A Spatiotemporal Approach to Tornado Prediction

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***Abstract*— Automated tornado detection or prediction techniques in the literature have all been based on analyzing "signatures" of tornadoes that appear in Doppler radar velocity data. Attributes of these signatures are derived from radar data, as well as the near-storm environment, and associated with observed tornadoes. This associated database has been used to train neural networks and support vector machines to automatically classify radar signatures.**

In this paper, we formulate the tornado prediction problem differently. Instead of devising a machine intelligence approach to classify detections, we formulate the problem as a spatio-temporal one: of estimating the probability of a tornado event at a particular spatial location within a given time window.

In this paper, we also describe our initial approach to addressing this differently formulated problem. We use a least-squares methodology to estimate shear, morphological image processing to estimate gradients, fuzzy logic to generate compact measures of tornado possibility and a classification neural network to generate the final spatio-temporal probability field.

I. Detecting Tornadoes

The Tornado Detection Algorithm (TDA) [1] is the automated method used by the National Weather Service (NWS) to detect and diagnose tornadic circulations. It was designed to examine the velocity difference between adjacent velocity gate pairs at constant range and at each radar elevation angle.If the velocity difference exceeds a specified threshold, the velocity pair is termed a shear segment and used to construct 2D features at multiple difference thresholds ranging from 11m/s to 35m/s. The 2D features are then utilized to construct 3D features based on vertical continuity criteria.

One of the problems with the TDA approach is the heavy reliance on thresholds at each stage of the processing. The Mesocyclone Detection Algorithm (MDA) [2] was designed to detect and retain a wide range of circulations of varying size and strength until the final stage. Attributes for each MDA-detected circulation were computed from the radial velocity data. These circulations sensed on radar were matched by hand to tornadoes detected on the ground, and this ideally classified dataset (hereafter: MDA ground truth) was used by [3] to train a neural network to automatically classify MDA detections as tornadic or non-tornadic.

The original MDA ground truth dataset was enhanced to incorporate near-storm environment (NSE) data and used by [4] to classify MDA circulations as tornadic or non-tornadic. Tornadoes are rare-event situations and when these neural network classifiers were considered using specially formulated measures of performance [5], it was found that neither the MDA or the MDA+NSE neural network approaches was sufficiently skilful. In fact, [4] found that the incorporation of NSE data provided only a marginal increase in skill.

[6] described a method for discriminating between tornadic and non-tornadic detections based on empirical orthogonal functions, finding that it achieved a high probability of detection. [7], [8] compared neural networks and support vector machines in the context of tornado forecasting, finding that support vector machines and Bayesian neural networks provided significantly higher skill compared to traditional neural networks. [9] found that a hybrid approach using rule-based support vector machines yielded good performance both in terms of a high probability of detection and a low false alarm rate.

A. A Spatio-Temporal Formulation

A real-time test of algorithms and displays developed as part of the Warning Decision Support System – Integrated Information (WDSS-II) was carried out in the National Weather Service Forecast Office (NWS-FO) at Norman, OK in the Spring of 2004. [10], reporting on the real-time test, note that users of algorithm information prefer the algorithm information to carry information in terms of spatial extent rather than numerical or categorical information. For example, hail information associated with storm cells was rarely used, but grids of estimated hail size were heavily utilized in forecasting situations. We hypothesize that the reasons for such a preference may be that:

- A spatial grid provides a much better measure of uncertainty.
- A spatial grid created using continuous functions of observed parameters is more robust than classified entities since problems of association and matching these entities over time are side-stepped.
- Spatial grids of probabilities are more amenable to human interrogation and decision making.

Thus, one motivation for this research is that users would probably prefer spatial grids of tornado likelihood to classified circulation features.

