A NEURAL NETWORK APPROACH TO TORNADO FORECASTING  
IN NORTH ALABAMA AND SOUTHERN MIDDLE TENNESSEE

by

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A THESIS

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Tornado prediction continues to be a challenging task for operational meteorologists, given uncertainty revolving around the complete understanding of tornadogenesis. Within the County Warning Area (CWA) assigned to the National Weather Service (NWS) in Huntsville, Alabama, more than 250 tornadoes were reported between 1979 and 2010. For this study, four severe weather parameters that are frequently recognized by forecasters during tornado prediction are analyzed. These parameters, Convective Available Potential Energy (CAPE), Convective Inhibition (CIN), 0-3km Storm Relative Helicity (SRH$_{0-3km}$), and Lifted Index (LI), are extracted from the North American Regional Reanalysis (NARR) dataset for the time period 1979 through early 2010. Parameter values obtained from the NARR dataset are then ingested into an algorithm known as a neural network (NN), which excels in pattern recognition similar to the learning process of the brain. To examine the parameters and their tornadogenesis influence, three variable categories were created to incorporate different parameter combinations for NN training purposes. From performance error analysis, the NN was unable to distinguish recognizable patterns within the larger dataset of all tornadoes. However, results from F3 and greater trainings revealed that the NN found patterns allowing the discrimination between tornadic and non-tornadic storms, given a training performance error of 0.001%. Yet, due to the small dataset available for F3 and
greater tornado training, it was determined these training sets do not provide a sufficiently reliable NN for operational use. In parameter analysis, results found that though CAPE is necessary for deep convection it is not a distinguishing factor in identifying storm type, whereas SRH$_{0-3km}$ discriminated well between F3 and greater tornado events and non-tornado events. Even though this study did not create a functional tornado prediction algorithm, findings provide a promising outlook to the application of a NN in tornado prediction.

Abstract Approval: Committee Chair  ________________________________
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Graduate Dean  ________________________________
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CHAPTER ONE

INTRODUCTION

Through the dissemination of severe weather warnings, National Weather Service (NWS) operational meteorologists serve to protect lives, property and raise weather awareness within the community. This is often a challenging task due to the atmospheric complexity, especially tornado events. To what degree thermodynamic and kinematic processes within the troposphere, such as instability and wind shear, influence severe weather has been the focus of meteorological research for years. Numerous studies and field experiments, technological advancements of weather observation tools such as weather radars, and computer models collectively continue to improve severe weather research. However, after analysis of storms through these methods, all necessary elements for tornadogenesis continue to be partially understood.

Tornadoes are extremely dangerous weather phenomenon capable of destructive devastation to life and property. An extensive research study by Ashley (2007) found that nearly 1400 tornadoes affect human lives every year within the United States (US). All 50 US states during this 126-year time frame reported at least one tornado touch down within their borders, with only Alaska, California, Hawaiʻi, Nevada, Rhode Island, and Vermont not recording a tornado-related casualty. Even though they occur across the
country, research tends to focus on localized regions where the occurrence of tornadoes is mostly likely. Tornado alley, an area of the US highly conducive to tornado development, serves as a prime location for tornado-related studies (e.g. Bluestein and Parker 1993; Wakimoto and Atkins 1996; Burgess et al. 2002; Brooks and Doswell 2002). With over 1,000 miles from one end to the other, tornado alley traditionally covers an area extending from Texas northward through South Dakota.

Aside from the highly active region of Tornado Alley, more studies are directing their attention towards the southeast US for tornado research due to its secondary maxima in tornado occurrence. Nicknamed “Dixie Alley”, Stakely (1957) as well as others (Gerard et al. 2005; Jackson and Brown 2009; Dixon et al. 2010), investigated the region from east of the Mississippi river, including the Mississippi and lower Tennessee Valleys. The origin of Dixie Alley remains unknown (Gerard et al. 2005). Different from the primarily flat terrain located across Tornado Alley, additional factors contribute to the challenge of forecasting tornadoes in Dixie Alley including topography and increased forestry, as well as the greater incidence of nocturnal tornado events.

Meteorologists have utilized various methods to better predict tornado activity. From decision tree methods (Colquhoun 1987) to a currently used Tornado Vortex Signature (TVS) algorithm (Wieler 1986), meteorologists continue to create and utilize forecasting tools, in addition to other resources, to improve the difficult forecasting task as their understanding of severe weather improves. For example, meteorologists are unable to detect that a tornado is on the ground from radar, but by identifying a TVS signature, which identifies areas of rotation within a convective storm, meteorologists are aware of the potential for tornado development for a specific storm (Wieler 1986). This
study strives to enhance the predictability of tornadoes within the NWS Huntsville County Warning Area (CWA) of Dixie Alley by creating and providing an additional weather prediction tool.

Neural networks (NN) are algorithms capable of recognizing patterns from data sets and solving intricate problems stemmed from the data provided. Pattern recognition is essential to weather predicting, though atmospheric patterns recognized by operational meteorologists can vary due to their past weather experience, creating pattern bias. To overcome this bias, a NN would be able to incorporate several atmospheric data sets for almost 32 years, and attempt to discover correlations between parameters not recognized by meteorologists. If correlations are found, then atmospheric conditions favorable for tornadogenesis could be applied into a forecasting tool to enhance forecasting performance and awareness for operational meteorologists at NWS Huntsville. As a result, this additional information would allow for improvement upon staffing preparation, weather awareness within the community, and forecasting decisions.

For this study, data ingested into the neural network will consist of sounding-derived parameters commonly recognized conducive to tornadogenesis by forecasters. Calculated parameters from upper-air sounding data, such as Convective Available Potential Energy (CAPE) and Lifted Index (LI), in addition to others, allow meteorologists to indicate the stability of the atmosphere from meteorological sites worldwide (Moncrieff and Miller 1976; Galway 1956; Peppler 1988). This data provides beneficial information to forecasters regarding thermodynamic and dynamic interactions between air parcels and their surrounding environment, extremely important for identifying areas of convection (Wallace and Hobbs 2006; Petty 2008). By incorporating
four parameters correlated to past tornado events originating in the NWS Huntsville CWA, researchers in this study remain optimistic. If the NN shows ability to find and recognize atmospheric patterns favorable for tornadogenesis, this application would enhance forecasting performance. It is hypothesized that given these variables, the NN will be able to find a pattern within the data and the corresponding storm event.

The following chapters will present essential information regarding tornadogenesis and neural networks significant to this research. Following, data and methods implemented in this study are examined, closing with results, conclusions and anticipated future work.
CHAPTER TWO

THUNDERSTORMS, TORNADOGENESIS, AND
CONVECTIVE PARAMETERS

Though tornadogenesis is not completely understood, meteorologists recognize the general atmospheric conditions favorable for tornado development. In this chapter, an overview of thunderstorms and tornadogenesis will be reviewed. In addition, sounding-derived indices commonly identified in the tornado prediction process, specifically those examined in this study, are analyzed.

2.1 Convective storms

2.1.1 Thunderstorms

A cumulonimbus cloud that produces thunder and lightning is recognized as a thunderstorm. Thunderstorms are generally benign, but can produce damaging winds, hail, flooding, and isolated tornadoes. On occasion, thunderstorms can become severe. As an agency under the National Oceanic and Atmospheric Administration (NOAA), the primary mission of the National Weather Service (NWS) is to protect life and property. The NWS defines a severe thunderstorm as possessing at least one of the three conditions: 1) wind speeds equal to or in excess of 50 knots, 2) measured hail of 1 inch, 3) tornado. For an ordinary thunderstorm to transition into a severe thunderstorm, certain atmospheric conditions are imperative, and will be discussed later in this chapter.
Through aircraft and balloon measurements, the first attempt to better understand thunderstorms and their structure was conducted in the late 1940s. Known as the Thunderstorm Project, this two-year study (1946-1947), collected atmospheric data from thunderstorms in Florida and Ohio (Byers and Braham, Jr., 1948). Analyzing data solely from Florida convection, this study was able to identify the life cycle and atmospheric circulations of thunderstorms. It was found that thunderstorms encounter three development stages throughout their life cycle (Figure 2.1). These stages (cumulus stage, mature stage and dissipating or anvil stage) help identify the cycle of the updraft and downdraft, and their direct involvement with thermodynamics conducive to thunderstorm development. The entire life cycle of a typical thunderstorm is short-lived, with approximately 15 to 30 minutes during the cumulus stage, 15 to 30 minutes for the mature stage, and roughly 30 minutes to complete the dissipating stage (Byers and Braham 1949).

![Figure 2.1: Three stages of thunderstorm life cycle: (a) the cumulus stage, (b) the mature stage, (c) the dissipating stage. Taken from Byers and Braham (1948).]
Prior to the development of the cumulus stage, a combination of ample low-level moisture, a lifting mechanism, and an unstable air mass is critical to create a favorable environment necessary for convective development (Byers and Braham 1948). In addition to these, once the thunderstorm has developed, the amount of available wind shear and vorticity (horizontal and vertical) will determine the type, strength and severity of a storm. When a moist, warm air mass at the surface underlies a cold, dry layer aloft, the environment is considered conditionally unstable. Through the process of condensation, cloud formation can occur given water vapor present in the atmosphere. In order for this process to exist, the column of air must be saturated throughout the boundary layer up through the lifting condensation level (LCL). The LCL is defined as the level at which a parcel of air is lifted dry adiabatically until saturated (Glickman 2000; hereafter AMS Glossary). Without a fully saturated column of air, water vapor available to the air parcels will evaporate if not vertically lifted quickly. In many instances, air parcels need an added lifted mechanism. In association with the warm (less) dense air at the surface, lifting sources can be from that of a frontal boundary, orographic lifting, differential heating or low level convergence.

Warm air is less dense and more buoyant than cold air, allowing the warm air rise and air parcels to accelerate upward. This upward acceleration combined with low-level convergence will create the updraft, considered the most important feature in this stage (Lemon and Doswell 1979). Thunderstorms typically consist of one updraft and respectively, one downdraft. As an air parcel transitions from a warm environment into a colder environment, pressure will decrease causing the air parcel to expand and cool. As
a result, water vapor will condense into water droplets. From condensation, latent heat is released, which allows for the air parcels to continue rising.

The level of free convection (LFC) is defined as at which point the air parcel would become warmer than its surrounding environment, signifying the level of positive buoyancy (AMS Glossary). Once the air parcels have lifted to their LFC, the amount of available potential energy in the atmosphere will determine whether they will continue to rise, and create convection, according to the parcel theory (AMS Glossary). The parcel theory assumes that above the LFC, air parcels will rise adiabatically (no heat is added or removed). This positive buoyancy within the atmosphere is defined as Convective Available Potential Energy (CAPE; Moncrief and Miller 1976). Measured in Joules per kilogram (J/kg), CAPE is calculated by measuring the kinetic energy available in the air at the LFC and integrating up to the measured buoyancy of the equilibrium level (EL). As defined in Houze (1993), the mathematical expression for CAPE is:

\[
CAPE = g \int_{LFC}^{z_T} \frac{\theta(z) - \bar{\theta}(z)}{\bar{\theta}(z)} \, dz,
\]

where \( g \) is the gravitational constant, \( LFC \) is the level of free convection, \( \theta \) is potential temperature for an air parcel that is lifted from \( z = 0 \) to \( z = z_T \), \( z_T \) is equilibrium level (EL), and \( \bar{\theta} \) is the environmental potential temperature.

Known as Convective Inhibition (CIN; Colby 1984), the amount of this inhibiting energy allows CAPE to build strong enough to support deep convection. The amount of CIN correlates to the amount of force needed by a lifting mechanism to allow the parcel to be lifted to the LFC (AMS Glossary). By this restraint, a stable layer
(inversion) is formed within the boundary layer known as a capping inversion. If an air parcel is unable to break free of this area of negative buoyancy then convection will be hindered, no matter if other conditions are favorable for development. This inversion allows for the amount of CAPE to increase. It is important for lifted air parcels to penetrate through this inversion so they can continue to ascend for convection to develop (Wallace and Hobbs 2006). For visual reference, Figure 2 illustrates marked areas of CAPE, CIN, LFC and EL. Once the atmosphere has undergone these processes, water droplets, or ice crystals (lifted above the freezing level) form, fair-weather cumulus clouds begin to appear. In addition, given the amount of CAPE, these cumulus clouds will vertically grow into cumulonimbus clouds indicating the first stage of the thunderstorm life cycle.

