ABSTRACT

Prediction of tornadogenesis is one of the great problems in meteorology. Most tornadic supercell thunderstorms that go on to produce tornadoes are scanned only with stationary long-range weather radar, which provide only coarse data. In this research, we write custom software to mine storm structure variables detected by the Mesocyclone Detection Algorithm (MDA) at the radar stations. Neural modeling in JMP is then used to perform an exploratory analysis of this data. Investigation of such techniques could eventually provide spotters in the field with data that would help them make more informed decisions about what storms to monitor.

KEYWORDS: Tornado Prediction, Neural Networks, JMP

INTRODUCTION

Each year, over one thousand tornadoes touch down in the United States that, on average, kill seventy people per year [http://www.ncdc.noaa.gov/climate-information/extreme-events/us-tornado-climatology, http://www.norman.noaa.gov/2009/03/us-annual-tornado-death-tolls-1875-present/]. The average lead-time between a tornado warning issued by the National Weather Service and a tornado affecting the warning polygon is thirteen minutes [http://www.noaa.gov/features/protecting/tornados101.html]. Because the United States has such explosive severe weather seasons, there are vast archives of meteorological data including radar scans, satellite images, verified severe weather event logs, weather model predictions, storm reports, and atmospheric discussions written by forecasters. Our goal is to use the free, publicly available archives to work toward discerning patterns in storm behavior that may help indicate a potential tornado touchdown.

METEOROLOGICAL BACKGROUND

A tornado outbreak day begins with a very particular wind field. It must support supercell thunderstorms – storms with a sustained rotating updraft. This wind profile is a “veering” profile – meaning that as altitude increases, the wind turns clockwise (Vasquez, 2009). Ideally, winds come out of the southeast at the surface, bringing moisture from the Gulf of Mexico. At the
highest levels in the atmosphere, the wind will come from the west, and will have significantly increased in speed with altitude. Another term that is used to describe winds is “backing” – this describes wind that rotates counterclockwise with time or space. Often, surface winds from the southeast are described as “backed” winds, as they have rotated slightly counterclockwise relative to the winds aloft (Vasquez, 2009). Backed winds at the surface contribute to an overall veering wind profile. The difference in speed and direction of the wind at varying heights in the atmosphere gives air masses the tendency to roll horizontally (Vasquez, 2009). This causes an updraft that punches through such air masses to acquire rotation. Overall, the concept of varying wind speed and direction is known as “wind shear,” and is a key ingredient for severe thunderstorm development. Wind shear from the surface to the 6km level is key for storm longevity; it separates the precipitation-filled downdraft region from the updraft (Vasquez, 2009). Shear from the surface to the 1km level is important for actual development of tornadoes; it is an important mechanic for keeping warm, moist air (known as inflow) coming into the storm (Vasquez, 2009). In the absence of strong 0-1km shear, the rear-flank downdraft (a downward wind resulting from interaction of winds aloft with the updraft tower of the storm) can choke off inflow and cause premature death of an updraft.

Thermodynamics are also crucial to the formation of supercell thunderstorms and tornadoes. Warm air at the earth’s surface that has the tendency to rise is the basis of all thunderstorms. Both the magnitude of the difference between the temperature of air parcels at the surface and air aloft and the level of moisture at the surface play a part in determining how much energy is available for convection, a measure known as CAPE (Convective Available Potential Energy) (Vasquez, 2009). CAPE is calculated by integrating the difference in temperature between a rising air parcel and the environment around it. Higher dew points (higher moisture) contribute to effective instability due to moist parcels of air cooling more slowly (Vasquez, 2009 pg. 130). Convective Inhibition, also written as CIN or CINH, refers to a warm air mass aloft that can serve as a cap, preventing all but the strongest updrafts from becoming thunderstorms. This can prevent convection altogether, or prevent all but the strongest updrafts from forming storms, effectively making the few storms that do form more intense due to fewer updrafts vying for the same fuel tank (Vasquez, 2009).