Another motivation for this research is that previous attempts at classifying circulation features using statistical techniques have yielded unsatisfactory results. The fact that using the near storm environment (NSE) information provides only a marginal improvement in skill gives us a hint of the reason. It is known that tornado genesis is more likely under certain atmospheric conditions than others. One possible reason that the data don't provide additional skill might be that the NSE data vary very slowly in space. Thus, even where a tornado is likely, there are many more non-tornadic circulations than tornadic ones. This is true of nearly every input feature to the classification neural networks. Thus, the very poor performance of these automated classifiers.

A new formulation is needed where it is not necessary to classify circulation features based on poorly differentiated input features. It would be ideal if such a formulation were spatial in nature. This, then, is our new formulation of the tornado "detection" problem: *Estimate the probability that there has been or will be a tornado in a 1kmx1km area on the ground within the previous or next 30 minutes.* This is not exactly the same as a tornado detection algorithm because of the incorporation of the temporal element in the formulation. The resulting probability will be a spatio-temporal one and captures the idea that even if only one of ten circulations in an area is tornadic, the entire area has experienced a tornado. It has the advantage of more closely matching what a forecaster, or the general public, is interested in – where and when a tornado is likely. It will also enable smarter use of spatially varying scientific data such as the NSE.

II. Method

This section describes our approach at solving the spatio-temporal tornado detection/prediction problem.

A. Forming the Truth Field

The MDA ground truth database was used to form the truth field. In that database, [2] associated circulations seen on radar to tornadoes observed on the ground within the next 20 minutes. We used these hand-truthed circulations as a starting point and mapped the radar circulation locations at every volume scan to the earth's surface. To account for the spatial variability of the hand-truthed circulations, their movement between volume scans of radar data and the uncertainty involved with the size of the circulation, we gave each circulation detection an influence radius of 5km. A pixel in the ground truth field at a particular instant in time was assigned "1" if a tornadic radar signature was observed within 5km of this pixel in a 30-minute window centered around that instant.

Shown in Figure 1 is the truth field. Although the image shows each F-scale as different, we chose to formulate the problem independent of F-scale since the F-scale is based on damage done and might be independent of circulation strength.

B. Space-time correction

It should be noted that Figure 1 shows the movement of the tornadic circulations with time. The longer paths correspond to tornadic circulations currently strong on radar while the single block indicates a tornadic circulation that will, in 20 minutes, produce a tornado. All of our observed data will correspond only to the current time. Thus, the data have to be space-and-time corrected to indicate where the tornado is likely to be based on current observations.

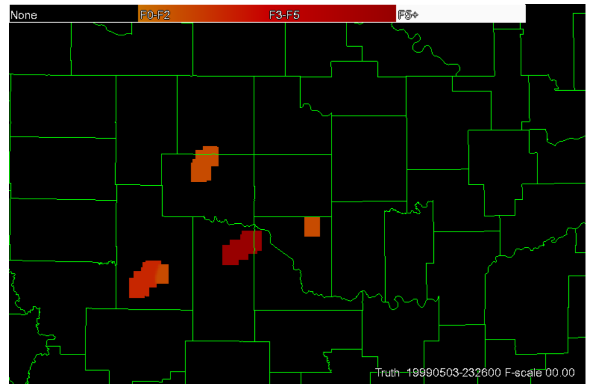

Fig. 1. A spatial field that indicates areas where a tornado existed in a 30-minute window centered around 23:26 on May 3, 1999 UTC. Although the image shows F-scale intensity, our target field is a spatial field that has only 1s and 0s.

For intervals as short as 30 minutes, a linear forecast is quite skilful [11]. The linear forecast is based on the movement of clusters of radar reflectivity values estimated from time frames 10 minutes apart. Thus, the observed data will be used to make a prediction and then advected backwards and forwards corresponding to the movement of the observed data over time. During the training process, the truthed circulations should be placed where they are expected to be at the current time. For long-lived detections, we can simply use the current location of the detection. Circulations not currently visible, but which will become visible over the next 30 minutes, will have to be coasted back to where they would have been had they been visible.

