It might be supposed, following Vivekanandan et al. (1999), that the likelihood of hail in storms with reflectivities less than 45 dBZ is zero. Hence, the hail membership for storms with maximum reflectivity values less than 45 dBZ would be assigned a value of 0. It's known that the probability of hail increases as reflectivity increases. At a maximum reflectivity of 50 dBZ nearly all storms might be considered to contain hail. Hence, storms with maximum radar reflectivity of ≥ 50 dBZ would be assigned a hail membership value of 1. Storms with reflectivities between 45 and 50 dBZ would have some degree of membership in the hail storm class. The degree of membership might increase linearly over the interval or, if climatological information is available, can be defined by some nonlinear function. Hail membership functions might be defined regionally, e.g., the likelihood of hail in Florida with storms having maximum reflectivities < 50 dBZ might be less than that in Oklahoma due to elevated freezing levels and weaker storm dynamics.

As noted, fuzzy logic is a promising tool for solving complex problems. For example, polarimetric radars provide a suite of measurements that relate to the properties of hydrometeors illuminated by the radar beam. Additional information beyond radar reflectivity, radial velocity, and spectrum width is available which should facilitate hydrometeor classification. Compared to rain, hail typically associates with low differential reflectivity, high linear depolarization ratios, low correlation coefficients between reflectivity at horizontal and vertical polarization, and, if the hail is in the Mie scattering range, large fluctuations in differential propagation phase. Potentially each parameter can be used to define parameter-specific membership functions for hail. Final "hail" or "no hail" decisions would be based on a weighing of the results for each parameter. The redundancy inherent in the suite of polarimetric measurements should drastically reduce false alarms and may even be useful for estimating hail stone size (see also last year's report). Other potential applications are in general hydrometeor classification and rainfall estimation. Several applications in quantitative precipitation estimation might be possible. Fuzzy logic might be used to apply range corrections based on precipitation type (stratiform or convective), to account for bright bands and changes in phase (liquid or solid), to apply climatological adjustments, and to make adjustments based on gauge–radar comparisons. One of the primary sources of error with fixed-radar reflectivity rainfall estimators associates with changes in drop size. With polarimetric radars it is possible to compute median drop diameters. This information could be used in a fuzzy system to adjust the coefficient of radar reflectivity estimators.

3.3.5 Neural networks

Artificial neural networks (NNs) are among the more complicated data mining tools. A variety of types (feedforward, recurrent, and hybrids), the use of hidden layers, and questions regarding training and size of the training dataset can discourage their use. Nonetheless, the list of applications is growing rapidly. Neural networks are modeled after the way the brain operates and learn by example. Indeed, NNs make an association with the biological neuron, the interconnections with other neurons, and the signals generated when thresholds are reached. Neural networks can solve complex (nonlinear) problems where the governing physics is not known. Solutions are fairly tolerant of input imprecisions.

An overview of how neural networks function is given by Brierley and Batty (1999). The article includes Fortran 90 code for a short illustrative program. [General, less technical discussions of NNs can be found at the Exclusive Ore (http://www.xore.com) and Z Solutions (http://www.zsolutions.com) web sites.] Artificial neural networks are simple computer programs designed to find nonlinear relationships in data without having a preconceived concept of how input data and desired outputs are related. The procedure is statistical in approach but has characteristics of rule-based systems. A simple feedforward multilayer network consists of an input layer which contains the relevant variables, one or more hidden layers of neurons, and an output layer. The input data are transformed by weights and neurons as it passes through the network. The output represents a transformation between input (independent) and output (dependent) variables. As implied by its name, the flow in a feedforward network is in one direction. Networks in which neuron outputs may feed backward either to themselves or other neurons in previous layers are referred to as recurrent networks. In recurrent networks the error is "backpropagated" by adjusting the weights at each node (see Silverman and Dracup 2000). Typically, each input variable is connected to each of the neurons in the hidden layer. Each hidden neuron sums all the weighted inputs (the variable times the connecting weight). The summed value is passed through an "activation function" before being weighted again and passed to the next layer. Outputs are usually binary.

Neural networks are trained with a subset of the historical data that contains representative inputs and outputs. Training establishes the weights that optimize the desired output with the input variables. Training involves the minimization of a cost function. Network tuning and testing is performed by varying the number of neurons and by applying the network to withheld historical data. Training increases exponentially as the size of the dataset increases. Optimization is accomplished by conducting random or patterned searches in which performance is judged by the gradient-descent technique. The activation function must be differentiable. S-shaped functions permit the network to solve nonlinear problems. Logistic and hyperbolic tangent functions are commonly used because they vary over nice limits (0–1 and −1–1, respectively). The logistic function has the form

$$\frac{1}{1 + e^{-x}}$$

where x is the sum of all weighted inputs at the node (neuron). Because logistic and hyperbolic tangent functions have near-linear regions they can also approximate linear problems.

Training involves passing through the data numerous times and making small adjustments to the weights. The size of the adjustment determines the learning rate. Training ends after a set number of passes through the data, when the residual error falls below a specified threshold, or when the added improvement by additional passes is insignificant. Training is complicated by decisions that must be made regarding the number of nodes, number of hidden layers, the choice of activation function, learning rate, and the setting of parameters and thresholds.

Research indicates that neural networks generally outperform linear regression models, persistence, and nowcasting methods. A possible problem with neural networks is that of overfitting the training data by having too many hidden neurons. Overfitting is also a potential problem with noisy data. Too few nodes can result in poor accuracy. Importantly, neural networks do not represent physical models, nor do they give physical insight to the particular problem addressed. Outputs are determined by the domain of the inputs. Extrapolations outside the data domain have no basis. If network performance is judged by a metric involving least-square errors, it is possible that the network solution can be dictated by outliers. It is also possible that the network solution represents a local error minimum rather than a global minimum.

There have been numerous papers concerned with neural networks and applications in the scientific literature. Particular applications include signal detection and compression, data filtering, parameter estimation, pattern recognition and reconstruction, and time series analysis. Many applications can be found in issues of Signal Processing and IEEE publications. The entire November 1997 issue of Signal Processing was dedicated to neural networks. IEEE Proceedings with special issues on neural networks include Volume 78, September and October 1990 and Volume 84, October 1996. Of interest is the article by Widrow and Lehr (1990) which gives an early history of neural network development and an overview of how various networks operate. The IEEE Transactions on Signal Processing had a special issue on neural networks in November 1997 (Volume 45). Additional papers can be found in the issue for May 1998 (Volume 46). IEEE Workshops on Neural Networks for Signal Processing are held annually and papers are compiled in meeting proceedings.

3.3.6 Genetic algorithms

Genetic algorithms are another tool set patterned after biological processes. The tool mirrors the Darwinian principal that over time natural selection will result in the fittest species. When applied to data mining, this refers to the use of genetic methods to optimize models. The algorithms employ fitness functions (chromosomes) to cluster data points within groups. They also incorporate operators which allow for copying and altering the data descriptions. These operations are said to be analogous to reproduction, mating, and mutation.

3.3.7 Some applications

Among recent fuzzy logic applications having a meteorological flavor is the study of Shao (2000) who describes a fuzzy categorization system for determining road conditions. Infrared measurements made with a vehicle-mounted system are used to map road surface temperatures. The information is then combined with standard meteorological observations in a road-ice prediction model. Data interpretation requires some expertise in mapping and meteorology. The thermal mapping products are classified (based on spatial measurement variation) as extreme, intermediate, and damped. Moreover, actual road conditions are sensitive to cloud cover, cloud type, and, to a lesser extent, wind speed and humidity. Four fuzzy sets for the latter variables are described. Several references to other fuzzy logic applications are also given.

Cornman et al. (1998) describe a fuzzy logic application for estimating Doppler moments from wind profiler spectral measurements. The system removes spurious signals from birds, aircraft, ground clutter, and radio frequency interference and corrects for velocity and range folding. The scheme features mathematical analyses (gradient and curvature terms), fuzzy logic, global image processing, and incorporates the signal-to-noise ratio as a quality control measure. Atmospheric signals and contaminants are distinguished by the magnitudes of computed gradient and curvature terms. Four fuzzy sets (for gradients, curvature, the distance of velocity peaks from zero, and symmetry) are used for clutter detection. Composition is accomplished by linearly weighing the various membership functions. The global analysis removes isolated features with small total membership values and retains coherent features with high total membership values. This is accomplished with a density weighting procedure in which each point is weighted according to the number of neighboring points whose total membership value is above a specified threshold.