In the mature thunderstorm development stage, through collision and coalescence, water droplets and/or ice crystals will grow and become dense as the updraft persists to vertically circulate through the atmosphere. Hydrometeors that can no longer be supported by the updraft will fall to the ground coinciding with a rush of outwardly exerted cold air, indicating that a downdraft has formed (Byers and Braham 1948). An important factor to downdraft development is the thermodynamic process of entrainment, in which air from the surrounding environment mixes with the air column of the updraft (Byers and Braham 1948, Lemon and Doswell 1979). Given the characteristically low wind shear values with ordinary thunderstorms, as the precipitating downdraft overlaps the dry updraft, the updraft will inherently disperse. As a result, the entire storm will enter into its last life cycle and dissipate (Lemon and Doswell 1979, Wallace and Hobbs 2006).
2.1.2 Multi-cell thunderstorms

In some instances multi-cell (non-supercell) storms can produce tornadoes, but convective storms most favorable for producing tornadoes are most often supercell storms. Through investigating tornadic events in northern Alabama, it has been found that a majority of tornadoes that develop in this area are associated with mesoscale convective systems and convective lines (Knupp et al. 1996, Trapp 2005). At different stages in their life cycle, multiple convective cells can cluster together creating multi-cell thunderstorms. These storms can form in association with squall lines, mesoscale convective systems (MCS), or from splitting of supercell thunderstorms (Djurić 1994). For squall lines or a MCS, numerous cells develop and in many cases, redevelop, due to a storms’ gust front, or along the leading edge of a boundary. A gust front is comprised of cold air from the downdraft as it extends outward of the parent storm, producing an enhanced lifting mechanism for development downstream of the current storm.

2.1.3 Supercells

Supercell thunderstorms consist of a violently rotating updraft (coinciding with a present downdraft) developing in an area with strong vertical shear larger than 20 ms\(^{-1}\) (Holton 2004). With a longer duration than ordinary thunderstorms, the life cycle of a supercell can last hours (Lemon and Doswell 1979), and are most associated with large hail, damaging winds and isolated tornadoes. In order for a rotating updraft (mesocyclone) to develop, horizontal vorticity at the surface must be lifted by the storms apparent updraft and tilted. Horizontal vorticity is generated by strong vertical wind shear, which is the change in wind speed and/or direction with height (AMS Glossary). The amount of this horizontal vorticity that is parallel to a storms inflow region is defined
as streamwise vorticity. This vorticity measures storm-relative winds within the storm and the rate of change at which as height increases, winds veer (Davies-Jones 1984). Streamwise vorticity is important when calculating the helicity of a storm in determining its potential to produce a rotating updraft. One lifted vertically by the updraft, the horizontal vorticity will transition into vertical vorticity, but only in the mid-level section of the storm and not at the surface (Markowski and Richardson 2008). This vertical vorticity will result in a rotating updraft.

Given this dynamical change in the storm structure, a second downdraft develops in addition to the updraft and coinciding downdraft. These two downdrafts are defined as the forward-flank downdraft (FFD) and the rear-flank downdraft (RFD). A typical supercell structure, the FFD is located in the region of falling precipitation downstream of the updraft, whereas the RFD is upstream of the updraft, as illustrated in Figure 2.2 (Lemon and Doswell 1979).
2.1.3 Tornadogenesis

A tornado is a violently rotating column of air that extends from a convective storm to the surface (AMS Glossary). The vortex created as a result of tornadogenesis is noted to be one of the most forceful localized areas of vorticity found within the atmosphere (Lemon and Doswell 1979), often creating damage. In post event surveys, meteorologists use the enhanced Fujita scale (EF scale) to rate the tornado’s strength based on the observed damage. On a scale of 0-5, this rating scale allows meteorologists to estimate the wind speeds and strength of the tornado based on the damage path left behind. Theodore Fujita created the original Fujita scale rating system in the early 1970s, and in 2007, the revised version of this scale (EF) was implemented into NWS offices in
early 2007 (Doswell et al. 2009). For simplicity of this study and the time frame examined, all tornadoes referenced will be according to their F-scale value.

In order for a tornado to develop from a supercell, a column of vertical velocity must extend from the storm down to the surface (Markowski and Richardson 2008). Once a supercell has a rotating updraft, it is necessary for the above ground level (AGL) rotation to reach the surface. Often influenced by tilting of vertical velocity and the developed FFD and RFD, supercells will split in two, creating a left-moving and a right-moving storm. In the right-moving storm, typically the tornado-producing storm, it is essential to know if it will rotate cyclonically and essentially produce a tornado. To measure this likelihood, the storm-relative helicity (SRH; Davies-Jones et al. 1990), or storm-relative environmental helicity is a mean of measure often used by forecasters. SRH measures the amount of streamwise vorticity, a vector component of vertical velocity, within the inflow region of the storm (AMS Glossary).

SRH is a commonly used factor in predicting tornadogenesis used to indicate the probability that a supercell updraft will rotate cyclonically, and often examines the 0-3 km AGL. With cyclonic rotation, this will allow for vertical vorticity to reach the ground through advection by the downdraft. Through this, the vorticity will be stretched to the surface and increase in rotation, resulting in the formation of a tornado. The initiating factor for low-level rotation has been of much speculation from various studies. While some studies suggest that a change in baroclinicity at low-levels initiates low-level rotation (Rotunno and Klemp 1985), others suggest that this surface baroclinicity is not necessary for tornadogenesis (Markowski et al. 2002). As found in Markowski et al. (2002), different characteristics account for the development of nontornadic supercells.
and tornadic supercell storms. In situations where the mesocyclone incorporates air parcels from within the RFD, if the air temperature of the RFD is much colder than the surrounding environment, then the surface environment could become too stable. If this occurs, then vorticity available at the surface would be insufficient. Other situations noted increased values of CIN, even though high CAPE values were present (Markowski et al. 2002).

When presented with a favorable environment, predicting whether or not a convective storm will produce a tornado remains one of the most difficult tasks for operational meteorologists. While often associated with supercells, tornadoes can also spawn from nonsupercell storms (Wakimoto and Wilson 1989). A nonsupercell tornado occurs when low-level available vorticity allows for a tornado to form in a case where a midlevel mesocyclone is nonexistent (Davies-Jones et al. 2001; Wakimoto and Wilson 1989). Tornado development across the NWS Huntsville CWA is most often attributed to nonsupercell storms. However, on occasion supercell storms will develop and produce tornadoes in this area as well, therefore both storm types will be discussed. Pattern recognition, parameter examination and tornado climatology are three useful forecasting methods for operational meteorologists when predicting tornadoes regardless of storm type (Johns and Doswell 1992). The structure constructed in this study represents these three methods.

Tornado prediction for nonsupercell storms can be much more difficult than when considering a supercell storm. Favorable environment conditions recognized in either situation by meteorologists are applied to future event forecasting processes. These continuous patterns of similar environmental characteristics allow meteorologists to use
pattern recognition when forecasting similar situations (Johns and Doswell 1992). Given the location of the NWS Huntsville CWA, it is theorized that a combination of the topographic features across the domain (Appalachian Mountains and Cumberland Plateau), which can cause shear variations (Gaffin and Parker 2006) and the interaction of mesoscale boundaries play a role in the development of tornadoes.

2.2 Atmospheric parameters

Common thermodynamic and kinematic parameters frequently correlated to tornadogenesis are examined in this study. These indices have been found useful in the tornado forecasting process, in association with other synoptic and mesoscale features. In past studies, Rasmussen and Blanchard (1998) (hereafter RAB 1998), Rasmussen (2003), Thompson et al. (2003), and Jackson and Brown (2009) all utilized proximity soundings as a data source for severe thunderstorm and potential tornadic storms. These studies mainly focused on the region earlier noted as Tornado Alley, with the exception of Jackson and Brown (2009), which directed their research to the southeastern portion of the US. These proximity-sounding studies investigate the instability parameters, as well as thermodynamic features that are likely for tornado development. As an alternative to using a proximity sounding data source, this study will utilize an upgraded reanalysis data set that incorporates upper air soundings, surface observations, and other various attributes to be discussed in Chapter 4 (Mesinger et al. 2006). This study will look at four universally known and commonly assessed parameters; CAPE, CIN and SRH (previously defined), in addition to Lifted Index (LI; Galway 1956). Data extracted from this data source, will coincide with tornado events and then be ingested into a NN.
2.2.1 CAPE

Even though CAPE cannot be single-handedly used as an indicator of atmospheric vertical motion (Doswell and Rasmussen 1994), CAPE give forecasters an idea of the state of instability in a near-storm environment. As recognized by Blanchard (1998), it should be understood that CAPE is not representative of a simple measurement of atmospheric instability. Instead, it is the measure of a parcel’s buoyant energy integrated vertically, and will vary dependent of the atmospheric depth calculated.

With a data set of over 6000 proximity soundings from 0000 UTC, RAB (1998) created a baseline climatology of tornadoes by investigating commonly used tornado forecasting parameters, such as CAPE and SRH. Considering three different storm types (nonsupercell thunderstorms, supercells without significant tornadoes, and supercells with significant tornadoes), they were able to analyze the predictability of each of the examined parameters and their correspondence to a storm type. Overall CAPE was found to be distinguishable between all three different storm types. $\text{CAPE}_{0-3\text{km}}$, however, did not show the same significance, especially between supercells and supercells with significant tornadoes (RAB 1998). In a similar study, Jackson and Brown (2009) utilized proximity soundings to identify near-storm environments favorable for tornadogenesis in the Southeast region of the United States. Similar to RAB (1998), they found that CAPE values for tornadic storms were significantly higher than those of non-tornadic thunderstorms. Additionally, $\text{CAPE}_{0-3\text{km}}$ values for non-tornadic supercells were much higher than those found within non-significant tornadoes (F0-F1 tornadoes). In both studies, it was found that in most cases of CAPE, values of non-tornadic storms greatly overlap in value from tornado producing storms. The non-tornadic cases in these studies
accounted for thunderstorms that either produced damaging winds, hail, or lightning (RAB 1998, Jackson and Brown 2009). Pertaining to this study as will be discussed in Chapter IV, non-tornadic storms are classified as either having storm reports of damaging wind, hail, or non-severe thunderstorm cases (either ordinary thunderstorms or non-convective days).

In a two-year warm season study investigating severe convective storms in Europe, CAPE, \( \text{SRH}_{0-3\text{km}} \), along with other sounding parameters were obtained from the T799 European Centre for Medium-range Weather Forecasts (ECMWF) analyses (Kaltenböck et al 2009). For comparison, storm environments in Europe greatly compare to those found in the Southeast US during their defined cool season (Brooks 2007). From their study, Kaltenböck et al (2009) CAPE served as a good indicator in distinguishing between thunderstorms and severe thunderstorms. CAPE values within the study indicative of tornado development were defined as having moderate values, where larger amounts of CAPE were strongly correlated with hail events. This suggests that vast amounts of CAPE are not needed for tornadogenesis process but is still necessary for updrafts and convection (Kaltenböck et al 2009).

2.2.2 CIN

Too much CIN is can inhibit convection without a significant lifting force exerted on the air parcels. The same result can occur if too little CIN exists (as described in section 2.1). Compared to the previously discussed results of CAPE from RAB (1998), results presented CIN values suggesting distinguishing thresholds between tornadic and
non-tornadic storms. They found that approximately three-fourths of the sounding data associated with supercells which produced tornadoes exhibited less CIN (less than 21 J kg\(^{-1}\)) than values associated with non-tornado producing supercells, which illustrated a range of values with a median of 35 J kg\(^{-1}\) up through over 100 J kg\(^{-1}\) (RAB 1998). However, it should be acknowledged that with these results, values observed in RAB (1998) did not consider surface-based parameters (Davies 2004).