C. Quality Control of Radar Reflectivity

From the point of view of automated applications operating on weather data, echoes in radar reflectivity may be contaminated. Our application, for example, will require that echoes in the radar reflectivity moment correspond, broadly, to "weather". This is important because, as [12] observed, a large number of false positives in the MDA are caused in regions of clear-air return. We need quality-control of radar reflectivity data so that we indicate tornado possibility only in areas of weather activity.

A quality-control neural network [13], found to outperform the quality-control technique currently used on the WSR-88D network, was used to clean up the reflectivity data. This cleaned up reflectivity data were then used for the computation of gradients and as an indicator of the presence of weather activity.

D. LLSD

Traditional methods of calculating rotational and divergent shears from Doppler radial velocity data can give results that vary widely from the true value of shear for the meteorological feature being sampled [14]. These methods are affected by noisy data, the azimuthal offset of sample volumes from the center of the feature, and the radar viewing angle. The MDA and TDA rely simply on the difference of the maximum and minimum radial velocity within a rotation or divergence feature. This method, termed “gate-to-gate shear”, is plagued with uncertainties in the values of the shear estimates as well in locating the center of a shear feature [15].

[14] introduced a two-dimensional, local, linear least squares (LLSD) method to minimize the large variances in rotational and divergent shear calculations. The polar radial velocity data are first median filtered. Then, a plane is fit on the data within a neighborhood the size of which is nearly constant in Cartesian space i.e. using more range gates closer to the radar. The gradient of the fit plane in the azimuthal direction gives the azimuthal shear, while the gradient in the radial direction gives the divergence. These two robust measures are used in place of gate-to-gate shear.

E. Tornado Possibility

[16] used WDSS-II implementations of the quality-control neural network, the LLSD technique of estimating azimuthal shear and radial divergence and method of remapping, and combining, polar radar data onto equi-latitude-longitude grids [17]. They found several signatures in the azimuthal shear composites (i.e. maximum absolute magnitude regardless of the height). In addition to the rotation signatures, it was discovered that tornadoes were more likely in regions exhibiting high positive shear and high negative shear and proximate to high reflectivity values. This idea was implemented in [18] where the proximity criterion was satisfied by using the Watershed algorithm of [19] separately on positive and negative shear areas and comparing those regions to a Watershed segmentation of reflectivity data. It was found that this proximity criterion served to identify all the tornadoes in the MDA ground truth dataset.

We found that the Watershed segmentation approach yielded very noisy segmentation results, and that simple proximity criteria would, by themselves, suffice. The proximity criteria were defined by morphological dilation [20] of the negative and positive shear field separately and looking for areas of overlap. The morphologically dilated azimuthal shear fields are shown in Figure 2.

1) Gradient estimation: Tornadoes are more likely in the areas of a storm that exhibit tight gradients in reflectivity, and are in the lagging region of any supercellular structures. For example, for a storm moving north-east, tornadoes are more likely in the south-west region of the storm. Thus, it would be useful to isolate areas that exhibit strong gradients in that direction. While a truly multiresolution approach to determining directional gradients would be preferable, we found that computing gradients over larger distances (not just a pixel away) on smoothed reflectivity fields in the directions of interest sufficed (See Figure 3).

2) Fuzzy combination: Having created spatial fields of areas with tight gradients in the appropriate directions and of areas proximate to high positive and negative shear, we aggregated these spatial fields using a fuzzy logic weighted aggregate. The breakpoints for the aggregates were chosen by manual comparison of the spatial fields to the ground truth spatial field, such that a number of pixels in each tornado would gain high fuzzy possibility scores. A tornado possibility field created using this method is shown superimposed by the ground truth in Figure 4

3) Classification: The fuzzy tornado possibility field was then clustered using region growing [20] and the properties of each region were determined. The properties were computed from the values at each pixel in the region of any other spatial fields. The spatial fields will include data from numerical models, such as the NSE, and from non-radar remote sensors such as lightning activity. For now, the input fields are just local statistics (mean, variance, minimum and maximum) computed in a 9x9 neighborhood on the various inputs to the fuzzy possibility field. To avoid problems inherent in the matching of spatial clusters, no time-dependent properties (such as a rate of increase) are used.