The development of a fuzzy logic algorithm for detecting AP in Archive Level II data is described by Kessinger et al. (1999). The fuzzy logic approach was picked over rule-based and NN systems because of performance and ease of implementation. Membership functions were constructed for mean radial velocity, spectrum width, the texture of the signal-to-noise ratio, the standard deviation of the radial velocity, and the vertical gradient of reflectivity between 0.5 and 1.5^{o} antenna elevation. The individual interest fields are weighted to determine the contamination. The AP detection problem is complicated on the WSR-88D because the spatial resolution of Doppler and reflectivity measurements differ and because the measurements are not made simultaneously at the lowest two antenna elevations. Also, the fact that the azimuthal location of the radial measurements changes from scan to scan makes it difficult to incorporate time continuity. Preliminary results show the algorithm has skill in identifying AP. A possible use of the algorithm is to define regions where clutter filters should be turned on. A planned system upgrade is a reflectivity compensation routine to mitigate bias introduced by notch filtering.

Fuzzy logic-based systems serve as the core of hydrometeor discrimination algorithms being developed for polarimetric radars. Vivekanandan et al. (1999) give an overview of the scientific basis for hydrometeor discrimination and a short description of how fuzzy classifiers are applied. Expected radar parameter ranges for various hydrometeors are shown in $Z_H - Z_{DR}$ and $Z_H - K_{DP}$ space (see also Section 2.7.2). Algorithm output is demonstrated with a cross-section through a severe thunderstorm.

Liu and Chandrasekar (2000) propose a hydrometeor classification algorithm that has both fuzzy logic and neural network components. A decision tree system was rejected because the measurement set for different hydrometeors is not mutually exclusive and trees do not easily allow for measurement errors. Statistical models were considered too difficult to construct given that joint probabilities for the five pertinent polarimetric variables are not known. The described neuro-fuzzy system was thought to have the advantages of rule-based systems and a capability for learning by inserting observations. Beta membership functions of the form

$$\beta(x, m, a, b) = \frac{1}{1 + [((x-m)/a)^2]^b}$$

were defined where m is the center value of the function, a is its width, b is the slope, and x is the measurement value. [Those for Z_H and Z_{DR} are described in detail.] Prior (expert) knowledge is incorporated in the construction of the fuzzy sets and if–then inference rules. Weights for each of 10 hydrometeor classes are determined as the product of the fuzzy numbers for the 5 radar measurements and the measurement height. The class with the largest numerical value is the designated hydrometeor. In the examples given, the fuzzy logic system is mapped as layers in a feedforward neural network. When in situ observations are available, the misclassification error can be backpropagated to adjust system parameters. The system performed plausibly on summer and winter storms used in development.

A neural network for detecting anomalous propagation echoes has been developed by Grecu and Krajewski (2000). System predictors, determined from volume reflectivity scan information, are 1) the advection velocity of the radar echo, 2) the coefficient of variation of echo velocities, 3) height of the echo above the base scan, 4) height of the reflectivity maximum, 5) the reflectivity value, 6) the distance to authentic data pixels, 7) the coefficient of variation of the reflectivity values, 8) a measure of significant fluctuations, and 9) a horizontal gradient term. Although a decision tree might be implemented in this case, it might not be as computational efficient over time. The training dataset consisted of events that were exclusively AP or rain. With this approach mixed-echo events would be classified by the dominant echo type. A backpropagating (recurrent) system was used. Network output was binary; radar pixels were classified as either rain or AP. It is assumed that once a pixel in the base scan is classified, all pixels above it have the same classification. Although histograms of the nine selected features for AP and rain overlapped, the first three features differed significantly. Application to several events showed that the percentage of misclassified pixels varied from 0.5 to 6.8%. The network gave marked improvement compared to a quadratic discrimination function. Tests revealed that selection of the training dataset was not trivial and that the network would not perform well on events for which it was not trained. Other experiments investigated the impact of the training dataset size.

In another radar application, Bellerby et al. (2000) propose a multilayer feedforward neural network to estimate rainfall with multispectral imagery from the Geostationary Operational Environmental Satellite (GOES). For training, measurements from NASA's Tropical Rainfall Measuring Mission (TRMM) precipitation radar were matched with satellite measurements from visible and 4 infrared (IR) channels. A total of 45 input values defined the essential characteristics of the image data. These included measurements from the IR bands (mostly mean values over subsets of the interest area and standard deviations), an image texture parameter, time changes over the previous 30 min, and the time of day. The first hidden layer contained 200 sigmoidal neurons, whereas the second layer had 100 neurons. The second layer was found necessary because many simple satellite inputs at the edges of rain areas produced very different outcomes. A linear combination of outputs from the second layer was used to estimate the rainfall. Training was evaluated with the gradient descent method. The two-layer network outperformed both a network with a single hidden layer and a linear regression method. A comparison of network and modified GOES precipitation index (GPI) estimates with those from the precipitation radar revealed higher correlations but larger overall bias with the neural network.

A NN application in precipitation prediction is described by Silverman and Dracup (2000). The central hypothesis was that regional precipitation is driven by the circulation at 700 mb and that the wind patterns could be used to make long-term rainfall predictions. A concise summary of neural network attributes is given. The paper then details steps taken in network development and training.

A time series application in rain runoff is presented by Furundzic (1998). The basic assumption is that time series of rain gauge observations contain sufficient relevant information in a statistical or dynamic form to draw inferences about runoff behavior. Factors influencing the runoff relate to watershed slope, meteorology (e.g., temperature, humidity, and rainfall duration and intensity), antecedent soil moisture, soil composition, and the degree of urbanization. The neural network approach to the rain–runoff (RR) problem was deemed appropriate because of inherent nonlinearities and the large time and space variations that characterize the interrelation between rain and runoff. Runoff models tested included a network with three multilayer perceptrons and a self-organizing feature and a stepwise regression model that assumed linear relationships among variables. The neural network markedly improved the runoff estimate. Advantages of the neural network are believed to be the high tolerance of imprecision and uncertainty in the inputs, distributed processing, an ability to generalize, computational parallelism, and learning capability.

A heuristic paper on neural networks, typical of many in the literature, is that of Yuval (2000) which describes a modification to network training. The procedure is designed to optimize training by minimizing a generalized cross-validation function. Questions regarding the level of fitting for training data and how to select the model that gives the best prediction are addressed. Performance is judged in terms of bias and variance. Poor fits to the data create bias whereas overfitting (often in response to noise) results in high variance. The latter problem can be alleviated through the introduction of some bias by imposing additional constraints–a technique referred to as regularization. The problem is to choose a regularization parameter when system noise sources and levels are not known. Optimization is achieved when the generalized cross-validation function is minimized. This is accomplished by choosing the regularization parameter such that the sensitivity of the final model to successively leaving one datum out is a minimum. The method is demonstrated on a synthetic dataset consisting of time-dependent westerly winds with imposed large-scale eddies and is applied to the prediction of surface temperatures during El Niño events. As an aside, Yuval notes that neural networks do not supersede dynamical models but promote the understanding and prediction of phenomena until dynamical models are developed.

Lakshmanan (2000) fine tuned an algorithm for bounded weak echo region (BWER) detection with a genetic algorithm. At the core of the BWER algorithm is a rule-based system that consists of 20 fuzzy attribute sets. The genetic algorithm is used to optimize the membership functions. The tuning of the fuzzy sets is accomplished in stages (generations) in which bad data points (bad genes) are weeded out. The genetic code that determines the fitness of the data point is called a chromosome. The latter are composed of genes (the fuzzy sets). The genetic algorithm does not change the shape of the membership function but optimizes the fuzzy system by changing its breakpoints. The procedure is outlined and a metric for evaluating fitness is described. Tuning is performed on a "truthed" dataset. Sets of chromosomes with high detection probabilities are retained for inclusion in successive generations. The procedure stops when new chromosomes are no longer identified. Application of the genetic algorithm does not guarantee optimality; hence, hybrid schemes pair the algorithm with a search routine to find optimal chromosomes. The algorithm was tuned on a dataset consisting of five cases containing 200 volume scans. CSIs with test datasets varied from 0.17 to 0.50.

4 BIBLIOGRAPHY OF RELATED RESEARCH

This section summarizes scientific articles relating to existing and potential WSR-88D algorithms that have appeared in recent journals, society bulletins and announcements, and conference proceedings. Although the breadth of topics is broad, the reviewed papers are believed to be of general interest. Each article is given a subjective rating as to its perceived relevance to the NEXRAD program. In general, a "low impact" rating refers to articles of general interest. Case studies and applications using WSR-88D data and articles on data mining fall into this category. "Moderate impact" usually refers to research that could lead to improvements of existing algorithms or research that is likely to be important in the future. Radar polarimetry falls into this category. "High impact" articles represent research that is closely related to existing algorithms and technical needs. Importantly, ratings are not an indication of research quality.