In Markowski et al. (2002), it was suggested that the potential for tornado development is greatly correlated to thermodynamic parameters derived from surface-based parcels. Davies (2004) examined sounding analyses derived from the rapid update cycle (RUC). Storm events selected included storms in which local NWS office had issued tornado warnings, but in many cases did not develop a tornado (Davies 2004). Events with sufficient CAPE values were clearly identified and were compared with CIN (surface-based and mid-level) values for tornadic and non-tornadic storms to identify their influence in tornadogenesis (Davies 2004). Results showed that low values of mid-level (ML) CIN were associated with the tornadic events, most distinguishable between non-tornadic events and significant tornado events (defined as F2-F4). It was also found that CIN values between 50 and 100 J kg\(^{-1}\) could potentially determine the likelihood of tornado development and serves as a general threshold (Davies 2004). In addition to MLCIN, surface-based (SB) CIN was also tested, and showed almost identical results to those of the MLCIN, especially with the inclusion of F1 tornadoes (Davies 2004). These results are similar to those found in RAB (1998) suggesting that forecasters should be aware of the environment and associated CIN values in place during a severe weather
event. This prior knowledge could affect the warning decision process in a case of issuing tornado warnings for localized convection (Davies 2004).

2.2.3 SRH

Several studies have investigated the critical role that SRH plays in the development of tornadoes (Kerr and Darkow 1996, Thompson et al. 2006, Markowski et al. 1998, RAB 1998, Jackson and Brown 2009). As noted earlier, the development of a tornado in a supercell can be highly conducive if large values of SRH are present. Markowski et al. (1998) and others have found an issue regarding SRH when it comes to discriminating between a tornadic and non-tornadic storm. SRH can be extremely variable within the environment in short time frames. When considering SRH$_{0-3km}$, due to its temporal and spatial modifications, this variability will not be accounted for when using sounding-derived data sources in predicting tornadoes a few hours in advance.

Common values of SRH can vary depending on the significance of the tornado. More significant and violent tornadoes (F2-F5) tend to have higher SRH values than those for weaker tornadoes (Jackson and Brown 2009). In comparing SRH$_{0-3km}$ to SRH$_{0-1km}$, Rasmussen (2003) and Jackson and Brown (2009) both found that events of SRH$_{0-1km}$ showed higher indication of a correlation between SRH$_{0-1km}$ and tornadoes. However, SRH$_{0-3km}$ still indicates significance in its ability to discriminate between significant tornado events and non tornado events (Kerr and Darkow 1996, Kaltenböck et al. 2009, Jackson and Brown 2009). Kaltenböck et al. (2009) found that large values of SRH$_{0-3km}$ were correlated to significant tornadoes (F2/F3) and damaging wind events. Of the two storm event types, the larger SRH$_{0-3km}$ values were found for damaging wind
events rather than tornadic events. These findings suggest that a possible relationship between significant tornadoes and damaging wind events exists. This relationship is hypothesized to originate from either a common process necessary for thunderstorm downdrafts and tornado development or the possibility that erroneous storm reports of tornado events were incorrectly identified as damaging wind events, and vice versa. Overall, findings suggest that SRH$_{0\text{-}3\text{km}}$ values are more beneficial in discriminating between non-significant (F0/F1) and significant (F2/F3) tornadoes. It should be noted that in all cases examined in the study (e.g., weak tornadoes, strong tornadoes, hail events, wind events, etc), SRH$_{0\text{-}3\text{km}}$ values overlapped within the middle 50% (Kaltenböck et al. 2009).

2.2.4 LI

The three previous parameters, CAPE, CIN and SRH, are frequently used in determining the likelihood of tornadogenesis development. However, as our fourth parameter examined in this study, LI is primarily used as an indicator for thunderstorm development (Galway 1956). LI is an instability parameter used to determine the convective state of the atmosphere. Though this may sound similar to the measurement of CAPE, the two parameters differ (Galway 1956; Moncrief and Miller 1976; Blanchard 1998). The output values generally have no distinction between tornado and non-tornado events; however, it has been found in past studies to look at tornado events in a synoptic setting (Ferguson et al. 1985). LI is determined by calculating the sum difference between the temperature of an air parcel at 500 millibars (mb) (T$_{p, 500}$) from the temperature of the environment at 500 mb (T$_{500}$) (Peppler 1988). For T$_{p, 500}$, by taking the temperature from the parcel, which is lifted adiabatically from the surface layer up to
500 mb, it is suggested to represent the temperature within an updraft (Peppler 1988). This is a general calculation for LI, where past studies have used different pressure levels in their calculation. Although there is no specific threshold for LI values, Miller (1967) used -2 as an indicator of severe weather development. If temperature of the parcel is warmer than its surrounding environment, the LI value will be negative, signifying that the atmosphere is unstable (DeRubertis 2006). From his study, DeRubertis (2006) created a threshold of LI values through analyzing various parameters throughout the specified time frame utilizing radiosonde data collected from sites across the entire US. LI values equal to or greater than 0 signified a stable atmosphere, where values of 0 to -3 indicated a “marginally unstable” atmosphere, values -3 to -6 were “moderately unstable”, and so forth (DeRubertis 2006).
CHAPTER THREE

NEURAL NETWORKS

In addition to a general background of tornadogenesis, it is imperative that a broad knowledge of neural networks (NN) is understood. The origin of neural networks is briefly reviewed, followed by the basic logistics of NN of those implemented in this study. Concluding is a literature review of neural network applications in meteorology.

3.1 Neural systems and neural networks

In 1943, as an attempt to solve complex problems using an information processing system, McCulloch and Pitts (1943) created the perceptron. This was the first artificial neuron structure, or “network”, imitating a simple neuron from the human brain (McCulloch and Pitts 1943, Caudill 1990, Heaton 2010). A neural network (NN), also known as artificial neural network, is an interconnected structure that essentially mimics the neural system in that it can be trained to recognize patterns. Essentially, NNs are used to recognize patterns that may include extreme subtleties not easily recognized by the human brain. The structure of a NN is one that is similar to the structure found within a human brain nerve cell (or neuron), including axon, dendrite and synapse type structures (Caudill 1990).
It is estimated that over 100 billion nerve cells (neurons) exist in the human brain (Caudill 1990; McCann 1992; Gurney 1997). When a stimulant of any sort occurs, a process begins to “excite” neurons, creating a chain reaction. McCann (1992) uses the example of listening to a piano. As explained in Audesirk (1996), when a stimulus is created from another neuron or an outside environment source it sends out a signal. In the brain, this signal is a chemical neurotransmitter that has been passed on from another neuron. This signal is received by a dendrite, which is an outwardly extending tendril and is attached to the cell body of a neuron. If this signal exceeds what is defined as the potential (negative or positive), it will create an output signal for the neuron. If the designated threshold of potential is met, this potential will “fire” on through the axons and be transmitted to the next neuron. A collection of axons (nerves) are made up of long, thin fibers, which can reach a length of one meter in the human body. At the point where the axon and the dendrite of the downstream cell body meet is known as the synapse, or synaptic terminal (Audesirk 1996). The “weight” of a synapse is variable dependent on their obtained strength transmitted through the axon. This strength will determine if they do or do not release a neurotransmitter, completing a full cycle of the nerve cell (Caudill 1990). Figure 3.1 illustrates a visual reference for overlaying the schematic of a brain nerve cell to an artificial neural network structure.
Figure 3.1: Schematic illustrating node structures found in NN and their correlation to an actual brain nerve cell. The input data layers acts as the dendrites in a brain neuron where data is fed into the neuron. The data is processed through the node and if activated will transmit data through an interconnect. The interconnection between the two nodes represents the axons between nerve cells. The junction of where the interconnect and the node meet is the synapse, identical to that of a synapse in a nerve cell.

Similar to that of a brain neuron, the NN structure consists of a net of “nodes” (neurons) which are interconnected by different layers, where the amount of layers depends on the NN type. When input data is ingested into a neural network, it acts as a stimulant. Random weights are assigned to the data. The weight is multiplied by the input value and if the sum exceeds the threshold amount, then the node will “fire” (Heaton 2010), sending the information through the interconnect to another node. It should be noted that the value of the weights will vary throughout the learning process. Where the interconnect and the new node meet is the synapse which consists of varying weights, which allow for the NN to recognize patterns within the data (Heaton 2010).
3.2 Neural network logistics

A formal definition of a NN from Gurney (1997):

A neural network is an interconnected assembly of simple processing elements, 
*units* or *nodes*, whose functionality is loosely based on the animal neuron. The 
processing ability of the network is stored in the interunit connection strengths, or 
*weights*, obtained by a process of adaptation to, or *learning* from, a set of training 
patterns.

Essentially, as input data is passed through the structure, the NN attempts to 
“learn” the pattern between the data input and the data output, and mimic the behavior in 
future applications. Two learning techniques are available to a NN; 1) supervised 
learning, and 2) unsupervised learning. In supervised learning, the known ideal output to 
the corresponding input data is supplied to the NN. In doing this, the NN trains itself to 
solve the problem of the pattern between the input and ideal output (Heaton 2010). 
Specifically, when given an input, the threshold to reach the known outcome is guided, 
and when done repeatedly, it is forced to learn the correct pattern, without being 
influenced by possible outlying information (Samarasinghe 2007). Unsupervised 
learning is a process in which an ideal output is not supplied. As a result, the NN will 
take the input data and, after undergoing a series of training runs, will create an ideal 
output that it finds suitable for the given problem (Caudill 1990; Heaton 2010). By 
providing the input variables with an ideal output (tornado or non-tornado), it is decided 
that supervised learning is best suited for this study.
In addition to a type of learning process, several other factors are necessary to complete the NN structure. This includes architectures, training techniques, and activation functions. To accommodate a wide variety of problem solving needs, numerous types of components have been created. Linear, non-linear and complex data are all suitable for NN use (Samarasinghe 2007). Given the capability of each individual component, it is important to create a sturdy platform by selecting those elements which best suit the problem at hand (Caudill 1990; Gurney 1997). In some situations the outcome of a problem can only be solved through one technique, where with more complex problems, the solution can achieved more than one way. NN are suited for problems that can be solved by pattern recognition, classification, or prediction; not problems easily solved using computer programming (Heaton 2010).

Several architectures are available for NN purposes, such as a Hopfield NN (crossbar networks unique to associative memory) and Self Organizing Map (SOM; used to create data classified groups) (Caudill 1990; Heaton 2010). Best suited for this study is a feed-forward (perceptron) NN, and is one of the most commonly used structures. Given the data used in this study, a multi-layer perceptron (well-suited for a nonlinear problem) will be used. Ideal for pattern recognition, this structure incorporates a layer (or two) hidden between the input layer and the output layer (Figure 3.2). This hidden layer is connected to both the input and output layer by two sets of weighted links; input to hidden layer weighted link(s) and the hidden to output layer weighted link(s). Given a nonlinear complex problem, the neuron processing relies on the hidden layer to find links from the input layer to the output layer (Sarmarasinghe 2007). There is not a set number of hidden neurodes that should be used in any given situation, and there can be instances
of having too large of a hidden layer (Heaton 2010). In order for the NN to learn, the connected weights are continuously changed until the strength of the weight produces the ideal output, undergoing a series of “trial-and-error” attempts. This process is defined as training the network (Caudill 1990; Heaton 2010; Sarmarasinghe 2007).

![Diagram of a simple feed-forward network](image)

Figure 3.2: A simple feed-forward network illustrating the (a) input layer, (b) hidden layer, and (c) output layer.
A training technique sufficient for supervised learning is propagation, commonly associated with feed-forward NNs (Caudill 1990; Gurney 1997; Heaton 2010; Sarmarasinghe 2007). To teach a NN, propagation training will undergo a series of iterations. Through a series of iterations with the data, weighted connections are adjusted at the end of its loop through the data until they “connect” the input to the ideal output, improving the error rate. The percent difference found between the ideal output and the actual output created by the weighted connections is defined as the error rate. This calculation is done using the Root Mean Square (RMS) error (Heaton 2010). Heaton (2010) defines RMS mathematically as:

$$x_{rms} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (actual_i - ideal_i)}$$

where $actual_i$ is the actual output found by the NN, $ideal_i$ is the ideal output provided by the supervised learning, and $n$ is the number of values (Heaton 2008). Adjustments to the weights are applied in a group at the conclusion of multiple iterations, referred to as batch training (applied in the software used in this study). It is important to train a NN, so that when it is presented with values not given in the training set, it is able to handle the problem given (Heaton 2010). By using batch training, or learning, it helps reduce the error found during the training process because it applies weight adjustments at the end of a group of iterations, rather than at the end of a single iteration (Samarasinghe 2007).