Once storms initiate, deep rotation in an updraft due to wind shear creates a feature known as a mesocyclone. The rotation of the mesocyclone helps a storm become more severe through a positive feedback loop. Because of the intense rotation, a low-pressure system forms at the core of rotation. This helps siphon more high-CAPE air up into the storm, serving to further intensify the updraft. As the mesocyclone intensifies, it elongates and draws closer to the ground. Once rotation drops to the ground, a tornado is born (Vasquez, 2009).

During the process of storm initiation, mesocyclone generation, and tornado touchdown, a storm is continuously scanned by radar stations. In addition to measuring the quantity of precipitation in the air, the velocity of the precipitation is measured with each scan. Each scan contains up to sixteen different tilts of the radar dish, providing a three-dimensional view of motion within the storm. This set of tilted scans, of which one such pattern is pictured below, is known as a volume coverage pattern (VCP) [http://www.srh.noaa.gov/jetstream/doppler/vcp_max.htm] and is crucial for detection of three-dimensional features such as mesocyclones. The MDA then scours the resulting data for rotation detected on multiple tilts that can be vertically correlated. If such persistent rotation is found in the vertical direction, the algorithm generates metrics describing the circulation, which are what we use in this study.
The metrics produced by the MDA processing each tilt of the VCP are packaged and placed in MDA radar product files available for public download on National Weather Service servers, and are later placed in the National Climatic Data Center’s Severe Weather Data Inventory. The generated metrics used in this study are explained below and the definitions can be found at: http://www.wdtb.noaa.gov/courses/doc/topic1/Word/SCAN_Tables.pdf.

1. Base (LL_BASE) – The lowest detected rotation in the storm, in thousands of feet. It could be very high and at the lowest tilt, or very close to the radar at low level, but not necessarily at the lowest tilt. Thus, range should be taken into account when using this variable.
2. Depth (DEPTH_KFT) – The height of the rotating portion of the storm, measured in thousands of feet.
3. Strength Rank (STR_RANK) – This is a value calculated by the MDA; it is a measure of mesocyclone strength according to a formula defined in the radar system combining other variables listed here.
4. Low altitude rotation velocity (LL_ROT_VEL) – Rotational velocity at the lowest scan level in knots.
5. Maximum rotation velocity (MAX_RV_KTS) – Maximum detected rotational velocity in knots.
6. Height of maximum rotational velocity (MAX_RV_KFT) – Height of maximum detected rotational velocity, in thousands of feet.
7. Low altitude gate-to-gate shear (LL_DV) – The maximum difference between two adjacent velocity pixels (bins) in knots.
8. Age – This is calculated based on detection timestamps.
9. MSI (MSI) – Mesoscale strength index – a measure of the strength of a mesocyclone according to an algorithm run by the radar.
10. MSIR – MSI rank. Derived by ranking all the MSI’s of all the detected mesocyclones by a single radar station.
11. Relative depth (DPTH_STMRL) – Percent of a storm’s core that is rotating. This indicates whether or not the rotation is persistent through the entire updraft, or just a portion of it.
12. Range (RANGE) – Distance of the detected circulation from the radar, in nautical miles. This measure is important due to its linear effect on the minimum beam height of radar, thus affecting quality of measurements at great distance.

METHODS

First, records for all mesocyclone detections by the new digital mesocyclone detection algorithm were downloaded from the archives of the National Climatic Data Center (NCDC). This set
included approximately 4.8 million records, spanning from December 2006 when the rollout of the new algorithm began to early January 2014. The set was restricted to only detections from January 1, 2008 to December 31, 2013, to ensure that every NOAA long-range weather radar installation was using the new algorithm. These mesocyclones were then grouped spatiotemporally; for each given mesocyclone detected and assigned a circulation ID by a radar station, a circulation detected no more than eight minutes prior to the given circulation by the same radar with the same circulation ID was considered a match. Each mesocyclone detection was processed so that all radar-indicated mesocyclones were in logical groups.

Next, the storm event database was downloaded from the NCDC archives. This database encompasses all confirmed severe weather events, including surveyed damage paths of confirmed tornadoes. Due to the update from the Fujita Scale to the Enhanced Fujita Scale in February 2007, this dataset was also restricted to January 1, 2008 to December 31, 2013. Any incomplete records were, if possible, repaired. Any irreparable records, such as those that do not indicate where a tornado began or ended, were discarded. Once processed, this dataset included 8,676 individual tornado events.