REVIEWED PAPERS:

Anagnostou, E. N., and W. F. Krajewski, 1999a: Real-time radar rainfall estimation. Part I: Algorithm formulation. *J. Atmos. Oceanic Technol.*, **16,** 189-197.
[High impact, potential modification to the precipitation processing subsystem. The paper describes a multi-step process for estimating rainfall with radar reflectivity and adjusting estimates with rain gauge observations. Key algorithm components include adjustments for the vertical profile of precipitation, hybrid scan construction (lowest two elevation angles), precipitation type classification, precipitation advection, and mean field bias adjustment.]

Anagnostou, E. N., and W. F. Krajewski, 1999b: Real-time radar rainfall estimation. Part II: Case study. *J. Atmos. Oceanic Technol.*, **16,** 198-205.
[High impact. An evaluation of the algorithm described in Part I of this study is presented. The paper begins with a demonstration of an optimization technique for determining the controlling parameters of the algorithm and shows how the parameters are inter-related. Application to a dataset acquired in east-central Florida follows. Results show essentially no system bias and relatively high correlation between gauge and radar-estimated amounts. A 20% reduction in error over the PPS is achieved.]

Anagnostou, E. N., W. F. Krajewski, and J. Smith, 1999: Uncertainty quantification of mean-areal radar-rainfall estimates. *J. Atmos. Oceanic Technol.*, **16,** 206-215.
[Low impact. The authors develop a methodology for determining the contribution of the variance in gauge area-point rainfall (sampling) differences to the variance of radar–gauge ratios. The ratios are treated as a stochastic process in which errors (expressed in terms of ratios) are assumed to be lognormally distributed with zero covariance. Area–point differences in the gauge-observed rainfall contributed up to 60% of the variance in gauge–radar comparisons. The errors were a function of radar grid size, the distance of the gauge from the center of the averaging domain, and the distance from the radar. Application to precipitation regimes other than Florida is not straightforward because detailed statistical information on the small-scale structure of the precipitation is required.]

Bellerby, T., M. Todd, D. Kniveton, and C. Kidd, 2000: Rainfall estimation from combination of TRMM precipitation radar and GOES multispectral satellite imagery through the use of an artificial neural network. *J. Appl. Meteor.*, **39,** 2115-2128.
[Low impact. The paper describes an artificial neural network for estimating rainfall with visual and infrared images from the Geostationary Operational Environmental Satellite. The network is trained with measurements from NASA's precipitation radar (PR) and is verified with PR measurements and rain gauge observations. Improvement is found over the older GOES

Precipitation Index (GPI) estimation technique.]

Biggerstaff, M. I., and S. A. Listemaa, 2000: An improved scheme for convective/stratiform echo classification using radar reflectivity. *J. Appl. Meteor.,* **39,** 2129-2150.
[Low impact. A study was undertaken to improve the partitioning of convective and stratiform precipitation in a previously published algorithm. Model enhancements include terms for vertical and horizontal gradients of reflectivity and bright bands. The proposed model does not suffer from the obvious misclassification flaws in the earlier study. It's unclear whether the classification changes will result in significant improvements in heating rates and rainfall estimates.]

Black, J. E., and N. R. Donaldson, 1999: Comments on "Display of bird movements on the WSR-88D: Patterns and Quantification". *Wea. and Forecasting,* **14,** 1039-1040.
[Low impact, information only. This note is in response to a paper by Gauthreaux and Belser (1998)[8] concerning the use of the WSR-88D for monitoring bird migrations. The original paper attempted to estimate the migration traffic rate of birds from measured reflectivity. Black and Donaldson assert that reflectivity is more closely related to the number of birds. (In truth, the relation between birds and reflectivity is likely to be complicated because birds are Mie scatterers.) The flux of birds would be given by their number and their speed. The authors suggest bird speeds can be estimated from the Doppler information. In their reply, Gauthreaux and Belser compute the bird density and show a linear relation with reflectivity (linear units). The correlation is high (0.89) and better than that between traffic rate and reflectivity in dBZ. The correlation may be strongly influenced by two data points.]

Bowles, J. B., and C. Peláez, 1995: Application of fuzzy logic to reliability engineering. *IEEE Proceedings,* **83,** 435-449.
[Low impact. Applications in estimating failure rates in complex manufactured goods are described. The paper begins with a brief introduction to membership functions and how fuzzy logic tools operate. Fuzzy fault trees are also introduced for determining likely system outcomes when failures do occur.]

Brandes, E. A., J. Vivekanandan, and J. W. Wilson, 1999: A comparison of radar reflectivity estimates of rainfall from collocated radars. *J. Atmos. Oceanic Technol.,* **16,** 1264-1272.
[Low impact, system evaluation. Rainfall estimates for storms in Colorado and Kansas from a research radar and WSR-88Ds were examined. Storm-to-storm bias factors and correlation coefficients between estimated and gauge observed rainfalls were very similar for collocated radars suggesting that much of the observed variance in these parameters stems from meteorological factors.]

Brierley, P., and B. Batty, 1999: Data mining with neural networks–An applied example in

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[8] Gauthreaux, S. A., Jr., and C. G. Belser, 1998: Display of bird movements on the WSR-88D: Patterns and quantification. *Wea. and Forecasting,* **13,** 453-464.

understanding electricity consumption patterns. *Knowledge Discovery and Data Mining*, M. A. Bramer (Ed.), The Institution of Electrical Engineers, London, 240-303.
[Low impact. The authors give a nice overview of how neural networks operate. An application designed to understand and predict electricity consumption is examined in detail. Usage has yearly, weekly, and diurnal components and is influenced by holidays, the length of day light, and weather. Experiments with varying numbers of hidden nodes are described. Rudimentary Fortran 90 code for a backpropagating multilayer NN is provided.]

Brown, R. A., J. M. Janish, and V. T. Wood, 2000a: Impact of WSR-88D scanning strategies on severe storm algorithms. *Wea. and Forecasting,* **15,** 90-102.
[High impact, user awareness issue. The influence of vertical sampling resolution on algorithm output for VCP-11 (14 elevation) and simulated VCP-21 (9 elevation) scans is examined. For storms relatively close to the radar and extending above 5^{o} elevation, algorithm output can differ significantly in a large percentage of cases. Estimated vertical depths of features differ more than 60% of the time. Moreover, there is a tendency for feature depths to be smaller with VCP-21. Other parameters such as VIL are consistently larger. The differences seem significant enough that different warning thresholds may be justified. The authors recommend that VCP-11 be used in convective situations whenever warnings may be required.]

Brown, R. A., V. T. Wood, and D. Sirmans, 2000b: Improved WSR-88D scanning strategies for convective storms. *Wea. and Forecasting,* **15,** 208-220.
[High impact. A procedure for optimizing radar scans is proposed. Constraining parameters are the selected minimum and maximum elevation angles, an assumed storm height, and the maximum allowable storm height underestimate. The latter parameter dictates the number and spacing of elevation angles. The procedure should result in VCPs with increased low-level sampling of distant storms, more regularly spaced elevation angles, and a reduction in the "cone of silence" above the radar. By maximizing the rotation rate, temporal sampling can also be increased.]

Brunkow, D., V. N. Bringi, P. C. Kennedy, S. A. Rutledge, V. Chandrasekar, E. A. Mueller, and R. K. Bowie, 2000: A description of the CSU-CHILL National Radar Facility. *J. Atmos. Oceanic Technol.,* **17,** 1596-1608.
[Low impact, description of a research polarimetric radar. The paper describes the S-band dual-polarization radar operated by Colorado State University. Dual transmitters and receivers are featured. The radar can operate by alternate transmission of horizontally and vertically polarized signals or the transmitters can be triggered simultaneously to produce $\pm 45^{o}$ linear or right-hand or left-hand circular polarization states. The radar reportedly has the sensitivity to measure LDR signals of -34 dB when signal-to-noise ratios are >35 dB. A procedure for calibrating Z_{DR} with sun scans and LDR measurements is presented.]

Büchner, A. G., J. C. L. Chan, S. L. Hung, and J. G. Hughes, 1999: A meteorological knowledge-discovery environment. *Knowledge Discovery and Data Mining*, M. A. Bramer (Ed.), The Institution of Electrical Engineers, London, 204-226.
[Low impact. The article details the desired attributes of a data mining system for meteorological

datasets.]

Campos, E., and I. Zawadzki, 2000: Instrumental uncertainties in *Z–R* relations. *J. Appl. Meteor.,* **39,** 1088-1102.
[Low impact. Radar reflectivity estimators are derived from DSD measurements obtained with three different instruments. Relations are constructed by performing a linear regression between 10logZ and logR, a nonlinear regression between Z and R, and a regression between logR and 10logZ which was then inverted. The computations produced three sets of estimators that differed significantly in their coefficients and exponents. The total variation was similar to that in Z–R relations reported in the literature.]