Each of the regions was then compared to the ground truth. If a corresponding tornado was observed in the ground truth field, the region was classified as being tornadic. The tabular data, relating the properties of each region to its tornadic/non-tornadic classification, was used to train a classifier. We divided the data set consisting of 40 time steps (spaced 30 minutes apart) extracted from three different storm days into a training/ validation and independent test set. The training set contained 530 regions of which 86 were tornadic. The test set contained 132 regions of which 21 were tornadic.

TABLE I

RESULTS: PERFORMANCE MEASURES

Measure	Validation	Test
POD [21]	0.71 +/- 0.04	0.87 +/- 0.05
FAR [21]	0.35 +/- 0.06	0.35 +/- 0.03
CSI [22]	0.51 +/- 0.05	0.60 +/- 0.04
HSS [23]	0.61 +/- 0.06	0.69 +/- 0.04

We then trained several feed-forward neural networks (with different numbers of hidden nodes) on the training data set, stopping early when the performance of the network on the validation set started to suffer (using cross-entropy as our measure of performance). This was repeated several times on different combinations of training/validation data and the best performing network, along with the threshold at which the Heidke Skill Score (HSS [23]) was maximum, was selected. The best network had 4 hidden nodes and the best threshold was 0.4. This network was tested on test cases drawn randomly from the independent test set. The 95% confidence interval is reported. Results of the training stage and test run are shown in Figure 5 and Table I. The reported skill scores (Probability of Detection, False Alarm Ratio, Critical Success Index and Heidke Skill Score) are scalar measures commonly used in rare event situations [5].

III. CURRENT AND FUTURE RESEARCH

There are three broad avenues that we are pursuing. One is to obtain more spatial inputs into the region classifier. Such inputs should include data from other sensors (such as

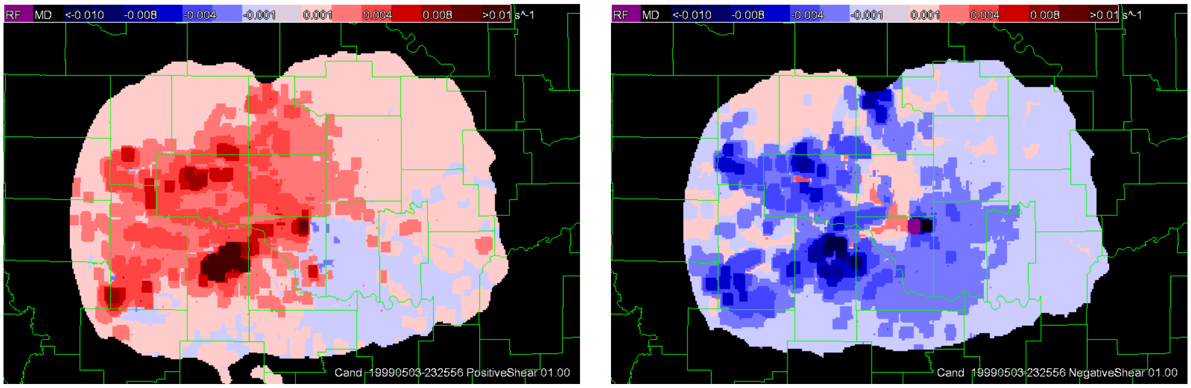

Fig. 2. Morphologically dilated positive (left) and negative (right) azimuthal shear fields. Pixels having both high positive and high negative values are proximate to vortices or rotation.