With radar-indicated features properly grouped and tornado tracks prepared, it was possible to correlate mesocyclone groups to confirmed tornado damage paths. For each tornado damage path, mesocyclone detections between six minutes prior to tornado touchdown and the end time of the tornado event were retrieved. The latitude and longitude of each detection was compared to the interpolated location of the tornado. Detections within ten nautical miles of a confirmed tornado track were considered close enough for correlation, due to the inherent inaccuracy of the position of a radar-indicated mesocyclone aloft in a highly sheared supercell thunderstorm. Only one mesocyclone group per radar station was chosen. This decision was made to avoid erroneously associating a newly emerging circulation with a dissipating tornado. Therefore the mesocyclone group with a detection in closest proximity to the tornado track was considered a successful association, with all other circulations being ignored.

After matching mesocyclone tracks to tornado events, 43,872 individual mesocyclone detections were isolated that could be connected with confirmed tornado events, either at the moment of the scan or in the circulation’s future. This count includes every scan of a persistent mesocyclone that produced a tornado. From these records, training sets for a neural network could be generated. Additional values, such as time to tornado touchdown, were computed using the mesocyclone-group-to-tornado matchings, by comparing a mesocyclone scan timestamp to the time of touchdown of a confirmed tornado event.

We used this data, which contained 43,872 tornado-associated observations and 3.8 million unassociated observations of the 12 variables described above to conduct an exploratory analysis in JMP.

Tornado prediction has previously been analyzed in the meteorology literature using Neural Networks. In the study by Marzban and Stumpf (1996), a feed-forward neural network was used to process the outputs from the mesocyclone detection algorithm to try to predict tornadogenesis. Twenty-three inputs were used, including all found in this study plus eleven not included in the current mesocyclone detection algorithm. The additional variables used by Marzban and Stumpf (1996) include values describing the diameter of a mesocyclone, additional wind shear characteristics, and convergence values. These values are not available in the current mesocyclone detection algorithm and were therefore omitted from our study since they could not be obtained. Marzban and Stumpf (1996) also used one day of severe weather
data consisting of 3,258 circulations, 235 of which were tornadic; our study draws on the National Climatic Data Center’s Severe Weather Data Inventory to ensure a dataset that is widely varied and large in scope. Our data includes 3.8 million circulations, 43,872 of which are tornadic, over 1,825 days of records. For our initial analysis, we used a random sample of 2,500 circulations, 2,000 of which were tornadic. The aim of this study is to culminate in an operational tool for use by forecasters and researchers during severe weather events.

Neural networks are classifiers that are known to work well on data with complex relationships that are not easily determined. Traditional feedforward neural networks (see Figure 2) are multi-layer networks that consist of an input layer, one or more hidden layers, and an output layer. A heuristic algorithm, such as backpropagation or a genetic algorithm, is used to adapt the weights on the connections between the layers and an activation function, often referred to as a squashing function, is applied at the nodes in the hidden layer to allow the neural network to handle non-linear data. There are not rigid rules to determine how many hidden layers or nodes to use. Therefore, the design of a neural network often requires a trial and error process. Since a neural network is a supervised learning technique, it requires labeled training data to optimize the weights. Therefore, three sets of data are typically employed: 1) a training set, which consists of labeled observations used to adapt the weights, 2) a validation set, also labeled, which is used to determine if the accuracy of the model is acceptable, and 3) the data to be classified, which is unlabeled and consists of the observations the user wishes to classify.

RESULTS

To begin our initial investigation of our data, we calculated some descriptive statistics and some histograms of our variables. The descriptive statistics for our variable set are provided in Table 1, and the distribution for two selected variables is found in Figure 3. Notably, the average mesocyclone has a strength index at the high end of NOAA’s standard for a “moderate” strength mesocyclone [http://www.srh.noaa.gov/jan/?n=local_research_nssl_wdss]. Several of the variables, MSI, LL_DV, and LL_ROT_VEL have outliers that exceed the average value, potentially highlighting the need to normalize or otherwise transform the data to maximize its value in a neural network. The distribution of the values, a sample of which is shown in figure 3, is extremely bottom-loaded, with most values falling very close to the average.