Ciach, G. J., and W. F. Krajewski, 1999: Radar–rain gauge comparisons under observational uncertainties. *J. Appl. Meteor.*, **38,** 1519-1525.
[Low impact. The influence of radar and gauge measurement errors on the direct nonlinear regression (Z to R), inverse nonlinear regression to (R to Z), and probability matching method for estimating the exponent of Z–R relations is examined. Results show that the direct method always overestimated the exponent due to errors in reflectivity measurements. Reverse regression always underestimated the exponent. The probability matching method, which is susceptible to both radar and gauge errors, was found to be the geometric mean of the two regression methods.]

Cios, K., W. Pedrycz, and R. Swiniarski, 1998: *Data Mining: Methods for Knowledge Discovery,* Kluwer Academic Publishers, Boston, 495 pp.
[Low impact, a technical reference for data mining. Individual chapters cover rough sets, fuzzy logic, Bayesian methods, and neural networks.]

Cornman, L. B., R. K. Goodrich, C. S. Morse, and W. L. Ecklund, 1998: A fuzzy logic method for improved moment estimation from Doppler spectra. *J. Atmos. Oceanic Technol.,* **15,** 1287-1305.
[Low impact. Doppler velocity estimates are improved by application of fuzzy logic to identify point targets, velocity and range folding, radio interference, and ground clutter in spectral moments. An overview of tool development is given.]

Cox, E., 1992: Fuzzy fundamentals. *IEEE Spectrum*, 58-61.
[Low impact. The paper presents a short description of how fuzzy logic tools operate and system components. An example, in which the operation of a steam turbine is controlled using temperature and pressure inputs, is outlined.]

de Elía, R., and I. Zawadzki, 2000: Sidelobe contamination in bistatic radars. *J. Atmos. Oceanic Technol.,* **17,** 1313-1329.
[Low impact, an evaluation of bistatic radar systems. The paper presents a forthright discussion of sidelobe issues with bistatic radar systems. Problems can be acute because sidelobes are about twice as strong as that with monostatic weather radars. Moreover, problems are further complicated by the characteristics of the transmitting and receiving systems. The paper describes

a simulation model for evaluating contamination and presents several examples. Contamination typically occurs in areas of low reflectivity with nearby strong precipitation.]

Desrochers, P. R., and S. Y. K. Lee, 1999: Wavelet applications for mesocyclone identification in Doppler radar observations. *J. Appl. Meteor.,* **38,** 965-980.
[Moderate impact, possible algorithm upgrade. A B-spline wavelet serves as the basis for a mesocyclone detection algorithm. The wavelet produces a filtered rendition of the mesocyclone that retains the dominant scales. Azimuthal shear segments are then computed for the filtered mesocyclone and used to define a search region for velocity extrema in the original data. The mesocyclone is then designated by an ellipse which encompasses the extrema. An illustrative example is given. Further testing seems warranted.]

Doviak, R. J., V. Bringi, A. Ryzhkov, A. Zahrai, and D. Zrnić, 2000: Considerations for polarimetric upgrades to operational WSR-88D radars. *J. Atmos. Oceanic Technol.,* **17,** 257-278.
[High impact, prospects for polarimetric observations with the WSR-88D are discussed. Issues investigated include the potential impact of the current three-spar feed horn support on the polarization measurements. Although one spar is in the vertical, it's concluded that this configuration results in less sidelobe contamination of the polarimetric variables than a four-spar X-shaped arrangement. Antenna measurements made after the installation of a dual-port antenna feed (to accommodate horizontal and vertical polarizations) indicated that the radar still met the original specifications for sidelobe levels. The authors recommend a linear polarization basis whereby horizontally and vertically-polarized pulses are transmitted and received simultaneously.]

El-Magd, A., V. Chandrasekar, V. N. Bringi, and W. Strapp, 2000: Multiparameter radar and in situ aircraft observation of graupel and hail. *IEEE Trans. Geosci. Remote Sensing,* **38,** 570-587.
[Low impact, information only. Simulations suggest that radar reflectivity is more sensitive to hail density than to axis ratios and particle orientation. Consequently, it's argued that differences between radar-measured reflectivity and that calculated from in situ hail observations are due to density fluctuations. From small reflectivity differences (< 1 dB), hydrometeor densities of 0.915 to 0.945 g cm^{-3} were inferred for a hail region, suggesting the hail was wet. Densities of 0.48 to 0.62 g cm^{-3} were found for conical graupel indicating it was dry. Because in situ measurements are required, there are no algorithm implications.]

Fulton, R. A., 1999: Sensitivity of WSR-88D rainfall estimates to the rain-rate threshold and rain gauge adjustment: A flash flood study. *Wea. and Forecasting,* **14,** 604-624.
[High impact, deficiencies in the precipitation processing subsystem for estimating radar bias are discussed. The current PPS bias adjustment procedure is examined for a heavy rain event. The bias is determined by comparing gauge reports to the radar estimate at the nine surrounding radar data bins. If the gauge report is within the range of radar values, it is assumed that the radar is unbiased. If the gauge report is outside the range of radar values, the closest radar estimate is used to determine the bias. This procedure underestimates the actual bias. Substantial improvement was found at independent test gauges when the bias was determined either from the data bin within which the calibrating gauge resided or by taking an average of the nine data bins.]

Furundzic, D., 1998: Application example of neural networks for time series analysis: Rainfall–runoff modeling. *Signal Processing,* **64,** 383-396.
[Low impact. Runoff is predicted with multilayer neural network-based models. Input consists of gauge observations and thirty-five parameters representing watershed topographic, geographic, geologic, and sociological factors. The networks show marked improvement over a stepwise regression model.]

Gorgucci, E., G. Scarchilli, and V. Chandrasekar, 1999: Specific differential phase estimation in the presence of nonuniform rainfall medium along the path. *J. Atmos. Oceanic Technol.,* **16,** 1690-1697.
[Moderate impact, could be important if the WSR-88Ds are modified for polarimetric capabilities. A scheme is proposed to account for bias in estimates of specific differential phase (K_{DP}) that arises from the filtering of the differential propagation phase (Φ_{DP}) measurement whenever the profile of Φ_{DP} is not linear. The technique capitalizes on the consistency among the polarimetric variables and attempts to recover detail in the K_{DP} profile by making adjustments in accordance with computations of specific differential phase made from radar reflectivity and differential reflectivity measurements.]

Gorgucci, E., G. Scarchilli, and V. Chandrasekar, 2000a: Practical aspects of radar rainfall estimation using specific differential propagation phase. *J. Appl. Meteor.,* **39,** 945-955.
[Moderate impact, could be important if the WSR-88Ds are modified for polarimetric capabilities. The paper extends the study of Gorgucci et al. (1999). Biases due to the parameterization of K_{DP} estimators, non-uniform precipitation paths, and the use of non-linear estimators are quantified.]

Gorgucci, E., G. Scarchilli, V. Chandrasekar, and V. N. Bringi, 2000b: Measurement of mean raindrop shape from polarimetric radar observations. *J. Atmos. Sci.,* **57,** 1406-1413.
[Low impact, possible refinement to rainfall estimation with polarimetric radar. Differential reflectivity and specific differential phase are sensitive to hydrometeor shape. It's shown that the axis ratio associated with the drop median volume diameter can be computed from Z_H, Z_{DR}, and K_{DP} to an accuracy within 10%. Potentially, the information could lead to fine tuning of polarimetric rainfall estimators.]

Grecu, M., and W. F. Krajewski, 2000: An efficient methodology for detection of anomalous propagation echoes in radar reflectivity data using neural networks. *J. Atmos. Oceanic Technol.,* **17,** 121-129.
[Moderate impact, possible WSR-88D application. Results of an experiment in anomalous propagation detection are described. Nine potential predictors representing properties of radar reflectivity fields serve as input to a neural network. The network was trained on datasets characterized by precipitation-only and AP-only events. Network performance was significantly better than that with a statistical technique using a quadratic discrimination function. Possible improvement to the method–which might be helpful in mixed AP and precipitation events–would be to add the Doppler fields to the detection scheme.]

Gremillion, M. S., and R. E. Orville, 1999: Thunderstorm characteristics of cloud-to-ground lightning at the Kennedy Space Center, Florida: A study of lightning initiation signatures as indicated by the WSR-88D. *Wea. and Forecasting,* **14,** 640-649.
[Moderate impact, potential air mass thunderstorm algorithm. A capability to “predict” the onset of lightning in thunderstorms would have utility not only for monitoring rocket launches at the Space Center but also for the aviation industry and those engaged in outdoor activities. Lightning typically begins when the temperature in convective updrafts falls below -10^{o}C. For a reflectivity of 40 dBZ and a temperature of -10^{o}C a POD of 0.84, a FAR of 0.07, and CSI of 0.79 were determined. The median lead time was 7.5 min.]