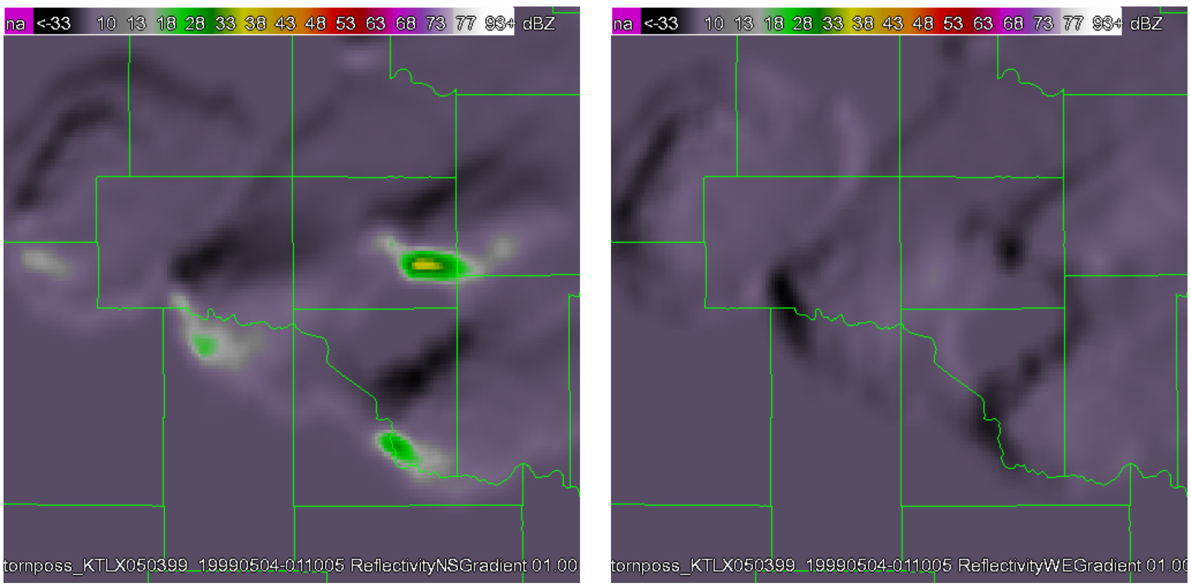

Fig. 3. Gradient in the North-South and West-East directions computed by computing the large-distance gradient on a smoothed reflectivity field. Because of the direction of movement of this storm, the North-South gradient is more interesting.

cloud-to-ground lightning, total lightning and satellite infrared temperature). Secondly, we need to generate the spatial input data for many more storm cases, at the very least for the 83 cases that have associated MDA ground truth (See [4]). Thirdly, we are examining ways to improve certain aspects of our solution.

Because the formulation of the problem involves prediction as well as detection, it is necessary to guess where tornadoes are likely to form in the future. For that purpose, it is necessary to detect and follow storm fronts. Our research on this problem so far has focused on creating detection algorithms for gust fronts using correlation templates [24] that use entropy measures to match areas likely to be part of a front and fuse signatures detected in both reflectivity and shear fields. The correlation found is a spatial quantity (See Figure 6) and could be one of the inputs used by the classifier.

In the case of shear data, we simply used the proximity of positive shear to negative shear. As with reflectivity gradients, utilizing the directionality of these shear areas will reduce the incidence of false positives. In fact, [16] noted that there were signatures of tornadic circulations that could be seen in the shear fields. One research activity is focused on automated detection of these shear signatures and creating a "soft computing" method of representing the presence or absence of these shear signatures in a spatial field.

It is also known that there are precursors to tornadoes, such as updrafts, that can be seen in radar data. It will be necessary to utilize updraft detection algorithms such as that of [25] and create spatial representations of such proximity.