In the process of training a feed-forward NN, the data undergoes a series of forward passes and backward passes. Starting at the input layer, a forward pass
introduces the NN to the data provided, continuing forward through the output layer. In doing so, the NN is exposed to the ideal output and correlates it to the given input, creating an output (Heaton 2010). With a backward pass, the NN will begin at the output layer and progress backward through to the input layer, again calculated the error between the ideal output and actual output of each neuron. A gradient of the error will be calculated, and will be determined by the training technique used and its corresponding activation function chosen for the NN structure (Heaton 2010).

The backpropagation is a technique highly used with feed-forward networks, but in the early 1990s, an upgraded, more efficient version of this technique was created. Resilient propagation (RPROP) is ideal for multi-layer feed-forward networks. In backpropagation, the network “learns” by implementing a gradient descent calculation which contains the weight values, the learning rate, and the output (Riedmiller and Braun 1993). A learning rate is a way to scale the derivative, where a certain percentage is emphasized on the weights and then applied to the gradient (Riedmiller and Braun 1993; Heaton 2010). In this method, weights and threshold values are trained as a whole. Problems surfaced from using the learning rate, skewing the error and changing the strength of the weights in an insufficient way, and when a momentum term was incorporated to account for this error, it showed no improvement (Riedmiller and Braun 1993). RPROP differs in that it uses the adaption-rule instead of the gradient descent method, and does not require a learning rate or momentum value to be assigned, as in backpropagation (Riedmiller and Braun 1993; Heaton 2010). Delta values between weights are not predetermined for through each individual iteration the weights and threshold values will be corrected accordingly given the individual delta values. This is
not done considering the partial derivative which is used in backpropagation learning (Riedmiller and Braun 1993). This allows for an individual set of weights and a threshold value to be trained, versus the entire net of weights and threshold values. A simplified version of the calculation as defined in Riedmiller and Braun (1993) is as follows:

\[
w_{ij}^{(t+1)} = w_{ij}^{(t)} + \Delta w_{ij}^{(t)},
\]

(3.2)

where \(w_{ij}\) is the weight from node \(j\) to node \(i\). Each time a NN is trained using this method various weights are applied, varying the pattern recognition each time (Heaton 2010). For more in-depth details regarding RPROP, please reference Riedmiller and Braun (1993).

The activation function (nonlinear) chosen for a NN is important for it is responsible for the task of a neuron “firing” or not given the data presented, converting the value into the output value. Ideal for a supervised, feed-forward network is the logistic sigmoid activation function (Heaton 2010; Samarasinghe 2007). The mathematical function representing this activation is:

\[
f(x) = \frac{1}{1 + e^{-x}},
\]

(3.3)

where the input value is \(x\), and the base of natural logarithm is \(e\) (Samarasinghe 2007, Heaton 2010). Mathematically, the output bounds for the sigmoid function are 0 to 1, and the input range is from -10 to 10, as illustrated in Figure 3.3. The slope of the function represents the rate at which the function is changing, and is greatest when it crosses the
y-axis (Samarasinghe 2007). Given the range of the output bounds, it is critical that the ideal output values ingested into the NN be within that range.

Figure 3.3: Illustration of the logistic sigmoid function (taken from Heaton 2010).

3.3 NN and meteorology application

For years, NNs have been used to solve intricate problems, such as financial forecasts (Kutsurelis 1998) and face recognition (Rowley et al. 1998). However, as an attempt to enhance forecasting ability of various weather phenomena, the investment of a NN into meteorological research only began to surface in the late 1990s. Due to their expertise in pattern recognition, a NN seems to be an ideal application for weather prediction. When operational meteorologists produce weather forecasts, they are ideally implementing pattern recognition stored in their brain, and translating that knowledge into a prediction. NN are not intended to replace human forecasters, but instead serve to create an enhanced data source useful to forecasters. Previous studies have used NNs for various implications such as damaging wind prediction (Marzban and Stumpf 1998), precipitation forecasting (Hall 1998; Kuligowski and Barros 1998), and tropical
cyclogenesis statistical model forecasts (Hennon et al. 2005). Others have incorporated their ability of pattern recognition into ozone modeling (Narasimhan et al. 2000; Gupta 2010), severe hail size (Marzban and Witt 2001) and dewpoint temperature prediction (Shank et al. 2008). While a majority of studies showed promising results, continued research for NNs applications in meteorology is needed.

As of 2010, three studies had already investigated the use of neural networks for thunderstorm (McCann 1992; Manzato 1995) and tornado prediction (Marzban and Stumpf 1996). McCann (1992) created two NNs intended for significant thunderstorm forecasting, utilizing surface-based LI and surface moisture convergence data. One of the NN implemented data values to forecast for areas of no significant convection, whereas the other forecast for areas of significant convection, if a significant thunderstorm advisory had been issued or not (ideal output) (McCann 1992). A dataset compiled of 750 randomly chosen points accounted for four defined regions, east of the Rocky Mountains. Of those 750 data points, less than 25% of the data points were able to display a pattern recognized by the NN, which was suggested to be a result of the limited data input. Implementing 150 random data points, the results found in this study showed adequate results promising for the future of NNs in weather prediction with an output performance score of 85%.

In a similar study, Manzato (2005) used over 50 sounding-derived indices to create two NN to forecast thunderstorms in Italy, including CAPE, CIN and relative helicity. Two additional datasets were also incorporated into the NN based on transformed data defined in Manzato (2005). One NN was created to predict the occurrence of a thunderstorm, and another to predict the intensity of a thunderstorm.
From the Udine sounding station, upper air data collected every six hours (0000, 0600, 1200, and 1800) (Manzato 2005) was used to create a database of 5775 events. Each six-hour period represented a case and had to consist of at least one cloud-to-ground lightning, which left the database with 1526 events. From the 50+ indices, the NNs were found to be successful for operational use and have been utilized since 2001.

Marzban and Stumpf (1996) created and trained a NN to identify the Mesoscale Detection Algorithm (MDA) that was constructed by the National Severe Storms Laboratory (NSSL). Each National Weather Service (NWS) office across the country is equipped with a Weather Surveillance Radar: 1988 Doppler (WSR-88D), which is the source of all radar-data used by NWS meteorologists. Within each WSR-88D, the MDA application software is installed and is utilized during severe weather events. The purpose of MDA is to observe radial velocity patterns from thunderstorm vorticies and detect rotation within supercells (which are covered in chapter two), often an indication of circulation and a possible tornado on the ground (Marzban and Stumpf 1996). Marzban and Stumpf (1996) found the neural network results to have a better positive outcome in its performance level for tornado prediction when compared to the others methods mentioned in their study.
CHAPTER FOUR

DATA AND METHODOLOGY

4.1 Domain

The focus of this study is aligned across the County Warning Area (CWA) designated to the National Weather Service (NWS) Forecast office in Huntsville, AL (hereafter NWS Huntsville). With a total of 14 counties which they are responsible for (Figure 4.1), three counties in Southern Middle Tennessee and 11 counties in Northern Alabama, this area is susceptible to severe weather, including tornadoes, year-round.

Figure 4.1: NWS Huntsville County Warning Area. The thick, solid line indicates the Alabama-Tennessee State border.

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Prior statistical data created by NWS Huntsville depicts that the primary peak season for severe weather is March, April, and May, followed by a secondary peak in November (Figure 4.2). These peak seasons are due to the location of the jet stream in relation to the CWA and its collaboration with an influx of warm gulf moisture from the Gulf of Mexico.

Figure 4.2: Statistical illustration of tornado events by month for NWS Huntsville CWA. Adapted from Weber (2006).

In the heart of the Tennessee Valley, the NWS Huntsville CWA is comprised of several topographic regions, such as the southern tip of the Appalachian Mountains in the northeastern section, as well as several plateaus and smaller mountains area wide (Figure 4.3), that affect the weather experienced throughout the region. These geographical features can allow enhancements of weather situations due to orographic lifting, as well as contribute to creating additional boundaries to convective events. Additionally, this diverse topography creates safety hazards to human lives and property in the event of a
dangerous situation. Dense areas of forests and large areas covered by terrain can endanger highly populated communities by obscuring their vision of impending severe weather, especially that of an approaching tornado.

Figure 4.3: Topography map of NWS Huntsville CWA. Lighter shades of green represent valleys, darker shades of brown represent plateaus and hills with the highest terrain in shades of gray and white. Created using ArcGIS software.

4.2 Severe Weather Parameters

As presented in chapter two, observed both in tornadic and non-tornadic events, CAPE, CIN, SRH and LI parameters are evaluated in this research. In specific, surface-based CAPE (SBCAPE), surface-based CIN (SBCIN), 0-3 km SRH (SRH\textsubscript{0-3km}), and LI are assessed. Superimposing detailed information pertaining to both tornadic and non-tornadic events, values assigned to these four parameters are extracted using a reanalysis
dataset, which will be discussed in the next section. In extracting data from the reanalysis, values obtained were from the previous model 3-hr interval in relation to the time of the event. For example, if the event occurred at 1145 UTC, then the data values extracted for the event came from the 0900 UTC run. The same is true for an event that occurs at 0030 UTC; the data collected were from 0000 UTC.

4.3 North American Regional Reanalysis Dataset (NARR)

The National Centers for Environmental Prediction (NCEP) North American Regional Reanalysis (NARR) is the primary data source of this severe weather study. The data used in this study was obtained from the National Oceanic and Atmospheric Administration - Earth System Research Laboratory (NOAA/ESRL) Physical Sciences Division, but is available from other online sources as well. With a 32-kilometer (km) resolution, it offers high temporal and spatial coverage. This dataset is an enhancement of NCEPs prior reanalysis dataset, the NCEP National Center for Atmospheric Research (NCAR) Global Reanalysis (Mesinger et al. 2006). The earlier version of NCEPs reanalysis (NCEP GR), which has a much coarser resolution of 2.5° x 2.5°, was used to gather data pertaining to severe weather research in the US, but this dataset lacks detailed information and spatial resolution best needed for mesoscale systems (Kalnay et al. 1996; Grumm et al. 2005). Another fallback to the NCEP GR is its lowest temporal resolution, available only at 6-hour (hr) intervals, where the NARR has as low as 3-hr intervals available. During a mesoscale system event, it is common for sudden atmospheric conditions to occur, allowing data to become highly temporally and spatially variable. Availability of larger datasets from these smaller temporal intervals allows for
atmospheric variations from small-scale events to be clearly observed, which would otherwise go unnoticed in model runs with larger temporal intervals.

NARR data is primarily used to study the variability in both sea and land interactions. From the previous reanalysis, more data is available in the NARR, and the NARR has the ability to collectively observe variability experienced on land and over the oceans (Mesinger et al. 2006). Another enhancement from the previous reanalysis is the calculated variable sets offered. Useful to this study and other severe weather research, certain severe weather parameters are accessible through the dataset, as well as other atmospheric and related science variables at different pressure levels, temporal intervals, and below ground such as soil moisture and temperature, accumulated total precipitation, downward shortwave radiative flux and precipitable water for the entire atmosphere (Kalnay et al. 1996; Grumm et al. 2005; Mesinger et al. 2006).

Output data from the NARR are derived from several sources such as the NCEP Eta model, rawinsondes, drop sondes, aircraft, surface and geostationary satellite data, all of which were available for the global reanalysis (Mesinger et al. 2006). With respect to the upgrade undergone to create the NARR, and enhancing the available resources, additional datasets were incorporated including precipitation, sea surface temperatures (SST), and a variety of others. A complete list of data sources used to construct the NARR is available in Mesinger et al. (2006). These added resources greatly increase the utility of the NARR, but given this additive, additional errors within the data error are likely as well.