Harrison, D. L., S. J. Driscoll, and M. Kitchen, 2000: Improving precipitation estimates from weather radar using quality control and correction techniques. *Meteorol. Appl.,* **6,** 135-144.
[Moderate impact. The paper begins with a short description of potential problems in radar estimates of rainfall and then describes data quality control measures and bias adjustment procedures implemented by the Meteorological Office in the United Kingdom. Rainfall estimates are adjusted for the vertical profile of reflectivity and for mean radar bias due to calibration. Comparison with hourly rain gauge observations shows improvement in rainfall estimates, as indicated by a drop in RMSEs of ~30%. Long-term comparisons between radar and gauges are found useful for verifying the utility of the profile correction scheme, for reducing range-dependent errors, and for identifying regions with residual problems relating to clutter and beam occultation.]

Howard, C. M., and V. J. Rayward-Smith, 1999: Discovering knowledge from low-quality meteorological databases. *Knowledge Discovery and Data Mining,* M. A. Bramer (Ed.), The Institution of Electrical Engineers, London, 180-203.
[Low impact. The article discusses issues relevant to data mining with meteorological databases. Topics covered are data preprocessing to remove outliers, data quality issues, inserting missing values, discretization, feature selection, the data mining operation (search for rules), and desired features of tool kits.]

James, C. N., S. R. Brodzik, H. Edmon, R. A. Houze Jr., and S. E. Yuter, 2000: Radar data processing and visualization over complex terrain. *Wea. and Forecasting,* **15,** 327-338.
[Low impact, information only. Data streams from WSR-88Ds in mountainous terrain are enhanced by the addition of underlays to show topography based on 30-s digital elevation data from the Defense Mapping Agency and the National Aeronautics and Space Administration. The information is displayed as color contours, filled contours, or raster plots. The authors assert the information aids in the interpretation of radar echoes and the identification of areas where widespread precipitation may be intensified or suppressed by orography. Also, the overlays, particularly in vertical cross sections, are useful for evaluating data quality in regions of clutter and beam blockage.]

Kessinger, C., S. Ellis, and J. VanAndel, 1999: An algorithm to detect anomalously-propagated ground clutter. Preprints, *15th International Conf. on Interactive Information and Processing Systems for Meteor., Ocean., and Hydro.,* Amer. Meteor. Soc., Dallas, Texas, 310-313.

[Moderate impact. An AP detection algorithm that incorporates fuzzy logic is proposed. Designations are based on the magnitude of the radial velocity, the spectrum width, the texture of the reflectivity and radial velocity fields, and the vertical gradient of reflectivity. Details of the membership functions and defuzzification are not given. The implemented procedure is designed to define areas where clutter filters would be applied.]

Klazura, G. E., J. M. Thomale, D. S. Kelly, and P. Jendrowski, 1999: A comparison of NEXRAD WSR-88D radar estimates of rain accumulation with gauge measurements for high- and low-reflectivity horizontal gradient precipitation events. *J. Atmos. Oceanic Technol.*, **16,** 1842-1850.
[Moderate impact, evaluation of the precipitation processing subsystem. WSR-88D rainfall estimates for high and low reflectivity gradient storms were compared to rain gauge observations. On average, rainfall was slightly overestimated for the high gradient (convective) storms. However, underestimates occurred at short radar ranges. This was attributed to the use of a reflectivity composite of the lowest four elevation angles. The small mean overestimate could be caused in part by smoothing of reflectivity gradients. Precipitation in the low gradient storms was underestimated by more than a factor of two and also exhibited a range dependent bias. Possibly, low-reflectivity gradient storms are characterized by drops with relatively small median diameters.]

Lakshmanan, V., 2000: Using a genetic algorithm to tune a bounded weak echo region detection algorithm. *J. Appl. Meteor.*, **39,** 222-230.
[Moderate impact, possible WSR-88D algorithm. The use of a genetic algorithm for fine tuning the breakpoints of fuzzy logic membership functions in a BWER detection algorithm is described. Techniques for optimization and estimating the fitness of the tuned algorithm are discussed. Results of training and test runs with CSIs $\leq$ 0.5 may be more indicative of problem difficulty rather than the power of the tuning method.]

Lazarus, S., A. Shapiro, and K. Droegemeier, 1999: Analysis of the Gal-Chen single-Doppler velocity retrieval. *J. Atmos. Oceanic Technol.*, **16,** 5-18.
[Low impact. A series of tests with simple analytical radar reflectivity and radial wind fields are used to determine the influence of measurement errors on retrieved wind fields. In some cases the error impact can be reduced by changing the relative weights of the reflectivity and radial velocity fields. Mean wind retrieval improves as the analysis domain increases. Because observed radar data have complex error structures, extension of the results to wind fields retrieved in an operational setting is not straightforward.]

Lee, W.-C., B. J.-D. Jou, P.-L. Chang, and S.-M. Deng, 1999: Tropical cyclone kinematic structure retrieved from single-Doppler radar observations. Part I: Interpretation of Doppler velocity patterns and the GBVTD technique. *Mon. Wea. Rev.*, **127,** 2419-2439.
[Moderate impact, possible algorithm. A scheme for retrieving simple asymmetric flow patterns in tropical cyclones observed by a single ground-based radar is presented. The method was tested on analytical wind fields with tangential, radial, and translational components. Tests were extended to asymmetric systems by superimposing disturbances with wavenumbers 1–3.

Components of observed flows are retrieved by comparing the observed radial wind pattern with modeled flows and determining least-squares differences. Axisymmetric circulations were well retrieved. Wind fields in simulated cyclones with translational components and azimuthal disturbances were retrieved with some distortion. The cause of the distortion can be identified by the characteristics of the zero Doppler velocity contour.]

Lee, W.-C., and F. D. Marks Jr., 2000: Tropical cyclone kinematic structure retrieved from single-Doppler radar observations. Part II: The GBVTD-simplex center finding algorithm. *Mon. Wea. Rev.,* **128,** 1925-1936.
[Moderate impact, possible algorithm. The GBVTD method for retrieving the wind field in tropical cyclones was modified by a procedure to more accurately determine the circulation center. The iterative method is based on constructed triangles which are continually changed through reflection, contraction, and expansion in a search for the tangential wind maximum. Testing with an analytical dataset suggested cyclone centers could be located with an accuracy of 0.34 km. Application to a typhoon indicated errors in an operational setting may be as large as 2 km. Potential problems identified were missing data sectors and weak velocity gradients.]

Liou, Y.-C., 1999: Single radar recovery of cross-beam wind component using a modified moving frame of reference technique. *J. Atmos. Oceanic Technol.,* **16,** 1003-1016.
[Low impact. The method of wind field retrieval based on the reflectivity conservation equation is extended by adding cost function terms for mass conservation and vertical vorticity. The method is applied to model data. Compared to methods using the reflectivity conservation equation alone, the added constraints significantly improve the correlation between the retrieved and model wind field and reduce root-mean-square errors. A series of tests suggest the method is robust with respect to measurement errors and can produce reasonable estimates of the wind from reflectivity alone.]

Liu, H., and V. Chandrasekar, 2000: Classification of hydrometeors based on polarimetric radar measurements: Development of fuzzy logic and neuro-fuzzy systems, and in situ verification. *J. Atmos. Oceanic Technol.,* **17,** 140-164.
[Moderate impact, potential algorithm if the WSR-88D is modified for polarimetry. A procedure for hydrometeor classification that incorporates fuzzy logic for hydrometeor designation and a neural network for adjusting fuzzy logic parameters is described. The procedure is successfully applied to three convective events and a rain–snow event. The paper includes a nice discussion of fuzzy logic systems and gives schematic representations of the membership functions used for summer and winter storms.]

MacKeen, P. L., H. E. Brooks, and K. L. Elmore, 1999: Radar reflectivity-derived thunderstorm parameters applied to storm longevity forecasting. *Wea. and Forecasting,* **14,** 289-295.
[Low impact, nominal value as a potential algorithm. The study attempts to predict the remaining lifetime of thunderstorms from radar reflectivity generated parameters provided by the storm cell identification and tracking (SCIT) algorithm and the hail detection algorithm (HDA). Storm characteristics weakly correlated with longevity were the maximum reflectivity, height of the reflectivity maximum, center of mass height, height of the 40-dBZ core, cell-based VIL, and storm top. Linear and multiple regression correlation coefficients were low ($\leq$ 0.43). Hence, the

authors see little value in the reflectivity-based predictions. Future efforts will incorporate the velocity information, environmental conditions, and output from a cloud model.]