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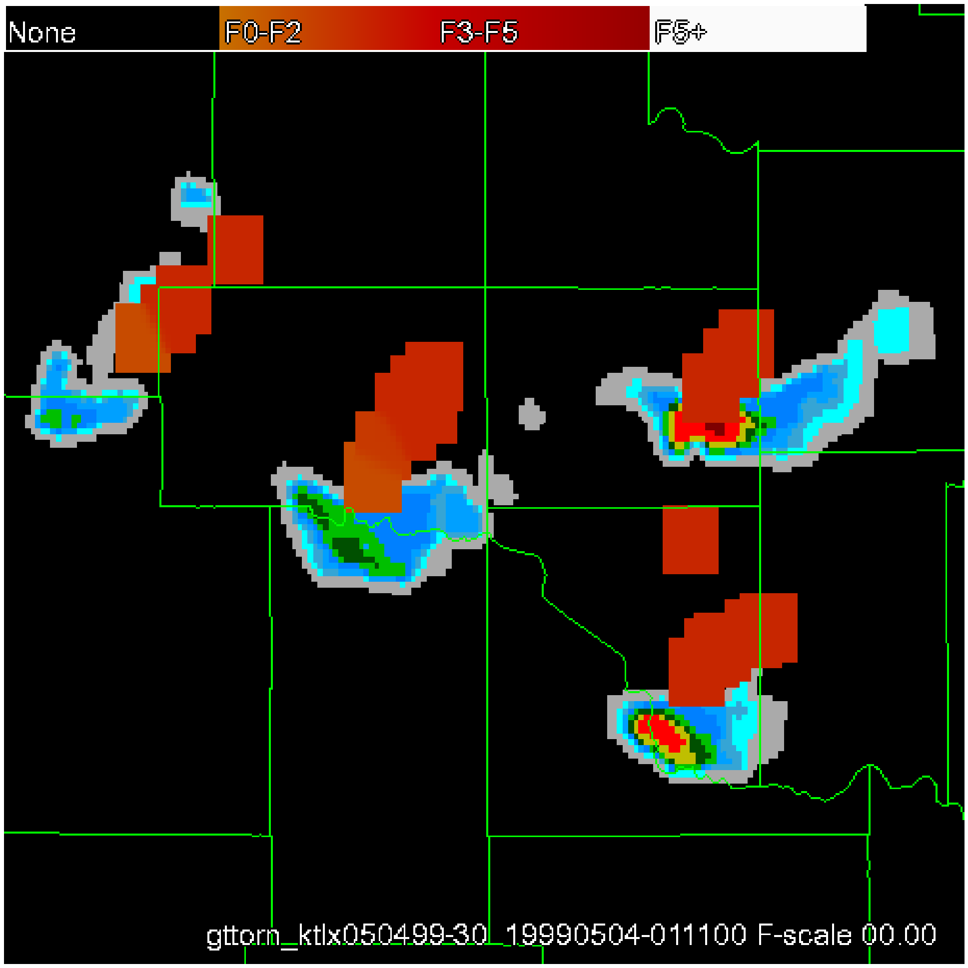

Fig. 4. Various spatial inputs are combined in a fuzzy manner into a "tornado possibility" spatial field. This field matches observed ground truth (the red blocks) closely.

of Commerce. We thank Amanda Adams for collecting and managing the radar data.