Data commonly analyzing instability indices likely for severe weather development is often collected via upper air soundings. In previously noted studies, RAB
(1998), Rasmussen (2003), Thompson et al. (2003), Darden (2007), Jackson and Brown (2009), proximity soundings were collectively used for examining these severe weather parameters. In all these studies, their domains encompassed areas much larger than the one considered in this study. NWS Huntsville does not provide upper-air data necessary for this study for it is not equipped as an upper-air sounding site; therefore the closest sites are Nashville, TN, Birmingham, AL and Jackson, MS (Figure 4.4), with the closest site approximately 80 km away from any county within the NWS Huntsville CWA.

![Diagram](image.png)

Figure 4.4. Plotted locations of upper-air sounding sites including Jackson, MS (KJAN), Birmingham, AL (KBMX), Peachtree City, GA (KFFC) and Nashville, TN (KBNA). Huntsville International Airport (KHSV) is plotted to reference general location of NWS Huntsville CWA.
In lieu of its temporal and spatial resolution, and added data resources, it was decided that the NARR would operate as the resource for severe weather parameters critical to this study. In considering the spatial accuracy for this data, its high-resolution would account for all parameter values affected by a large-scale airmass fueling the convective storm environments. Figure 4.5 depicts the spatial data point source of the NARR data (denoted by a “+”). It is recognized, however, that this consideration may inhibit spatial accuracy of parameter values extracted due to the location of the grid point and that of the storm and its corresponding location of storm airmass and inflow location. Although upper-air soundings are available through the Redstone Arsenal Meteorological team located in Huntsville, AL, they are not responsible for collecting data on a daily basis. Therefore, this resource would be inadequate for testing purposes regarding climatological data necessary in this study. It should be noted that for real-time operations, this data is available and used by the NWS Huntsville forecasters during severe weather operations.
Figure 4.5: Illustration of available data points of the NARR across North Alabama and Southern Middle Tennessee. Points denoted with a “+” indicate data source points and red box depicts a general area that encompasses the NWS Huntsville CWA.
4.4 Tornado database

Even though tornado records for the domain date back hundreds of years, available data from the NARR includes data beginning with 1979 through the early months of 2010. The revised climatology data for the NWS Huntsville CWA will consist of all tornado events between 1979 and 2010. That data extracted for the NN will consist of events from 1979 through early 2010. For completeness and accuracy, four separate sources are used to compile the tornado database for this study.

4.4.1 Data cases

This study will analyze tornadoes whose initial touch formation locations are within the limits of the NWS Huntsville CWA. To meet these specifications, the Online SeverePlot (SVRPlot) (Hart 1993) from the Storm Prediction Center (SPC) is used, where detailed information of events, including their beginning latitude and longitude location, is stored. This database is composed of severe weather (tornado, hail and wind) reports obtained from NWS offices nationwide, and for accuracy purposes is correlated with the National Climatic Data Center (NCDC) StormData publication. As previously mentioned, NWS guidelines state that for a thunderstorm to be considered severe it must meet two of the following criteria: 1) hail greater than or equal to 1.0 inch, 2) damaging winds at or greater than 58 mph or 3) tornado. Sources of these reports are from storm surveys conducted by NWS meteorologists, certified SKYWARN storm spotters, media, and the general public. Several issues arise while using these storm reports due to their potential inaccuracy, or even those severe weather events that occur in low populated
areas and are never reported. However, for the best accuracy of storm reports, it is best to use those from SPC and NCDC.

Sequential to the creation of the tornado database, it was established that a total of 247 tornadoes initially touched down in the NWS Huntsville CWA between January 1979 and April 2010. Approximately 8% (20) of these tornadoes developed within tropical systems. For the purpose of this study, these 20 events were eliminated from the database created in this study. After this reduction, the database had a remaining total of 227 tornado cases. Overall results from these statistics will be presented in Chapter 4.

Aside from the renovated tornado database, other data was ingested prior to the retrieval of NARR data. At any point when training a NN, data that does not reach the solution of the problem at hand is necessary for the algorithm to find a pattern between the different possible outcomes. In this study, it would be necessary for the NN to find a pattern between the tornado cases, not to be confused with similar environments conducive to hail and wind cases and other non-tornadic cases. Hail and damaging wind cases, plus null cases are incorporated. Null cases are defined as days in which severe weather was not reported or documented. These cases include days of non-severe convection and non-convective days. All hail, wind, and null cases occurred throughout the year in various locations across the NWS Huntsville CWA. Using extreme caution for accuracy measures, hail and wind cases are obtained from SPCs SVRPlot, making certain that none of these cases occurred on the same day as a tornado. To obtain a smaller database of days that did not incur any severe weather reports, SPC SVRPlot was again used.
4.4.2 Quality control

To ensure quality and accuracy, documented events extracted from SPC SVRPlot (Hart 1993) are compared to a tornado database created by NWS Huntsville, which derived its information from NCDCs Storm Data and Grazulis’s Significant Tornadoes 1680-1991 and Significant Tornadoes Update 1992-1995 (Weber 2006). If minor discrepancies were found between these two databases, further research through NCDCs Storm Data publication, the NCDC Storm Event database and NEXRAD Radar data available from NCDC was conducted. Both sources, the NCDC Storm Data and NCDC Storm Event database, are assembled by storm reports received from NWS offices nation-wide.

4.5 Data extraction

Once a database of tornado, hail, wind, and null cases was composed, the corresponding data was extracted. This database includes information regarding dates of the event (month, day, and year), time of the event, beginning and ending locations (latitude and longitude), and the Federal Information Processing Standard (FIPS) county code assigned to the counties in the CWA, used to ensure accuracy of all case locations. To extract variable values used in this study, database information was overlayed with NARR data for each individual case location. With a 32-km grid spread across the CWA, if the location did not fall onto a grid point, the nearest grid point was found and data from that location was extracted.

At the completion of data extraction using the NARR, all four variables were examined for possible errors and unrealistic values. Minor differences were seen during
this process. It was concluded that these differences could be associated with potential errors caused by interpolation or grid match locations chosen by the extraction program, issues regarding the time of the event compared to the time that the data was extracted for, and/or observation data errors.

Prior to ingesting the data into the NN, it was sorted into different sets for testing purposes. This variety of group arrangements is done in order to see if the algorithm responds differently to the different combinations of variable groupings. Each test set is divided depended on its F-scale rating as well as the amount of cases tested in each study. It is important to note that all tornadoes considered in this study are recognized by their F-scale rating. This division on F-scale rating is to observe if it better recognizes patterns based on the inclusion of weaker tornadoes, significant tornadoes, or solely violent tornadoes, given the variety of F-scale rated experienced throughout the NWS Huntsville CWA. From 1979 through April 2010, preliminary results indicate that 41% of tornadoes across this area are rated F0. Prevailing as the lowest rating possible given to a tornado event, caution is required when analyzing a group consisting only of F0 tornadoes. It is estimated that a small quantity of tornadoes classified with an F-0 rating were possibly mistaken for severe wind damage, and vice versa (per personal communication with NWS Huntsville staff, Michael Coyne, Chris Darden, and Andy Kula). It is because of this that not all runs included the F-0 rated tornadoes. Other training datasets included arranged combinations of different F-scale ratings, such as F2 and greater, and instability parameters at the time of the tornado (described in next section). Aside from the aforementioned instability parameters, other variables implemented into the training datasets are season, time, and storm type (tornadic versus non-tornadic). These three
classifications are defined in Table 4.1, 4.2, and 4.3, accordingly. A complete description of the training sets will be given in the next section.

<table>
<thead>
<tr>
<th>Month</th>
<th>Mar-April-May</th>
<th>June-July-Aug</th>
<th>Sep-Oct-Nov</th>
<th>Dec-Jan-Feb</th>
</tr>
</thead>
<tbody>
<tr>
<td>Season</td>
<td>Spring</td>
<td>Summer</td>
<td>Fall</td>
<td>Winter</td>
</tr>
<tr>
<td>Assigned value</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
</tbody>
</table>

Table 4.2: Value assigned to events falling within the determined time categories.

<table>
<thead>
<tr>
<th>Time (UTC)</th>
<th>0000-0600</th>
<th>0600-1200</th>
<th>1200-1800</th>
<th>1800-0000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assigned value</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
</tbody>
</table>

Table 4.3: Storm types and assigned classifications.

<table>
<thead>
<tr>
<th>Storm Type</th>
<th>Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tornado</td>
<td>1</td>
</tr>
<tr>
<td>Hail, no tornado</td>
<td>0</td>
</tr>
<tr>
<td>Wind, no tornado</td>
<td>0</td>
</tr>
<tr>
<td>No weather</td>
<td>0</td>
</tr>
</tbody>
</table>

4.6 Data preparation for Neural Network

Due to the wide range of values being fed into the neural network for training, all values were transformed using a mapped normalization method. For normalization, all
values are transformed to range between zero and one. From Heaton (2010), the following equation was used:

\[
f(x) = \left( \frac{x - a}{b - a} \right) \cdot (y - z) + z,
\]

where \(a\) (minimum) and \(b\) (maximum) are the lowest and highest values that can be reached by the specified variable, \(x\) is the value undergoing normalization, \(y\) is the low value that the normalization will amount into (in this case 0), and \(z\) is the high value that the normalization will amount into (in this case 1). Again, when normalizing values, the range will be between zero and one, hence why \(y\) is zero (for the lowest value possible), and \(z\) is one (for the highest value possible). Once all input variable values were normalized, they were then divided into predetermined combinations for testing purposes. These specific groupings are highlighted in Table 5.
Table 4.4. Data sorted into numerous arrangements for training NN. Event total is the overall number of storms used in the training set, tornado rating depicts the F-scale rated tornadoes used in the training set, tornado total are the number of tornado cases used in event. Following are cases which included SBCAPE, SBCIN, SRH\(_{0-3km}\), and LI.

<table>
<thead>
<tr>
<th>Test Run</th>
<th>Event Total</th>
<th>Tornado Rating</th>
<th>Tornado Total</th>
<th>CAPE</th>
<th>CIN</th>
<th>SRH</th>
<th>LI</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>360</td>
<td>F0, F1, F2, F3, F4</td>
<td>180</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>A2</td>
<td>360</td>
<td>F0, F1, F2, F3, F4</td>
<td>180</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>A3</td>
<td>360</td>
<td>F0, F1, F2, F3, F4</td>
<td>180</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>B1</td>
<td>220</td>
<td>F1, F2, F3, F4</td>
<td>110</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>B2</td>
<td>220</td>
<td>F1, F2, F3, F4</td>
<td>110</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>B3</td>
<td>220</td>
<td>F1, F2, F3, F4</td>
<td>110</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>C1</td>
<td>80</td>
<td>F2, F3, F3</td>
<td>40</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>C2</td>
<td>80</td>
<td>F2, F3, F4</td>
<td>40</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>C3</td>
<td>80</td>
<td>F2, F3, F4</td>
<td>40</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>D1</td>
<td>30</td>
<td>F3, F4</td>
<td>15</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>D2</td>
<td>30</td>
<td>F3, F4</td>
<td>15</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>D3</td>
<td>30</td>
<td>F3, F4</td>
<td>15</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>

As depicted in Table 4.4, numerous runs were designed, each incorporating different variable combinations for input nodes. In addition to CAPE, CIN, SRH and LI, all training sets included Time and Season as input variables. All fixed datasets were created to allow the NN several opportunities to recognize atmospheric patterns capable of supporting tornadogenesis. Aside from the datasets presented in Table 4.4, another group of datasets is presented in Table 4.5. The original datasets each contain various totals of storm events. To warrant results that may show statistical significance and distinguish between different tornado events, test runs A, B, C, D, E, and F were created, all of which acquire identical storm event totals. Datasets used in test runs A, B and C include F1-F4 tornadoes, whereas test runs D, E, and F include only F2-F4 tornadoes, all with 40 tornado and 40 non-tornado events. It is important to add that test runs D, E, and F are duplicates of test runs 7, 8, and 9 from Table 5.
Table 4.5: Comparison of sorted datasets including all tornadoes examined (F1 and greater) and significant tornadoes and greater (F2 and greater). There are 40 total tornado events in the F1 and greater dataset (E1, E2, E3), which differs from the 100 total tornado events in the F1 and greater dataset (B1, B2, B3), defined in Table 4.4.