Marzban, C., E. D. Mitchell, and G. J. Stumpf, 1999: The notion of “best predictors”: An application in tornado prediction. *Wea. and Forecasting,* **14,** 1007-1016.
[High impact, the study relates both to the current tornado detection algorithm and general algorithm development. An important issue when developing algorithms for solving complex problems with a large number of potential contributing parameters is the determination of “best predictors”. The authors argue that the strength of individual predictors is best assessed by a bivariate analysis between the independent variable and each candidate dependent variable. Bivariate approaches suggested are the computation of the linear correlation coefficient, the use of performance parameters such as the critical success index (CSI) and the Heike skill score (HSS) to determine algorithm threshold values, and finding event probabilities as a function of predictor value. The methods were applied to the WSR-88D tornado detection algorithm. Some input parameters are highly correlated and hence provide redundant information. The range parameter has no predictability. By making yes–no decisions at various thresholds, optimum values can be determined. Thresholds that maximize CSIs and HSSs may differ. Variables with good predictive skill are thought to be those with large probability variation as a function of parameter value.]

May, P. T., T. D. Keenan, D. S. Zrnić, L. D. Carey, and S. A. Rutledge, 1999: Polarimetric radar measurements of tropical rain at a 5-cm wavelength. *J. Appl. Meteor.,* **38,** 750-765.
[Low impact, information only. The utility of the specific differential phase parameter at C band is investigated. Results show much higher correlations and less bias between rain rates computed from K_{DP} and rain gauges than with Z_H. A significant K_{DP} rainfall underestimate on a small drop day suggests some dependence on the DSD. Correcting radar reflectivity measurements for blockage and attenuation reduced the overall bias with reflectivity and caused the RMSEs with reflectivity to converge with those for K_{DP}.]

Mendel, J. M., 1995: Fuzzy logic systems for engineering: A tutorial. *IEEE Proceedings,* **83,** 345-377.
[Low impact. An introduction to fuzzy logic systems and an extended list of references is given. The article features a comparison of fuzzy logic and other models such as probability and presents mathematical formulations for the various components of fuzzy systems.]

Michelson, D. B., and J. Koistinen, 2000: Gauge–radar network adjustment for the Baltic Sea Experiment. *Phys. Chem. Earth (B),* **25,** 915-920.
[Moderate impact, could lead to improved rainfall estimates. A two-step adjustment procedure for improving rainfall estimates with gauge observations is described. A second-order range-dependent adjustment is determined using gauge–radar pairs to account for the vertical profile of reflectivity. Calculations are made with logarithms to achieve a more normal distribution of data points. Small rainfall accumulations and data pairs that differ by more than 2 standard deviations from the mean distribution are eliminated from the analysis. Data pairs from several past days may be included to ensure a stable sample size. The range-adjusted precipitation field is then subjected to a distance-weighing scheme of recent gauge–radar pairs to make additional local

adjustments. The net effect is a precipitation map that is free of bias and has an increased explained variance between radar-derived and gauge-observed rainfalls (0.30 versus 0.18).]

Nanni, S., P. Mezzasalma, and P. P. Alberoni, 2000: Detection of hail by polarimetric radar data and hailpads: Results from four storms. *Meteorol. Appl.,* **7,** 121-128.
[Low impact, polarimetric radar application. Experiences with the differential hail signal (H_{DR}) for storms in Italy are presented. Because measurements are made at C-band, constraints are imposed to limit attenuation problems and consequent spurious hail designations. Other constraints are designed to reduce problems associated with 15 min sampling. A probability of detection of 0.9, a critical success index of 0.6, and a false alarm rate of 0.3 were determined.]

Nicosia, D. J., E. J. Ostuno, N. Winstead, G. Klavun, C. Patterson, C. Gilbert, G. Bryan, J. H. E. Clark, and J. M. Fritsch, 1999: A flash flood from a lake-enhanced rainband. *Wea. and Forecasting*, **14,** 271-288.
[Low impact, product evaluation. Rainfall estimates from the Cleveland, Ohio WSR-88D (KCLE), using the default Z–R relation, for a flash flood produced by a slow moving rainband near Erie, Pennsylvania were ~40% less than the observed peak rainfall. Rainfall in an adjacent region of convective precipitation was overestimated. Application of the relation $Z=250R^{1.2}$ improved the estimates in the flood region but created overestimates of 200–400% in the area of convection. The underestimate of the flood rainfall is attributed to “warm rain” processes occurring below the radar beam. It is also possible that the drops were uncharacteristically small.]

Otsuka, K., T. Horikoshi, S. Suzuki, N. Sonehara, and M. Fujii, 1999: Local precipitation forecast based on retrieval of similar echo patterns in radar images. Preprints, *15th International Conf. on Interactive Information and Processing Systems for Meteor., Ocean., and Hydro.,* Amer. Meteor. Soc., Dallas, Texas, 99-102.
[Low impact. A new approach to forecasting weather patterns is described. Forecasts are made by comparing observed precipitation patterns with the historical record and determining previous outcomes for similar events. Hence, the technique embodies elements of the nearest neighbor approach to forecasting. The problem is reduced to describing the motion and texture of observed reflectivity patterns with eigenvectors and eigenvalues. The goodness of fit is expressed by an index. Exemplary pattern designations and forecasts are given.]

Pereira Fo, A. J., and K. Crawford, 1999: Mesoscale precipitation fields. Part I: Statistical analysis and hydrological response. *J. Appl. Meteor.,* **38,** 82-101.
[Moderate impact, algorithm extension. A methodology for optimally combining radar and gauge observations is described. The weight received by the two precipitation fields is based on their two-dimensional covariance/correlation structures. The adjusted rain field has characteristics of both fields. The technique was evaluated by inserting unadjusted and gauge-adjusted rainfall accumulations into a hydrologic runoff model. The unadjusted radar estimates from the Twin Lakes WSR-88D (KTLX) were found to underestimate the rainfall by 28% which in turn caused the runoff to be underestimated by a factor of 3 to 5.]

Petersen, W. A., L. D. Carey, S. A. Rutledge, J. C. Knievel, N. J. Doesken, R. H. Johnson, T. B. McKee, T. Vonder Haar, and J. F. Weaver, 1999: Mesoscale and radar observations of the Fort Collins flash flood of 28 July 1997. *Bull. Amer. Meteor. Soc.,* **80,** 191-216.
[Low impact. Rainfall estimates made from the Cheyenne, Wyoming WSR-88D (KCYS) using the NEXRAD default Z–R relation were found to be a factor of 2 less than observed. Rainfall estimates were essentially unbiased for the tropical Z–R relation. Importantly, the KCYS estimates were about 25% less than that with a research radar–an indication of a possible calibration error. Polarimetric measurements with the research radar suggest that the underestimates with radar reflectivity may be due to small drops. Although rainfall estimates increased for polarimetric estimators, the underestimate persisted.]

Protat, A., and I. Zawadzki, 1999: A variational method for real-time retrieval of three-dimensional wind field from multiple-Doppler bistatic radar network data. *J. Atmos. Oceanic Technol.,* **16,** 432-449.
[Low impact, a possible low-cost multiple radar network. The paper describes a method for computing the wind field with a bistatic radar network. The network consists of relatively inexpensive passive broad-beam, low-gain radar receivers which measure obliquely scattered signals from pulses transmitted by a primary radar. Measurements from multiple receivers are combined with a variational procedure. The technique is demonstrated with examples.]

Ryzhkov, A., D. Zrnić, and R. Fulton, 2000: Areal rainfall estimates using differential phase. *J. Appl. Meteor.,* **39,** 263-268.
[Moderate impact, polarimetric rainfall estimation study. It is shown that rainfall estimates for watersheds with dimensions $\gtrsim$10 km can be improved by computing the rain rate from the total change in Φ_{DP} over rays through the watershed rather than using the distribution of K_{DP} at all data points within the watershed. By using the change in Φ_{DP}, computational requirements and potential problems related to statistical errors and bias introduced by reflectivity gradients are much reduced. A bias reduction from 13 to 8% and a lowering of FSEs from 25 to 18% were achieved with the proposed method. The trade-off is a loss of information regarding the distribution of rainfall within the watershed.]

Sachidananda, M., and D. S. Zrnić, 1999: Systematic phase codes for resolving range overlaid signals in a Doppler weather radar. *J. Atmos. Oceanic Technol.,* **16,** 1351-1363.
[High impact. A scheme for retrieving overlaid (range-folded) echoes is described. Transmitted signals are systematically phase coded and returned signals are multiplied by decoding factors. Echoes from a specified trip are made coherent, but echoes from other multiples of the unambiguous range are phase modulated so that they appear as noise and make no contribution to the desired coherent signal. Tests show the proposed scheme is more robust than random-phase coding.]

Sachidananda, M., and D. S. Zrnić, 2000: Clutter filtering and spectral moment estimation for Doppler weather radars using staggered pulse repetition time (PRT). *J. Atmos. Oceanic Technol.,* **17,** 323-331.