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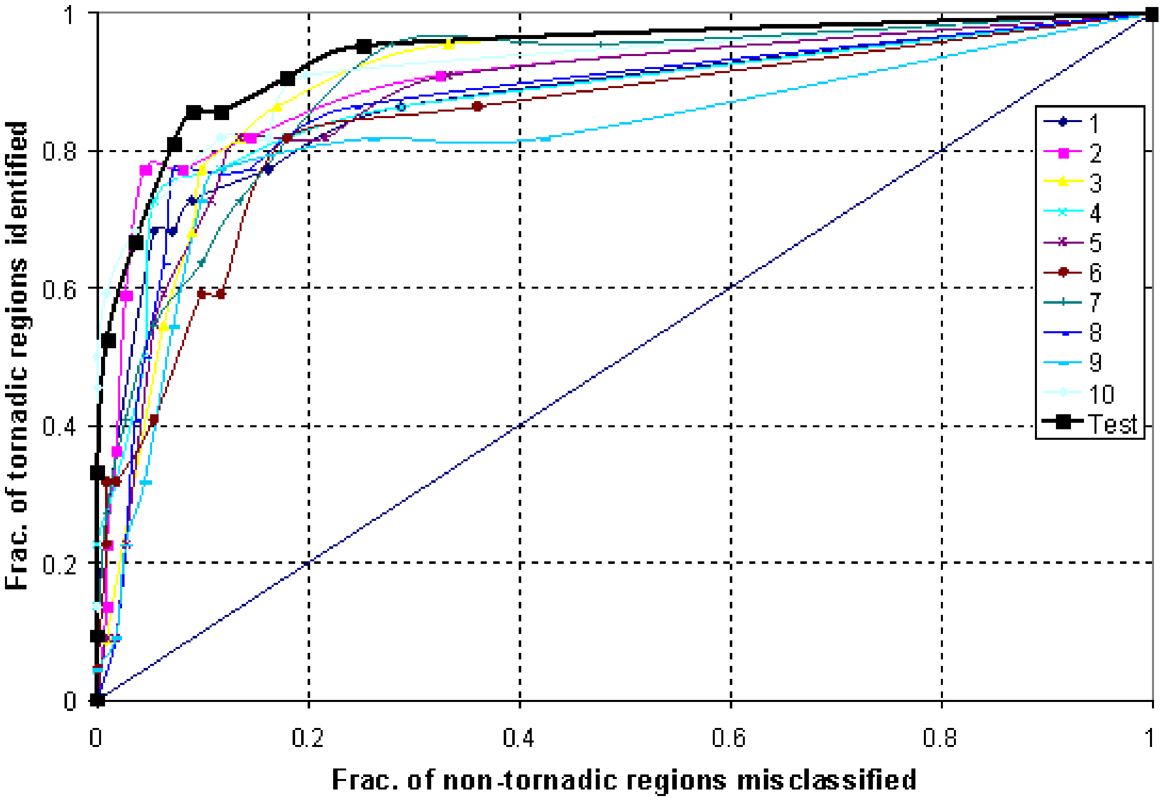

Fig. 5. ROC curve showing performance of different bootstrapped neural networks (the numbered runs) and the best validation network on the test set as the output threshold is varied.

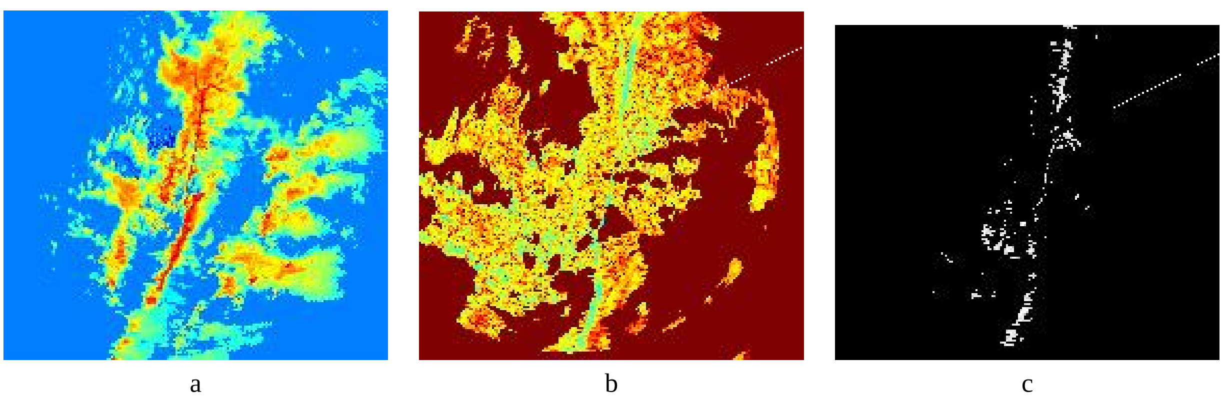

Fig. 6. Data and products from KGWX on Dec. 18, 2002. (a) Radar reflectivity (b) Azimuthal shear computed from the velocity data (c) Detected gust front

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