<table>
<thead>
<tr>
<th>Test Run</th>
<th>Event Total</th>
<th>Tornado Rating</th>
<th>Tornado Total</th>
<th>CAPE</th>
<th>CIN</th>
<th>SRH</th>
<th>LI</th>
</tr>
</thead>
<tbody>
<tr>
<td>E1</td>
<td>80</td>
<td>F1, F2, F3, F4</td>
<td>40</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>E2</td>
<td>80</td>
<td>F1, F2, F3, F4</td>
<td>40</td>
<td>X</td>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>E3</td>
<td>80</td>
<td>F1, F2, F3, F4</td>
<td>40</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>D1</td>
<td>80</td>
<td>F2, F3, F4</td>
<td>40</td>
<td>X</td>
<td></td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>D2</td>
<td>80</td>
<td>F2, F3, F4</td>
<td>40</td>
<td></td>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>D3</td>
<td>80</td>
<td>F2, F3, F4</td>
<td>40</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>

4.7 Neural Network Application

Noted as a highly efficient java-based NN program by users, the Encog Workbench 2.5 is used in this study. Created in 2010, Encog Workbench 2.5 offers an assortment of NN training architectures, techniques and additional other implementations useful to NN implementations. As described in Chapter 2, a NN consist of input neurons, a hidden layer of neurons, and output neurons. In order to train a NN using various datasets, a NN framework must be distinguished. This includes a NN architecture, type of learning, training technique and an activation function.

4.7.1 Neural network set-up

Feed-forward is an architecture type of NN commonly used, and is generally associated with a type of backpropagation training (Heaton 2010). As described in chapter 2, a feed-forward NN defines the “flow” of data as it is ingested through a neural network. Data is loaded into the input layer, advanced through the hidden layer, and processed through to the output layer. An example of the feed-forward NN for test A1 is
depicted in Figure 4.6. For a learning technique, supervised learning was best suited for this study. With each event in the input data, its coinciding output value was identified. If a tornado occurred, a “1” was assigned to the output, whereas if a tornado did not occur a “0” was assigned. With this type of learning, the NN is given data input and its known output, which gives the algorithm the task of discovering the pattern which allowed for the input values to equal the given output value.

Figure 4.6: Schematic of algorithm for dataset A1. The structure consists of variables Time, Season, SBCAPE, SBCIN, SRH0-3km, and LI ingested into the input layer; a hidden layer with two hidden nodes (H1 and H2), and an output layer.
The training technique used in this NN is resilient propagation (RPROG) due to its high efficiency in supervised feed-forward NNs using Encog (Heaton 2010). Unlike a more outdated general backpropagation technique, RPROG does not use learning rates or other assigned values necessary to the backpropagation algorithm. It is recognized as the best training technique in terms of its accuracy and ability to utilize several input variables (Chen and Su 2010). In this technique, the delta value calculated between the input node and hidden and output nodes is calculated individually for each connection. This allows the delta values to gradually alter until the NN matrix has finally settled and an ideal weight matrix has been met for the success of the NN training (Heaton 2010). For an activation function, sigmoid, best suited for this NN, was chosen as described in chapter two.

4.7.2 Training process

With a NN set up of a supervised feed-forward NN using the RPROG algorithm and the sigmoid activation function, each dataset is complete to be ingested into the NN. It is important to acknowledge that when training a NN which contains a hidden layer, the decision is assigned to the operator to determine the number of hidden nodes to include. In regards to hidden nodes, a specific set amount is undefined to any particular case. Advice for the number of hidden nodes often suggests to be less than or equal to the number of input nodes, but again the correct number of hidden nodes to use in a given problem is unknown. In the interest to evaluate the number of hidden nodes best suited for each individual case, each dataset was trained multiple times, each using a different amount of hidden nodes. These multiple attempts included 2, 4, 6, 8, and 10 hidden
nodes. Each dataset was carefully reviewed as it ran through numerous iterations, ensuring that the NN did not under-train or over-train, skewing the results found. After each dataset run, training performance percent errors were documented. Results of new tornado climatology for the NWS Huntsville CWA as well as NN training results are presented in Chapter 4.
CHAPTER FIVE

RESULTS AND DISCUSSION

In addition to creating a new tornado prediction tool, this research presents the opportunity to revise the NWS Huntsville CWA tornado climatology for years 1979 through 2010. Numerous training sets were ingested into a NN to examine how well it “learned” patterns conducive to tornadogenesis based off of instability parameters. These patterns would derive from the input variables of Time, Season, SBCAPE, SBCIN, \( \text{SRH}_{0-3km} \) and LI and its corresponding output value signifying it as a tornado event or non-tornado event. These convective parameters, examined in numerous studies (e.g., RAB 1998, Rasmussen 2003, Davies 2004, Jackson and Brown 2009, Kaltenböck et al. 2009) and by forecasters pertaining to severe weather development, were chosen as a starting point to investigate patterns in atmospheric conditions conducive to tornadogenesis. Derived from the various datasets specifically created for the NN training, results appear promising and reveal beneficial information regarding hazardous weather across the domain. Modified tornado climatology statistics are discussed first, followed by the NN training performance.
5.1  NWS Huntsville tornado climatology (revised)

Within the past 31 years, a total of 243 tornadoes (Figure 5.1) touched down within the NWS Huntsville CWA, with nearly 41% rated as F0/EF0. The time frame examined in this study is not identical to that of Weber (2006), but new statistics continue to show correlation within the overall trends and statistics for the localized area. It is imperative to note that these 243 tornadoes do not include tornadoes within tropical systems; however statistics including tropical influenced tornadoes were created for NWS Huntsville. If tornadoes within tropical cyclones were included in this study, the final tornado count would be 263. For the duration of the 31-year study, no F5/EF5 rated tornadoes occurred within the 14 counties. In NWS Huntsville CWA history, dating back through the late 1800s, only two F5 tornadoes have touched down. These tornadoes were two of a six total F5 rated tornadoes from the April 1974 Super Outbreak. Devastating lives from AL/MS northward to MI, a total 148 tornadoes were confirmed in this tornado outbreak, including 40 rated F4 tornadoes (Grazulis 1993).
Figure 5.1: NWS Huntsville tornadoes categorized by F-scale rating (1979-2010). The actual number of tornadoes is denoted in the numerical value above bar graph.

Defined in a study by Kis and Straka (2010), nocturnal tornadoes occur between sunset and sunrise. Figure B illustrates that approximately 76% of tornadoes within the NWS Huntsville CWA occurred between 1800 UTC and 0600 UTC, with 35% of those tornadoes being nocturnal. Of these 185 tornadoes, 123 occurred between 1800 UTC through 0000 UTC, and 62 tornadoes between 0000 UTC through 0600 UTC. Given the time of year, sunset tornadoes would not be considered until roughly 2200 UTC. According to Ashley (2007), nocturnal tornadoes are held accountable for 40% of tornado-related casualties, yet account for less than 25% of all tornado events across the US. This casualty statistic correlates sufficiently to a time period where humans are less likely to be weather aware, especially through the overnight hours when many are sleeping. Due to these distractions, humans are unable to receive pertinent weather
information disseminated by the NWS and local media, alerting them of quickly deteriorating and hazardous weather conditions. As a result, heavy emphasis for the importance acquiring NOAA All-Hazards weather radios has become important in the role from local media and NWS offices area wide to enhance severe weather awareness.

![Graph showing the number of tornadoes by time of event](image.jpg)

**Figure 5.2:** NWS Huntsville CWA tornadoes categorized by time of event (1979-2010). The actual number of tornadoes is denoted in the numerical value above bar graph.

Of all tornado events, nocturnal tornadoes are the least studied, and often are greatly overseen or grouped into the same classification as daytime tornadoes (Kis and Straka 2010). Studies often focus on tornadoes that occur during the late afternoon and early evening hours, as reviewed in this study by RAB (1998) and Rasmussen (2003). This study does not discriminate between daytime and nocturnal tornadoes; it encompasses all tornadoes by neglecting bias of event occurrence. For training set
purposes, time of event data was binned into four separate groups as an attempt for the
NN to find a pattern for tornadoes cases of all different time periods, and recognize subtle
atmospheric differences derived from different diurnal cycles.

For statistical purposes, tornadoes were categorized by seasons of spring (March,
April and May), summer (June, July and August), fall (September, October and
November), and winter (December, January and February). Often studies categorize
tornado seasons by warm season and cold season, but to incorporate the year-round
tornado threat in this study, these four seasons were used. Figure 5.3 illustrates that the
NWS Huntsville CWA continues to have a primary peak in the spring, followed by a
secondary peak in the fall. This supports previous statistics found indicating that
tornadoes pose a threat year-round (Grazilus 1993, Weber 2006). Highlighted in Table
5.1, it is seen that a majority of the F0/F1 tornadoes occur during the spring season
(March-April-May). Interestingly, it is depicted that two of the five F4 tornadoes
occurred during the winter season, followed by two in spring and one in fall.

<table>
<thead>
<tr>
<th>F-Scale</th>
<th>Spring</th>
<th>Summer</th>
<th>Fall</th>
<th>Winter</th>
</tr>
</thead>
<tbody>
<tr>
<td>F0</td>
<td>65</td>
<td>13</td>
<td>14</td>
<td>7</td>
</tr>
<tr>
<td>F1</td>
<td>64</td>
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<td>10</td>
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<tr>
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<td>0</td>
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<td>2</td>
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<tr>
<td>F4</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>F5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
Figure 5.3: NWS Huntsville CWA tornado events categorized by season (1979-2010). The actual number of tornadoes is denoted in the numerical value above the bar graph.

5.2 NN training performance

From Chapter 3, numerous training sets were compiled for NN training purposes. The varieties of training sets are assembled to include different F-scale rated tornadoes and input variable combinations. Data set training performances are presented by category of predetermined input variable combinations. It should be noted that all box-and-whisker plots (BW plots) from each test are identical, for example, Test A1 BW plots are identical to Test A2 BW plots, because the same data is used but the variable categories are different. The numerical value in the “Test” title represents the input variable included in the training set by category. BW plots will be presented several times to compare their findings to the NN training performance speculated.
5.2.1 Category 1: Time, Season, SBCAPE, SBCIN, SRH_{0-3km} and LI

As previously defined, training sets in category 1 incorporate all input variables (Time, Season, SBCAPE, SBCIN, SRH_{0-3km} and LI). To reiterate, all input data is normalized accordingly and output data is assigned a one for “tornado” and a zero for “non-tornado”. Test A accounts for F0 and greater tornadoes, Test B for ≥ F1 tornadoes, Test C for ≥ F2 tornadoes, and Test D includes F3 and F4 tornadoes. Figure 5.4 illustrates the training performance results for in the instance of all variables. The training error (%) found within the NN is automatically derived calculating the different (% error) between the ideal output and the actual output found by the NN and is automatically calculated by the NN. This calculation uses the RMS equation introduced in Chapter 3. Training performance error essentially illustrates the NNs inability to recognize a pattern between the given input data and known output of the events. All training runs endured numerous iterations, most reaching hundreds of thousands of iterations while closely monitored to ensure that overtraining did not occur. For all F3 and greater cases, only a few thousand iterations were encountered due its rapid ability to recognize patterns in the given cases.
Figure 5.4: NN Training performance error for Category 1 with input variables Time, Season, SBCAPE, SBCIN, SRH$_{0-3km}$ and LI. Decimal numerical values represent the NNs ability to train.

Of the attempted test runs in this category, Test A1 ranked highest at 41.81% in training performance error, followed by Test B1 at 38.40%. Test A had a total of 360 events, including 180 tornado events and 180 non-tornado events, where Test B had a lower total of 230 events, including 115 tornadoes and 115 non-tornadoes. Training performance errors of this magnitude are indicative of the NNs inability to delineate between tornado and non-tornado cases based on the chosen input variables. BW plots presented in Figs. 5.5 and 5.6 illustrate that parameter values for both tornado and non-tornado events used in the training sets are non-linear. These BW plots indicate that all parameter values overlap between tornado and non-tornado events. The similarity of
values between SBCAPE and SRH reflect those alike found in RAB (1998), Davies (2004), and Brown and Jackson (2009).