[High impact, a potential solution to the ground clutter problem. A method is discussed for estimating spectral parameters (mean power, mean velocity, and spectrum width) from staggered radar pulses. Variable PRTs are used to generate a uniform time series from which the spectral parameters are estimated. The procedure involves a Fourier transform, a filtering operation to remove the clutter, and a deconvolution to reconstruct the spectrum. Reportedly, reconstructed spectra have less bias than other spectral methods and yield improved mean velocity estimates even when clutter is absent.]

Seo, D.-J., J. Breidenbach, R. Fulton, and D. Miller, 2000: Real-time adjustment of range-dependent biases in WSR-88D rainfall estimates due to nonuniform vertical profile of reflectivity. *J. Hydrometeor.*, **1,** 222-240.
[Moderate impact, possible adjustment procedure for removing range-dependent biases from rainfall estimates. The paper describes a proposed method for removing biases in radar reflectivity rainfall estimates due to bright bands. Examples are shown for two cases with severe beam blockage. Modest improvements occur in the correlation coefficient between radar-estimated and gauge-observed rainfalls and in RMSEs.]

Shao, J., 2000: Fuzzy categorization of weather conditions for thermal mapping. *J. Appl. Meteor.*, **39,** 1784-1790.
[Low impact. The paper describes a fuzzy classification system for determining road conditions. Infrared measurements from a vehicle-mounted system are used to map road surface temperatures. The thermal mapped products, classified in fuzzy categories, such as extreme, intermediate, and damped, are combined with cloud cover, cloud type, wind speed, and humidity observations in a model for predicting road icing conditions.]

Silverman, D., and J. A. Dracup, 2000: Artificial neural networks and long-range precipitation prediction in California. *J. Appl. Meteor.*, **39,** 57-66.
[Low impact. The paper outlines a neural network for estimating rainfall from circulation patterns at 700 mb. Experiments are conducted with variable numbers of hidden nodes, different training datasets, and withheld parameters.]

Smyth, T. J., T. M. Blackman, and A. J. Illingworth, 1999: Observations of oblate hail using dual-polarization radar and implications for hail-detection schemes. *Quart. J. Royal Meteor. Soc.*, **125,** 993-1016.
[Moderate impact, implications for polarimetric hail detection algorithms. The paper gives an excellent discussion of issues related to hail detection with polarimetric radar. Topics covered are past observational studies, theoretical considerations, and a discussion of fall modes that are so critical to measurement interpretation. A simulation shows that a unique relation between K_{DP} and radar reflectivity (rain rate) does not exist. Observations from an unusual hailstorm are then examined. Large Z_{DR} values in the region of hail suggest that the hail was oblate and fell with its major axis close to horizontal. Detection algorithms that assume hail tumbles as it falls would have failed. An examination of the differential phase measurements revealed a large backscatter component due to Mie scattering. The lack of a unique relation between K_{DP} and rain rate and the presence of Mie scatterers dictated that hail detection algorithms based on K_{DP} (e.g.,

Balakrishnan and Zrnić, 1990)[9] would also fail. A new algorithm is proposed that makes use of the consistency between polarimetric parameters. K_{DP} is computed from the observed radar reflectivity and differential reflectivity and compared to that computed from the radar measured distribution of Φ_{DP}. Significant differences (values > ±5° km^{-1}) signify hail.]

Straka, J. M., D. S. Zrnić, and A. V. Ryzhkov, 2000: Bulk hydrometeor classification and quantification using polarimetric radar data: Synthesis of relations. *J. Appl. Meteor.,* **39,** 1341-1372.
[Moderate impact, research related to radar polarimetry. This is an important paper which reviews the scientific basis for hydrometeor classification with polarimetric radar. The described research will serve as the foundation for a hydrometeor classification algorithm if the WSR-88D is modified for polarimetry. The paper begins with an overview of the polarimetric variables and follows with detailed explanations of expected signatures for various hydrometeors. Numerous references are given.]

Stuart, N. A., 1999: Operational considerations of the WSR-88D precipitation processing subsystem during the convective flooding event of 11 August 1994 in northern Virginia. *National Wea. Digest,* **23,** 21-31.
[Low impact, product evaluation. Radar rainfall estimates for a flash flood made by two radars at distances > 90 nm are compared. Rain accumulations for one radar (the Dover Air Force Base WSR-88D, KDOX) were 5–6.2 inches versus 3–4 inches for the Wakefield, Virginia WSR-88D (KAKQ). The estimates from KDOX more closely matched gauge observations. A contributor to the KAKQ underestimate is thought be a lower maximum reflectivity threshold for rainfall accumulation (53 versus 70 dBZ).]

Timothy, K. I., T. Iguchi, Y. Ohsaki, and H. Horie, 1999: Test of the specific differential propagation phase shift (KDP) technique for rain-rate estimation with a Ku-band rain radar. *J. Atmos. Oceanic Technol.,* **16,** 1351-1363.
[Low impact. Utility of the specific differential propagation phase for rain rate estimation is compared to that for radar reflectivity and differential reflectivity. The study concludes that, when all factors, such as, calibration error, DSD variations, ... etc. are considered, K_{DP} estimators are superior for rain rates > 40 mm h^{-1}.]

Torres, S. M., and D. S. Zrnić, 1999: Ground clutter canceling with a regression filter. *J. Atmos. Oceanic Technol.,* **16,** 1364-1372.
[High impact, data processing issue. The use of regressive clutter filters is examined. Filter response is dictated by the number of samples to which the regression is applied and the degree of the polynomial. The degree broadens the notch width. Tests show greater suppression of clutter and greater retention of weather signals than with fifth-order elliptic clutter filters currently used on the WSR-88D.]

[9] Balakrishnan, N., and D. S. Zrnić, 1990: Estimation of rain and hail in mixed-phase precipitation. *J. Atmos. Sci.,* **47,** 565-583.

Trapp, R. J., 1999: Observations of non-tornadic low-level mesocyclones and attendant tornadogenesis failure during VORTEX. *Mon. Wea. Rev.,* **127,** 1693-1705.
[Low impact. Kinematic flow properties of dual-Doppler derived wind fields for three tornadic and three non-tornadic mesocyclones are examined. Tornadic mesocyclones are distinguished by greater low-level vertical vorticity and smaller maximum tangential wind radii. Swirl ratios, essentially the ratio of the tangential and radial wind components, were *greater* for non-tornadic mesocyclones than for tornadic mesocyclones. The author postulates that higher swirl ratios associate with Reynolds numbers that suppress strong radial inflows and consequently prevent the amplification of mesocyclone vorticity by stretching. Given the small sample size and possible deficiencies in the low-level Doppler-derived wind fields, independent confirmation seems warranted.]

Trapp, R. J., E. D. Mitchell, G. A. Tipton, D. W. Effertz, A. I. Watson, D. L. Andra Jr., and M. A. Magsig, 1999: Descending and nondescending tornadic vortex signatures detected by WSR-88Ds. *Wea. and Forecasting,* **14,** 625-639.
[Moderate impact, warning implications should be further quantified. Analysis of Archive Level II measurements from 52 tornadic storms disclosed that 52% of the time tornadogenesis was preceded by a descending tornado vortex signature (TVS). Typically, differential velocity maxima were first detected between 2 and 7 km above ground. Non-descending tornadoes were associated with vortex signatures that formed at low levels and frequently intensified upward. Tornadoes produced by descending TVSs had lead times that averaged about 10 min longer than the non-descending variety. Their maximum velocity differences were also greater. Six of seven tornadoes examined in squall lines were associated with non-descending TVSs.]

Ulbrich, C. W., and L. G. Lee, 1999: Rainfall measurement error by WSR-88D radars due to variations in Z–R law parameters and the radar constant. *J. Atmos. Oceanic Technol.,* **16,** 1017-1024.
[Low impact, could help clarify rainfall underestimates. To explain radar–gauge differences a series of experiments were conducted in which the coefficient and exponent of the WSR-88D default Z–R relationship were varied to determine potential effects on estimated rainfalls. Results suggest underestimates of ~25% for stratiform rain and overestimates of 33% for convective rains are likely on average. Because the biases are much smaller than observed with some WSR-88Ds, the authors conclude that large discrepancies must be due to radar calibration errors. A comparison of radar reflectivity measurements from the WSR-88D near Greer, South Carolina (KGSP) and a disdrometer implied the radar is 3.4 dB too low.]