The next step of our exploratory analysis was to create a set of 2,500 observations, including 2,000 records of mesocyclones that were confirmed to have a tornado under them twenty minutes after the scan and 500 mesocyclones that did not. We then used the neural modeling feature of SAS’s JMP software to obtain preliminary results. A neural network was configured with ten hidden nodes and a holdback value of 0.33 for validation.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Average</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>LL_BASE</td>
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<td>8.38</td>
<td>30</td>
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<tr>
<td>DEPTH_KFT</td>
<td>0</td>
<td>13.73</td>
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<tr>
<td>STR_RANK</td>
<td>3</td>
<td>6.11</td>
<td>25</td>
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<td>LL_ROT_VEL</td>
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<td>123</td>
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<tr>
<td>MAX_RV_KTS</td>
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<td>168</td>
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<tr>
<td>MAX_RV_KFT</td>
<td>0</td>
<td>10.75</td>
<td>39</td>
</tr>
<tr>
<td>LL_DV</td>
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<td>48.89</td>
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<tr>
<td>AGE</td>
<td>0</td>
<td>13.29</td>
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</tr>
</tbody>
</table>
The preliminary results with $R^2$ of 0.482 for the training data and 0.479 for the validation data (shown in Figure 3) point towards the possibility of developing successful neural network models for tornado prediction. We expect the $R^2$ values to improve as we continue to refine the input data, the input data transformations and the network design, including the size of the hidden layer, the learning parameters, and the stopping criteria.
JMP provides profiler predictions to facilitate the understanding of the impact of the input layer variables on the prediction. We are in the process of verifying the relationships identified in the profile predictions with scientifically documented atmospheric behaviors to better understand what the neural network has successfully captured and what relationships the neural network has not captured.

In Figure 5, we can see the profiler output from JMP. These profiler graphs help us understand the general impact of the variables on our prediction. If the slope is negative, take for example MSIr, it means that as the MSI rank of a mesocyclone increases (as it is ranked lower), the chance of a given circulation being associated with a tornado drops significantly. This is most likely due to competition between storms for warm air to fuel the updraft. Increasing strength rank interestingly negatively correlates with a tornado prediction in this set, suggesting that the radar algorithm may assign higher strength rank values erroneously. Low-level rotational velocity, low-level gate-to-gate shear, and MSI all exhibit a behavior in which the variable ramps up tornado threat to a point, then begins to negatively affect a prediction of a tornado. This may be caused by the resolution (and therefore range) of the scan, and requires further examination.

Range was included in the inputs in order to allow the neural network to learn that more distant scans may be less reliable; it appears to have worked well, with the variable showing a positive trend as scans become more reliable, until a peak at around 60 miles, and then the farther a circulation is from the radar, the less likely a positive prediction is to be made due to the low number of sweeps of the radar beam that hit a given circulation (see Figure 1). Storm relative depth of rotation appears to have a significant impact on the tornadic potential, as it ramps up probability of a positive prediction until around 70% relative depth. Altitude of the maximum rotational velocity appears to have minimal effect until about 12,000 feet, at which point it begins increasingly affecting the outcome of the neural network; this warrants further investigation. Age appears to have very little effect on the outcome of the network beyond ten minutes. It exhibits a slow dip and slow resurgence between ten minutes and two hours, most likely indicating that a circulation that can persist for more than an hour is in an area very favorable for production of tornadoes.
DISCUSSION AND CONCLUSIONS

This study constituted our data collection phase and preliminary model analysis of a neural network for tornado prediction. Our results indicate, that while we have significant work left to do in designing the network and manipulating the variables used, there is promise of using the technique in this context. Future work will entail significant testing of different model parameters and continued exploration of the variables used. In addition to comparison of our results with other methods, we will also begin a second data collection to obtain more variables to use in our analysis. Additionally, we have begun experimentation with a Python-based neural network library that will allow us to customize our algorithm. The insight gained from this preliminary analysis has assisted us in defining needs for the second data collection phase, as well as given us a baseline from which to experiment with the neural network design and the algorithm design.

REFERENCES