Even though overlap occurs for LI values in both tornado and non-tornado cases, it is interesting to mention values for non-tornado cases are substantially greater (more positive) and occur over a wider range with values extending from -8 to +24, with the 25th percentile between -2 and 0 and the 75th percentile zero roughly +6. Even though there are no set guidelines for defined LI values, it is commonly inferred that positive values such as these are expected for non-tornado events given that severe weather likely for LI values of negative one through -8. A good estimate of LI values is depicted in DeRubertis (2006), as noted in chapter two. LI values from Test B depicted greater (more positive) values for the non-tornado cases as well. The low end of 25th percentile begins at zero and increases up through a maximum value of 24. On average, SRH_{0-3km} values are greater for Test B versus Test A. On the assumption that reported F0 tornadoes may be skewed by erroneous storm reports due to their weakness, it is suggested that SRH_{0-3km} is not a reliable parameter to distinguish between tornadoes and non-tornadic severe weather in regards to cases including weak (F0 and F1) tornadoes.
Figure 5.5: Box-and-whisker plots (SBCAPE, SBCIN, SRH_{0-3km}, LI) for F0 and greater tornadoes. The extending whiskers represents the 10th (lower) and 90th (higher) percentiles; the upper threshold of the box represents the 75th percentile; the lower threshold of the box represents the 25th percentile; and the horizontal line indicates the median. Asterisks represent “outlier” values.
Figure 5.6: Box-and-whisker plots (SBCAPE, SBCIN, SRH_{0-3km}, LI) for F1 and greater tornadoes. The extending whiskers represents the 10\textsuperscript{th} (lower) and 90\textsuperscript{th} (higher) percentiles; the upper threshold of the box represents the 75\textsuperscript{th} percentile; the lower threshold of the box represents the 25\textsuperscript{th} percentile; and the horizontal line indicates the median. Asterisks represent “outlier” values.
Training performance error for Test C1 showed slight improvement with an error of 28.94%. Despite the lower error compared to that found in Test A1 and Test B1, it is reinstated that Test C training sets are composed of 80 total events, including 40 tornado cases and 40 non-tornado cases. Given the small data set of Test C, and even smaller Test D, results found from these two tests are examined with caution. In addition to training performance improvement from Test A and B, the training performance of 0.001% for Test D showed great ability to recognize patterns for F3-F4 tornado events when compared with non-tornado events. This test of data consists of 30 total events, with 15 tornado cases and 15 non-tornado cases. By removing F0 and F1 tornado events, BW plots for Test C (Figure 5.7) and Test D (Figure 5.8) continue to illustrate minor improvement in delineating between parameters values of tornado cases versus non-tornado cases.

SBCAPE values decreased from the mid-3000 J kg\(^{-1}\) including higher outliers, to below 2500 J kg\(^{-1}\) for the F2 and greater tornadoes solely by removing the influence of weak tornadoes. Additionally, by removing F0, F1 and F2 tornado data, SBCAPE values for F3-F4 tornadoes decreased to below 2000 J kg\(^{-1}\), similar to values found in RAB (1998) and Jackson and Brown (2009). LI values decreased, signifying the likelihood of severe weather. SBCIN value differences were not sufficient between Tests A, B, or C. However, in Test D, SBCIN values were “greater” (more negative) for tornadic storms than values found for non-tornadic storms. For SRH\(_{0-3}\)km, significant differences in values surface in the cases of F2 and greater (Test C) and F3 and greater (Test D), where the least amount of data overlap is found within Test D.
Figure 5.7: Box-and-whisker plots (SBCAPE, SBCIN, SRH₀-₃km, LI) for F2 and greater tornadoes. The extending whiskers represents the 10th (lower) and 90th (higher) percentiles; the upper threshold of the box represents the 75th percentile; the lower threshold of the box represents the 25th percentile; and the horizontal line indicates the median. Asterisks represent “outlier” values.
Figure 5.8: Box-and-whisker plots (SBCAPE, SBCIN, SRH0-3km, LI) for F3 and greater tornadoes (Test 4). The extending whiskers represent the 10th (lower) and 90th (higher) percentiles; the upper threshold of the box represents the 75th percentile; the lower threshold of the box represents the 25th percentile; and the horizontal line indicates the median. Asterisks represent “outlier” values.
5.2.2 Category 2: Time, Season, SBCAPE, and SRH$_{0-3km}$

Inspired by the results of the BW plots examined above for all input variables, additional training sets for two additional input variable combinations were created and fed through the NN. Because only subtle differences were found between variables, it is at the interest of this study to see if the NN performs better when only given certain variable values. Category 2 input variables consist of Time, Season, SBCAPE and SRH$_{0-3km}$. Displayed in Figure 5.9, training performance error found in Test A2, B2, C2 and D2 is similar those training performance results for Test A1, B1, C1 and D1.

Figure 5.9: NN Training performance error for Category 2 with input variables Time, Season, SBCAPE, SBCIN, SRH$_{0-3km}$ and LI. Decimal numerical values represent the NNs ability to train.
With a training performance error of 40.82%, Test A2 had the greatest training error of all the data sets in this category. In comparison to the 41.81% error found from Test A1 for all six input variables, it is observed that training error performance did not improve for Test A2. With a training performance error of 40.71%, Test B2 decreased up approximately 3% in performance from the previous training error of 38.40% error for Test B1. SBCAPE and SRH$_{0-3km}$ values combined continue to withstand any influence in the NNs ability to discern between tornado and non-tornado events. To support these findings, BW plots are displayed, presenting SBCAPE from Test A and B in Figure 5.10 and SRH$_{0-3km}$ from Test A and B in Figure 5.11. These results are to those found in RAB (1998) and Davies (2004).
Figure 5.10: Box-and-whisker plots of SBCAPE for Test A (F0 and greater) and Test B (F1 and greater). The extending whiskers represents the 10th (lower) and 90th (higher) percentiles; the upper threshold of the box represents the 75th percentile; the lower threshold of the box represents the 25th percentile; and the horizontal line indicates the median. Asterisks represent “outlier” values.
Figure 5.11: Box-and-whisker plots of SRH\textsubscript{0-3km} for Test A (F0 and greater) and Test B (F1 and greater). The extending whiskers represent the 10\textsuperscript{th} (lower) and 90\textsuperscript{th} (higher) percentiles; the upper threshold of the box represents the 75\textsuperscript{th} percentile; the lower threshold of the box represents the 25\textsuperscript{th} percentile; and the horizontal line indicates the median. Asterisks represent “outlier” values.
Of the test runs conducted in this category, data for F2 and greater tornadoes demonstrated the greatest training performance for the chosen input variables. With less than 2% improvement from Test C1, Test C2 had a performance error of 27.63%. Comparing the SBCAPE and SRH$_{0-3km}$ BW plots for Test C, it is evident that the removal of F0 and F1 data increases the NN performance. In the case of Test D2, atmospheric conditions favorable for violent tornadoes compared to that of non-tornadic storms continued to illustrate patterns easily recognized by the NN, with a performance error of 0.001% for Test D2.
Figure 5.12: Box-and-whisker plots of SBCAPE for Test C (F2 and greater) and Test D (F3 and greater). The extending whiskers represent the 10th (lower) and 90th (higher) percentiles; the upper threshold of the box represents the 75th percentile; the lower threshold of the box represents the 25th percentile; and the horizontal line indicates the median. Asterisks represent “outlier” values.
Figure 5.13: Box-and-whisker plots of SRH_{0-3km} for Test C (F2 and greater) and Test D (F3 and greater). The extending whiskers represent the 10th (lower) and 90th (higher) percentiles; the upper threshold of the box represents the 75th percentile; the lower threshold of the box represents the 25th percentile; and the horizontal line indicates the median. Asterisks represent “outlier” values.
5.2.3 Category 3: Time, Season, SBCIN, SRH\textsubscript{0-3km}, and LI

Variables affiliated with category 3 test runs include Time, Season, SBCIN, SRH\textsubscript{0-3km} and LI (Figure 5.14). This combination of variables is used as an attempt to observe how the performance of the NN varies by excluding influence from SBCAPE values.

![Figure 5.14: NN Training performance error for Category 3 with input variables Time, Season, SBCIN, SRH\textsubscript{0-3km} and LI.](image)

Similar to test runs A1 and A2, Test A3 obtained the highest percent training error in performance in its category. Again, the training error of 40.63% found from this category shows no improvement from that of Test A1 and A2. With the removal of F0 tornado data, Test B3 training performance error decreased to 30.05%, approximately an 8% drop from Test B2. Likewise, Test C3 shows improvement in its performance with an
error of 16.46%, slightly under a 15% improvement from Test C2. It is also noted that the NN continued to distinguish patterns between violent tornadoes and non-tornado events in Test D3. BW plots for Tests A3 and B3 for SBCIN (Figure 5.15), SRH_{0-3km} (Figure 5.16), and LI (Figure 5.17) are examined accordingly. These plots are followed by SBCIN (Figure 5.18), SRH_{0-3km} (Figure 5.19), and LI (Figure 5.20) for Tests C3 and D3.
Figure 5.15: Box-and-whisker plots of SBCIN for Test A (F0 and greater) and Test B (F2 and greater). The extending whiskers represents the 10th (lower) and 90th (higher) percentiles; the upper threshold of the box represents the 75th percentile; the lower threshold of the box represents the 25th percentile; and the horizontal line indicates the median. Asterisks represent “outlier” values.
Figure 5.16: Box-and-whisker plots of SRH\textsubscript{0-3km} for Test A (F0 and greater) and Test B (F1 and greater). The extending whiskers represents the 10\textsuperscript{th} (lower) and 90\textsuperscript{th} (higher) percentiles; the upper threshold of the box represents the 75\textsuperscript{th} percentile; the lower threshold of the box represents the 25\textsuperscript{th} percentile; and the horizontal line indicates the median. Asterisks represent “outlier” values.
Figure 5.17: Box-and-whisker plots of LI for Test A (F0 and greater) and Test B (F1 and greater). The extending whiskers represents the 10th (lower) and 90th (higher) percentiles; the upper threshold of the box represents the 75th percentile; the lower threshold of the box represents the 25th percentile; and the horizontal line indicates the median. Asterisks represent “outlier” values.
Figure 5.18: Box-and-whisker plots of SBCIN for Test C (F2 and greater) and Test D (F3 and greater). The extending whiskers represents the 10th (lower) and 90th (higher) percentiles; the upper threshold of the box represents the 75th percentile; the lower threshold of the box represents the 25th percentile; and the horizontal line indicates the median. Asterisks represent “outlier” values.
Figure 5.19: Box-and-whisker plots of SRH₀-3km for Test C (F2 and greater) and Test D (F3 and greater. The extending whiskers represents the 10ᵗʰ (lower) and 90ᵗʰ (higher) percentiles; the upper threshold of the box represents the 75ᵗʰ percentile; the lower threshold of the box represents the 25ᵗʰ percentile; and the horizontal line indicates the median. Asterisks represent “outlier” values.
Figure 5.20: Box-and-whisker plots of LI for Test C (F2 and greater) and Test D (F3 and greater). The extending whiskers represent the 10th (lower) and 90th (higher) percentiles; the upper threshold of the box represents the 75th percentile; the lower threshold of the box represents the 25th percentile; and the horizontal line indicates the median. Asterisks represent “outlier” values.
5.2.4 Statistical comparison of two training sets

The combined total of tornado and non-tornado events in test runs of A, B, C, and D ranged from a total of 360 to a total 24. In evaluating test datasets A through D, these total event inconsistencies hindered the ability to compare these results statistically correct. Therefore, in addition to Test C, a training set consisting of F1 and greater tornado data was created, Test E. In this set, there are a total of 80 events, with 40 tornado events and 40 non-tornado events, equivalent to that of Test C. Identical to previous dataset methods, these 80 cases were chosen at random. Training performance errors are shown in Figs. 5.21 and 5.22.