Vignal, B., H. Andrieu, and J. D. Creutin, 1999: Identification of vertical profiles of reflectivity from volume scan radar data. *J. Appl. Meteor.,* **38,** 1214-1228.
[Moderate impact, could be important for improving rainfall estimates. A methodology for computing distributed vertical reflectivity profiles from volumetric radar data is described. Profiles of reflectivity, normalized to the lowest radar elevation angle, are computed for small radar domains at a spacing of ~20 km. The discrete profiles are input into a theoretical model that accounts for radar beam filtering with range. A case study illustrates that useful detailed vertical structure can be retrieved by the method. A substantial improvement in the RMSE of

surface rainfall estimates (43 versus 11%) was found when the technique was applied to observations made with an elevated radar beam.]

Vignal, B., G. Galli, J. Joss, and U. Germann, 2000: Three methods to determine profiles of reflectivity from volumetric radar data to correct precipitation estimates. *J. Appl. Meteor.*, **39,** 1715-1726.
[Moderate impact, could be important for improving rainfall estimates. Surface rainfall estimates are evaluated after adjusting radar-observed profiles of reflectivity and extrapolating them to ground. Tested methods included a climatological profile, an hourly mean profile based on radar measurements within 70 km, and local profiles on a 20 km grid. All methods improved the rainfall estimates. The climatological profile lowered the RMSE from 44% (for unadjusted reflectivity measurements from the lowest antenna elevation angle) to 31%. Application of the mean reflectivity profile lowered the RMSE to 25%, and the distributed VRP method lowered the error to 23%. The authors suppose that mean profiles are less susceptible to clutter and beam blockage and that the distributed VRP method will be more advantageous when the region of interest is relatively flat.]

Vivekanandan, J., D. N. Yates, and E. A. Brandes, 1999: The influence of terrain on rainfall estimates from radar reflectivity and specific propagation phase observations. *J. Atmos. Oceanic Technol.*, **16,** 837-845.
[Moderate impact, polarimetric radar study. The advantage of specific differential phase for estimating rainfall in mountainous regions where the radar beam is partly blocked is demonstrated. Comparison with radar reflectivity-derived rainfall estimates revealed that the reflectivity estimates were lower than that from specific phase, and the percentage difference was nearly linearly related to the amount of blockage.]

Vivekanandan, D. S. Zrnic, S. M. Ellis, R. Oye, A. V. Ryzhkov, and J. Straka, 1999: Cloud microphysics retrieval using S-band dual-polarization radar measurements. *Bull. Amer. Meteor. Soc.*, **80,** 381-388.
[Moderate impact, potential algorithm if the WSR-88D is modified for polarimetry. A fuzzy logic technique for classifying radar returns in hydrometeor, biological, and ground echo categories is described. Designations are made by employing membership functions weighted according to how strongly each polarimetric measurement matches supposed characteristics for each classification type.]

Westrick, K. J., C. F. Mass, and B. A. Colle, 1999: The limitations of the WSR-88D radar network for quantitative precipitation measurement over the coastal western United States. *Bull. Amer. Meteor. Soc.*, **80,** 2289-2298.
[Low impact, a difficult problem not readily solved. An assessment of the WSR-88D network for making quantitative precipitation estimates along coastal sections of California, Oregon, and Washington is given. PPS products in cold seasons are compromised by low freezing levels, shallow precipitation, and blockage by mountain ranges. The authors estimate that precipitation estimates can be made in only one third of the region. They recommend that scanning angles be reduced to 0^o or less at some radar sites, that additional radars be placed in some coastal areas,

and that research be conducted to combine radar and rain gauge data in overlap areas.]

Widrow, B., and M. A. Lehr, 1990: 30 years of adaptive neural networks: Perceptron, Madaine, and backpropagation. *IEEE Proceedings,* **78,** 1415-1442.
[Low impact. Topics covered in this review article include the history of neural networks, how various networks operate, and their training.]

Wood, V. T., and R. A. Brown, 2000: Oscillations in mesocyclone signatures with range owing to azimuthal radar sampling. *J. Atmos. Oceanic Technol.,* **17,** 90-95.
[Low impact. The influence of radar distance on the deduced strength and width of mesocyclones detected with discrete azimuthal samples is examined by simulation. Oscillations in mean rotational velocity of several meters per second and discontinuous fluctuations in mesocyclone diameter on the order of 5 km are shown.]

Yamada, Y., and M. Chong, 1999: Vad-based determination of the Nyquist interval number of Doppler velocity aliasing without wind information. *J. Meteorol. Soc. Japan,* **77,** 447-457.
[Low impact, the technique appears most applicable for determining strong mean winds. A velocity unfolding technique based on the coefficients of a second order VAD analysis is proposed. It is shown that the proper Nyquist interval can be determined by modifying the zeroth-order coefficient so that differences are minimized. Simulations show that the technique is sensitive to measurement errors and non-linearities in the wind field. Application to real data indicates measurements must extend over azimuthal sectors of at least 130 to 160^{o}.]

Young, C. B., A. A. Bradley, W. Krajewski, and A. Kruger, 2000: Evaluating NEXRAD multisensory precipitation estimates for operational hydrologic forecasting. *J. Hydrometeor.,* **1,** 241-254.
[Low impact, an evaluation of gauge-adjusted radar rainfall products. The study examines gauge-adjusted precipitation maps constructed by the Arkansas-Red River Basin River Forecast Center. The assessment is based on Stage III rainfall analyses and compares a simple mean radar bias correction method with a technique whereby ratios of radar estimates and gauge observations are inversely weighted by distance. The latter method produced precipitation fields with less artifacts (rings, spokes, and range bias) and smaller RMSEs. In the absence of a detailed error analysis, attributed to the lack of independent gauge observations and knowledge of precipitation characteristics on scales < 4 km, the authors were reluctant to declare one product better than the other.]

Yuval, 2000: Neural network training for prediction of climatological time series, regularized by minimization of the generalized cross-validation function. *Mon. Wea. Rev.,* **128,** 1456-1473.
[Low impact. The training of a neural network is evaluated with hybrid cost functions that gauge system performance. The paper seeks to optimize model development by minimizing a generalized cross-validation function which is integrated during the training period and applied to subsets of the data. The sensitivity of the final model is evaluated by withholding selected input parameters.]

Zawadzki, I., W. Szyrmer, and S. Laroche, 2000: Diagnostic of supercooled clouds from single-Doppler observations in regions of radar-detectable snow. *J. Appl. Meteor.*, **39,** 1041-1058.
[Moderate impact, possible tool for detecting icing in the terminal area of airports. The paper describes a proposed algorithm for estimating supercooled liquid in stratiform precipitation. The radar data are examined to determine the snow content and to verify the model through self consistency. The wind field is derived with a variational analysis of the radar reflectivity and radial velocity measurements. A cloud model is then initialized with the retrieved wind field and a local sounding. The model is integrated forward to steady state. The excess of water vapor above saturation (determined from the deduced vertical velocity and observed moisture profile) is portioned between deposition on snow and condensation on supercooled cloud drops.]

Zrnić, D. S., T. D. Keenan, L. D. Carey, and P. May, 2000: Sensitivity analysis of polarimetric variables at a 5-cm wavelength in rain. *J. Appl. Meteor.*, **39,** 1514-1526.
[Low impact, information only. Simulations with Marshall–Palmer and gamma DSDs are used to determine the effects of large drops on polarimetric variables and estimated rain rates at C band. The calculations show important resonant effects for drops with diameters $\gtrsim$ 5 mm. Polarimetric parameters are sensitive to the distribution shape (exponential or gamma) and to the maximum drop diameter. Greatest impacts are with radar reflectivity because of the 6th power dependency on diameter. Among polarimetric variables, K_{DP} is least affected. K_{DP} and Z_H,Z_{DR} rain rate estimators are found to be fairly insensitive to the presence of large drops, but Z_H,Z_{DR} estimators would be subject to attenuation. The latter problem can be corrected with K_{DP}. The study finds that polarimetric rainfall estimates at C band are more robust than those from radar reflectivity. The authors state that better knowledge of large drop concentrations would further improve the estimators.]

APPENDIX: LIST OF ACRONYMS AND SYMBOLS

CSI	Critical success index
DSD	Drop-size distribution
FAR	False alarm rate
FSE	Fractional standard error
H_{DR}	Differential hail signal
IEEE	Institute of Electrical and Electrons Engineers, Inc.
K_{DP}	Specific differential phase
NN	Neural network
POD	Probability of detection
PPI	Planned position indicator
PPS	Precipitation Processing Subsystem
R	Rain rate
RMSE	Root-mean-square error
SCIT	Storm cell identification and tracking
TVS	Tornado vortex signature
VAD	Velocity azimuth display
VCP	Volume coverage pattern
VIL	Vertically integrated liquid
VRP	Vertical reflectivity profile
WSR–88D	Weather Surveillance Radar–1988 Doppler
Z	Radar reflectivity factor
Z_{DR}	Differential reflectivity
Z_H	Radar reflectivity factor at horizontal polarization
Φ_{DP}	Differential propagation phase