![Figure 5.21: NN Training performance for F1 and greater tornadoes (Test E), with 40 tornado events and 40 non-tornado events. Error for category 1 input variables (Time, Season, SBCAPE, SBCIN, SRH\textsubscript{0-3km}, and LI), category 2 input variables (Time, Season, SBCAPE, and SRH\textsubscript{0-3km}), and category 3 input variables (Time, Season, SBCIN, SRH\textsubscript{0-3km}, and LI).](image-url)
Figure 5.22: NN Training performance for F2 and greater tornadoes (Test C), with 40 tornado events and 40 non-tornado events. Error for category 1 input variables (Time, Season, SBCAPE, SBCIN, SRH$_{0-3km}$, and LI), category 2 input variables (Time, Season, SBCAPE, and SRH$_{0-3km}$), and category 3 input variables (Time, Season, SBCIN, SRH$_{0-3km}$, and LI).

Incorporating all six input variables (category 1) into the dataset, both tests indicate that the NN struggled to training using the given data, with an error of 38.45% for Test E and 28.94% for test C. By eliminating SBCIN and LI (category 2), the F1 and greater tornado dataset (Test E) decreased to a 25.38% error, where Test B had a corresponding 27.63% error, less than 1% difference from the previous run. With a 16.46% training percent error, Test C showed to have the best results out of all the variable combinations, when eliminating SBCAPE. However, Test E had a training performance error of 30.30%, which made the training set of category 2 variables the
second best choice for training data. Figure 5.23 and 5.24 illustrate the BW plots associated with training sets E and C.

Figure 5.23: Box-and-whisker plots of SBCAPE, SBCIN, SRH0-3km, and LI for Test E (F1 and greater for 80 total events). The extending whiskers represents the 10th (lower) and 90th (higher) percentiles; the upper threshold of the box represents the 75th percentile; the lower threshold of the box represents the 25th percentile; and the horizontal line indicates the median. Asterisks represent “outlier” values.
Figure 5.24: Box-and-whisker plots of SBCAPE, SBCIN, SRH_{0-3km}, and LI for Test C (F2 and greater). The extending whiskers represent the 10\textsuperscript{th} (lower) and 90\textsuperscript{th} (higher) percentiles; the upper threshold of the box represents the 75\textsuperscript{th} percentile; the lower threshold of the box represents the 25\textsuperscript{th} percentile; and the horizontal line indicates the median. Asterisks represent “outlier” values.
As seen in previous results for all test runs, SBCAPE values in Test E (F1 and greater) overlap greatly between tornadic and non-tornadic events, noting that SBCAPE values were lower than those observed in the non-tornadic events. It is suggested that SBCAPE, even in a smaller dataset, does not discriminate enough to be used as a distinguishing parameter in an event looking to weaker tornadoes, but it is still thermodynamically critical in forecasting deep convection. This revisits the suggestion that with weaker tornadoes, more small-scale factors will need to be incorporated into the forecasting process. Similar thoughts can be directed towards SBCIN and LI values. Though SRH$_{0-3km}$ values indicated overlap between the two different storm types, values consistently illustrated that higher values of SRH$_{0-3km}$ were accounted for in tornadic storms when compared to the non-tornadic storms. Overall considering that Test E and Test C had decent training performance errors, these results are not sufficient enough to apply benefit to forecasters at this time. Applying such a small dataset to a pattern recognition algorithm does not expose the NN to an adequate amount of patterns in which would be considered necessary for a reliable source.

5.3 Overview and discussion

To evaluate the results, all training performances are examined in Table 5.2 and Table 5.3. These results will be introduced by the four “test” sets (F0 and greater, F1 and greater, F2 and greater, and F3 and greater) evaluating their performance across all three categories.
Table 5.2: Comparison of final performance percent errors for Test A, B, C, and D, when trained for Category 1, Category 2 and Category 3.

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<thead>
<tr>
<th>Test Run</th>
<th>Category 1</th>
<th>Category 2</th>
<th>Category 3</th>
</tr>
</thead>
<tbody>
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<td>40.63%</td>
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<tr>
<td>Test C (F2+)</td>
<td>28.94%</td>
<td>27.63%</td>
<td>16.46%</td>
</tr>
<tr>
<td>Test D (F3+)</td>
<td>0.001%</td>
<td>0.001%</td>
<td>0.001%</td>
</tr>
</tbody>
</table>

Table 5.3: Comparison of final performance percent errors for Test E and C, when trained for Category 1, Category 2 and Category 3.

<table>
<thead>
<tr>
<th>Test Run</th>
<th>Category 1</th>
<th>Category 2</th>
<th>Category 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test E (F1+)</td>
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<td>25.38%</td>
<td>30.30%</td>
</tr>
<tr>
<td>Test C (F2+)</td>
<td>28.94%</td>
<td>27.63%</td>
<td>16.46%</td>
</tr>
</tbody>
</table>

Overall, training runs conducted for Test A illustrate that the NN was unable to find pattern recognition between F0 and greater tornadoes and non-tornado events, with an average of 43% performance error. It is suspected that parameter values obtained for previous F0 tornadoes across the NWS Huntsville CWA are potentially creating noise within atmospheric patterns. It is believed that, in addition to a favorable environment for severe weather, it only requires a small-scale weak boundary to generate an F0 tornado, which has in fact been observed on several occasions. For this reason, parameter values could quickly change and more so could not be recognized from the data extracted from the NARR data set. As a result, favorable conditions differing severe thunderstorm events from F0 tornadoes would not be recognized by the NN. These similar weak-defining conditions seem to apply to results from Test B. An overall was observed in the NN’s ability to recognize patterns including data for F0 tornadoes and greater.
However, an improvement was observed in Test B3, where all variables excluding SBCAPE were tested for pattern recognition. This indicates that even though SBCAPE is a significant instability parameter necessary for the development of convection and severe weather, it may not be a parameter necessary to discern between a tornado event and a non-tornado event. As a result, it is beneficial for forecasters to acknowledge that SBCAPE should not be a primary deciding factor in tornado prediction.

Compared to the inclusion of F0 and F1 tornadoes, the NN performance for F2 and greater tornado events showed improvement. For F3 and greater, the NN revealed an ability to train and recognize a pattern within the data. While this was to some extent expected, these results are exercised with caution. It is known that environments favorable for weaker tornadoes in many instances will likely differ from those environments necessary for significant to violent tornadoes. Factors that can greatly influence this are the variable terrain in place across the NWS Huntsville CWA, which can enhance tornado development. For the time period 1979 through 2010, Figure 5.25 displays all tornado event touchdown locations overlayed across the topography map previously seen earlier in this study.
Figure 5.25. Topography map of NWS Huntsville CWA with tornado formation locations denoted in yellow inverted triangles. Lighter shades of green represent valleys, darker shades of brown represent plateaus and hills with the highest terrain in shades of gray and white. Created using ArcGIS software.

Though the NN revealed training ability for F3 and greater tornado events, for a NN to sufficiently train, numerous data points are extremely essential. This allows the NN to be exposed to a vast variety of possible patterns significant for the development of these tornadoes, and as its primary characteristic, the ability to recognize subtleties in the data not easily recognized by humans. Given a larger sample size, the NN will have the opportunity to recognize several pattern variations in attempting to solve its initial problem. For Test C, 40 tornado events were included in the training data set, which accounts for approximately 16% of all tornadoes that have occurred in the NWS Huntsville CWA. In addition in Test D, tornado data accounts for 4.9% of all tornadoes, with 12 tornado events used. These smaller data sets are initially a result of the low occurrence of significant to violent tornadoes. However, to supply sufficient data needed
for training a NN, a larger data set will be needed. Future work involving the expansion of available data for the enhancement of this study is presented in the next chapter. Storm-environment parameter values portrayed in BW plots were similar to those found in RAB (1998), Davies (2004) and Jackson and Brown (2009).
CHAPTER SIX

CONCLUSION AND FUTURE WORK

The purpose of this study was to create an automated tool to enhance tornado forecasting performance and awareness for operational meteorologists at the NWS Huntsville WFO. In this attempt, sounding-derived parameters commonly utilized by forecasters during hazardous weather operations were investigated. These parameters, surface-based CAPE, surface-based CIN, SRH_{0-3km}, and their ability to discriminate between tornado and non-tornado events, were examined. Parameter values from a thirty-one year tornado database created for the NWS Huntsville CWA were extracted from the North American Regional Reanalysis (NARR) dataset, and ingested into a neural network. Neural networks mimic the human brain as processing systems that excel in pattern recognition. They are commonly used to recognize subtleties within complex datasets often not easily recognized by humans.

Training datasets for this study consisted of variable and tornado intensification combination sets. Due to nonlinear parameter values, results showed that for all tornadoes (F0-F4), the NN was unable to “learn” the difference between tornado and non-tornado events during the training process. Training datasets for significant tornadoes (at least F2), training performance improved, but still did not indicate that the NN had
learned patterns within the atmospheric conditions. For tornadoes (F3-F4), the NN trained successfully to below 1% performance error. However, given the localized area of this study, the dataset available for F3-F4 tornadoes was extremely small (15 tornado events and 15 non-tornado events). Unfortunately, a small dataset does not provide an adequate amount of patterns to be recognized by the NN. This limited data hinders atmospheric conditions from being well represented, and thus would not be equipped for operational use.

Box-and-whisker plots of the training datasets illustrated that tornado and non-tornado parameter values overlapped, indicating nonlinearity within the data, especially for F0-F4 and F1-F4 tornado events. Given the difficulty of tornado prediction for this reason, the overall nonlinearity was partially recognized by forecasters. Because of this it was anticipated any subtleties present in the provided parameters that the NN would recognize them. Considering violent tornadoes, comparisons of SRH$_{0-3km}$ demonstrated that though a good portion of values overlapped, higher values correlated with tornado events, and lower values correlated with non-tornado events. This suggests that SRH$_{0-3km}$ values may serve beneficial to forecasting for potentially dangerous tornado events. While potential energy plays an important in the development of deep convection, results suggest that SBCAPE does not perform well in discriminating between tornado and non-tornado events, and would not recommend solely using this parameter to forecast future events.

Even though this tool is not operationally ready, results are still promising, insinuating that numerous opportunities still present themselves for performance improvement and the future creation of an operational tool beneficial to forecasters. It
should be acknowledged that creation of this tool would also serve to accommodate forecasters from different forecast-experience background. Future work will assess the potential of incorporating new variables into the training sets. At the time of this study, SBCAPE, SBCIN, SRH$_{0-3km}$, and LI are the only available derived variables from the NARR. However, other data has been made available that would allow for the calculation of new indices, such as SRH$_{0-1km}$. In addition, new derived parameters may become readily available in the near future. New studies are beginning to suggest that SRH$_{0-1km}$ could add beneficial findings to tornadogenesis in addition to SRH$_{0-1km}$. However, it is noted that a majority of indices originate from the main variables presented in this case, but results could show improvement.

Apart from severe weather parameters, other variables to consider for future implementation are lifting condensational level (LCL) and dew point. These two parameters would incorporate a moisture parameter, where moisture is a key component to convection. The LCL is the point at which the air parcel is saturated, signifying the location of a cloud base. General severe weather knowledge acknowledges that the lower the LCL height, the more favorable the environment may become for tornadogenesis. If LCL heights are closer to the ground, then extremely strong buoyancy is not necessarily needed for convection. Dew points describe how much moisture is present in the current environment, and may be beneficial as well to the discrimination between tornado and non-tornado events through patterns recognized by a NN.

An issue raised in this study was also connected to the sample size available. The NWS Huntsville CWA is a small area, inhibiting the likelihood of an extremely large dataset. As previously mentioned, within the past 31 years, only 243 tornadoes have
occurred within the domain, not including tornadoes influenced by tropical systems. In addition, 10% of these data were set aside for validation purposes if the NN had, in fact, trained. As a result, it is considered that the domain be expanded to incorporate a more abundant data set. A larger data set would allow for more examples to be examined by the NN for pattern recognition, especially for the significant and violent tornadoes. Given the “trial-and-error” approach necessary for NN training, as in any other research, it has not been determined the extent of the domain expansion. However, it will be noted that regions near coastlines will be not included.
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